UNIVERSITY OF ZIMBABWE

FACULTY OF SOCIAL STUDIES

DEPARTMENT OF ECONOMICS

Analysis of Factors Influencing Smallholder Farmers' Participation in Non-Farm Employment Activities and their Impact on Food Security: The Case of Mbire District, Mashonaland Central Province, Zimbabwe.

BY:

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Dissertation Submitted in Partial Fulfilment of the Requirements of the Master of Science Degree in Economics

May 2019

Declaration

This dissertation is entirely my own work and references have been made where other sources were used. I do here by declare that this piece of work have not been previously submitted for the award of another degree at any university around the world.

Signed:_______________ **Date:** 16 August 2019

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Dedication

I dedicate this piece of work to my lovely wife, LaToya and to my great, lovely, amazing and supportive family.

Acknowledgements

I would like to express my sincere gratitude to my supervisor, Dr. C. Mumbengegwi for your guidance throughout this research and your constructive criticism and valuable comments that induced critical and creative thinking in doing my research. The completion of this work would have been impossible without your guidance.

My sincere gratitude also goes to Mr. M. Chundu, Dr. C. Pindiriri and Dr. T. Chuma for your support, your valuable comments and constructive criticism.

I would also want to send my gratitude to my brother (Zebedia Tendai Mundowa) and his wife (Wimbai Mundowa) for their financial and emotional support throughout my university life.

To Prosper Ziyadhuma, Raynold Runganga and the rest of Masters in Economics (MEC) class of 2019, I would like to thank you guys for your immense support in data collection and the ideas you gave me to build my research. You are awesome guys. I always appreciate your teamwork.

A special word of thanks to the African Economic Research Consortium (AERC) for their financial support and research training through the Joint Facility for Electives (JFE) that I have attended in Nairobi, Kenya under the Collaborative Master's Program (CMAP) in 2018. My specific thanks also goes to Dr. Jean Brou for the econometrics training at JFE, particularly on treatment evaluation and the Propensity Score Matching (PSM) technique, which have been adopted in this dissertation.

My sincere gratitude to the AERC, JFE, CMAP class of 2018 for their support and ideas. I would also want to send my specific gratitude to Derrick Mbalule of Makerere University, Uganda, who gave me the ideas and insights in this field of research especially in topic shaping.

Above all, for without the Almighty God, I would not have done this work.

Abstract

This dissertation investigates the factors influencing smallholder farmer's decision to participate in non-farm employment activities and the impact of this on rural households' food security status *in the Mbire District of Zimbabwe. The analysis uses a treatment evaluation model and the associated propensity score matching (PSM) technique, which permits the comparisons between the food security status of smallholder farmers who participate in non-farm employment activities and those who do not. Estimation of propensity scores enable us to identify the factors influencing smallholder farmers' decision to diversify into non-farm employment activities. The results indicate that a number of demographic (gender and education of household head), infrastructural (internet access and distance to the main road) and farm level characteristics (land size, livestock herd owned and productive assets) have qualitative and quantitatively different impacts on rural households' participation in non-farm employment activities. Further, the empirical analysis confirms that diversifying into non-farm employment activities improves rural households' food security status. The results imply that non-farm employment activities can be a way out of food insecurity in Mbire district. The study therefore recommends the government and NGOs to induce the rural households to diversify into non-farm activities as they improve their food security status since the climatic conditions in the district are not well suitable for agricultural practices.*

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List of Acronyms

AME	Average Marginal Effects
ATET	Average Treatment Effect on the Treated
BLUE	Best Linear Unbiased Estimator
CARE	Cooperative for Assistance and Relief Everywhere
CLRM	Classical Linear Regression Model
FAO	Food Agricultural Organisation
FGD	Focus Group Discussion
GoZ	Government of Zimbabwe
IFAD	International Fund for Agricultural Development
KBM	Kernel Based Matching
MEA	Marginal Effects at Averages
MLE	Maximum Likelihood Estimation
NGO	Non-Governmental Organisation
NNM	nearest Neighbourhood Matching
OLS	Ordinary Least Squares
PSM	Propensity Score Matching
RM	Radius Matching
SDG	Sustainable Development Goals
SGR	Strategic Grain Reserve
SSA	Sub-Sahara Africa
USAID	United States Agency of International Development
WB	World Bank
WFP	World Food Program

ZIMSTAT	Zimbabwe National Statistics Agency
ZimVAC	Zimbabwe Vulnerability Assessment Committee

CHAPTER ONE

INTRODUCTION AND BACKGROUND

1.1 Introduction

One of the major public policy challenges facing Sub-Sahara Africa (SSA) is feeding its growing population and alleviating food insecurity, especially among food-deficit rural farm households (Owusu *et al*., 2011). Participating in non-farm employment activities[1] is one of the most widespread coping strategies used to combat food insecurity by food-deficit farm households. The factors influencing the choice to participate and the implications of this participation on food security are not altogether known. Some strands of literature suggest that non-farm employment activities improve rural households' incomes and food security (Mishra and Rahman, 2018; Seng, 2015; Shehu and Sidique, 2013), while others suggest that it has no or even negative effects (Pfeiffer *et al*., 2009; Kinuthia *et al*., 2018). Knowledge of these factors would help inform policy makers in government to identify those rural households most vulnerable to food insecurity and to design more accurately targeted policy interventions. This study investigates non-farm employment activities as a coping strategy to combat food insecurity among rural households in Mbire district of the Mashonaland Central Province of Zimbabwe. It seeks to identify the factors influencing rural farm households' participation in non-farm employment activities and the implications of their participation on food security[2].

Zimbabwe is ranked 108th out of 119 on the Global Hunger Index (World Food Program (WFP), 2018): making it one of the most food-insecure countries in the developing world. While most districts in Mashonaland Central Province are largely food-secure, as they lie in agro-ecological regions 2A and 2B, which are more suitable for agricultural production, the same cannot be said of Mbire district of the same province. Mbire is located in the low-lying mid-Zambezi valley forming part of agro-ecological regions 4 and 5, which makes it unsuitable for agriculture, especially food crop production due to its high temperatures and low and unpredictable rainfall

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[1.] Any gainful employment sought by the family labourer off the household farm, which include fishing, trading, construction, transport, agro-processing and gold panning (Tran *et al*., 2015).

[2.] Exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life (World Food Summit, 1996).

patterns (Fritz *et al*., 2003). As a result, Mbire is one of the four out of sixty rural districts of Zimbabwe experiencing high levels of food insecurity; with between 39 and 42 per cent of households being food insecure (Zimbabwe Vulnerability Assessment Committee (ZimVAC), 2018). Thus, smallholder farmers in Mbire district largely rely on incomes from non-farm employment activities, food aid from the government and humanitarian organisations[3] to cope with food insecurity (Nyamwanza, 2014).

1.2 Background to the Study

Hunger and famine, being results of food insecurity have been always problems in the Southern Africa region, Zimbabwe included. Like other developing nations, Zimbabwe is renowned for its high dependence on agriculture. According to the Zimbabwe 2012 population census, 70 percent of the population of the country derives its livelihood from agriculture, which is mostly dependent on rain fed farming (Zimbabwe National Statistics Agency (ZIMSTAT), 2012). Rural smallholder farmers (peasants) also dominate the agricultural sector, which contribute 75.6 percent of the national poverty (Food Agricultural Organisation (FAO), 2018). According to these statistics, poverty and food insecurity are rural phenomena in Zimbabwe. This means that the government and humanitarian organisations should focus more on rural areas to significantly alleviate national poverty and food insecurity.

The total number of food insecure people in Zimbabwe was 1 490 024 (translating to 250 000 households) in 2017 (ZimVAC, 2017). Extreme poverty is more prevalent in rural areas where 23 percent of the households typically do not have enough resources to meet their minimum daily food needs (ZIMSTAT, 2017). The food insecurity situation is even worse in Mbire district of Mashonaland Central, with 39.57 percent of the households facing chronic and severe food insecurity (ZimVAC, 2018). According to FAO (2018), smallholder farmers in the district are constantly facing problems of recurring food insecurity due to low and erratic rainfall, floods, high population (translating to high dependency ratio) and extremely high temperatures of up to 40^{o}C in summer. The government of Zimbabwe (GoZ) and some humanitarian organisations are implementing various policies and programs in an attempt to alleviate food insecurity through

[3.] Zimbabwe Red Cross Society, CARE Consortium and World Food Program.

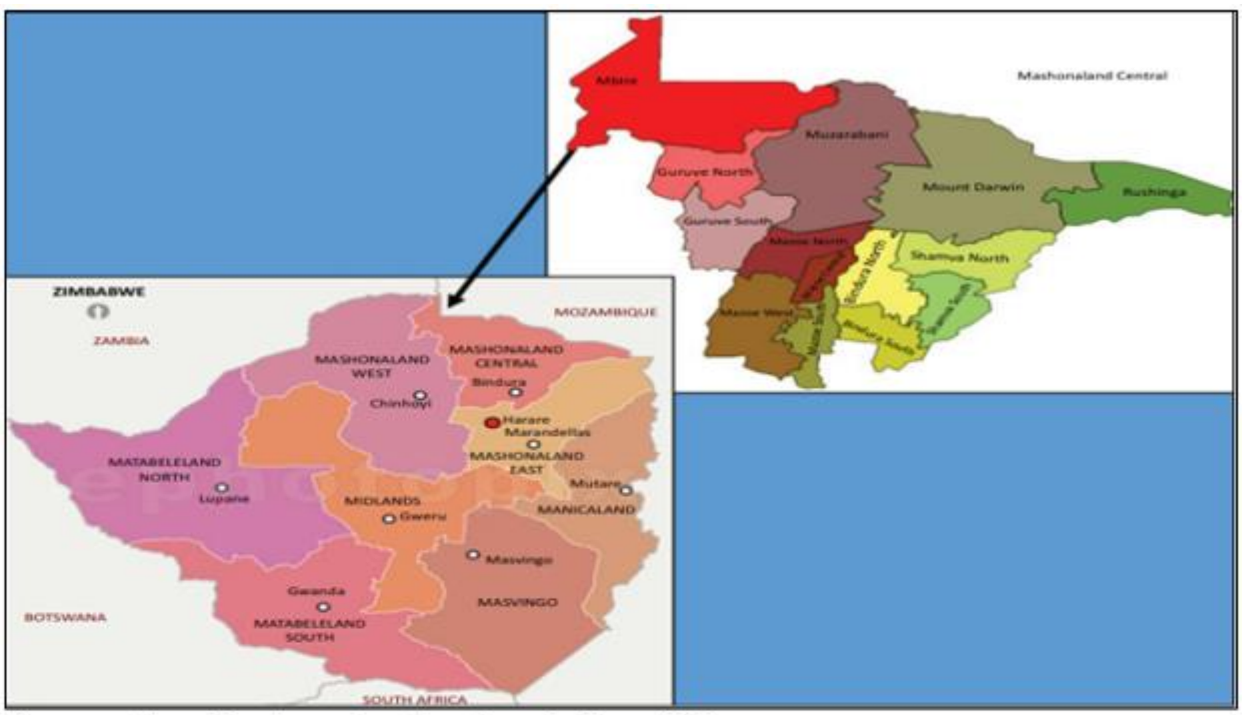
improving agricultural productivity and yields, direct food hamper provision and cash transfers (FAO, 2018).

However, these efforts by the government of Zimbabwe and non-governmental organisations (NGOs) have not yielded the expected positive outcome to improve food security as evidenced by the increasing food insecurity trend (ZimVAC, 2018). Therefore, achieving the goal of food security through increasing agricultural food production alone is insufficient. There are other widely applied coping strategies to food insecurity problem such as participation in non-farm employment activities. However, some studies and policy makers underestimate the role of non-farm employment to curb the problem of food insecurity. In the Mbire district, smaller proportion of the households have been observed participating in non-farm employment activities (Nyamwanza, 2014). It is therefore worrisome that the bigger proportion of households (67% according to the study survey data) in the district is still dedicated to farming as the sole source of livelihood, and that the GoZ is applying "*one-size fits-all*" policies and programs to alleviate food insecurity through seeking to increase agricultural production across all rural areas despite their climatic differences.

Furthermore, enhancing non-farm activities in Zimbabwe has not been well coordinated with the rural agricultural development policies. However, some households (33% according to the survey data) in Mbire district are already adopting non-farm employment to cope with food insecurity challenge. According to the International Fund for Agricultural Development (IFAD) (2011), increasing yield alone may not suffice but there is also need to consider other possible food security improving activities such as participation in non-farm employment activities. Therefore, small rural household farmers in Mbire district might need to increase their involvement in non-farm activities such as fishing, petty trade, tannery, gold panning, and full-time or part-time wage employment. This has a direct impact on food security by increasing expenditure on food and indirectly through increasing agricultural production and productivity by enabling the households to finance agricultural inputs and productivity enhancing technology.

Mbire district (Figure 1) forms the major part of the low-lying mid-Zambezi Valley in Zimbabwe's Mashonaland Central Province. Households in Mbire district primarily work in their own fields during the cropping season, but some of them are engaged in non-farm employment regardless of the season to supplement their agricultural produce, government and donor aid, which are not adding up (Nyamwanza, 2014). The area is characterised by low and erratic rainfall and floods occurring simultaneously because the Zambezi River has its source in the equatorial region, which receives high rainfall amount throughout the year and the district is located in a valley (basin) that collects the water flowing from other big rivers such as Angwa and Mazowe Rivers. In the absence or in the presence of little rainfall, farmers in Mbire district constantly face food shortages and crises (Nyamwanza, 2014). As a result, many households in the district are net food buyers, purchasing up to 65 percent of their maize from the market since they do not produce enough food to meet their yearly requirements. On average, their food purchases make up 56 percent of household expenses (ZimVAC, 2016). Thus, focusing on agricultural production alone may not be enough to alleviate the problem of food insecurity.

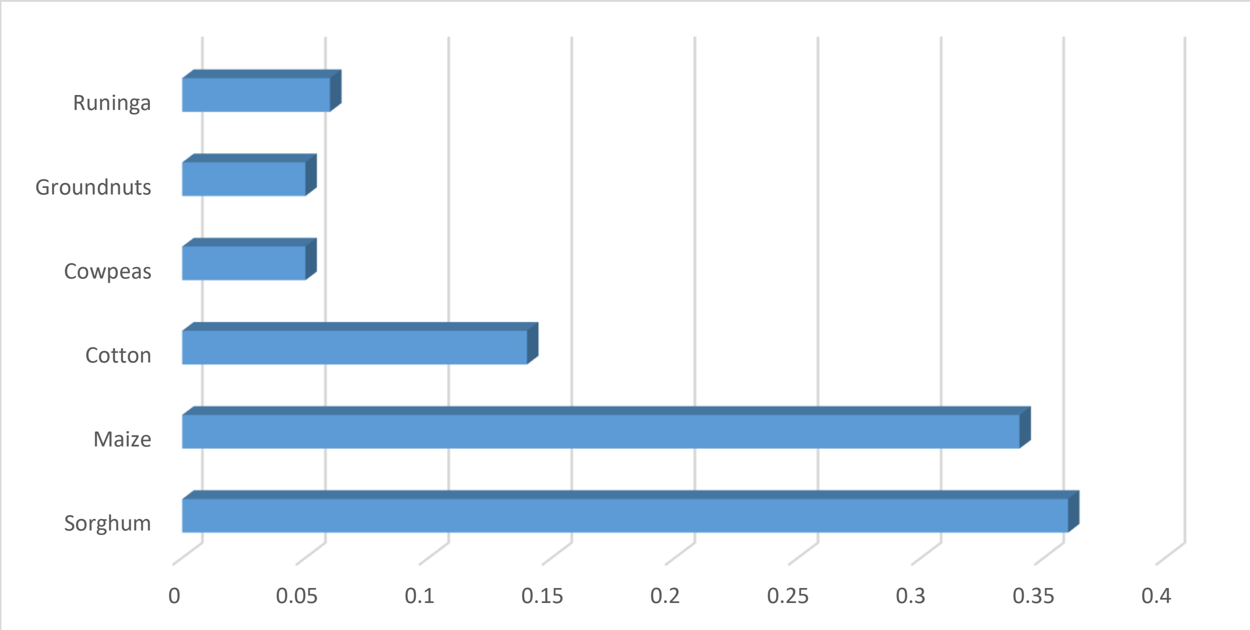
Figure 1: Map showing the location of Mbire district in Zimbabwe



Source: Adapted by the author from Google Maps 2018

There are a number of crops grown in Mbire district. Figure 4 present the various types of crops grown and their proportions in terms the proportion of the land occupied by each crop.

Figure 2: Types of Crops Grown and a Share of Each Crop on the Cultivated Land



Source: Author's illustration using Survey data (2019)

The main crops grown in the district are sorghum and maize as depicted in figure 2. Maize and sorghum occupy larger part of the cultivated land with 34 percent and 36 percent respectively. Runinga is the new upcoming cash crop grown in Mbire district. The small grain is not yet popular, but people are increasingly growing it since it does not require lots of rainfall and it fetches good prices in the market.

Policy makers should consider focusing not only on agriculture but also on the non-farm sector as it helps improve agricultural yields, income, create employment and alleviate food insecurity among rural households (Tran *et al*., 2015). Nevertheless, most governments undermine the role of the non-farm activities because they are considered to be of low productivity in nature, produce low quality outcomes, not sustainable, and wither as a country develops (Nyamwanza, 2014). More so, farm household model of Singh *et al*. (1986) posit that participating in non-farm activities depletes the labour allocated to farm production, which might diminish yields from the farm and can contribute to food insecurity if the marginal productivity of labour from the non-farm activities is less than the marginal productivity of labour in farm production.

However, there is no consensus in literature pertaining to the implications of participation in non-farm activities on rural households' food security status. Some studies on non-farm employment show that farmers in the rural economy participate in non-farm activities in order to alleviate food insecurity (Agyeman *et al*., 2014; Osarfo *et al*., 2016). Nevertheless, withdrawal of scarce resources such as capital and labour from farm to non-farm sector hampers investment in farm technologies and land conservation resulting in reduced agricultural production (Haggblade *et al*., 2010; Zereyesus *et al*., 2017). Similarly, a negative relationship between non-farm income and agricultural yield is expected where non-farm income is used for consumption or further investment in non-farm activities as opposed to investing in farming activities (Pfeiffer *et al*., 2009). Reallocation of farm family labour to non-farm employment activities decreases the available pool of family farm labour and may result in agricultural output loss, and declining or stagnating agricultural income (Adjognon *et al*., 2017; Scharf and Rahut, 2014). On the other hand, the motivation to engage in non-farm activities vary across geographical areas depending on demographic[4], infrastructural[5] and farm level[6] characteristics (Chikobola and Sibusenga, 2016; Shehu and Sideque, 2013). The current study therefore seeks to unravel the factors that influence the farm households' decision to participate in non-farm employment activities in Mbire district and its impact on food security.

1.3 Research Problem

Most households in the Mbire district are suffering from chronic and severe food insecurity (ZimVAC, 2018). In line with the Sustainable Development Goal (SDG) number two[7], the GoZ and some non-governmental organisations are intervening to alleviate the food insecurity problem in the country by enhancing food agricultural production through input provision. Despite these efforts, the food insecurity situation in the district is remaining persistent and is on a rising trend (FAO, 2018). A smaller proportion of the households in the district has been observed participating in non-farm employment activities as a coping strategy to curb food insecurity (Nyamwanza, 2014). The interest of this study therefore emanates from two matters of concern. Firstly, to clarify

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[4]. Such as sex, consumer-worker ratio, age and educational attainment of the household head and.

[5]. Such as road infrastructure, market and electricity accessibility.

[6]. Such as land holding, assets ownership and credit accessibility.

[7]. Seeks sustainable solutions to end hunger in all its forms by 2030 and to achieve food security.

on the mixed evidence in literature pertaining to the factors that influence the rural farm households' decision to participate in non-farm activities. The second issue of concern is an extension of the latter; the impact of participation in non-farm activities on food security is ambiguous in the non-farm employment literature. There is conflicting evidence on the impact of participating in non-farm activities on households' food security status. Dabalen *et al*. (2004) and Hoang *et al*. (2014) provide empirical evidence to the effect that participating in non-farm activities has a positive impact on food security while Pfeiffer *et al*. (2009) found the opposing effect. This therefore motivated the researcher to explore the factors influencing the rural households' choice to participate in non-farm activities and the impact of participation on rural households' food security status.

The existing empirical literature on the impact of participating in non-farm activities on rural households' food security status were merely comparing the consumption expenditure of the participants relative to the non-participants without taking into account other factors that may dive household to participate. The propensity score matching (PSM) technique and the treatment evaluation model employed by the current study eliminate the possible self-selection bias into participating by controlling for observable and unobservable factors that may influence the rural households' decision to participate in non-farm activities.

1.4 Research Objectives

The objectives of this study are two-fold:

- To identify factors that influence rural farm households' choice to participate in non-farm activities.
- To estimate the impact of participation in non-farm activities on rural farm households' food security status.

1.5 Research Questions

- What are the factors that influence rural farm households' involvement in non-farm activities?
- What impact does non-farm participation have on rural farm households' food security status?

1.6 Research Hypothesis

- Demographic, infrastructural and farm level characteristics significantly influence the rural farm households' decision to participate in non-farm activities.
- Participation in non-farm activities has a positive impact on rural farm households' food security status (Households who have participated in non-farm activities are expected to be relatively more food secure than the non-participant households).

1.7 Rationale/Justification of the Study

The factors influencing the choice to participate in non-farm activities vary across farm households depending on their demographic, infrastructural and farm level characteristics. Knowledge and identification of these factors will provide insights into appropriate policy incentives to induce farmers to participate in non-farm activities, hence the need to carry out this research. More so, accurately targeted policy incentives will induce rural farm households to participate or to increase the participation in non-farm employment activities thus helping to curb the problem of food insecurity.

1.8 Methodology

The methodology of this study used the theoretical and empirical literature to identify the factors influencing rural household's choice to participate in non-farm activities and the impact of participation on food security. The logistic model was specified to estimate and identify significant factors influencing the rural household's choice to participate in non-farm activities. The treatment evaluation model associated with the propensity score matching (PSM) was specified to estimate the average gain of participation in non-farm activities in terms of food security status. Primary cross-sectional data obtained from a sample drawn from Mbire district was used in this study.

1.9 Organisation of the Rest of the Dissertation

In the next chapter, both the theoretical and the empirical literature review are presented. Chapter three gives detailed outline of the methods and procedures used while chapter four presents the results and the interpretation of the estimation results. Lastly, chapter five summarises, concludes and outlines the policy recommendations and suggestions for further studies.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter reviews relevant theoretical and empirical literature that develops a conceptual framework for the specification of an estimable empirical model of factors influencing smallholder farmers' choice to participate in non-farm employment activities and its impact on household food security.

2.2 Food Security Definition and Evolution

According to World Food Summit (1996), food security exist when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life. Food security is comprised of four interrelated pillars, which are availability**,** access, utilisation and stability of all the three pillars**.**

Food Availability

In 1974, World Food Summit defined food security as the availability at all times of adequate world food supplies of basic foodstuffs to sustain a steady expansion of food consumption and to offset fluctuations in production and prices. Food availability is about the food supply side emanating from sufficient food production, distribution and exchange. The improvement in food availability requires farming systems that are productive and sustainable. In addition, to improve on this aspect of food security, policies to enhance agricultural production should be put in place. The government of Zimbabwe is mainly focusing on improving this aspect of food security by enhancing agricultural productivity across all rural areas. This is evidenced by the facilitation of programs such as the presidential input support scheme carried out every year and the command agriculture initiated in 2016/2017 agricultural season. In Zimbabwe, food security is synonymous with maize availability in Strategic Grain Reserve (SGR) (Muhoyi *et al*., 2014).

Food Accessibility

In 1983, FAO expanded the food security concept to include the economic access by poor people to access the basic food they need. Following Sen (1982) who found that people were suffering from poverty and famine when the food was abundantly available, the food security definition was then revised to include the aspect of food accessibility. This was happening because people had no access to food though it was available because of lack of capacity to purchase food from the markets. Food accessibility, therefore, captures both the economic and physical access to food, which include affordability, allocation and preferences. Two main types of this aspect include direct access to food (a household produces food for itself using its own resources), and the economic access (indirect) (a household purchases food produced elsewhere). The economic access can be improved by improving market access for rural smallholder farmers by allowing them to generate income from non-farm activities. The GoZ and other stakeholders such as NGOs may need to focus on this pillar of food security in Mbire district since enhancing food availability through enhancing agricultural production has not been sufficient due to very low rainfall and extremely hot temperatures experienced in the area.

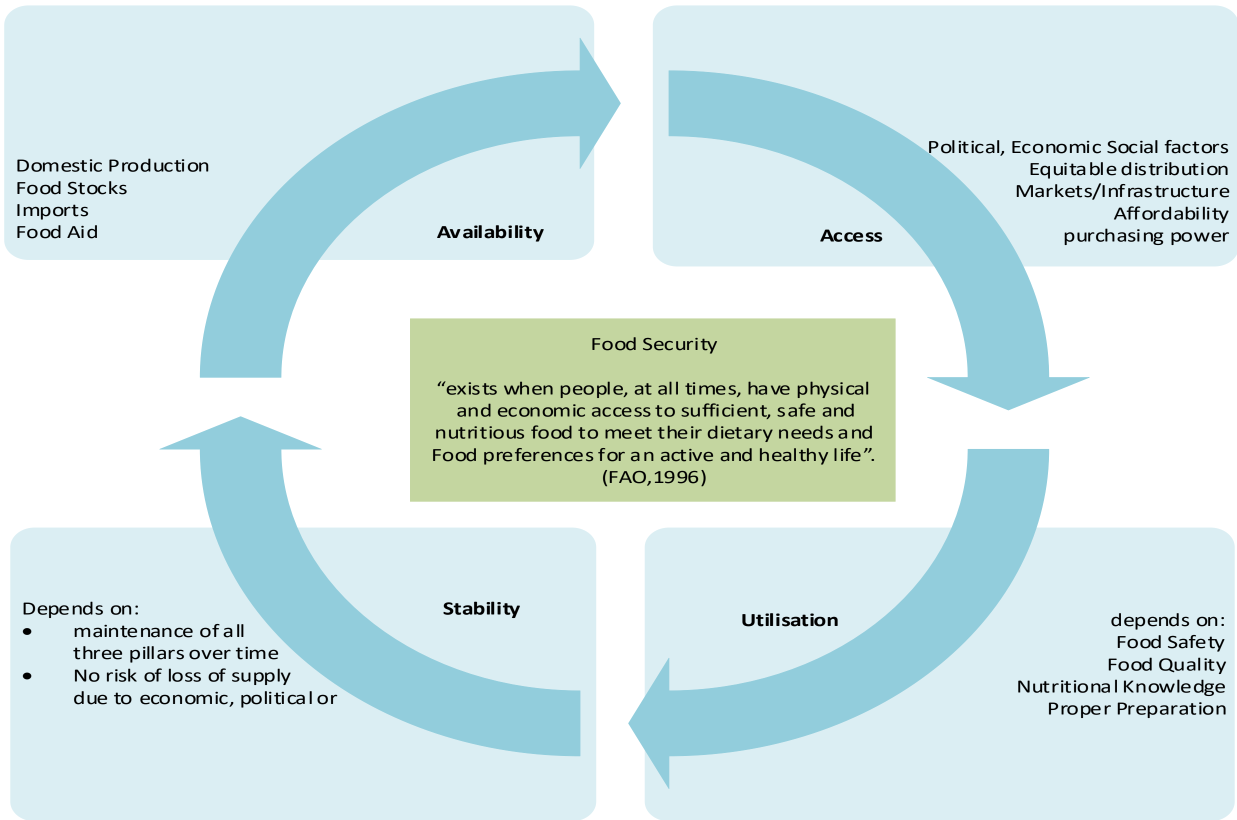
Food Utilisation

The third pillar of food security is the food utilisation, which concerns how the food is prepared and integrates various nutrients for a balanced diet. This involves households or individuals' ability to obtain sufficient food over time. This also has implications for the transitory, seasonal or chronic types of food security. This aspect of food security include food metabolism by individuals, which affects quality and quantity of food taken by each member of the household. The nutritious status is affected by food preparation, feeding habits, diversity of their diet and intra-household distribution. Thus, food-utilisation aspect of food security is enhanced by increasing diversity in diets, improving nutrition and food safety, reducing post-harvest loss and value addition to food when preparing it. In Zimbabwe, huge population is still facing the food accessibility problem (FAO, 2018). The government may need to address the issue of food accessibility first, and then move to the aspect of food utilisation. Thus, this study focus on food accessibility.

Stability

Stability is about the sustainability of the three aforementioned food security pillars and being food secure at all times. According to Devereux (2006), transitory food insecurity can result due to a bad season, for example, the Elnino-induced drought of 2016/2017 and the cyclone Idai of March 2019 drastically affected the agricultural output in Zimbabwe. A shift in employment status and food inflation may also lead to a transitory food shortage. When there is food inflation, the poor are deprived of their food purchasing power. Figure 3 summarises food security and its pillars.

Figure 3: Food Security and its Pillars



Source: Adapted from Maxwell (1996)

2.3 Theoretical Literature Review

Dualism models postulated the coexistence of both the advanced (industrial) sector and the backward (agricultural sector) in a developing country. The agricultural sector is assumed to be overpopulated and land is non-reproducible which imply that the marginal productivity in the agricultural sector is zero. The marginal productivity of labour in the industrial sector is assumed to be positive hence offering higher wages than in the agricultural sector. This difference in marginal productivities and wage rates between these two sectors facilitate the costless transfer of labour from the backward sector to the industrial sector where the labourers will be earning higher incomes and have their wellbeing and food security status improved. Lewis (1954) postulates that there is constant supply of labour to the industrial sector hence the industrial sector will be continuously growing while the agricultural sector is stagnant. Fei and Ranis (1964) refined the Lewis model to say that the agricultural sector will eventually be commercialised when the surplus labour got exhausted in the agricultural sector, the sectors will begin to compete in terms wages for labour hence the two sectors will begin to grow simultaneously. Marginal productivity of labour is therefore influenced by households' demographic, infrastructural, income and farm level characteristics such as household head's age, education level, income from the agricultural sector, land size and livestock ownership which in turn facilitates the transfer of labour to the industrial sector.

More so, Harris and Todaro (1970) developed a rural-urban migration model. The major assumption of the model is that the migration decision is based on the expected income differentials between the rural and urban areas rather than just wage differential as postulated by Lewis and Fei-Ranis models. This implies that rural-urban migration can be economically rational if the expected urban income exceeds expected rural income. In this model, for someone from the rural to be hired for a formal sector job, it is necessary to be physically present in the urban areas where the formal sector jobs are located. In the Harris-Todaro model, more workers search for formal sector jobs than are hired. Those not hired end up unemployed ex post. Open unemployment, though a feature of the world was not a feature of the Lewis model. The variables explaining the rural households' decision to participate in urban employment are the same as implicitly suggested by the Lewis and Fei-Ranis models explained above, though Lewis and Fei-Ranis models ignored the issue of unemployment.

These dual economy model help answer both the study research questions on the factors influencing the rural households' decision to participate in non-farm activities and the impact of participation on food security. According to the Lewis and Fei-Ranis models, participating in non-farm employment (urban employment) has a positive impact on rural household food security as they are enticed by higher incomes to work in urban areas. However, this can only be true if those who participate in urban employment repatriate their incomes in form of money or food back to their families in the rural. In the Harris-Todaro model, participating in non-farm urban employment can have a positive impact on rural households' food security if the migrants got employed while it can have no or negative impact on rural household food security if the migrants remain unemployed as they will need to source food from the already food-deficit rural household. More so, the dualism theories are actually labour migration theories, which explain the individuals' decisions to shift from the agricultural sector to the industrial (non-farm) sector, but not participating in both sectors as considered by the current study.

Agricultural household models of Chayanov (1966) and Singh *et al*. (1986) model the rural farm household's decision to allocate its labour between farm and non-farm work. Unlike in the dualism models discussed above, the farmer will be participating in both the farm and non-farm work by allocating its total time endowment between these two activities. In the drudgery averse model of Chayanov (1966), a peasant household is assumed to be acting as both a firm and a consumer trying to maximise both the utility from consuming agricultural produce and also to maximise production, but also disliking the back breaking nature of the peasant farm work, therefore, the peasant household tend to allocate its time endowment between farm and non-farm work (leisure). In the peasant household model, the major determinant of labour allocation decision is the consumer to worker ratio (c/w) which is the ratio of household size to number of household members who actually work in the field. The household is expected to spend more time on the farm if the consumer to worker ratio is relatively high since the household will be having a relatively higher food demand, otherwise it will spend less hours in the field. In this model, working more hours in the field improves the rural households' food security since non-farm labour allocation is mainly considered leisure and brings no income. In this model, participating in non-farm activities have a negative impact on rural households' food security since there will be uncompensated lost farm production by spending more hours on non-income earning leisure. This model ignored the fact that non-farm labour allocation may also produce income that may outweigh the lost farm production output. For example, a peasant farmer may use his/her own non-farm labour allocation to work for a wage or income earning self-employment activities such as trading and gold panning. In Mbire district, spending more hours in the field does not improve agricultural yield due to poor climatic conditions, hence more non-farm labour allocation may improve food security if the off-farm labour allocation are used for income earning activities.

Like the Chayanov model, the farm household model of Singh *et al*. (1986) models the farm labour supply decision between the farm and off-farm. Again, the farmer is assumed to be both a consumption and production unit at the same time. The household is assumed to be maximising the household joint utility subject to budget, production and time endowment constraint. This means that a rural household maximises both profit and the utility function simultaneously. Unlike the Chayanov drudgery averse model, which assumed away the existence of the labour market in the rural sector, which led to the splitting of the total peasant time endowment between only leisure and on farm work, the Singh *et al*. model assumed the existence of the labour market where the peasant can hire in or out labour. According to the farm household model, the farm total time endowment is split among on-farm work, leisure and off-farm work that brings income for the household. In this case, if the household's off-farm income outweighs the lost farm production, the off-farm labour participation will have a positive impact on rural households' food security status, otherwise it will have no impact if the lost production is equivalent to the income gained from off-farm employment and a negative impact if the income from the off-farm employment is outweighed by the opportunity cost of lost production. From this model, it can be deduced that the participation in non-farm activities can have a positive, negative or no effect of rural households' food security status. Due to the ecological conditions in Mbire district, non-farm activities are expected to be more productive than farm activities, hence a positive impact on rural household food security status is expected.

There are two channels that can translate the effect of the non-farm employment participation to rural household food security status, which are direct and indirect channels (Matshe and Young, 2004). The direct way is when the incomes from the non-farm activities are used on food expenditure, hence improving the rural households' food security. The food expenditure involve expenditure on the staple food, cooking oil and other basic and luxury food commodities. The indirect channel is operational when the non-farm incomes are used to finance agricultural productivity enhancing inputs to boost agricultural productivity and or production, hence improving food security status of the households. Matshe and Young (2004) found the non-farm income to have positive spinoffs in agricultural productivity in Shamva District of Mashonaland Central of Zimbabwe. This was possible since the district is located in agro-ecological region 2[8] of Zimbabwe, which is mostly suitable for agricultural production, particularly maize production, which is the country's staple food. This means that the indirect channel was more prominent than the direct channel in Shamva district. However, given the climatic characteristics of Mbire district and its geographical location in agro-ecological region 4[9]

[8]. Receiving 700 – 1 050 mm rainfall per year confined to summer.

[9]. Receiving 450 – 600 mm rainfall per year. Subject to frequent seasonal droughts.

and 5[10] of Zimbabwe, where agriculture, specifically maize production cannot be best practiced, the indirect channel may be highly operational. Matshe and Young (2004) found individual characteristics (such as gender and education) and household/farm characteristics (such as land area accessible to the household, productive assets, remittances and the agricultural terms of trade) to be influential in rural household labour allocation decision. Some of these variables are incorporated in the study model as they closely resemble to the households in the study area. All the theoretical and some empirical literature reviewed together help constructing the study conceptual framework outlined below.

2.4 Conceptual Framework on the Decision to Participate in Non-farm Activities

According to the farm household model of Singh *et al*. (1986), a farm household is assumed to maximise the household's utility over consumption goods and leisure subject to time, budget, non-negativity and production constraints. Following Singh *et al*. (1986) and Owusu *et al*. (2011), we can have the following model:

$$U = U(X, H) \tag{1}$$

$$T = L_1 + L_2 + H \tag{2}$$

$$Q = Q(L_1, A) \tag{3}$$

$$PX = P_1 Q_1 - w_1 L_1 + w_2 L_2 + \bar{R} \tag{4}$$

$$L_1, L_2, H \geq 0 \tag{5}$$

Where equation (1) is the utility function (U) of a representative household defined over consumption goods (X) and leisure (H). Equation (2) is the total time endowment (T) exhaustively attributable to farm production (L_1), non-farm production (L_2) and to leisure (H). Equation (3) is the farm production function (Q), which is assumed to be a concave function of labour (L_1) and land (A). Equation (4) is the budget constraint where; P is the market price for purchased consumption good, w_1 and w_2 are wage rates for farm labour (reservation wage) and for non-farm labour (market wage rate) respectively. More so, in the budget constraint, P_1 and Q_1 is the price for

[10]. Receiving normally less than 500 mm rainfall per year, very erratic and unreliable. Northern Lowveld may have more rain but topography and soils are poorer.

farm output and annual quantities of farm output produced and sold respectively and $\bar{R}$ is the exogenous income.

Solving the households' utility maximisation problem, we get the following first order condition for optimal time allocation across farm work, non-farm work and leisure:

$$\frac{\partial U}{\partial L_i} = w_i \frac{\partial U}{\partial Q} - \frac{\partial U}{\partial L} = 0 \qquad (6)$$

Rearranging equation (6) to make the farm and non-farm wage rate the subject of the formula we have:

$$w_i = \frac{\partial U / \partial L}{\partial U / \partial Q} \qquad (7)$$

When the rural farm households have allocated their time to farm, non-farm and leisure activities, their derived farm and non-farm labour supply functions are given as:

$$L_1 = L_1(w_1, w_2, P_1, P; Z) \qquad (8)$$

$$L_2 = L_2(w_1, w_2, P_1, P, R; Z) \qquad (9)$$

where Z summarizes all the demographic, infrastructural and farm level characteristics that influence the rural farm households' reservation (w_1) and non-farm wages (w_2). The rural farm household will participate in non-farm activities if the market wage rate (w_2) is greater than the reservation wage (w_1). However, these marginal productivities of labour are not observable. What is only observable is whether the household has participated in non-farm activities or not. Thus, $L_i = 1$ if $w_2 > w_1$ and $L_i = 0$ if $w_2 \leq w_1$. Where: $L_i = 1$ if the household has participated, and $L_i = 0$, if otherwise. Hence, the decision to participate can be modeled using the index functions and the binary response models (Cameron and Trivedi, 2007).

2.5 Empirical Literature Review

Most empirical studies on non-farm employment assumed a positive relationship between non-farm participation and food security, which does not always hold. This led to the bigger strand of the empirical literature (such as, Shehu and Abubakar, 2015; Agyeman *et al*., 2014; Chikobola and Sibusenga, 2016; Yesuf, 2015; Matshe and Young, 2004) to concentrate on only the determinants of the decision to participate in non-farm activities, leaving out the implications it has on food security unraveled. These studies found that the rural farm households' decision to participate in non-farm activities is influenced by demographic, infrastructural and farm level characteristics. The demographic characteristics comprise of gender, age, marital status, educational attainment of the household head, dependency ratio and household size, while the infrastructural characteristics include the access to electricity, public transportation and proximity to the market and farm characteristics that include fixed assets, livestock holding and land ownership. These studies were generally using the same set of variables and the only differences were emanating from the variable measurement, but most of them were significant with their signs varying by location. The logistic and the probit models were used to quantify the determinants of the choice to participate in non-farm activities since the dependent variable (decision to participate in non-farm activities) is dichotomous, taking the value of 1 if the household has participated in non-farm activities, and 0 otherwise. The Probit and the logit models yield qualitatively similar results (Amemiya, 1985). The current study will adapt most explanatory variables from these existing studies as the factors influencing the rural households' choice to participate in non-farm employment and food security status.

Non-farm participation does not always have a positive influence on rural households' food security as assumed by most empirical studies. Shehu and Sidique (2013), Mishra and Rahman (2018) and Seng (2015) investigated the effect of participation in non-farm activities on rural household food security in Nigeria, India and rural Cambodia respectively. These studies used primary data at household level. Using various econometric estimation techniques, these studies found that the participation in non-farm activities positively influence rural households' food security-status. However, the other strand of the literature found a negative or no relationship between non-farm income and rural households' food security via various channels. Kinuthia *et al*. (2018) found that participation in non-farm activities has no effect on rural households' food security status and households' welfare in East Africa (Tanzania and Uganda), while Pfeiffer *et al*. (2009) and Amare and Shiferaw (2017) revealed a negative impact of the non-farm participation on rural households' food security status through an indirect channel. Family labour was found to be more productive than hired labour in Mexico by Pfeiffer *et al*. (2009) which explained the result found.

It is important to analyse both the factors influencing the choice to participate in non-farm activities and the implications of that participation on rural households' food security status. The factors influencing rural households' decision to participate in non-farm activities are important as they give out important policy variables when the government wants to stimulate non-farm employment, given that they improve food security. At the same time, the policy makers cannot stimulate non-farm employment blindly without knowing its implications on rural households' food security status. Kinuthia *et al*. (2018), Irohibe and Agwa (2014) and Babatunde and Qaim (2010) looked into both the determinants of the choice to participate in non-farm activities and the effect it has on food security status. Likewise, the current study analyse both the factors influencing the choice to participate in non-farm employment and the impact on food security.

The techniques used to estimate the effect of participation in non-farm activities on rural households' food security status in most non-farm studies are not really convincing to answer the posed research questions and to address the study objectives. Descriptive statistics used by Kinuthia *et al*. (2018) to estimate the effect of participation in non-farm activities on food security status in East Africa (Tanzania and Uganda) may be condemned to be biased since it only uses the summary of sample data to draw conclusions about the population, without controlling for other factors. Structural equations model is used to determine the relationships among variables without giving the actual impact of one variable on the other. This means that the structural equation model used by Babatunde and Qaim (2010) in Kwara State of North Central Region of Nigeria cannot be used for policy recommendations pertaining to the impact of participating in non-farm employment on non-farm activities, but can only hint on the direction of causality. For more clearer and better results, which may be useful for policy recommendation, other appropriate econometric techniques may be used to estimate the average benefit of participating in non-farm employment relative to nonparticipating households.

Treatment effects model and the propensity score matching (PSM) technique are the best in addressing experimental research questions (Cameron and Trivedi, 2009). The experimental objective is to determine the average impact, in terms of food security status of participating in non-farm activities relative to nonparticipating. The control group is the non-participant group and the experimental group is the participant group. This model works by comparing the average output (in terms of food security status) of the rural farm households who participated in non-farm activities and of those who did not diversify into such activities, after controlling for other observable and non-observable explanatory variables. There are few studies (Dabalen *et al*., 2004; Tran *et al*., 2015 and Osarfo *et al*., 2016) carried out to estimate the impact of non-farm employment participation on rural households' food security using the treatment evaluation model. These studies investigated the differences in food security status (measured by food-consumption per capita) between the households who were involved in the non-farm sector and those who did not diversify into non-farm activities. The regressors incorporated in their models were; educational attainment, age, gender, parents occupation, the presence of parents in the household, dependency ratio, land holding, livestock ownership, presence of road, electricity supply, presence of primary school and the presence of the agricultural extension services. The current study will adopt the treatment evaluation model and extract some relevant regressors that suits the study area.

It is more complex to capture broader variables such as welfare and wellbeing, which constitute many variables such as income, poverty, food security, and health status, which are difficult to capture in one index. Some studies (such as, Adjognon *et al*., 2017 and Scharf and Rahut, 2014) explored the relationship between rural non-farm activities (wage and self-employed) on household welfare and wellbeing in rural Malawi and Himalayas, respectively. These studies were then concluding on welfare effects using only one or two components of welfare. Consumption per capita were used to measure wellbeing, of which the larger proportion of it might have been spent on non-food items such as transport, hence biased conclusions on food security are likely. These studies were actually measuring one or two welfare variables and conclude on the overall welfare and food security, which may be biased since there might exist trade-offs amongst the welfare variables, resulting in various effects depending on the magnitude and direction of trade-off.

Few studies have narrowed down to examine the impact of non-farm activities on food security and food poverty. Ojeleye *et al*. (2014) investigated non-farm activities and their roles in food security in Kaduna State of Nigeria. The study used the primary data collected via structured questionnaires. Using the logit multiple regression model and the descriptive statistics, their study found that non-farm incomes positively affect households' food security status. More so, Zereyesus *et al*. (2016) analysed the determinants of food poverty and the impact of participation in non-farm work on households' food poverty using Feasible Generalized Least Squares (FGLS) and found non-farm income to be playing an important role in reducing the risk of food poverty. In the same vein, Tsiboe *et al*. (2016) and Osarfo *et al*. (2016) examined the determinants and the impact of non-farm income on food security and nutrient availability in Ghana. These studies have reduced the bias of the estimates brought about looking at the impact on a broader perspective; however, their measures of food security were focusing much on the food availability. According to Sen (1982), people were suffering from poverty and famine when food was available. The problem was of food accessibility (affordability) because even if the food is not available, people can import from other provinces or from other countries if they can afford. The current study will therefore focus on the food accessibility aspect to measure the households' food security status by asking the rural farm household heads if there existed, in the past 30 days; any member of the household who had fewer meals than normal due to lack of food accessibility, and the frequency at which it happened. This measure can better capture both food availability and accessibility as propounded by Coates *et al*. (2007).

To the researcher's best knowledge, there is only one study carried out in Zimbabwe by Matshe and Young (2004) on non-farm labour allocation decisions in rural households of Shamva District of Mashonaland Central. The double hurdle model was used which captures both the participation and the extent of the participation in terms of the labour hours allocated in non-farm activities. The explanatory variables were categorised into demographic, infrastructural and farm level characteristics. Gender, education, size of the land and productive assets were some of the significant variables and will be incorporated in the model adopted by the current study. Their study assumed that non-farm participation has a positive impact on food security, which is ambiguous in the non-farm employment literature as discussed above. However, the results from their study cannot be used for policy recommendations across all districts of Zimbabwe, like Mbire District of the same province because Shamva District receives normal to above rainfall and also differ in terms of other geographical, climatic and population densities. The empirical literature reviewed help to come out with the model and the variables to include in the models.

2.6 Conclusion

From the literature review and the conceptual framework discussed above it can be seen that the main factors influencing the decision to participate in non-farm activities are categorised into demographic, infrastructural and the farm level characteristics. More so, the discussion from this chapter provide insights that the treatment evaluation model and propensity score matching can better aid in answering the study research questions. The following section outlines the methodology and the estimation technique used in this study and present the estimable models specification.

CHAPTER THREE

METHODOLOGY AND MODEL SPECIFICATION

3.1 Introduction

This chapter specifies the empirical models to operationalise the conceptual model developed in chapter two in a form capable of empirical estimation of the factors influencing rural farm households' decision to participate in non-farm activities and the impact of this participation on rural household's food security. The section describes the data collection methods used, the sampling procedures, sample size, econometric methods and estimation techniques employed.

3.2 The Empirical Model of Participation in Non-farm Activities

Since the dependent variable on the determinants (participate = 1, 0 if otherwise) of the choice to participate in non-farm activities is binary rather than continuous, linear estimation techniques (e.g. Ordinary Least Squares or Linear Probability Model) yields biased results. Linear estimation techniques may yield negative variance of the error term and the probabilities may lie outside the reasonable range of between zero and one. Therefore, the Maximum Likelihood Estimation (MLE) techniques (e.g. Probit and Logit) are more appropriate to quantify the factors influencing the rural households'[11] choice to participate in non-farm activities (Cameron and Trivedi, 2009). According to Amemiya (1985), the Probit and logit models yield quantitatively similar results where $\hat{\beta}_{logit} = 1.6\hat{\beta}_{probit}$ or $\hat{\beta}_{logit} = 1.8\hat{\beta}_{probit}$ when the data are centered on the mean or zero respectively, hence the choice between the probit and the logit models doesn't matter. The current study will employ the logit model to answer the first study research question to identify factors that influence rural farm households' involvement in non-farm activities.

From the conceptual framework in the preceding chapter, we can model the rural farm households' decision to participate in non-farm activities using the index functions and the logit model since we cannot observe the wage differential between the farm and non-farm sector. What

[11]. According to the culture of the people in Mbire district, a "household" is defined as "people who live together and share food from a common pot" (Nyamwanza, 2014)

can only be observed is whether the farmer works in the non-fam sector or not. The model in equation (10) gives the index function:

$$\left.\begin{aligned} &L_i^* = \beta' Z_i + \xi_i \\ &L_i = 1 \text{ if } L_i^* > 0 \\ &L_i = 0 \text{ if } L_i^* \leq 0 \end{aligned}\right\} \tag{10}$$

Where L_i^* is the latent (unobservable) variable, which is the wage differential between the farm and the non-farm sector, and ξ_i is the random disturbance term. The variable Z_i is a vector of explanatory variables. The variables in Z_i have been informed by the literature reviewed in chapter two. The Z_i vector contains the demographic characteristics, which include household head age, household head gender, consumer-worker ratio and education level of the household head. It also contains the infrastructural characteristics (distance to the main road, credit access, cellphone ownership, and distance to the nearest market and electricity access) and farm level characteristics (land size, livestock holding and productive assets ownership). The variable $\beta'$is a vector of the coefficients of demographic, infrastructural and farm level characteristic variables. From equation (11), the rural farm household participate ($L_i = 1$) in non-farm activities only if the wage differential is positive ($L_i^* > 0$) that is if the market wage rate is greater than the reservation wage, otherwise the household does not participate ($L_i = 0$).

Due to Cameron and Trivedi (2009), the farm households' participation decision is modelled as follows:

$$\text{Prob}(L_i = 1|Z_i) = \text{Prob}(L_i^* > 0|Z_i) \tag{11}$$

$$= \text{Prob}(\beta' Z_i + \xi_i > 0|Z_i)$$

$$= \text{Prob}(\xi_i > 0 - \beta' Z_i|Z_i) \tag{12}$$

with $\xi_i \sim f(0,1)$ which is a symmetric probability density function (pdf). This therefore implies that:

$$\text{Prob}(L_i = 1|Z_i) = \text{Prob}(\xi_i < \beta' Z_i) \tag{13}$$

$$= F(\beta' Z_i) \tag{14}$$

Equation (14) is the cumulative density function (cdf), which is the probability of success (participate, in this case). Since this study is using the logistic model to model the decision to participate, F is the logistic distribution function which is usually denoted by a Greek latter Λ so that a cumulative density function (cdf) is:

$$Prob(L_i = 1|Z_i) = \Lambda(X) = \frac{e^X}{1+e^X} \tag{15}$$

where: $X = \beta' Z_i$, and the probability density function (pdf) given by:

$$\lambda(X) = \frac{\partial\Lambda(Z)}{\partial Z} \tag{16}$$

In the case of the binary dependent variable models, interpreting the coefficients inflates the impact, hence we interpret the marginal effects. Differentiating the estimated logistic model *w.r.t* Z_i we get the slope given by:

$$\frac{\partial E(L_i|Z)}{\partial Z_i} = \lambda(\beta' Z_i)\beta_i \tag{17}$$

There are two ways of calculating the marginal effects, which are: (i) Marginal Effects at Averages (MEA), that is at the average point of each individual variable or the (ii) Average Marginal Effects (AME) that is averaging all the slopes for individuals. In this study, we will interpret AME because averaging the dummy variables in MEA will not be meaningful. The AME are calculated as presented in equation (18):

$$AME = \frac{1}{n}\sum_{i=1}^{n}\frac{\partial E(L_i|Z)}{\partial Z_i} = \frac{1}{n}\sum_{i=1}^{n}[\lambda(\beta' Z_i)\beta_i] \tag{18}$$

where n is the number of households.

3.2.1 Justification and Measurement of Explanatory Variables in the Logit Model

Different variables were expected to influence the farm households' decision to participate in non-farm activities in the study area as informed by both theoretical and empirical literature reviewed. These variables include demographic, infrastructural and farm level characteristics. Demographic characteristics control for personal differences in endowments of skills and innate abilities among rural farm households. Farm level characteristics are a proxy for household wealth (income), which are likely to influence households' decision to participate in the non-farm activities and the infrastructural variables control for the impact of the local environment on the rural farm households' decision to diversify into non-farm activities. The variables in the logit model are explained below.

Participation in Non-farm Activities (*Treat*)

This is the dependent variable in the above specified logit model which is a dichotomous variable, which takes the value of 1 if the household has participated in non-farm activities in the past 12 months from the date of interview, and 0 otherwise. This variable is a dependent variable in the logit model. At the same time, it is an explanatory variable in the treatment evaluation model. The households who have participated in non-farm activities are referred to as "treated" and those who did not are "non-treated" in the treatment evaluation model. The households who have participated in non-farm activities are expected to be relatively more food secure than the non-participant households as suggested by both the theoretical and empirical literature reviewed.

Age of the Household Head (*Hhage*)

This demographic variable has an important bearing on the farm household head's decision to diversify into non-farm activities as household heads at their young age can probably engage in non-farm activities compared to their old age. However, older household heads might also have the experience and the links that could help them diversify into non-farm activities. Age of the household head is therefore expected to increase the probability of participating in non-farm activities. Tsiboe *et al*. (2016) used this variable and it was found to increase the probability of participation in non-farm activities. This variable was measured in terms of the age of the household head at the time of the interview.

Gender of Household Head (*Hhgend*)

Men are usually presumed to be more active than females with regard to experience and access to technology since they are socially expected to provide for their families. Hence, males are expected to have the higher probability of participating in non-farm activities than their female counterparts. The non-farm activities in rural areas are more strenuous, hence need more power which women may lack. Yesuf (2015) used this variable and found that males had higher probability of participating in non-farm activities than their female counterparts. This variable is dichotomous which will take the value of 1 if the household head is a male, and 0 otherwise.

Education Level of Household Head (*Hheduc*)

When an individual acquires more and more education, s/he either looks for full time formal wage employment in the non-farm sector or remain on the farm, but increase the diversification into non-farm activities by climbing up the agricultural value chain ladder or use the farm income to invest in the non-farm sector. Hence, the *a priori* sign of the coefficient of household head's education level is positive. Matshe and Young (2004) used this variable and found it to have a positive effect on the rural farm households' decision to diversify into non-farm activities. This variable is measured in terms of the number of years of schooling after the first 14 years of birth, which is post primary education. This measure was adapted from a study by Matshe and Young (2004).

Distance to the Nearest Market (*Dis_mkt*)

This variable measures the distance in kilometers from the household's home to the nearest market for non-farm products such as urban centers or growth points. These areas encourage non-farm activities by acting as centers for input purchase or sales and the demand for products. Long distance to the market is a barrier to the participation in non-farm activities, particularly trading. This means that proximity to these places give rise to diversified rural non-farm activities and higher non-farm incomes. The study therefore expected that, the shorter the distance to the market, the higher the probability of a households' participation in non-farm activities. Babatunde and Qaim (2011) used this explanatory variable and found it to reduce the probability of household head's participation in non-farm activities.

Distance to the Main Road (*Dis_mrd*)

This variable measures the distance in kilometers from the household's home to the main road. It is a proxy for the ease with which rural farm households can access the market for their products. The shorter the distance to the main road is, the easier it is for the rural farm households to get access to the markets. The study therefore hypothesized that the longer the distance to the main road, the lower the probability of households' participation in non-farm activities. Tsiboe *et al*. (2016) used this variable and found that the households who were far away from the main road have a lower chance of participating in non-farm activities.

Livestock Holding (*Livstk*)

This variable is proxied by the total number of cattle owned by a household. Livestock herd play an important role in determining the rural households' decision to participate in non-farm activities. A cattle herd can help boost the households' capital or liquidity by selling it when in need to start up a non-farm enterprise than to approach commercial banks for loans, which increases the farmer's chance to participate in non-farm activities. The *a priori* sign for the coefficient of this variable was a positive sign as found by Yesuf (2015).

Land Size (*Landsz*)

As the size of the land increases, *ceteris paribus*, the land productivity decreases and then output as well (according to the theory of inverse relationship between farm size and productivity). The study therefore hypothesised a positive correlation between land size and participation in non-farm activities as farm wage (reservation wage) is positively related to marginal land productivity. According to the inverse relationship between farm size and productivity, large farms produce low output, hence the households participate in non-farm activities to supplement their food and incomes. Tsiboe *et al*. (2016) used this variable and found its coefficient to have a negative correlation with non-farm participation decision. The variable was measured as the sum of the agricultural and residential land in hectares.

Consumer-Worker Ratio (*Conswkr*)

Inclusion of this variable is informed by Chayanov (1966) and is measured as the ratio of household size (food consumers in the household) to the number of household members who actually work in the field. The existence of the large number of family members with limited labour resources could have an implication on the decision to participate in non-farm activities due to increase in food demand with limited food supply. It is hypothesised that the consumer to worker ratio has a positive impact on the decision to participate in non-farm activities, as the household will be seeking to augment own agricultural food supply with the market purchased food.

Productive Assets Ownership (*Asset*)

The value of the total household assets owned was used to proxy farmer's wealth and or income. The household assets in Mbire district include ox-drawn ploughs, cars and scotch carts. Assets value eases liquidity constraints to participate in non-farm activities. When the households want capital to start up non-farm enterprises they simply convert their asset to money or approach the banks for loans and use their assets as collateral security. The current study therefore, hypothesised that the farmers who are wealthy have a higher likelihood of engaging in non-farm activities as found by Tran *et al*. (2015). This variable was measured in terms of the estimated value of the total household productive assets.

Access to Credit to Finance Non-Farm Enterprises (*Credt*)

Having access to credit eases the liquidity constraints faced by the rural smallholder farmers when they want to start non-farm enterprises (or credit can be used to support production activities and hence increase output thus reduced non-farm activities). This increases the likelihood of the households to diversify into non-farm activities. Shehu and Sidique (2013) found that households who had access to credit had a higher chance of participating in non-farm activities in relation to their counterparts, hence improving food security. The households who have access to credit to finance their non-farm enterprises such as trading can easily diversify into non-farm activities. The study therefore expected that the households who have credit access have the higher likelihood of participating in non-farm activities than those who have no access to credit. This variable is measured as a dichotomous variable, which takes the value of 1 if the household had accessed credit to finance non-farm activities in the past 12 months, and 0 if otherwise.

Internet Access (*Intnet*)

Due to fast changing technology, internet is now playing an important role in information dissemination, hence the use of this variable as one of the core regressors. This is measured as a dummy variable which takes the value of 1 if the household has access to internet, and 0 otherwise. If the household has access to internet it means that it can easily get access to non-farm opportunities through news and information from social networks such as WhatsApp. Most studies used cellphone ownership as an explanatory variable for the decision to participate in non-farm activities. This study expected that having internet access increase the probability of a households' participating in non-farm activities.

Table 1: Summary of Variable Definition and Measurement

	DEFINITION AND MEASUREMENT
Treat	1 if the household has participated in non-farm activities, 0 if not.
Fdinsec	Number of times when at least one member of the household ate fewer meals a day than normal (2 meals) due to lack of food accessibility (recall period of 30 days).
EXPLANATORY VARIABLES:	
Hhage	Age of household head at the time of interview in years.
Hhsex	Taking the value of 1 if household head is a male, 0 otherwise.
Hheduc	Number of years of schooling of household head after the first 14 years of birth (post primary education).
Conswr	Ratio of household members who work in the field to the household size.
Dis_mkt	Distance from household's home to the nearest non-farm market in kilometers.
Dis_mrd	Distance from household's home to main road in kilometers.
Livstk	Number of cattle owned by a household.
Landsz	Total land owned (agricultural plus residential in hectares).
Asset	Total value of all productive fixed assets of a household.
Credt	Taking the value of 1 if the household has taken credit in the past 12 month, 0 otherwise.
Intrnt	Taking the value of 1 if the household has internet access, 0 if otherwise.

3.3 The Empirical Model of the Impact of Participation on Food Security

The treatment/ impact evaluation model seeks to answer the second study research question to find the impact of households' participation in non-farm activities on rural farm households' food security status. The first step in the treatment evaluation model is to estimate the propensity scores for each household that participated in non-farm activities (participants/ treated) and household that did not (Non-participants/ non-treated) based on the observable characteristics (Z_i). The propensity score estimation is explained below.

3.3.1 Propensity Scores Estimation

The propensity scores are the probabilities of each individual in a sample to participate in non-farm activities given the explanatory variables. These are important in treatment evaluation model as it enables the matching of individuals with the same propensity scores to reduce the self-selection bias into non-farm employment participation. According to Rosenbaum and Rubin (1983), the propensity scores are estimated using either the logit or probit model in case of binary treatments, which are in turn used to quantify the average treatment effect on the treated (ATET). The current study employed the logit model. The model specification for the propensity scores is the same as that of the logit model specified in equation (16) given by:

$$Prob(z) = Prob[L = 1|Z = z] \qquad (19)$$

where $L = 1$ is the observable treatment (participating in non-farm activities) and 0 otherwise; Z is a vector of observable characteristics which are exactly the same included in the logit model.

The purpose of the propensity scores are to search for the comparable counterfactual households among all non-participating households to form the control (counterfactual) group, and then compare the mean outcome of the participants against that of the non-participants. The underlying idea of the propensity score matching (PSM) is that the control and treatment households with the same or closest propensity score have the same probability of diversifying into non-farm employment activities, under randomized experiments which are then matched to reduce the self-selection bias (Tran *et al*., 2015). The propensity scores are used for matching two sample groups in the treatment evaluation model explained below.

3.3.2 Treatment/ Impact Evaluation Model

After the estimation of the propensity scores, the treatment evaluation model then compares the mean outcomes (food security status) of participants with that of the counterfactual group that did not participate. The impact of the households' participation in non-farm activities on rural households' food security status is examined using the treatment/ impact evaluation model, which compares, on average, the difference between the food security status outcome of the households who diversified into non-farm activities and those who did not. The treatment evaluation model is specified in equation 20 as:

$$Y_i = \delta' C_i + \alpha L_i + v_i \quad (20)$$

where C_i denote the set of variables same as in Z_i which explain the household participation decision and hence Y_i (household food security status) while δ' is the vector of corresponding coefficients in the treatment evaluation model, L_i has the same definition as above and v_i is the treatment evaluation model error term.

Household food security status (Y_i) in the treatment evaluation model specified in equation 20 is the dependent variable and was measured in terms of the number of times when at least one member of a household had fewer meals a day than normal[12] due to lack of food accessibility. This measure of food security was adapted from Coates *et al*. (2007), which captures both the food availability and the accessibility in a household. Most of the subjective measures of food security only captures the food availability aspect of food security definition; hence, this measure is an improved measure (Coates *et al*., 2007). This measure of food insecurity is discrete (but count data) and will allow us to rank the households according to the severity of food insecurity of the households, where the households with higher number of times less than normal meals a day are considered to be relatively more food insecure.

The parameter of interest in equation (20) is:

$$\hat{\alpha} = ATET = E(Y_1 - Y_0|Z)$$

$$= E(Y_1|Z) - E(Y_0|Z)$$

$$\hat{\alpha} = E(Y_1|Z, L = 1) - E(Y_0|Z, L = 0) \quad (21)$$

which is the difference between the expected outcome[13] of the participants (Y_1) given a vector of explanatory variables (Z) and that the household has participated in non-farm activities ($L = 1$) and the expected outcome of the counterfactual group (Y_0) given a vector of explanatory variables (Z) and that the household did not diversify into non-farm activities ($L = 0$).

The treatment evaluation model has become a popular approach to estimate the average impact of an intervention (Caliendo and Kopeinig, 2008). This model estimates the difference

[12]. According to Nyamwanza (2014), a typical food secure household in Mbire district have two meals a day.

[13]. The average number of times when at least one member of a household ate fewer meals than normal.

between the outcome (food security status) of the households who participated in non-farm activities and those who did not participate. This difference in food security status after we have controlled for other explanatory variables is referred to as the average treatment effect on the treated (ATET). The treatment evaluation model is useful in experimental studies as it allows the researcher to make use of the existing data sources (primary cross sectional data), so that it is easy and quicker to implement than to look for the data on before and after an intervention which might not be available. More so, the treatment evaluation model does not consider the functional form linking the outcome (food insecurity status, in this case) to non-farm participation. This model also allows for the control of the likely self-selection bias on observable characteristics that may lead the household to diversify into non-farm activities (Caliendo and Kopeinig, 2008). In addition, the use of the associated propensity score matching (PSM) technique will reduce the bias attributable to both the observable and unobservable characteristics.

3.3.3 Treatment Evaluation Model Assumptions

There are three main treatment evaluation model assumptions that should be met when estimating a treatment evaluation model. These assumptions are the overlapping condition assumption, the balancing property condition and the conditional mean independence.

The Overlapping Condition (Matching)

This assumption states that each element in the treated group must have the matching counterpart (twin) in the non-treated group with the same characteristics that is propensity score. This can be mathematically expressed as $0 < \Pr(L = 1|Z) < 1$. If the propensity score lies within this range, it means that all individuals in the treated group have got twins in the non-treated group with the same or closest propensity scores. If $\Pr(L = 1|Z) = 1$ it means that there is no one with characteristics Z in the control group or there is no a twin to be matched with in the non-treated group. If $\Pr(L = 1|Z) = 0$ it means that there is no one with characteristic Z in the treated group. For the treatment evaluation to be feasible, the data should conform to this assumption, otherwise it is not feasible.

The Balancing Property Condition

This assumption states that for the individuals with the same propensity score, the treatment assignment should be random and should look identical in terms of the vector Z. Rubin (2008) recommends a treatment evaluation model that balances the confounding factors before looking at results for the estimated treatment evaluation model. Thus, we do not interpret the treatment evaluation model results before checking if the model has the balanced covariates (explanatory variables for the probability of participating in non-farm activities). The test checks if the distribution of the conditioning variables (pre-treatment characteristics) is not different across the treated and non-treated groups in the matched samples. More so, this test helps to check if the selection bias (due to observable characteristics) have been eliminated. This satisfies the matching requirements for calculating average treatment effects. The study used the balance box plot to check for the balancing condition.

Conditional Mean Independence

This assumption states that the outcomes (food security status) should be independent from the treatment assignment (L) once we control for pre-treatment characteristics (Z). Conditional from Z, the outcomes are independent from the treatment. The participation should not affect/ impact on the distribution of the potential outcome. This can be mathematically expressed as $Y_1, Y_0 \perp L|Z$ which means that that the outcome of an individual, whether being treated or not, should be independent or orthogonal to the treatment assignment given a vector of explanatory variables. If this assumption is not satisfied, it necessitates the estimation of the propensity scores, which are then used for matching to estimate the average treatment effect on the treated. In the study area, the decision to participate in non-farm activities is explained by demographic, infrastructural and farm level characteristics, hence the study will estimate the propensity scores.

3.3.4 Matching Algorithms

There are various matching algorithms suggested in the literature to match the treated and the control groups using the propensity scores. However, the current study will employ the Nearest Neighbourhood Matching (NNM) technique. The NNM consists of matching each participant with the non-participant that has the closest propensity score. The advantage of the NNM is that it allows for the replacement of the matches, which increases the average quality of matching.

However, this matching algorithm reduces the number of distinct non-participant observations used to calculate the mean for the counterfactual group.

3.4 Data Sources and Sampling

Mugenda and Mugenda (1999) defined a sample as a sub set of the population with the same characteristics selected to represent a given population. The study used a sample instead of a population due to geographical and financial constraints. The current study used the Cochran's (1977) formula for sample determination that is given by:

$$\boldsymbol{n = \frac{z^2pq}{e^2} = \frac{2.46^2(0.5)(0.5)}{0.1^2} = 152} \textbf{ Households}$$

Where, n is the sample size, z is the selected critical value of desired confidence level of 99% in this study, p is the proportion of an attribute that is present in the population (proportion of the households participating in non-farm activities in this case). According to Cochran (1977), if the proportion of the population with the desired attributes is not known it must be assumed to be a half of the population, hence $p = 0.5$ is used in this study since the proportion is not known. $q = 1 - p = 0.5$ is the estimated proportion of the population which have not participated in non-farm activities and e is the allowable error which is equal to ± 10 in the present study.

The study used the simple random sampling to select two out of seventeen wards in Mbire district [Chapoto (Ward 1) and Angwa (Ward 2)], which happened to be the most food insecure wards in Mbire district (ZimVAC, 2017), and closer to each other. According to the ZimVAC (2017), Mbire district is made up of approximately 18 130 households, with approximately 1 905 households living in Chapoto and Angwa wards.

One-stage cluster sampling technique was then employed, where the population was divided into two clusters (two wards that is Chapoto and Angwa). Equal number of respondents were then randomly selected from each cluster (ward) since the two wards have almost the same number of households (Nyamwanza, 2014). The probability proportionate to size was used to sample households to be interviewed from each administrative ward.

3.5 Research Instruments

The questionnaires were administered directly to the household heads in Mbire district during the period stretching from 11 to 24 February 2019. A structured questionnaire was used to collect data from the study participants. The open-ended questions allow the respondents (household heads) to respond in their own words and provide more detailed information for the study. The Focus Group Discussion (FGD) was used to gather general information about the target respondents during the data collection process. One focus group discussion was conducted. The FGD was comprised of seven members. The researcher with the supervisor from The University of Zimbabwe jointly reviewed the study questionnaire (see Appendix A) to check if they effectively and adequately address the study objective and research questions.

3.6 Pilot Testing

A pretest survey was conducted to enhance the effectiveness of the questionnaire and to validate the data during the collection process. The pilot study is useful since it can be used to estimate the time needed to complete each questionnaire and the total time needed to collect the data for the research. According to Mugenda & Mugenda (1999), a pretest sample should range between 1 to 10 percent depending on the size of the sample and in the current study; a pretest sample of 10 percent of the sample size (152) was used. During the pilot survey, fifteen questionnaires were administered; one key informant interview and one Focus Group Discussion (FGD) were conducted in Chapoto area (Ward 1) of Mbire district.

3.7 Ethical Considerations

Any research project should address the ethical consideration of the society as part of its design (Banister *et al*., 1994). The important ethical concerns of the people in Mbire district were taken into consideration by the study design. The author sought approval to carry out the study from the supervisor from in the economics department, University of Zimbabwe as well as consent from the local leadership in the Mbire district, which included chiefs, village heads and the department of agriculture extension (AREX). Consent at household level was also sought from the household heads accordingly, who were assured of confidentiality.

3.8 Data Collection Procedures

The data was collected with the household as a sampling unit. The researcher collected the data from the rural household heads in Mbire district with the help of three research assistants who were trained on how to collect the data and knowledgeable about the research topic and objectives. On spot checks for commission, completeness and omission errors were done during the interviews. Respondents were interviewed in their language, which is *shona*. After the data collection process, all the questionnaires were checked and edited for completeness and consistency. Data were then entered using excel.

3.9 Conclusion

The chapter presented the methodology that was employed to collect data for the key variables that were likely to influence the decision to participate in non-farm activities. Clarification on research instruments, model specification and data collection procedure were done. Also included in this chapter was the definitions and justification of variables. The next chapter will focus on the estimation, presentation and interpretation of the research results in order to provide answers to the research questions posed in the first chapter of this dissertation.

CHAPTER FOUR

ESTIMATION, PRESENTATION AND INTERPRETATION OF RESULTS

4.1 Introduction

This chapter focuses on the estimation, presentation and interpretation of results from the empirical models specified in chapter three. The factors influencing the rural farm households' choice to participate in non-farm activities and the impact of the participation on rural households' food security status are analysed starting with the descriptive statistics, and then followed by the presentation and interpretation of econometric results.

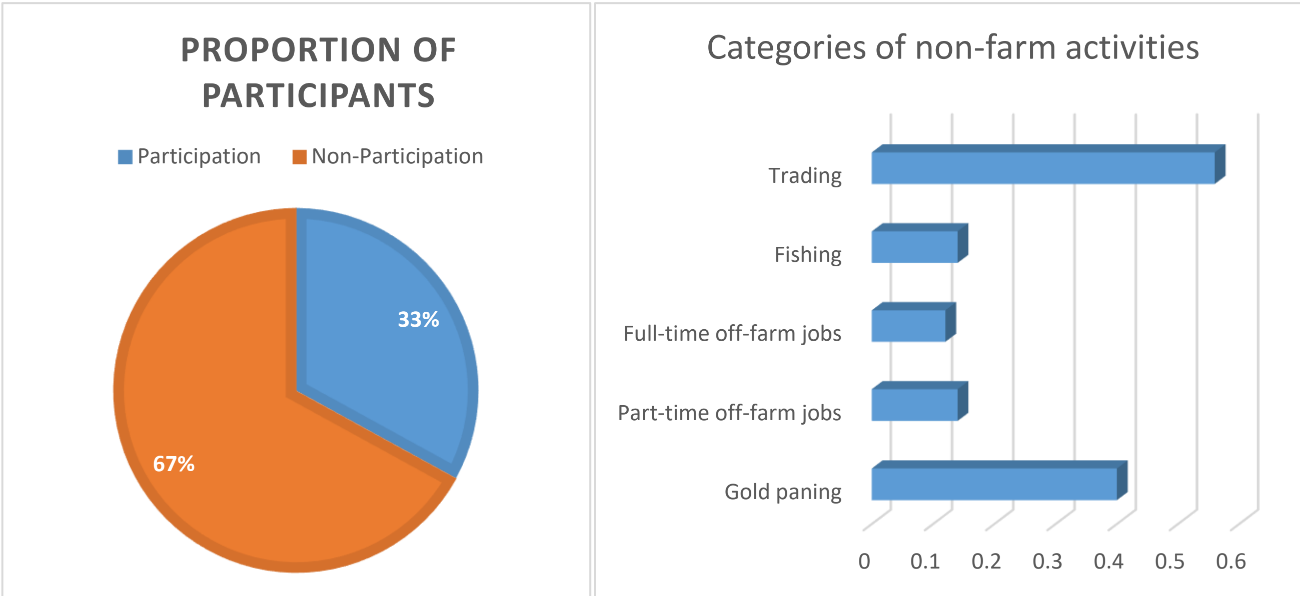
4.2 Descriptive Statistics

This section describes and summarises the data collected on the factors influencing the rural farm households' decision to participate in non-farm activities and the impact of the participation on food security. The independent variables are categorised into continuous and categorical variables.

4.2.1 Proportion of the Participants in Non-farm Activities and their Categories

The data from the sample drawn from the study area have shown that only 33 percent (translating to 47 households) of the households have participated in non-farm activities, and the rest did not. The non-farm activities carried out in Mbire district were petty trading, gold panning, fishing, part-time and full-time jobs. Petty-trading forms major part of the non-farm sector in Mbire district which constitute 56 percent of all activities in the non-farm sector. People in Mbire district mainly trade in masawu (natural indigenous fruits), maize and second hand clothing. Other non-farm activities almost share the same proportion with gold panning being the least practiced. Figure 3 shows these statistics.

Figure 4: Proportion of the non-farm Participants and the Categories of Non-farm Activities



4.2.2 Descriptive Statistics for Continuous Variables

Table 2 shows that on average household heads who participated in non-farm activities are younger than those who did not participate. The treated group has an average of 42 years against 47 for the non-treated group. More so, on average, the household heads who participated in non-farm activities have more schooling years than those who did not. Those who participated in non-farm activities have an average of five years of education after their primary education while those who did not participate have an average of one year of education after their primary education. The households who participated in non-farm activities have, on average, bigger household size of seven members than those who participated with an average of five members per household. Both the treated and the non-treated groups have almost the same consumer to worker ratio of two. The households who did not engage in non-farm activities have relatively longer distance to the main road and to the nearest market. The distances to the main road are 2.77 km and 8.497 respectively for the treated and non-treated groups respectively. The distances to the nearest market are 3.881km and 10.116 km for the treated and non-treated respectively. The households who diversified into non-farm activities have on average bigger livestock herds of five cattle than their counterparts who did not diversify into non-farm activities with an average of one cow per household. More so, the households who participated in non-farm activities have on average bigger land than their counterparts who did not participate. Those who participated have an average of 7.532 hectares, while those who did not participate in non-farm activities have an average of 5.783 hectares. Furthermore, the participants are on average wealthier than the non-participants are in terms of assets ownership. The participants have an average value of assets amounting to RTGS$1,071.27, while the non-participants have RTGS$364.94.

Table 2: Descriptive Statistics of the Continuous Variables

	Treated Group (Participants)			Non-Treated (Non-Participants)		
	Obs	**Mean**	**Std. Dev**	**Obs**	**Mean**	**Std. Dev.**
Hhage	47	42.064	10.852	97	47.113	13.340
Hheduc	47	5.106	2.267	97	1.737	2.263
Hhsz	47	5	2	97	7	3
Conswkr	47	2.058	0.704	97	2.200	1.716
Dis_mrd	47	2.277	1.392	97	8.497	5.931
Dis_mkt	47	3.881	2.359	97	10.166	6.921
Livstk	47	5.000	4.188	97	1.000	1.674
Landsz	47	7.532	3.719	97	5.738	3.084
Asset	47	1071.27	1223.46	97	364.94	1918.86

4.2.3 Descriptive Statistics for Categorical Variables

Table 3 shows that the proportion of females who participated (4.3%) in non-farm activities is significantly lower than the proportion of females who did not participate (45.4%) in non-farm activities. This means that males dominate the non-farm sector. More so, the proportion of the participants in non-farm activities who own cellphones (93.6 percent) is much higher than in the non-participant group (50.5 percent). The same applies in the internet access where 74.5 percent of the participants in non-farm activities have internet access while only 7.2 percent of the non-participant group have internet access. In addition, the proportion of the households who have access to credit (40.4 per cent) is relatively higher in the treated group than in the non-treated group of 2.1 per cent. From these descriptive statistics, the respondents who did not diversify into non-farm activities are generally more food-insecure relative to those who diversified.

Table 3: Summary Statistics of Categorical Variables

	Treated Group (Participants)				Non-Treated Group (Non-Participants)			
	Proportion	**Std.Err.**	**[95%Co Interval]**		**Proportion**	**Std.Err.**	**[95%Conf Interval]**	
Hhgendr								
Females	0.043	0.030	0.010	0.162	0.454	0.051	0.356	0.555
Males	0.957	0.030	0.838	0.990	0.546	0.051	0.445	0.644
Celphn								
No Cell	0.064	0.036	0.020	0.187	0.495	0.051	0.395	0.595
Owners	0.936	0.036	0.813	0.980	0.505	0.051	0.405	0.605
Intrnt								
No Acc	0.255	0.064	0.148	0.404	0.928	0.026	0.855	0.966
Access	0.745	0.064	0.596	0.852	0.072	0.026	0.034	0.145
Credt								
No Acc	0.596	0.072	0.446	0.730	0.979	0.015	0.919	0.995
Access	0.404	0.072	0.270	0.554	0.021	0.015	0.005	0.081

4.3 Pre-Estimation Tests Results

The study performed two tests before the estimation of the regression equations. These tests are carried out in order to make sure that the models satisfy all the necessary model assumptions and to make sure that the models are valid and can be relied upon. The multicollinearity was checked before estimating the propensity scores using the logit model. After the logit model estimation, the overlapping condition was then tested before the estimation of the treatment evaluation model.

4.3.1 Multicollinearity Check

One of the important assumptions of the Classical Linear Regression Model (CLRM) is that which requires the explanatory variables to be linearly independent (full rank). If there exist perfect multicollinearity among explanatory variables, the coefficients of the explanatory variables will be biased in that they will have larger variances (Gujarati, 2003). The coefficients of the pairwise matrix were all less than 80%, meaning that there was no perfect multicollinearity among the explanatory variables (see Gujarati, 2003). The multicollinearity is tested among the continuous explanatory variables only as categorical variables cannot be linearly related to other dummy and continuous variables. Table 4 shows the results from the multicollinearity test using the pairwise correlation matrix.

Table 4: Pairwise Correlation Matrix

Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
(1) Hhage	1.000						
(2) Hheduc	0.001	1.000					
(3) Dis_mrd	0.235	-0.083	1.000				
(4) Dis_mkt	0.143	-0.089	0.670	1.000			
(5) Landsz	-0.039	0.003	-0.229	-0.178	1.000		
(6) Livestock	0.016	0.039	-0.302	-0.255	0.285	1.000	
(7) Asset	0.099	0.105	-0.138	-0.177	0.237	0.364	1.000

4.3.2 The Overlapping Condition Check

This assumption states that for every explanatory variable there should be a positive probability of not participating, and should be less than one. The overlapping condition is the necessary assumption to be performed prior to the estimation of the treatment evaluation model because it ensures that the household heads in the treated group have the matching partners with closest propensity scores in the non-treated group, otherwise the matching will not be feasible and the treatment evaluation model cannot be run in STATA. This assumption was tested and found to be satisfied meaning that the comparability between the treated and the untreated groups was feasible and the treatment evaluation results could be reliably interpreted.

4.4 Diagnostic Test Results

To make sure that the regression models have been correctly specified and can be relied upon, the diagnostic have to be done after the estimation of each regression model. Hosmer-Lemeshow test was done to test the goodness of fit of the logit model. More so, to validate the reliability of the treatment evaluation model results, the balancing property condition was tested. The results of these tests are discussed below.

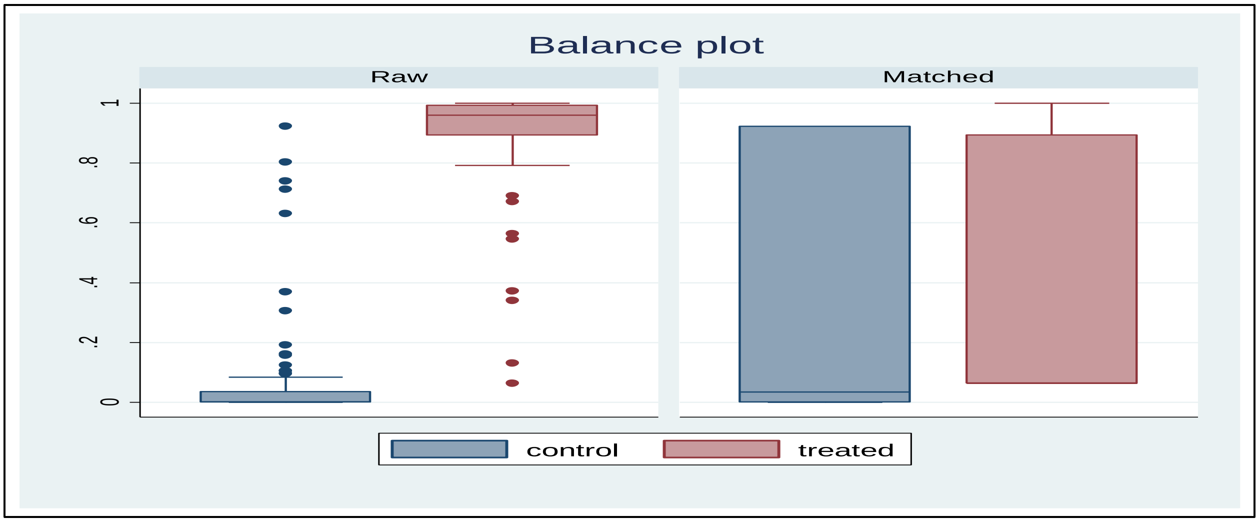
4.4.1 Goodness of Fit Test of the Logit Model

The goodness of fit of the logit model was tested using the Hosmer-Lemeshow test. The logit model used to estimate the propensity scores was of good fit. The p-value from the Hosmer-Lemeshow test results presented in Appendix D was 0.678. This result mean that the model was of good fit and the results can be reliably interpreted.

4.4.2 The Balancing Property Condition Check

The results of the test are presented in figure 5 and Appendix G. These results show that the balancing condition is satisfied. This implies that the distribution of the conditioning confounding factors did not differ across the treated and the control group in the matched samples. This confirms that there are no pre-treatment differences between the participants and non-participant households; meaning that the self-selection bias has been eliminated, satisfying the matching requirement for computing the average treatment effect on the treated (ATET).

Figure 5: The Balancing Condition Test Using the Balance Box plot



4.5 Econometric Results

The results from the logit and the treatment evaluation models are presented and interpreted below.

4.5.1 Factors Influencing Rural Households' Decision to Participate in Non-farm Activities

Table 5 presents the results from the logistic regression estimation. The coefficients of the logistic regression estimation only provides the sign of change but not the magnitude of change. Interpreting these coefficients inflates the impacts since the model is non-linear. The way to interpret the results from the maximum likelihood estimations (logistic in this case) is to estimate the marginal effects, which measure both the impact and the direction. Marginal effect is the actual effect of a unit change in each regressor on the participation decision probability. Table 6 presents the average marginal effects (AME) from the logistic regression estimation.

Table 5: Logistic Regression Output (Propensity Scores)

Treat	Coef.	Std.Err.	Z	P>z	[95%Conf.	Interval]
Hhgendr	2.607*	1.379	1.890	0.059	-0.095	5.309
Intrnt	2.628**	1.087	2.420	0.016	0.496	4.759
Dis_mrd	-0.568**	0.274	-2.070	0.038	-1.105	-0.031
Livestock	0.843***	0.281	3.000	0.003	0.293	1.393
Hheduc	0.513***	0.185	2.770	0.006	0.150	0.877
Hhage	0.078	0.241	0.320	0.747	-0.394	0.550
Hhage2	-0.001	0.002	-0.470	0.637	-0.006	0.004
Asset	-0.047**	0.020	-2.430	0.015	-0.086	-0.009
Dis_mkt	-0.037	0.145	-0.250	0.800	-0.320	0.247
Landsz	-4.105*	2.431	-1.690	0.091	-8.870	0.661
Credt	2.762	1.860	1.490	0.138	-0.883	6.408
Cons	-4.495	6.106	-0.740	0.462	-16.463	7.472

Number of obs = 144, LR Chi2(11) = 139.32, Prob > Chi2 = 0.000, Log likelihood = -21.2915

****** represent 1%, ** represent 5% and * Presents 10% level of significance***

The statistical significance of the regressors was tested using the p-value of the t-statistic. The null-hypothesis states that; the demographic, infrastructural and farm level characteristics have no significant effect on a rural farm households' decision to participate in non-farm activities. The null hypothesis was rejected when the p-value was found to be less than the conventional levels of significance (1%, 5% and 10%). A number of coefficients of the explanatory variables were found to be statistically significant which are interpreted after the estimation of the marginal effects. The insignificant coefficients are not interpreted.

Table 6: Average Marginal Effects from the Logistic Regression (PS Marginal Effects)

	dy/dx	Std.Err.	Z	P>z	[95%Conf	Interval]
Hhgendr	0.112**	0.056	1.980	0.047	0.001	0.222
Intrnt	0.113***	0.043	2.630	0.008	0.029	0.196
Dis_mrd	-0.024**	0.011	-2.240	0.025	-0.046	-0.003
Livestock	0.036***	0.010	3.520	0.000	0.016	0.056
Hheduc	0.022***	0.007	3.110	0.002	0.008	0.036
Hhage	0.003	0.010	0.320	0.748	-0.017	0.024
Hhage2	-0.000	0.000	-0.470	0.638	-0.000	0.000
Asset	-0.002***	0.001	-2.740	0.006	-0.003	-0.001
Dis_mkt	-0.002	0.006	-0.250	0.800	-0.014	0.011
Landsz	-0.176*	0.102	-1.730	0.083	-0.375	0.023
Credt	0.118	0.079	1.500	0.134	-0.036	0.273

dydx is for a unit change of the explanatory variable, discrete change from 0 to 1 for a dummy. *** represent 1%, ** represent 5% and * Presents 10% level of significance

4.5.2 Interpretation of the Logit Marginal Effects Results

The coefficient of the gender of the household head was positive and statistically significant at 5 percent level. In tandem with the *a priori* expectation outlined in chapter three, that being a male increases the probability of a household to engage in non-farm activities by 11.2 percent. This is because men are generally stronger enough to handle the strenuous non-farm activities carried out in Mbire district than their female counter parts. Few women can only handle non-farm activities such as gold panning and itinerant trading. Yesuf (2015) got the similar results in Ethiopia.

Regarding the access to internet, the study found the coefficient of internet access to be positive and statistically significant at 1 percent level. Having access to internet increases the probability of the household to participate in non-farm activities by 11.3 percent. This is in line with the study hypothesis outlined in chapter three. This holds true because a household with access to internet has relatively more access to non-farm employment opportunities, mainly via social media such as WhatsApp.

Supporting the results by Tsiboe *et al*. (2016), the coefficient of the distance from the farm to the main road was negative and statistically significant at 5 percent level. More so, in line with the study hypothesis, an increase in the distance to the main road by a kilometer reduces a household's probability to diversify into non-farm activities by 2.4 percent. This is justified since the major non-farm activity in the study area is itinerant trading; traders need to travel by public transport so walking long distance to the main road is quite discouraging and very tiresome.

The coefficient of livestock holding in the model was positive and statistically significant at 1 percent level. This is in line with the hypothesis outlined in chapter three. A unit increase in a cattle herd increases the household's chance to participate in non-farm activities by 3.6 percent. This is because livestock eases smallholder farmers' liquidity constraint. Livestock are liquid in the rural areas. Yesuf (2015) used the same variable in the non-farm employment model and found the same results.

The econometric analysis has shown that the coefficient of education level of the household head is statistically significant at 1 percent level meaning that education is a determinant of the rural households' participation in the non-farm sector, particularly in non-farm wage employment. The study shows that having some levels of education is associated with the higher probability of participating in non-farm activities. One-year increase in post primary years of education of a household head increases the chance of the household to participate in non-farm activities by 2.2 percent. This is because educated people look for less strenuous employment in the non-farm sector. In the study area, educated people are employed by the Grain Marketing Board (GMB) and by the Public Service Commission mainly as teachers and police officers. Matshe and Young (2004) used this variable in their non-farm labour allocation decision in Shamva and got the similar results.

The coefficient of assets ownership was negative and statistically significant at 1 percent level. A unit increase in the value of household assets decreases the probability of the household's participation in non-farm activities by 0.2 percent. This is contrary to the study hypothesis and to the results gotten by Tran *et al*. (2015). This is possibly because of the household assets mainly held in Mbire district such as ox-drawn ploughs and scotch carts, which are illiquid (cannot be easily converted to cash).

The study found the coefficient of the households' land size to be negative and statistically significant at 10 percent level. This means that a unit increase in household's land reduces the probability of that household to participate in non-farm activities by 17 percent. This is so possibly because large farms in Mbire district are more productive than small farms, hence households occupying large pieces of land are food self-sufficient then reducing their probability of participating in non-farm activities.

4.5.3 The Impact of Participation in Non-farm Activities on Households' Food Security

The study employed the treatment evaluation and the propensity scores matching (PSM) to quantify the impact of the decision to participate in non-farm activities on rural households' food security. Table 7 shows the results from the treatment evaluation using the PSM and the Nearest Neighbourhood Matching technique (NNM).

Table 7: Treatment Evaluation Using the PSM and the NNM Results

Fdinsec	Coef.	St.Err.	t-value	p-value	[95%Conf	Interval]
ATET						
(Treated < Non-Treated)	-4.285*	2.412	-1.78	0.076	-9.012	0.443

****** represent 1%, ** represent 5% and * Presents 10% level of significance***

4.5.4 Interpretation of the Treatment Evaluation Results

The dependent variable was measured as the number of times when at least one member of the household member(s) ate fewer meals per day than usual due to lack of food accessibility. The estimate of the average treatment effect on the treated (ATET) in table 7 is -4.285. This means that, on average, participation in non-farm activities reduce food insecurity by 4.285 times. This outcome is in tandem with the findings of Dabalen *et al*. (2004) that found the same results in rural Rwanda and Tsiboe *et al*. (2016) in Northern Ghana. These studies employed a similar estimation technique to investigate the impact of participation in non-farm activities on rural farm households' food security status.

4.6 Conclusion

The study found that demographic, infrastructural and farm level characteristics such household gender, internet access, distance to the main road, livestock holding, household head education level, asset holding and the land size significantly influence the rural households' decision to participate in non-farm activities. The chapter also revealed that the farm households' participation in non-farm activities has a positive impact on food security status of the rural households. The summary and conclusion of the findings from the study, policy implications and recommendations are presented in the proceeding chapter.

CHAPTER FIVE

SUMMARY, CONCLUSION AND POLICY RECOMMENDATIONS

5.1 Introduction

The chapter presents a summary, conclusion and policy recommendations from the study, which investigated the factors influencing rural farm households' choice to participate in non-farm activities and the impact it has on food security.

5.2 Summary and Conclusions of the Study

The study sought to investigate the factors influencing the rural households' decision to participate in non-farm activities and the impact of participation in non-farm activities on rural households' food security status using sample data collected from Mbire district of Mashonaland Central of Zimbabwe. The study identified factors such as household head gender, internet access, distance to the main road, livestock ownership, household head education attainment, land size and ownership of assets such as motorbikes, trucks, and scotch carts and ploughs as significant determinants of non-farm activity participation. The propensity score matching (PSM) technique was employed to eliminate the possible self-selection bias emanating from observable and unobservable factors that influence the rural households' decision to participation in non-farm activities. The rural households' food security was measured by the number of times when at least one member of the household had to eat fewer meals than normal, using a recall period of 30 days. The matching result from the treatment effects results shows that participation in non-farm activities have a positive and statistically significant impact on the rural households' food security status. This finding is consistent with the widely held view in the literature that non-farm income plays a pivotal role to improve their food security-status.

5.3 Policy Implications and Recommendations

The findings of this study suggest that participation in non-farm activities could be a pathway/coping strategy to improve rural households' food security status in Mbire district and other areas sharing the same characteristics with the study area. Any policies targeted at promoting rural household food security should go beyond just food production measures; they should address both the food production measures and measures that help generate additional incomes for rural farm households by promoting non-farm activities. This study is not advocating for non-farm activities as a substitute to farming, but as a reliable complement to farming activities, therefore policymakers should aim to promote rural households' participation in non-farm activities by increasing the access of rural households to physical, financial and human capital. Physical capital, which include good roads and general infrastructural development, will help to reduce transportation costs therefore easing the barriers to non-farm participation and enhance non-farm income.

Opportunities to work in the non-farm sector can also be enhanced by improving access to post-primary education in rural communities. Given that female-headed households are more prone to food insecurity and normally face the entry barriers to participate in non-farm activities in Mbire district, which exerts a positive and robust effect on household food security, policy measures could target them to increase their chance to diversify into non-farm activities in order to improve their food security. More so, there should be provision of light non-farm jobs for women like poultry and dress making to alleviate food insecurity among female-headed households. Promising policy measures that can help boost non-farm activities also include increasing the access of rural households to financial capital (credit) and non-price factors such as education and infrastructure.

The results imply that policy must focus on promoting non-farm employment opportunities in rural farming communities, given its impact on food security and incomes.

5.4 Suggestions of Further Research

This study mainly focused on the factors influencing the rural households' participation in non-farm activities and the impact on rural households' food security. It will be interesting if the non-farm activities are grouped in to various categories such as non-farm part-time employment, non-farm full-time employment and non-farm self-employment such that the researcher will find the factors influencing the rural households' decision to fall into each category using multinomial logit or multinomial probit models. More so, the future studies can be extended to look into the impact of this multi-treatment effect on rural household food security. This study could not go that far because there were no representative samples to represent some of the categories significantly.

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APPENDICES

Appendix A: Study Questionnaire

UNIVERSITY OF ZIMBABWE

FACULTY OF SOCIAL STUDIES

DEPARTMENT OF ECONOMICS

RURAL FARM HOUSEHOLDS SURVEY QUESTIONNAIRE

Good morning/ afternoon/ evening farmer, my name is Misheck Tussle Mundowa, a final year student at The University of Zimbabwe pursuing a **Master of Science Degree in Economics**. I am carrying out a research on factors influencing the rural farm household's choice to participate in non-farm activities and the impact of participation on food security. Your individual opinions will be used for academic purposes only. Kindly note that participation in completing the survey questionnaire is on a voluntary basis and you are free to stop when you do not feel like continuing, or not to answer at all. Confidentiality is guaranteed since there will be no need for the respondent's name. (***Please do not write your name, cell phone number or address, it remains anonymous***).

RURAL FARM HOUSEHOLDS SURVEY QUESTIONNAIRE

Date of data collection…………………………

Interviewer's code…………………………….

Location……………………………………..

SECTION A: DEMOGRAPHIC CHARACTERISTICS

1. Gender [0=Female 1=Male]
2. How old are you?
3. How many years did you spent on education after your first 14 years of birth?
4. How many children do you have?
5. How many of them are still dependent on you?
6. Do you have other dependents apart from your children? (No=0; Yes=1)
7. If Yes in 6, how many are they?
8. How many of your household members are adults (at least 16 years)?
9. How many are minors (under 16 years)?
10. How many of your household members who work in the farm field?

SECTION B: INFRASTRUCTURAL CHARACTERISTICS

11. Do you have a cellphone? (No=0; Yes=1)
12. If Yes in 11, Can you access internet on your phone? (No=0; Yes=1)
13. What is the approximate distance from your farm to the main road in kilometers?
14. What is the nearest approximate distance to where you sell your produce in kilometers?
15. Do you have electricity? (No=0; Yes=1)
16. If No in 15, do you have access to electricity? (No=0; Yes=1)

SECTION C: FARM CHARACTERISTICS

17. What is your total land size in hectares?
18. Which productive assets do you have?
19. How many livestock do have in the following categories?

Category	Cattle	Goats	Sheep	Donkeys	Pigs	Others **(specify)**
Code	1	2	3	4	5	6
Qty						

20. In the past 30 days, did any household member had to eat fewer meals than normal (2 meals) due to lack of food accessibility? (No=0; Yes=1)
21. If **Yes**, how often (how many times) did it happen?

Asset	Ox-drawn plough	Tractor	Scotch-cut	car	Other **specify**
Code	1	2	3	4	5
Qty					
Value					

SECTION D: INCOME

22. For the last agricultural season, what were your main agricultural crops, area, output, sales and value of sales?

Crop	Code	Area Planted	Output Harvested	Quantity Sold	Value of Output sold ($)
Maize	1				
Tobacco	2				
Cotton	3				
Other1(specify)	4				
Other2(specify)	5				
Total Area					

23. Have you or any member of your household participated in non-farm activities in the past 12 months? (No=0; Yes=1)
24. If Yes, which type of non-farm activities were they/you involved in?

Activity	Fishing	Trading	Gold panning	Part-time work	Full-time work	Other **specify**
Code	1	2	3	4	5	6
Tick						

25. Did you acquire any loan to finance your non-farm activities during the past 12 months? (No=0; Yes=1)

26. If Yes in 25, what was the source of the loan?

Source	Commercial Bank	Micro Finance	Farmers Cooperative	Friends	Other **specify**
Code	1	2	3	4	5
Amount($)					

Thank You! Maita Basa

Appendix B: Pairwise Matrix

```
. correlate hhage hheduc dis_mrd dis_mkt landsz livestock  asset  credt
(obs=144)

             |    hhage   hheduc  dis_mrd  dis_mkt   landsz livest~k    asset    credt
-------------+------------------------------------------------------------------------
       hhage |   1.0000
      hheduc |   0.0006   1.0000
     dis_mrd |   0.2351  -0.0834   1.0000
     dis_mkt |   0.1427  -0.0894   0.6700   1.0000
      landsz |  -0.0391   0.0031  -0.2288  -0.1782   1.0000
   livestock |   0.0163   0.0391  -0.3021  -0.2552   0.2854   1.0000
       asset |   0.0991   0.1046  -0.1382  -0.1765   0.2372   0.3638   1.0000
     credt |   0.0162  -0.0323  -0.1415  -0.1037   0.5450   0.1775   0.0756   1.0000
```

Appendix C: Logit Model Results (Propensity Scores Estimations)

```
. pscore $treatment $xlist, logit pscore(myscore) blockid(myblock) comsup
The treatment is treat

      TREAT |      Freq.     Percent        Cum.
------------+-----------------------------------
          0 |         97       67.36       67.36
          1 |         47       32.64      100.00
------------+-----------------------------------
      Total |        144      100.00
```

Estimation of the propensity score

```
Logistic regression                               Number of obs   =        144
                                                  LR chi2(11)     =     139.32
                                                  Prob > chi2     =     0.0000
Log likelihood = -21.291462                       Pseudo R2       =     0.7659

------------------------------------------------------------------------------
       treat |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
     hhgendr |   2.607088   1.378553     1.89   0.059    -.0948257    5.309001
      intrnt |   2.627617   1.087442     2.42   0.016     .4962699    4.758965
     dis_mrd |  -.5677396   .2740231    -2.07   0.038    -1.104815   -.0306642
   livestock |   .8432097   .2806631     3.00   0.003     .2931201    1.393299
      hheduc |   .5130595    .185453     2.77   0.006     .1495783    .8765408
       hhage |   .0776791   .2407539     0.32   0.747    -.3941898     .549548
      hhage2 |  -.0011714   .0024792    -0.47   0.637    -.0060306    .0036877
       asset |   -.047481   .0195682    -2.43   0.015     -.085834   -.0091281
     dis_mkt |  -.0366226   .1447819    -0.25   0.800    -.3203898    .2471447
      landsz |  -4.104501   2.431202    -1.69   0.091    -8.869569    .6605679
       credt |   2.762154   1.859933     1.49   0.138     -.883248    6.407556
       _cons |  -4.495454   6.106035    -0.74   0.462    -16.46306    7.472156
------------------------------------------------------------------------------
```

Note: the common support option has been selected

The region of common support is [.06353801, .99999998]

```
Description of the estimated propensity score
in region of common support

                 Estimated propensity score
-------------------------------------------------------------
      Percentiles      Smallest
 1%      .063538        .063538
 5%     .0954675       .0828725
10%     .1055351       .0849629       Obs                  64
25%     .4588659       .0954675       Sum of Wgt.          64

50%     .9079151                      Mean           .7233646
                        Largest       Std. Dev.      .3407163
75%     .9855851       .9999922
90%     .9989908       .9999984       Variance       .1160876
95%     .9999922       .9999997       Skewness      -.9625176
99%            1              1       Kurtosis       2.258029

******************************************************
Step 1: Identification of the optimal number of blocks
Use option detail if you want more detailed output
******************************************************
The final number of blocks is 6
This number of blocks ensures that the mean propensity score
is not different for treated and controls in each blocks
```

```
*******************************************************

Step 2: Test of balancing property of the propensity score

Use option detail if you want more detailed output

*******************************************************

The balancing property is satisfied


This table shows the inferior bound, the number of treated

and the number of controls for each block


  Inferior |

  of block |         TREAT

of pscore  |         0          1 |     Total

-----------+----------------------+----------

   .063538 |        10          2 |        12

        .2 |         2          2 |         4

        .4 |         0          2 |         2

        .6 |         3          3 |         6

        .8 |         1          4 |         5

        .9 |         1         34 |        35

-----------+----------------------+----------

     Total |        17         47 |        64


Note: the common support option has been selected



*******************************************

End of the algorithm to estimate the pscore

*******************************************
```

Appendix D: Marginal Effects of the Propensity Scores

```
. margins, dydx(*)


Average marginal effects                          Number of obs     =        144

Model VCE    : OIM


Expression   : Pr(treat), predict()

dy/dx w.r.t. : hhgendr intrnt dis_mrd livestock hheduc hhage hhage2 asset dis_mkt landsz
credt


------------------------------------------------------------------------------

             |            Delta-method

             |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]

-------------+----------------------------------------------------------------

     hhgendr |   .1117476   .0563419     1.98   0.047     .0013196    .2221757

      intrnt |   .1126276    .042784     2.63   0.008     .0287726    .1964826

     dis_mrd |   -.024335   .0108398    -2.24   0.025    -.0455806   -.0030894

   livestock |   .0361425    .010275     3.52   0.000     .0160039    .0562811

      hheduc |   .0219913   .0070644     3.11   0.002     .0081453    .0358372

       hhage |   .0033296   .0103514     0.32   0.748    -.0169589     .023618

      hhage2 |  -.0000502   .0001066    -0.47   0.638    -.0002592    .0001588

       asset |  -.0020352   .0007438    -2.74   0.006     -.003493   -.0005773

     dis_mkt |  -.0015698   .0062008    -0.25   0.800     -.013723    .0105835

      landsz |  -.1759313   .1015411    -1.73   0.083    -.3749482    .0230857

       credt |   .1183942   .0789742     1.50   0.134    -.0363923    .2731808

------------------------------------------------------------------------------
```

Appendix E: Hosmer-Lemshow Goodness of fit of the Logit model

```
. estat gof


Logistic model for treat, goodness-of-fit test


       number of observations =       144

 number of covariate patterns =       143

            Pearson chi2(131) =        55.77

                  Prob > chi2 =         0.6782
```

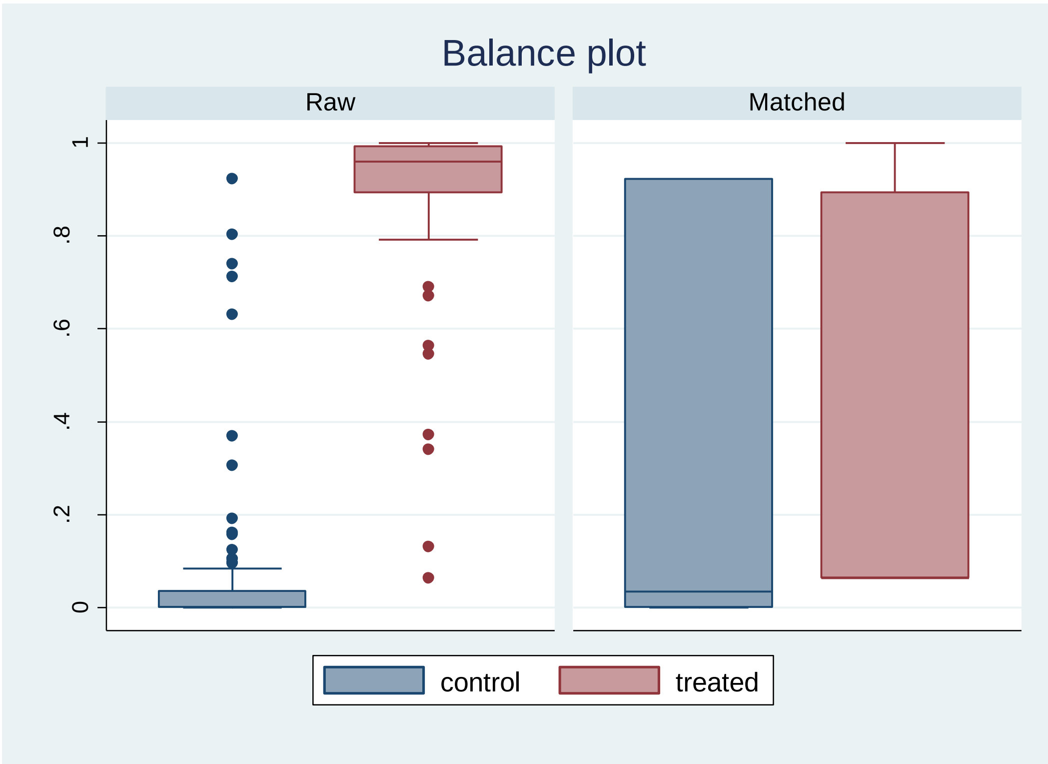
Appendix F: Treatment Effect Results

```
. teffects psmatch (fdinsec) (treat $xlist), vce(robust,) pstolerance(1e-8)

note: variance correction results in a negative variance estimate; ignoring the
correction term


Treatment-effects estimation                   Number of obs      =        144

Estimator      : propensity-score matching     Matches: requested =          1

Outcome model  : matching                                     min =          1

Treatment model: logit                                        max =          1

------------------------------------------------------------------------------

             |              AI Robust

     fdinsec |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]

-------------+----------------------------------------------------------------

ATET          |

       treat |

   (1 vs 0)  |  -4.284722   2.411946    -1.78   0.076    -9.012049    .4426048

------------------------------------------------------------------------------
```

Appendix G: Balancing Property Condition Check

Balance condition check using Box Plot

```
. tebalance box

note: refitting the model using the generate() option
```



Balance condition check using summary statistics

```
. tebalance summarize

note: refitting the model using the generate() option


  Covariate balance summary

                                             Raw      Matched

                          -----------------------------------------

                          Number of obs =          144          288

                          Treated obs   =           47          144

                          Control obs   =           97          144

                          -----------------------------------------
```

	Standardized differences		Variance ratio	
	Raw	Matched	Raw	Matched
hhgendr	1.075674	1.29625	.1662269	.2389851
intrnt	1.858377	-.1211946	2.871415	.8982233
dis_mrd	-1.443994	-.7894507	.0550678	.0263581
livestock	1.391787	.2063206	6.257344	3.908135
hheduc	.2991884	.0788568	2.952811	1.319566
hhage	-.4147193	.032369	.6587883	.4333913
hhage2	-.3961994	-.0432318	.5295267	.3207636
asset	.4386264	.3337244	.4085266	.2500612
dis_mkt	-1.215544	-1.383844	.1161667	.0835147
landsz	.3820275	.9176224	1.171369	.9537465
credt	.2574397	.5040926	.9458529	.5463589

Balance condition check using Kernel Density Plot

```
. tebalance density

note: refitting the model using the generate() option
```