AN EMPIRICAL INVESTIGATION ON THE EFFECTS OF FINANCIAL CREDIT ON HOUSEHOLD WELFARE: WHO BENEFITS MOST?

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A thesis submitted in partial fulfilment of the requirements of

Nottingham Trent University for the degree of

Doctor of Philosophy in Economics

Department of Economics

Nottingham Trent University, United Kingdom

December 2023.

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DECLARATION

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December, 2023

DEDICATION

I dedicate this Thesis to God Almighty and my Lord Jesus Christ whose help has seen me through so far. His words, ***"Whereas thou has been forsaken and no one went through thee, I will make thee an eternal excellency, a joy of many generations****". Amen.*

To my late Mum, who died during my academic pursuits and wished that I became the best I could be.

To all students and everyone who will not give up on life.

ACKNOWLEDGEMENTS

Firstly, I express my profound appreciation to my experienced supervisors, Dr. Dimitrios Bakas, Prof. Piers Thompson and Dr. John Ebireri. They accepted me as their supervisee and helped me set sail early in my PhD. They also recommended me for the NTU PhD studentship funding. Their invaluable and insightful comments have helped shape my thesis and inspired me to go beyond my comfort zones to improve on my research. Moreso, their commitments on issues relating to my career and professional development is unrivaled and I have learnt so many values from their rich expertise and experience.

I thank Dr Shang Jiang, my independent assessor who provided insightful feedback from my annual review monitoring yearly. Furthermore, I acknowledge the Nottingham Trent University PhD Studentship Committee for their PhD Scholarship support that enabled me to undertake this PhD. My Dad, Mr James Ezuma Onoh also encouraged me every time I faced difficulties and needed someone to talk to.

Abstract

This thesis includes six chapters analysing the effects of financial credit on household welfare. The motivations for this study stems from the need to understand how financial credit policies work best in welfare improvements and who benefits most from financial credit policies. These are eventually aimed at suggesting optimal financial credit strategies on targeted households. While the first chapter provides a general introduction of the thesis, the second chapter follows a novel quantitative systematic approach to answer the question on what the available evidence says on the effects of financial credit on welfare for Africa. The bulk of the existing evidence has focused on regression and descriptive analysis to give conclusions on the effect of micro-finance on welfare with few randomized control trials. Other systematic evidence has focused on financial inclusion like insurance, health, savings and their consequent effect on the economy. The findings show that 59% of the studies covered overall favours a positive direction of impact of micro-credit on welfare. However, when considering individual estimates rather than the overall conclusions of a paper, the evidence of this effect is more mixed, in terms of the number of estimates that show positive significant effects compared to the number of estimates that show insignificant effects.

The third chapter builds on the gaps highlighted by the systematic evidence to examine the impact of financial credit on household welfare for Nigeria. Prior to this research, micro panel causal evidence for lower-middle income economies is very scarce and arguments in literature has been conflicting due to endogeneity problems around selection bias and unobserved heterogeneity (time invariant factors), debates around the external validity of Randomized Control Trials (RCTs) and the inadequacies of cross-sectional study conclusions resulting in correlation results. The analysis addressed these endogeneity problems using a longer data period through the propensity score matching (addressing selection bias problems) and the difference in difference (addressing time invariant heterogeneity issues) methodologies. The results show that although financial credit improves welfare in terms of consumption per capita, this effect is not present for other welfare measures.

The fourth chapter attempts to answer the question of who benefits most from financial credit. The analysis goes beyond the usual mean effect regressions found in the previous literature to provide arguments to identify who really benefits from micro-credit. The results from this chapter suggest that there are heterogeneities in the welfare outcomes because of obtaining credit. Specifically, financial credit significantly affects households that are at the low to median quantiles of the distribution for the most part in African countries and hence, the need for governments and development organisations to target these households in their financial credit policies.

The fifth chapter investigates whether financial credit is sensitive to gender. The results show that economic and social factors and the interaction between them are important determinants of obtaining financial credit for both male headed and female headed households in African countries. There are found

to be positive effects from micro-credit on the various distribution of welfare for both genders. The effect is greater for female headed households.

The last chapter summarises the conclusions from the thesis with policy suggestions. As an implication from the thesis, financial credit improves welfare only in the short-run for specific welfare measures and for households categorised as low to median quantile levels for the most part. Furthermore, financial credit empowers the female headed households and can be used as a policy measure to encourage female headed households to allocate more time to income generating activities.

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Chapter 1 Introduction

Microfinance institutions, particularly micro-credit, have garnered significant interest from both development practitioners and scholars. This attention is due to the perceived potential of micro-credit in alleviating poverty and enhancing household welfare (Yunus 1998, 1999, Yunus and Heiden 2019, MIX and CGAP 2011). The provision of capital to households with limited assets and low incomes, enabling them to invest in self-employment activities like agriculture or micro-enterprises, is anticipated to contribute to improved welfare. In Africa, the bulk of the existing evidence has focused on regression and descriptive analysis to give conclusions on the effect of micro-finance on welfare. This in part reflects the limited number of micro-credit programmes to study. Empirical studies of the impact of finance on welfare have generated mixed results from both the credit demand and credit supply channels for various developed economies. Micro causal evidence for lower-middle income economies is very scarce as a consequence of limited availability of panel micro data. Further arguments are still on-going in the literature due to endogeneity problems around selection bias and unobserved heterogeneity (time invariant factors), which have not been accounted for. Similarly, debates around the external validity of Randomized Control Trials (RCTs) have been raised.

Consequently, the exigency to take on economic research programmes aimed at developing economic strategies and policies targeted at improving household welfare for low and lower-middle income countries provides a motivation for this study. In particular there is a need to understand to what extent findings from elsewhere in the world are applicable to Africa, which is believed to be the poorest region of the world, and characterised by higher levels of market failures, financial illiteracy and inequality (Ismi 2004, Chancel et al. 2022).

1.1 Research Questions

My research focuses on the effects of financial credit on household welfare. The main research question can be stated as follows:

1. What impact does the provision of financial credit have on household welfare?

The main research question can be broken down into a number of sub-questions that this thesis will seek to answer.

1A – *Does the relationship between financial credit and welfare vary by welfare measures?*
1B – *To what extent does the relationship between financial credit and welfare differ depending on the time elapsed since the provision of credit?*
1C – *Is there variation in the relationship between financial credit and welfare by the nature of the household?*
1D – *Is there any evidence that any relationship between financial credit and welfare may be operating through an empowerment effect?*[1]

In order to provide insights into policy and practice, it will be important, as much possible, to try to determine the extent that any relationship between financial credit and welfare represents a causal impact from financial credit to welfare. Therefore, to attempt to answer the research question and sub-questions outlined above the following analyses are undertaken.

1. A quantitative systematic review of the relevant literature is undertaken, in the second chapter, to summarise what the existing evidence suggests with regard to the relationship between financial credit and welfare in the African context.

[1] I focus on economic empowerment which relates to engaging in non-farm activities as a means to improving welfare. The choice of this measure relates to the fact that agricultural households could engage in non-farm businesses or start-ups that could improve their welfare or decision making (Garikipati 2008).

2. The next chapter empirically investigates the effects of financial credit on different welfare indicators over different periods of time. This analysis uses Nigeria as a case study to explore this.

3. The last two analytical chapters investigate which households would governments be best advised to direct finance in Africa. The first, of these chapters, considers whether household welfare plays a role and affects any impact of finance on welfare.

4. The next chapter examines whether financial credit is sensitive to gender. It considers if not only does the relationship between financial credit and welfare vary by the welfare level of the household, but whether the gender of the household plays a role. The relationship of financial credit with both welfare measures and empowerment (as defined by engaging in non-farm business activities) are both considered.

The following section will provide an outline of the structure of the remainder of the thesis, providing more detail on the analysis to be undertaken in the remaining chapters. It will highlight how the analysis to be undertaken is designed to answer the research questions as stated above.

1.2 Overview of Chapters

To answer the research questions of this thesis, different methodologies have been used to address the relevant gap(s) in the literature. While the first chapter introduces the thesis, the second chapter analyses the available evidence from the existing literature on the effects of financial credit on welfare for Africa. This chapter updates the previous narrative evidence (Van Rooyen et al. 2012) and systematically reviews the research focusing on the relationship between financial credit and welfare of households. It summarises the methodologies and analytic approaches employed in the previous literature, and considers if there are changes in the nature of this work over time and in particular after the Covid-19 pandemic[2].

Next, to address the issues of endogeneity present in the financial credit and welfare relationship and the limited available panel data evidence, as identified in the review of the existing literature in chapter two, chapter three investigates the effects of financial credit on different welfare indicators over different durations of time. In 2015, the Central Bank of Nigeria (CBN) introduced an intervention initiative aimed at extending financial credit to farm households across the country's six geopolitical zones. The primary goal was to enhance household welfare and agricultural productivity, ultimately reducing poverty levels. Farm households have the option to apply for these loans directly through banks or by utilising farmers' cooperatives and micro-finance institutions. The impact assessment of these credits on welfare indicators such as consumption per capita, income, food expenditure, non-food expenditure, and education expenditure, relies on informal information from the Central Bank of Nigeria and data from the World Bank Living Standard Measurement Survey (LSMS) dataset. This dataset provides insights into farm households that applied for and received loans in 2015, as well as the welfare levels of these households before (2012) and after (2016 and 2018) obtaining the loans.

Having found in chapter three that there is some evidence of a positive effect from financial credit on welfare after accounting for selection bias and time invariant unobservable endogeneity issues, although this is not necessarily present for all measures of welfare and does not persist through time, it is important to understand this relationship more deeply to provide insights for policymakers. Given the perceived importance of financial credit in alleviating poverty (Yunus 1998, 1999, Yunus and Heiden 2019, MIX and CGAP 2011) an obvious next step is to investigate whether it is those most in need that benefit from the positive effect identified in chapter three. That is, will financial credit positively improve the welfare of households who have different welfare levels and not just mean level welfare? Consequently, to understand the relationship better, it becomes necessary to investigate whether financial credit significantly improves welfare at different welfare distributions and not just at the mean level already established in chapter three.

[2] The study was divided into periods before the Covid-19 pandemic and periods after the Covid-19 pandemic to identify any difference(s) on the direction of effects on the impact of financial credit before and after the Covid-19 pandemic and to identify the number as well as the types of studies during and after the pandemic. This will highlight the gap in approach and results before and after the Covid-19 Pandemic.

The positive impact of financial credit on the welfare of those with lowest starting point found in chapter four suggests that for policymakers, financial credit provision potentially provides an effective tool. However, studies such as (Chant 2003, Garikipati 2008) suggest that women and the households they head are a group who suffer from poverty and disadvantage that results in lower welfare to a greater degree. However, the review in chapter two indicates that a vast bulk of studies have not considered if financial credit specifically benefits this group. To address this, the last empirical chapter (chapter five), focuses on investigating whether the effect of financial credit is sensitive to gender.

The concluding chapter, chapter six, gives further details of the recommendations and prospects for further research areas from the thesis. This helps to further highlight the contribution to knowledge made by the thesis theoretically, empirically and practically via policy recommendations. Limitations of the research are also noted.

1.2.1 Contribution of Study

For the second chapter, a quantitative approach to systematic review which is regarded as a valuable tool for drawing valid conclusions from the most relevant high quality evidence (DFID 2011, Petticrew and Roberts 2006) is employed to understand the evidence on the effects of financial credit on welfare for Africa. This approach allows me to present the evidence from the literature by categorising the results relating to the relationship between financial credit and welfare based on major conclusions of authors and number of estimates that are statistically significant for each study. 59% of the total studies included in African countries favours a positive relationship between micro-credit and welfare both before and after the Covid-19 pandemic. However, there is a mixed evidence relating to this relationship when the individual estimates, contained within the studies, are considered rather than the overall conclusions of the authors of these pieces of research. A high proportion of individual estimates indicate that no significant or even a negative relationship may be present. This chapter highlights the facts that panel micro data evidence on the effects of financial credit on welfare are very scarce. In addition, the bulk of the evidence are non-causal with problems of endogeneity been a major concern in the literature. At best, the bulk of the studies have focused on controlling for endogeneity stemming from selection bias problems but neglect it's combination with endogeneity problems from time invariant unobservable factors that affects welfare for a longer period of time.

Next, to investigate the effect of financial credit on different welfare indicators over different duration of time, chapter three employed panel data on households from Nigeria and a combination of the Difference-In-Difference (DID) and Propensity Score Matching (PSM) methodologies. This helps identify causal effects and addresses issues of endogeneity that arises from selection bias, in the receipt of funds, and unobserved heterogeneity of households as a function of time. Thereafter, the technique of Heckman et al. (1997) was used to estimate the Average Treatment Effect on the Treated (ATT) of receiving financial credit and the consequent effect on the different welfare indicators using a good counterfactual group of households who did not receive the credit. However, to control for time invariant unobservable factors (endogeneity stemming from unobserved heterogeneity) that may affect the results from the model, I combined the Propensity Score Matching model with a standard Difference-In-Difference model following the techniques of Willianson and Forbes (2013) using the propensity score weights generated from the matched samples. The results from the chapter show that although credit improves welfare (consumption per capita), this effect is not as evident for other welfare measures. There is also mixed evidence for the positive relationship when looking for evidence of credit having a lasting effect over longer periods of time.

The next empirical investigation in chapter four therefore considers the gap in the literature relating to "whom should government divert finance" ? The chapter deviates from the usual mean effect regressions in the literature to provide arguments on identifying who really benefits from micro-credit and the need for governments and developmental organisations to target these households instead of relying only on the usual trend of selecting those who should get credit based on credit metrics of commercial banks alone. The objective of the chapter was to identify the various welfare levels of households and see if financial credit has any effect across these levels of household welfare. The quantile regression econometric procedure was used to examine the effects of obtaining credit on the various distributions of welfare across a household panel dataset drawn from lower-middle (Nigeria and Tanzania) and low income (Ethiopia and Malawi) countries in Africa. In particular, the methodology proposed by Canay (2011) for quantile regression was utilised. This approach accommodates both unobserved heterogeneity and heterogeneous covariate effects. The utilisation of panel data further enables the incorporation of fixed effects, serving to manage certain unobserved covariates and address potential endogeneity concerns. The results were considered both for the whole dataset and also for households from specific groups of countries. The results of this chapter show that obtaining micro-credit possesses positive implications for households below certain welfare levels for both lower-middle (Nigeria and Tanzania) and low income (Ethiopia and Malawi) countries in Africa. For richer households however, there are minimal impacts of obtaining financial credit.

The last empirical chapter (chapter five), focuses on investigating whether the effect of financial credit is sensitive to gender using three methodological processes. First, to provide evidence in attempt to answer to the research questions as "what factors determine the acquisition of loans across male and female applicants?", I estimate a panel probit model on the determinants of obtaining credit across both genders controlling for fixed effects. This is done to identify potential supply and demand side factors that play important roles in loan acquisition across male and female headed households. Next, to determine whether there is asymmetry in outcomes from obtaining credit between the genders, I specify a quantile regression model similar to that in chapter four. Finally, to answer the question on "which of the two genders does obtaining micro-finance empower?", I specify a binary outcome Extended Regression Model (ERM). The model adequately accounts for any combination of endogenous covariates, nonrandom treatment assignment, and endogenous sample selection (Imbens and Newey 2009, Wooldridge 2010, Wooldridge et al. 2016, Wooldridge 2020). Results from the chapter show economic and social factors and the interaction between them are important determinants of obtaining financial credit for both male headed and female headed households in lower-middle (Nigeria and Tanzania) and low income (Ethiopia and Malawi) countries in Africa. Moreso, I find that there are effect gaps from the impact of micro-credit on the various distribution of welfare for both genders, with larger impacts on the female headed households. Micro-credit empowers the female headed households to engage in non-farm business activities, and can be used as a policy measure to encourage female headed households to allocate more time to income generating activities.

Chapter 2 What Does The Available Evidence Say on the Effects of Financial Credit and Welfare in Africa?

2.1 Introduction

The search for greater evidence on financial credit policies and the strategies to put in place for financial credit and welfare improvements, especially in low-income economies, provides a great motivation for this study. In this chapter, I provide broad conclusions on the relationship between micro-credit and welfare through a systematic review of the available evidence on the impact of micro-credit on welfare for African countries. More pertinently for the empirical analysis that follows in the later chapters, this chapter also notes the limitations of the existing studies and the gaps in knowledge that are still present. A quantitative approach to systematic review that is regarded as important for drawing valid conclusions from existing evidence (DFID 2011, Petticrew and Roberts 2006) is employed in this chapter.

Insightful evidence over the last two decades relating to the success of micro-finance, sometimes referred to micro-credit, stemmed from the works of Yunus (2007) and the Microcredit Summit Campaign of 2011 (Reed et al. 2012). However, the provision of micro-finance existed before this period as Brandt et al.(2012) show that obtaining finance at the household level was in existence in Europe before the 19th Century where either traders or the poor were provided with loan initiatives in countries like Germany and Ireland. While the micro-finance evidence has increased over time, other studies also show that about 31%

of the world's population lack access to financial services in the form of formal credit and savings (Caplan et al. 2021, Demirguc-Kunt et al. 2018). To address this, governments alongside non-governmental organisations have put in place many financial literacy and credit intervention programmes especially in developed countries to improve living conditions as well as improve financial inclusion (Mitton 2008, Pearce 2011, Sarma 2008, INFE 2012, Skimmyhorn 2016, Ismayilova et al. 2012, Kempson et al 2013, Nam et al. 2016). Notwithstanding, whether these programmes meet the expected outcome, especially when replicated in countries with different income levels, has been both an important question and the subject of debate by economists for nearly two decades.

Arguments on the impact of micro-finance on welfare is controversial (Van Rooyen et al. 2012, Benerjee et al. 2015). Proponents of micro-finance argue that obtaining financial credit or micro-credit enables entrepreneurs, poor households and loan recipients to engage in at least one of the following; expand their businesses, acquire more productive assets, increase investments, open new businesses, acquire more farmlands, which in turn increase their economic well-being in form of profit, food security, productivity, skill improvement, health, gender empowerment, income, nutrition, housing, etc (Afrane 2002, Barnes 1996, Barnes and Keogh 1999, Beck et al. 2004, Hietalahti and Linden 2006, Hossain and Knight 2008, Khandker 2001, Odell 2010, Schuler et al. 1997, UNICEF 1997, Wright 2000).

In contrast, however, other studies show opposing evidence to the publicised miraculous effects of micro-finance asserting that financial credit does not really affect the very poor (e.g Copestake et al. 2001, Hulme and Mosley 1996, Morduch 1998, Mosley and Hulme 1998, Zaman 2001); does not significantly raise income or has a mixed effect (Benerjee et al. 2015); or does not empower women (e.g Husain et al. 2010, Mayoux 1999, Rahman 1998). Some argue that a single financial credit intervention is not enough (Lipton 1996) and others portend the negative effects of financial credit showing evidence that financial credit does more harm because it raises inequality, increases financial services discrimination, increases workload and child labour, raises dependency, etc (Adams and Von Pischke 1992, Bateman and Chang 2009, Copestake 2002, Rogaly 1996).

Moreso, the over-indebtedness (inability to pay back loans) and poverty in many developing countries (India, Nicaragua, Pakistan, etc) where micro financial programmes have been implemented (Van Rooyen et al. 2012) has further confounded the claims in favour of micro-finance. One may question the context on which micro-finance really works and probe whether financial credit policies that have been implemented in developed or emerging economies would yield the same outcome for low-income African countries?

Earlier attempts to systematically review the effects of financial credit on various economic indicators are not without gaps. First, systematic review evidence for only African regions is quite scarce compared to studies that are global in nature leaving a gap of what conclusions can be drawn from different regions in Africa, especially for governments. While some studies focus on developed, emerging and developing non-African countries due to limited number of studies in Africa, some use a narrative approach to systematic review. Furthermore, no systematic review till date that I know of has been able to show evidence on the various effects of credit on household welfare on all the different regions of Africa nor show evidence on credit impact before and after the Covid-19 pandemic. This study improves on the existing evidence to fill these gaps using a quantitative approach. Previous studies focus on the global effect of various aspects of financial inclusion, one or more combinations of micro-finance, insurance, savings and health. For instance, systematic reviews that focus on the impacts of micro-insurance are Marr et al. (2016), Cole et al. (2012), Habib et al. (2016), Apostolakis et al. (2015), Awaworyi-Churchill et al. (2016), Awaworyi-Churchill (2015, 2014) while O'Grady (2016), Gash (2017) focus on the impacts of micro-savings. Furthermore, the health intervention systematic review studies include Lorenzetti et al. (2017), Bhageerathy et al. (2017), Orthon et al. (2016), Arrivillag and Salcedo (2014), Isangula (2012), O'Malley and Burke (2017). Duvendach and Maider (2019), Pande et al. (2012) and Gammage et al. (2017) focus on the impacts of financial inclusion. Other studies that take a global approach to micro-finance are Vaessen et al. (2014), Brody et al. (2015), Duvendack et al. (2011), Chilova et al. (2015), Peters et al. (2014), Gapolaswami et al. (2016), Yang and Stanley (2013), Palmkvist and Lin (2015), Madhani et al. (2015). While the results from these studies at a global level are quite noteworthy, a systematic review of evidence that has isolated the impact of micro-finance alone on welfare for low and lower-middle income African countries, at different regions, before and after the Covid-19 pandemic is still a gap yet to be filled. As the African context is different from other developing countries of the world, it's not known if the replication of these micro-credit programmes in Africa will yield similar results. Hence, this chapter fills this gap and attempts to understand the literature on the impacts of micro-finance on welfare in the context of Africa.

Furthermore, Van Rooyen et al. (2012) at the time, using a narrative approach to systematic review argue that micro-finance and micro-savings does harm as well as good to the poor, but the study is limited to very few relevant included papers (15) and leaves the gap whether same conclusions are realisable using a more improved statistical approach with more studies. To fill this gap, this study extends the scope to include available evidence on the impact of micro-finance on welfare till date for both low and lower-middle income African countries. Specifically, I have included 31 studies post the period covered by Van Rooyen et al. (2012).

Although the literature on financial credit is gradually increasing, most of the evidence stem from many Asian countries (Duvendack et al. 2011). However, theory suggests that financial credit could work differently or have various implications for different regions of the world subject to the levels of financial literacy, inequality, social cohesion, entrepreneurship, debt burden and attitude towards debt, population, income level and wealth, etc (Armendariz and Morduch 2010, Fisher and Ghatak 2011, MIX and CGAP 2011). The ambiguity due to an inadequate body of systematic evidence on the effects of financial credit on welfare thus provides the concern that drives this chapter.

On this ground, I believe there is an urgent need to understand and provide important conclusions from the micro-finance literature for Africa, which is the poorest region of the world and characterised by higher levels of market failures, financial illiteracy and inequality as compared to other continents of the world. To fill this gap, I expand the scope of the micro-finance literature to include available evidence on both low and lower-middle income African countries and also isolate the effects of financial credit on welfare using the systematic approach that is promoted as a valuable tool for bringing together the best quality, most relevant evidence (DFID 2011, Petticrew and Roberts 2006). These conclusions will help to provide a better understanding to developmental organisations (both governmental and non-governmental) from the existing research on financial credit and welfare for the African context.

The result of the quantitative systematic review show that the majority of available evidence in African countries favours a positive direction of impact of micro-credit on welfare. The categorisation of effect used in this study is based on authors' overall conclusions, which is checked in terms of the proportion of estimates reflecting this relationship. The proportion of individual estimates across all studies yielding each result is also considered. However, the scarcity of evidence in the North, Central African regions and mixed results mean it is not possible to draw firm conclusions about some aspects of the relationship. Studies show that a positive relationship is observed most commonly in the periods both before and after the Covid-19 pandemic.

Further sections of this chapter are as follows. Section 2.2 gives a brief discussion of the relevant theories of micro-finance and welfare while section 2.3 provides a description of the methods employed by the study. Sections 2.4 and 2.5 give further details of the measures and studies included. Section 2.6 presents the data analysis section while section 2.7 gives the discussion from the data analysis with policy suggestions.

2.2 Theories of Finance and Welfare

Several theories link micro-finance to welfare improvements. Enhancing welfare is anticipated through the provision of capital to individuals with restricted assets and households with low incomes, facilitating investment in self-employment ventures like agriculture or micro-enterprises. This section provides a brief discussion of major theories of finance and welfare that relates to this chapter.

2.2.1 Welfare Theory

Proponents of the Welfare theory (Abram Bergson 1938 and Paul Samuelson 1947) believe that the allocation of resources and goods affects social welfare. This is because the provision of resources could mean that such resources are used to meet the needs of households. Therefore, the welfare theory is directly connected to the examination of economic efficiency and income distribution, along with the impact of these factors on the overall well-being of individuals within the economy. In response to the needs of the targeted recipients, institutions strive to extend their reach to clients who are economically disadvantaged, and consequently more at risk, making them less likely to access credit from traditional banks. The welfare theory could extend to measure the improvement of the living standards of the poor people in the population because of accessing credit (Omoro and Omwange 2013). As per Narayan-Parker (2002), the enhancement of the well-being of impoverished individuals is evident in the growth of household assets and the augmentation of their abilities to engage, negotiate, influence, control, and hold institutions accountable for their lives. Consequently, it can be posited that empowerment is essential for impoverished individuals to assume control. Actions, activities, or structures should, therefore, focus on empowerment, yielding outcomes that contribute to an elevation in the well-being of those undergoing the empowerment process.

2.2.2 Formal and Informal Micro-finance Models

Both formal and informal micro-finance theories hinge on the source of provision of micro-finance. For formal sources, micro-credit is provided by the government mainly through banks. In terms of the indirect sources, credit could be through several sources (Herath

2018) as outlined now. Direct Money Lenders: are the first group and include professional money lenders, friends, relatives, neighbours and registered pawn brokers. The second group, Indirect Money Lenders, include retail and stock traders, agriculture product collectors and suppliers, paddy millers etc. Voluntary Credit Groups form a distinct category, representing unregistered entities with specific or diverse purposes such as saving and credit societies, welfare societies, and rotating credit and saving societies (ROSCAS). Independent Voluntary Movements (IVMs) refer to organisations that offer micro-finance services either as registered companies or registered national movements. However, governments may employ semi-formal sources like micro-finance banks and groups to reach out to the poor during intervention programmes.

For both formal and informal micro-finance models, the aim of credit givers is to provide funds for households to meet certain needs of households or objectives set out by credit givers. However, the extent to which those objectives (for example, improvement in welfare) are achieved after credit access is the interest of this study.

2.2.3 Imperfect Credit Market

Proponents of imperfect credit market theory suggest that the existence of credit market friction leads to credit rationing, subsequently influencing the trajectory of economic growth. The model of imperfect credit markets offers insights into the correlations between per capita income, credit rationing, interest rates, and factor prices (Ma and Smith 1996). Studies such as McKinnon (1973) and Shaw (1973) contend that the credit markets in developing countries are characterised as 'fragmented,' resulting in the inefficient allocation of investment funds. Additionally, the inadequate development of financial markets and the high transaction costs associated with them contribute to the underwhelming real performance observed in numerous less developed economies. Consequently, credit market imperfections carry significant implications for welfare. The theory posits that one crucial source of these imperfections is the presence of informational asymmetries, and a notable consequence is the prevalence of credit rationing. The substantial government interventions in financial markets, particularly in economies such as Africa, underscore the considerable importance of credit rationing.

The main objective of this chapter is to further understand and explore the conclusions of studies using the currently available evidence about the effects of micro-credit on various welfare outcomes for households. The theories discussed above suggest that the provision of finance and welfare improvements are linked. However, this chapter focuses more on the available empirical evidence on the effects of financial credit to show conclusions or the direction of the impact of financial credit on welfare for African countries.

2.3 Methodology

The study adopts a quantitative systematic review synthesis to provide answers for the main research question covered by this chapter which is to summarise what the existing evidence suggests with regards to the impacts of financial credit on welfare in the African context. The method of systematic review is regarded as important for drawing valid conclusions from the most relevant evidence (Higgins et al. 2019, DFID 2011, Petticrew and Roberts 2006). In addition to presenting evidence from studies, I also determine the direction of impact of micro-credit (positive, negative or mixed) by calculating the probability (percentage) of the direction of effect from the total number of estimates from the included studies. Generally, these methods relied on factors such as the purpose of the synthesis, the number and similarity of studies included in the review, the methodology used by each study, the level of detail available from the studies, the nature of the results reported in the studies. During the systematic review process, the quality of studies was also evaluated using the Scimago Journal Rating H-index and the total number of estimates per study. Following the standard procedures for systematic analysis to guarantee the inclusion of all the relevant literature in this study, I searched the four most highly used web sources, that is Google Scholar, Scopus, Embase, EconLit and conducted citation searches for all the literature included as well as for their references.

2.3.1 Data Search and Inclusion Criteria

The data in this review was from an extensive search of both published and non-published articles. Due to the relatively limited research for African studies on the impact of financial credit on welfare, the search included journals and non-journal articles. However, for the published articles, I also separate the included studies by the quality of journal. Hence, the data used in this analysis includes both published articles and unpublished but accessible articles (such as students' theses) on the effect of financial credit on welfare. These articles were either published in peer reviewed journals and database explored or available on-line as posted by authors. The search for articles was subjected to screening in several stages. First, as regards Africa as a region and not the world at large. I restrict the search on the impact of micro-credit on welfare for only African countries. I initially begin by including studies that isolates the impact of micro-credit on welfare levels such as consumption, income, health, wealth, food and non-food expenditures in Africa. Because of the interest in welfare at the household level, the study does not consider the effects of loans on the profits for businesses as this is out of the scope of this study. Studies that examine the impact of financial credit on welfare either using access to loans or other loan intervention programmes by governments and non-governmental organisations were included. Keywords such as "Financial-credit", "Micro-credit", "Micro-finance", "Credit-Access" were used [1].

Next, I segregate studies based on methodology used. I consider studies that are quantitative and qualitative methods. The quantitative studies were further divided into studies that attempts to examine the relationship between micro-finance and welfare in Africa using regression methods like Ordinary Least Squares (OLS), Probit, Propensity Score Matching (PSM), Instrumental Variables (IV), Heckman Selection approaches, and studies that concentrate on experimental methods from intervention programmes like Randomized Control Trials (RCTs). The descriptive studies were basically a mixture of T-test, Correlations, Chi-square and Analysis Of Variance (ANOVA).

Quantitative studies

A total of 36 quantitative studies were included which consist of 6 RCT works that examine the effects of financial credit on welfare and 30 studies that employ regression approaches. As one would expect, the African continent is characterised by studies that employ regression approach compared to those that employ experimental methods like RCTs due to the expensive nature of RCTs. Also, almost all the studies found are characterised by either one period cross-sectional data or at most, two period surveys. Appendix B provide a more detailed description of all the included quantitative studies.

Qualitative studies

A total of 10 studies that employ a descriptive approach were included. Of the 10 studies, a total of 5 were published and 5 unpublished. From the 5 published articles, only 2 were

[1] I also use keyword combinations as "Financial-credit AND Welfare","Micro-credit AND Welfare", "Micro-finance AND Welfare", "Credit-Access AND Welfare"

ranked by the Sci-mago journal rating. Further details are presented in Appendix B.

2.3.2 Sensitivity Analysis

As much as possible, I dissect the included studies by region in Africa which are basically the North, South, East, West, Central Africa regions and the overall Sub-Saharan African region (South, East, West and Central Africa combined) to see if there were heterogeneous effects from the included studies as a result of the region where the study was conducted. Furthermore, the study was divided into periods before the Covid-19 pandemic and periods after the Covid-19 pandemic to identify any differences on the direction of effects on the impact of financial credit before and after the Covid-19 pandemic and to identify the number as well as the types of studies during and after the pandemic. Journal quality (journal ranking) was compared alongside the reported evidence. Next, I dissect the included studies according the approach used by studies to address endogeneity problems and the type of outcome variable used by studies. This helps to identify gaps in endogeneity problems employed and the conclusions of studies, as well as what outcome variables have been mostly used in the literature compared to those scarcely used in relation to the conclusions of studies.

2.4 Measures

2.4.1 Response Variables

This study considered outcome variables that measure welfare mostly at the household level consistent with the objectives of this study. Therefore, focus was not on those reflecting the performance or profitability of businesses. The measures considered are therefore consumption, income, food and non-food expenditures, health expenditure, education expenditure, poverty indicators, wealth index, number of meals per day and household assets.

2.4.2 Explanatory Variables

With the need to keep focus on the aims of this chapter, which is to provide evidence on the effect of financial credit on welfare in Africa comes the need to be very particular about the choice of explanatory variables of the included studies. For most cases the explanatory variable is dichotomous, as it captures the participation (or not) in micro-finance programmes or intervention, where participation entails receipt of at least one loan.

2.4.3 Control Variables

The studies included contain a broad range of control variables considered as relevant in the literature. However, because the interest of the chapter is to provide evidence on studies that isolate the impact of financial credit on welfare, from the included studies, I consider all the included control variables in isolation and not their interaction with the major explanatory variable which is participation in loan programmes. Hence, I ensure that all the results from the included studies either from the explanatory or control variables on the response variables are in terms of stand-alone impacts. However, I provide a brief description of studies that consider the impact of micro-finance in interaction with other factors below.

2.4.4 Studies Excluded

A total of 9 studies were excluded. These were either the case where the impact of micro-credit was combined with other intervention programmes such as: training and innovation on the use of technology, the regulation of micro-credit, dependent variable as loan repayment; or alternatively other financial inclusion variables were variables of main interest, for example the role of social workers in empowering families with credit. Appendix B give a list of all the excluded studies. However, from the excluded studies, those that focus on financial inclusion or interaction between the effect of financial credit and other variables show evidence of positive impact.

2.5 Description of Included Studies

From the searches made as detailed in the data search section, I include 46 studies on the impacts of financial credit on welfare for only African Countries. Six of these studies are experimental studies on intervention programmes of micro-credit, that is Randomized Control Trials (RCTs), while the remainder are a mix of regressions and summary measures such as T-Tests, Chi-square and frequencies. One major observation is the scarcity of studies on financial credit and welfare for North African countries. Only one study covering Morocco was located in this area.

Thirty studies included follow a regression approach to estimation while ten follow a summary statistics approach. I also include the data structure of the studies, that is whether a cross-sectional approach was used or a panel data approach and the journal ranking of all the studies included. Another key observation is the scarcity of panel data studies on financial credit and welfare as nearly all the studies are cross-sectional. Furthermore, panel data studies with long periods of data are very scarce and this provides a gap in the literature for African studies. Further information and details of all the studies included are provided in the data analysis section.

After dissecting the included studies into regions of their analysis (see Table 2.11), the number of studies from the Western and Eastern regions constituted most of the available evidence (17 and 20 studies respectively). 5 of the studies included were from the South African regions while the Northern and Central African regions constituted only 3 studies.

Furthermore, the bulk of the evidence on the impact of micro-credit on welfare measures was conducted either before the Covid-19 period or used datasets before the pandemic for their analysis (a total of 44 studies). Only 2 were conducted after the Covid-19 pandemic and used data for this period.

2.5.1 Categorisation of the Effect of Credit

This study categorises the effect of financial credit on welfare based on major conclusions of authors and number of estimates that are statistically significant for each study. Where above 60% of the total estimates in a study are significant, an effect is recorded. Contrary to this, if less than 30% of the total estimates in a study are significant, I record no convincing effect. However, if a combination of significant and insignificant effects accounts for the 100% of the total estimates in a study in equal or near equal ratios, I record a mixed result, where the significant effect is mainly positive significant[2] while the insignificant effect are either positive or negative insignificant effect. In all cases, the effects categorised using these thresholds aligns with the conclusions drawn from the authors. For each case, on average

[2]However, for cases of negative significant effect, I record as negative significant effect for clarity

above 80% of the total estimates in each study are significant for studies that recorded significant effect while the total 100% of the combination of significant and insignificant effects from the total estimates for studies that show a mixed result. For more clarity, I show a cross tabulation on the data of the studies that recorded positive significant, positive insignificant, negative significant and negative insignificant results in the result section.

Table 2.1: Summarising the Included Studies

Author	Year	Source	Country	Data Type	Technique	Published	Effect
Adjei et al.	2009	Working paper	Ghana	cross-section	Summary-Stat	No	Positive
Akotey and Adjasi	2016	World Development	Ghana	cross-section	Heckman Selection/IV	Yes	Mixed
Alcino	2008	Thesis	Mozambique	cross-section	Summary-Stat	No	Mixed
Alemu and Genowo	2023	JKE	Ethiopia	cross-section	PSM	Yes	Positive
Ali and Awade	2019	Helyon	Togo	cross-section	Switching	Yes	Positive
Anne	2012	Thesis	Kenya	cross-section	OLS	No	Mixed
Annim	2018	Enterprise	Ghana	cross-section	OLS/Probit	Yes	Positive
Asraf et al.	2009	AER	Kenya	cross-section	RCT	Yes	No
Atamja and Yoo	2021	Sustainability	Cameroon	cross-section	Switching	Yes	Positive
Baiyegunhi et al	2010	AJAR	Ethiopia	cross-section	Switching	Yes	Positive
Barnes et al.	2001	project	Uganda	cross-section	Summary-stat	No	Positive
Bocher et al	2017	AJEMS	Ethiopia	cross-section	OLS/Switching	Yes	Positive
Brannen Corner	2009	Dissertation	Tanzania	cross-section	OLS/Probit	No	Mixed
Buchenrieder et al	2019	Agr Fin.Rev	Cameroun	Panel	Probit	Yes	Positive
Copestake et al	2001	Journ. Devt.Std	Zambia	cross-section	OLS	Yes	Mixed
Crepon et al	2015	AER	Morocco	cross-section	RCT	Yes	No
Dimova and Adebowale	2017	Development Studies	Nigeria	cross-section	Switching	Yes	Positive
Doocy et al.	2005	SocSci Medicine	Ethiopia	cross-section	ANOVA	Yes	No
Fafona et al	2015	Rev. Econs. HH	Côte d'Ivoire	cross-section	PSM	Yes	Positive
Fasanya	2012	JSDA	Nigeria	cross-section	Summary-stat	Yes	Positive
Ganle et al.	2015	World Development	Ghana	cross-section	Summary-stat	Yes	Mixed
Gebru and Paul	2011	JSDA	Ethiopia	Survey	T-Test	Yes	Mixed
Haddad and Maluccio	2003	Eco Dvt Cul Chag	SA	cross-section	IV	Yes	Positive
Idrissu et al	2017	Agric Fin.Rev	Ghana	cross-section	PSM	Yes	No
Karlan and Zinman	2010	Rev. Fin. Studies	South Africa	cross-section	RCT	Yes	Positive
Lastarria-Cornhiel and Shimamura	2008	Economies	Malawi	cross-section	OLS/Probit	Yes	Mixed

Table 2.1 Continued: Summarizing the Included Studies

Author	Year	Source	Country	Data Type	Technique	Published	Effect
Manja and Badjie	2022	SAGE	Gambia	cross-section	PSM	Yes	Mixed
Mejaha et al	2010	Nig Agr Journal	Nigeria	cross-section	OLS	Yes	Positive
Magezi and Nakano	2020	Jap.J Agric. Econs	Tanzania	cross-section	RCT	Yes	No
Mensah et al	2022	WJEMSD	Ghana	cross-section	PSM	Yes	Positive
Mera et al.	2019	JITLL	Ethiopia	cross-section	PSM	Yes	Positive
Metrine and Omoro	2019	ADFJ	Kenya	cross-section	Summary-stat	Yes	Positive
Mwansakilwa et al	2017	AJARE	Zambia	cross-section	PSM	Yes	Positive
Nakano and Magezi	2020	World Development	Tanzania	cross-section	RCT	Yes	No
Nanor	2008	Thesis	Ghana	cross-section	OLS/Heckman	No	Mixed
Nicholas Mugabi	2010	Thesis	Uganda	cross-section	Chi-square	No	Positive
Nwanesi	2006	Thesis	Nigeria	cross-section	Summary-Stat	No	Positive
Ogundeji et al	2018	Agrekon	SA	cross-section	Probit	Yes,	Positive
Okafor et al.	2016	IJMRI	Nigeria	Time -series	OLS	Yes	Neg
Okoyo et al	2021	Afr Fin.Rev	Ethiopia	cross-section	PSM	Yes	Positive
Owuor	2009	Agr Eco	Kenya	Cross-section	PSM	Yes	Positive
Ozoh et al	2022	IJMS	Nigeria	Cross-section	IV	Yes	Positive
Tekana and Oladele	2011	J Hum Eco	SA	Survey	OLS	Yes	Positive
Tita	2017	Thesis	SSA	cross-section	OLS	No	No
Torazzi et al	2015	American Economic Journal	Ethiopia	cross-section	RCT	Yes	No
Salia	2014	IJARBS	Tanzania	cross-section	PCA	Yes	Positive

2.6 Data Analysis

Figure 2.1 presents the summary funnel plot of all the included studies on the effects of financial credit on household welfare. Of the 46 studies included, 27 (59%) recorded positive statistical effect, 10 recorded mixed effects, 8 showed no convincing effect and 1 recorded a negative significant effect. Of the included studies, 37 are published while the remaining 9 studies are non-published articles either as thesis or available online as presented in Figure 2.2. Out of the 27 studies with a positive statistical effect, 24 are published while 3 are not and 5 from mixed effects studies are published. Figure 2.2 also show that only one study from the no effect articles is unpublished while the negative effect article is published.

Figure 2.1: Summary Funnel Plot of all Studies included with Decision of Effect

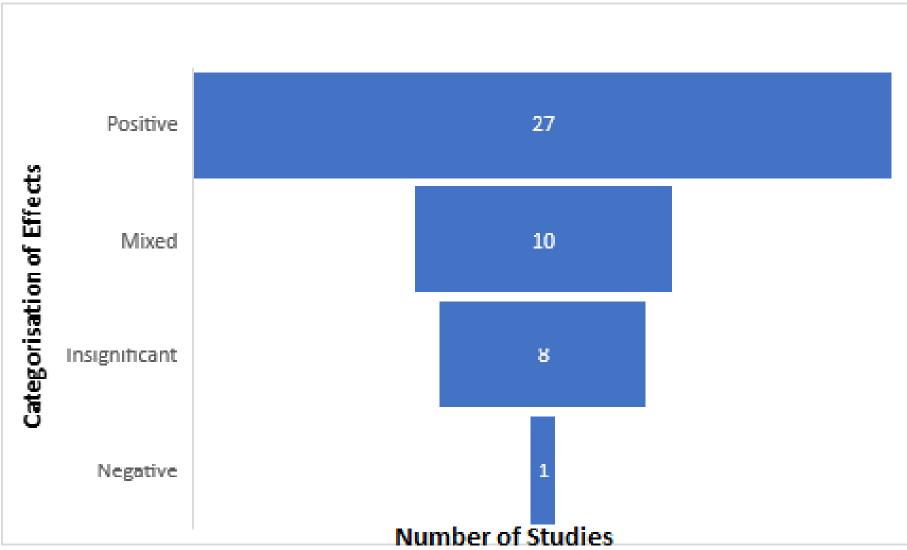


Figure 2.2: Studies by Publication

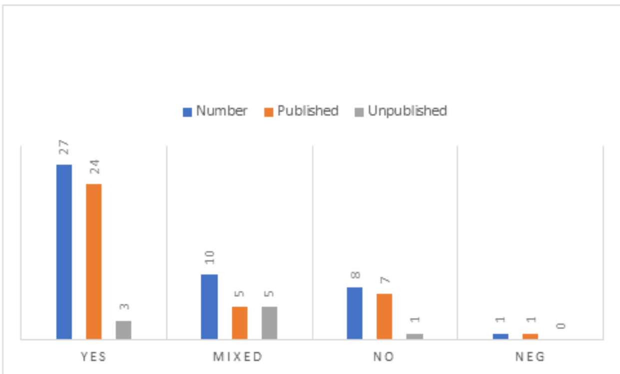
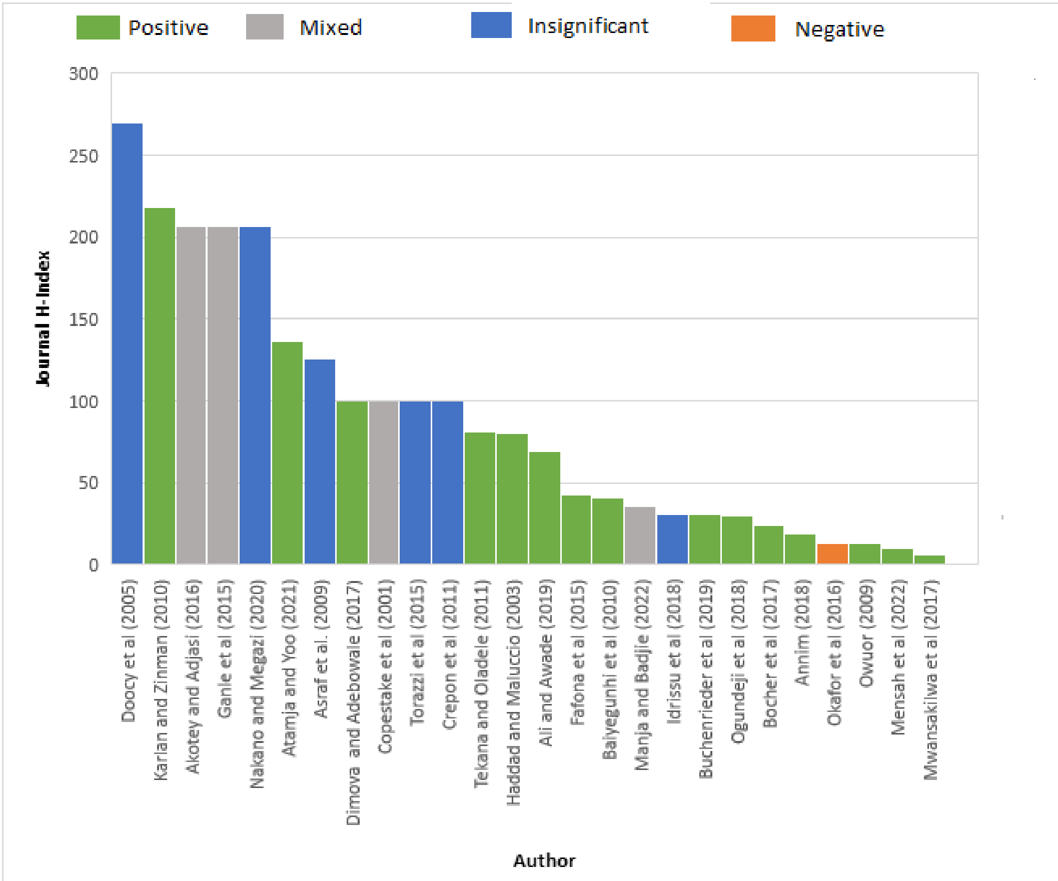


Figure 2.3 show the journal quality of all the published studies using the Sci-Mago Journal Rating (SJR) criteria and the effect identified. The RCT studies who recorded no convincing effect show highest impact factors in terms of publication followed by regression studies who

recorded a mixed effect. Studies that recorded positive statistical effect have on average lower impact factor apart from the Karlan and Zinman (2010) RCT published in Review of Financial Studies as indicated by the outlier.

Figure 2.3: Studies by Journal Quality



To provide insights for a more quantitative conclusion on all the studies, Table 2.2 presents a cross tabulation on the categorisation of effect by number of estimates. Four categories of outcomes are considered from the estimates of all the studies which are basically positive (significant), positive (insignificant), negative (significant) and negative (insignificant). The evidence shows that more estimates from studies (254) show a positive significant effect on the impact of financial credit on welfare compared to any of the other three results. The probability that an estimate is positive significant from the 526 estimates is 0.441 (44.1%).

However, if one compares the number of estimates that show positive significant effects

(254) to the number of estimates that show insignificant effects (299), then the evidence is quite mixed. Hence although more studies (27) show a positive significant effect of financial credit on welfare as indicated in Figure 2.1, there is mixed evidence if we consider the number of estimates that show positive significant effects compared to the number of estimates that show insignificant effect.

Table 2.2: Cross Tabulation on Categorisation of Effect by Number of Estimates

	Positive	Negative	Total
Significant	254	23	277
Insignificant	159	140	299
Total	413	163	576

Notes: Categorisation of effects was made using authors conclusion and the defined threshold in section 2.5

2.6.1 Regression Studies

To maximise the information in the data and show conclusions from the included studies by the methodological procedure of each study, I break the analysis into regression studies, descriptive studies and intervention studies (Randomized Control Trials). Table 2.3 presents the summary statistics of studies that employed regression analysis. A total of 30 regression studies were included with regression analyses as OLS, Probit, PSM, IV, Heckman Selection approaches. I have reported the specific approach of the analysis used by each study in Table 2.1.

Table 2.3: Summary Statistics for Regression Studies

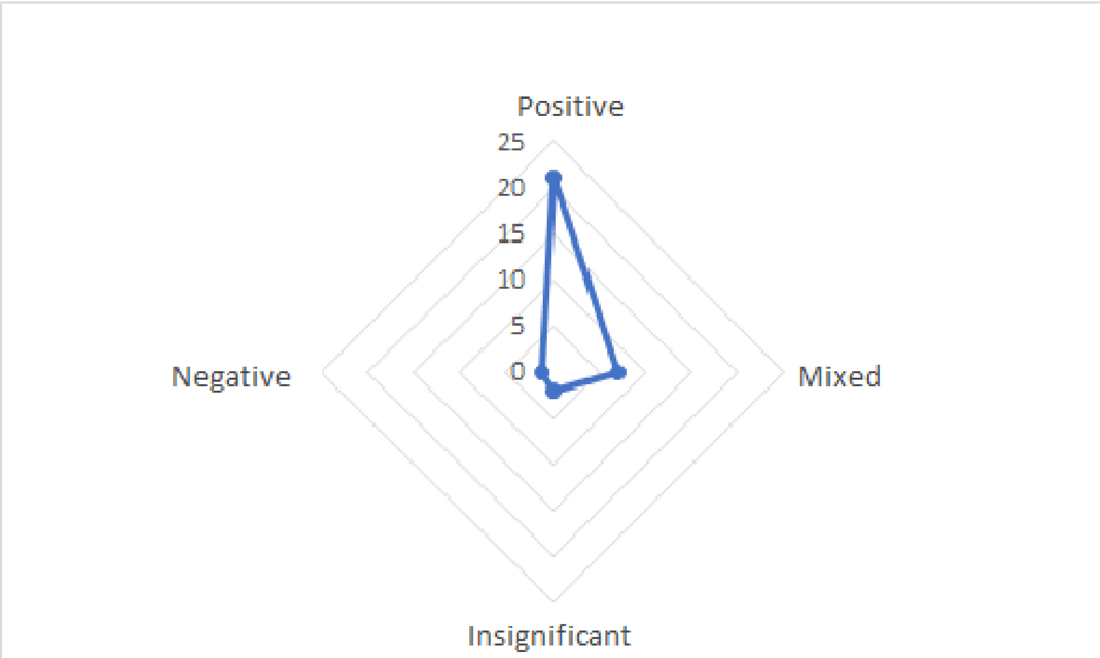
	Categorisation of Effect				
	Positive	Mixed	Insignificant	Negative	Number of Estimates
Published	20	4	1	1	169
Unpublished	0	3	1	0	88
Total	20	7	2	1	257

Notes: Categorisation of effects was made using authors conclusion and the defined threshold in section 2.5

Evidence from the regression studies show that most studies recorded that financial credit possess positive significant effect on welfare levels of households. Of the 20 studies that recorded positive significant impact, all are published. Furthermore, 7 studies showed mixed evidence with 4 studies published and 3 unpublished. For the 2 studies with no significant effect, one is published and the other unpublished. Only one study recorded a negative significant effect.

From the number of estimates in all the studies, 169 are contained in the published articles while 88 are not. However, if we consider the number of estimates in terms of the proportion of unpublished to published articles (88:169), then the number of estimates for the unpublished articles are quite high.

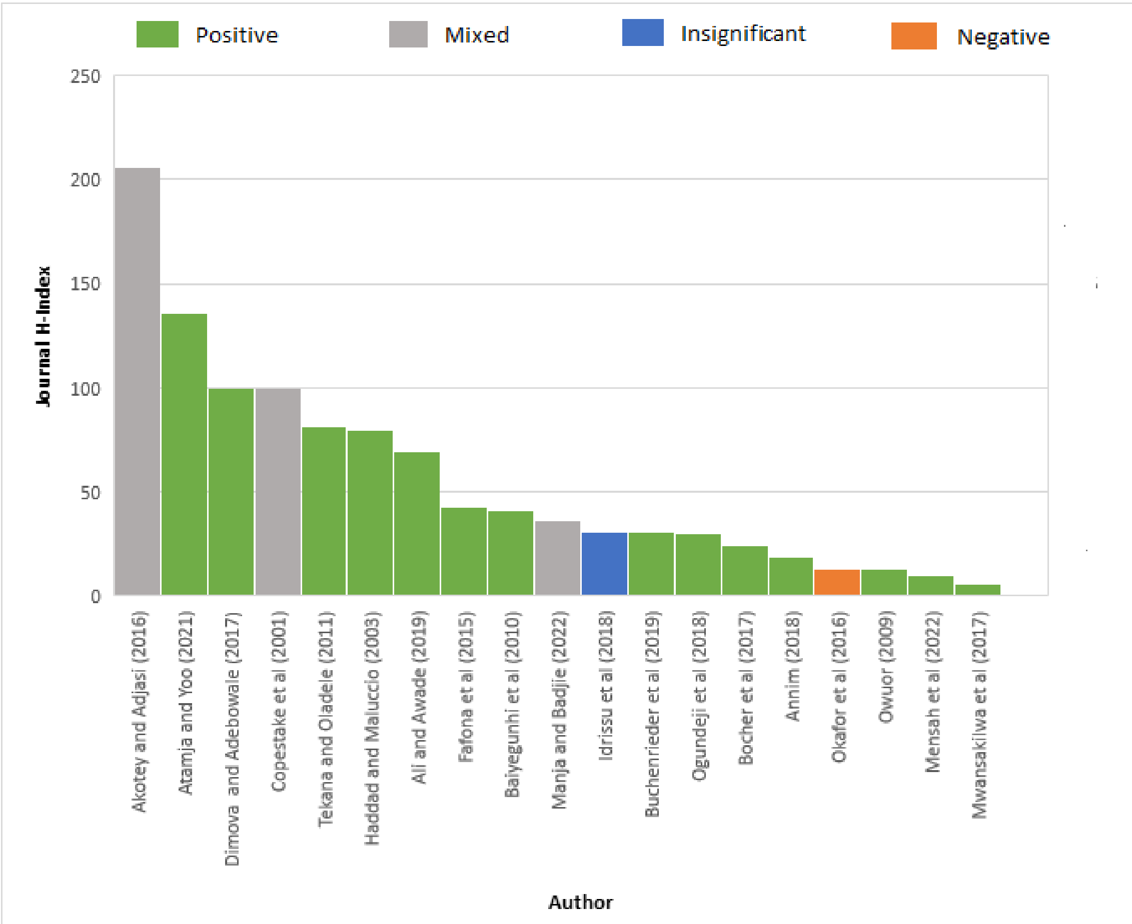
Figure 2.4: Radar Plot for Included regression studies



The radar plot in Figure 2.4 show a clearer detail of Table 2.3. From the plot in Figure 2.4, it's not difficult to see the direction of conclusion from regression studies on the effect of financial credit on household welfare in Africa. Hence for the available evidence, micro-credit possesses positive significant impact on welfare improvement in Africa in terms of the number of studies who follow regression methodological estimation procedures.

The journal quality of the published regression studies is presented below in Figure 2.5 with the average Sci-mago Journal Rating H-index as 56. From the 30 regression studies included, the unpublished studies and the published studies with no H-index are excluded from the bar chat.

Figure 2.5: Journal Quality of Published Regression Studies



In addition, to give more insights on the categorisation of effects by number of estimates from the included regression studies, Table 2.4 provides further details. The results from Table 2.4 show that more estimates from studies (161) show a positive significant effect on the impact of financial credit on welfare compared to any of the other three conclusions. Thus, for regression studies, the probability that a study gave a positive significant conclusion from the 30 studies and 257 estimates is 0.6264 (62.64%).

Table 2.4: Cross Tabulation on Categorisation of Effect by Number of Estimates

	Positive	Negative	Total
Significant	161	13	174
Insignificant	63	20	83
Total	224	33	257

Notes: Categorisation of effects was made using authors conclusion and the defined threshold in section 2.5

Moreso, unlike the case for all the studies reported in Table 2.3, if one compares the number of estimates that show positive significant effects (161) to the number of estimates that show insignificant effect (83), the evidence still suggest that the categorisation of effect largely favours a positive significant impact of financial credit on welfare. Thus, for regression studies, in terms of both number of studies and number of estimates, the literature shows a positive significant effect[3].

2.6.2 Descriptive Studies

A total of 10 studies that followed a descriptive approach were included. The descriptive approach employed by studies was basically a mixture of T-test, Correlations, Chi-square and ANOVA. Table 2.5 presents the summary statistics of studies that employed descriptive approach.

For the descriptive studies, a total of 6 studies recorded positive conclusions although only 2 of this number were published while the remaining 4 are unpublished. 3 studies recorded mixed results and only 1 study recorded no effect. The total number of estimates for the descriptive studies is 85 with 40 estimates from published articles and 45 from unpublished articles.

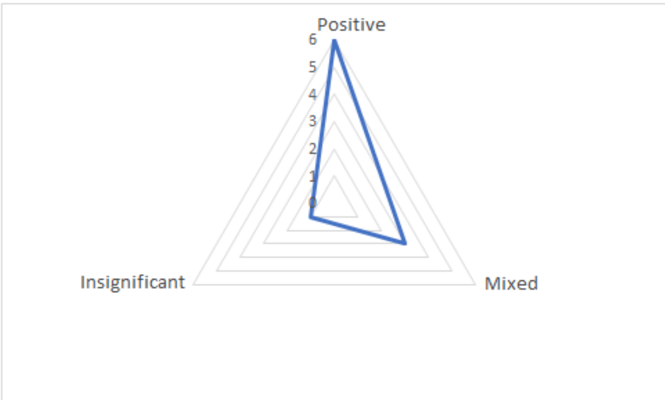
[3] Of 20 studies that recorded positive significant impact, 161 estimates of the 257 also recorded a positive significant impact

Table 2.5: Summary Statistics for Descriptive Studies

	Categorisation of Effect			
	Positive	Mixed	Insignificant	Number of Estimates
Published	2	2	1	40
Unpublished	4	1	0	45
Total	6	3	1	85

Notes: Categorisation of effects was made using authors conclusion and the defined threshold in section 2.5

Figure 2.6: Radar Plot for Descriptive Studies



There was a total of 5 published and 5 unpublished articles from the descriptive studies. From the 5 published articles, only 2 were ranked by Sci-mago journal rating thus making it difficult to present the journal quality for the 10 studies on a graph. However, in terms of the number of studies included, the evidence shows that the literature favours the direction that financial credit possesses positive effect on the welfare of households.

The cross tabulation in Table 2.6 show that 48 (56.5%) estimates recorded a positive significant effect compared to other categorisations. Thus, similar to the regression studies, the evidence in the descriptive studies included show that in both number of studies and number of estimates, the literature shows a positive significant impact on the effect of financial credit on the welfare of households.

Table 2.6: Cross Tabulation on Categorisation of Effect by Number of Estimates

	Positive	Negative	Total
Significant	48	1	49
Insignificant	35	1	36
Total	83	2	85

2.6.3 Studies with Randomized Control Trials

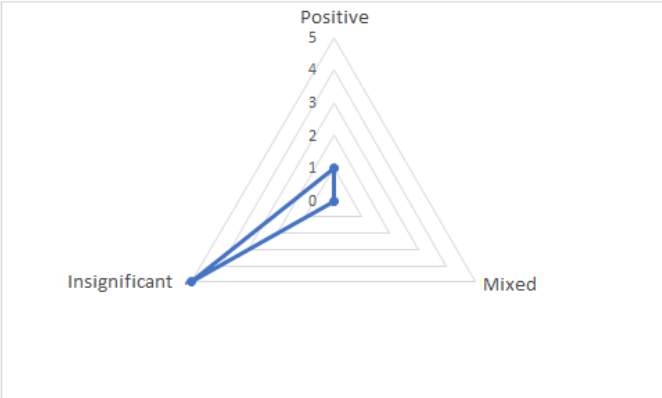
A total of 6 studies using randomized control trial methodology were included with Table 2.7 showing a summary. For the RCT studies, the effects were of two directions which was either positive or no convincing evidence (insignificant) compared to other methodologies which in addition showed mixed evidence. However, most of the studies showed no convincing evidence apart from one study. All the included RCT studies are published with the number of estimates as 234, which is quite large.

Table 2.7: Summary Statistics for Studies with Randomized Control Trials

	Categorisation of Effect		
	Positive	Insignificant	Number of Estimates
Published	1	5	234
Unpublished	0	0	0
Total	1	5	234

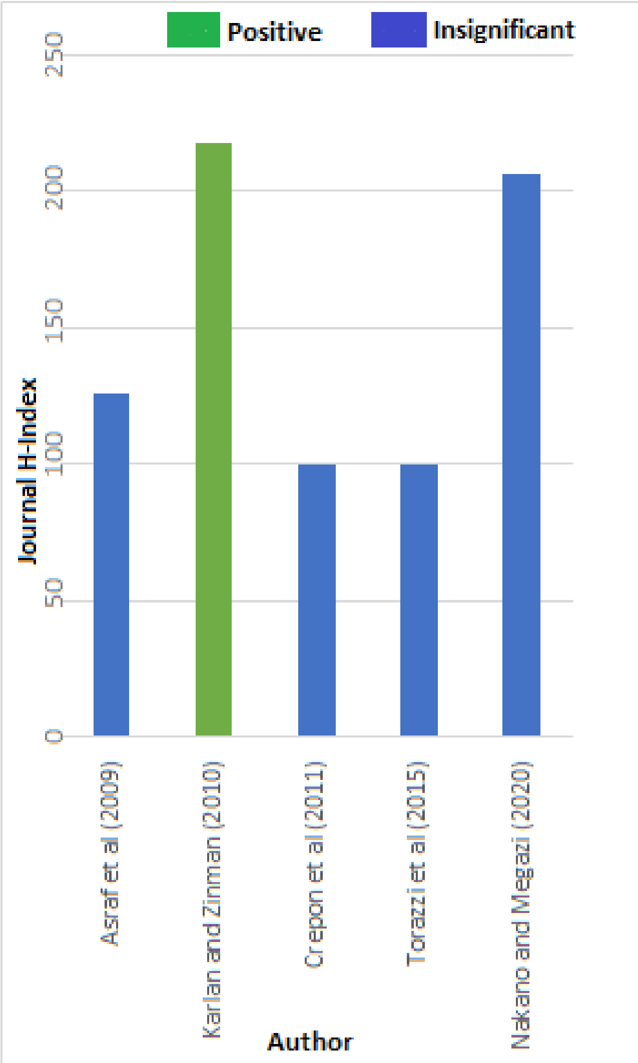
Notes: Categorisation of effects was made using authors conclusion and the defined threshold in section 2.5

Figure 2.7: Radar Plot for RCT Studies



The journal quality for the RCT studies are very high compared to studies that used either regression or descriptive measures. Figure 2.8 shows that SJR H-index for the included RCT studies. Apart from one study that is not captured in the SJR, others have relatively high SJR H-index with the mean H-index as 150.

Figure 2.8: Journal Quality H-index for RCT Studies



Using the cross-tabulation effects from the estimates of all the included RCT studies, these favour an insignificant effect of financial credit on household welfare (180 of the 234 estimates are insignificant in Table 2.8). Specifically, 76.9% of the estimates from these studies recorded no statistical effect which confirms the direction of effects from Table 2.7. Hence for the RCT studies, the overall conclusions of studies and results from individual estimates suggest that micro-credit has no convincing impact on the welfare of households.

Table 2.8: Cross Tabulation on Categorisation of Effect by Number of Estimates

	Positive	Negative	Total
Significant	45	9	54
Insignificant	61	119	180
Total	106	128	234

2.7 Further Analyses

Tables 2.9-2.13 presents the further analyses conducted by the study. First, Tables 2.9 and 2.10 show the categorisation of effects for studies that consider any form of endogeneity. Next, Table 2.11 show the categorisation of effects according to regions in Africa from which the included studies were conducted while Table 2.12 show the categorisation of effects by period before the Covid-19 and after the Covid-19 pandemic[4]. Finally, Table 2.13 show the categorisation of effects according to the outcome measures used by the included studies.

Studies that attempt to address endogeneity on the effects of financial credit on welfare employ methodologies such as the Propensity Score Marching (PSM), Heckman Selection, Endogeneity Switching, Instrumental Variables (IV) and Randomized Control Trials. Methodologies like the Propensity Score Matching (PSM), Heckman Selection and the Endogeneity Switching regressions were used to potentially address the selection bias problems. However, the methods do not address endogeneity from the unobservable time invariant factors. The studies that employed the Instrumental Variables approach attempt to address reverse causality issues. This is however hinged on the degree to which the instruments are valid and meets the exclusive restriction criterion for instruments (the instrument for financial credit has no direct effect on the outcome welfare variable except only through financial credit which is very difficult to verify). The Randomized Control Trials (RCTs) attempt to address the problems of endogeneity through randomization. However, the problems of

[4]Studies were categorised according to the time the analysis were conducted and not just the publication year. Studies that conducted analysis before the Covid-19 pandemic and used dataset before this period were categorised under studies before the Covid-19 pandemic. On the other hand, studies that conducted analysis after the Covid-19 pandemic and used dataset after this period were categorised under studies after the Covid-19 pandemic.

external validity of the experiment in other countries remains.

From Table 2.9, a total of 31 studies attempt to address potential endogeneity issues. 19 studies recorded a positive significant effect, 6 recorded a mixed effect while the remaining 6 recorded no significant effect. Nearly all the RCT studies recorded no significant effect. From the 31 studies, 28 are published articles.

Table 2.9: Summary Statistics for Studies that addressed potential Endogeneity Problems

	Categorisation of Effect			
	Positive	Mixed	Insignificant	Number of Estimates
Published	19	3	6	524
Unpublished	0	3	0	87
Total	19	6	6	511

Notes: Categorisation of effects was made using authors conclusion and the defined threshold in section 2.5

However, the cross tabulation in Table 2.10 show that 211 (41.29%) of the individual estimates studies recorded a positive significant effect, which is quite low. Hence, if one considers the categorisation of effect in terms of the estimates from studies that potentially address endogeneity problems, the result is still quite mixed although more tilted towards there being no significant effect.

Table 2.10: Cross Tabulation on Categorisation of Effect by Number of Estimates for Endogeneity Studies

	Positive	Negative	Total
Significant	211	24	235
Insignificant	132	144	276
Total	343	168	511

Table 2.11 indicates that there is scarce evidence on the effects of micro-credit on welfare for regions in North Africa (only one study found in Morocco) and Central Africa

(two studies in Cameroon). The results for the effect of micro-credit on welfare in these two regions are mixed. For North Africa, the categorisation of effect is no convincing evidence and for Central Africa, one study recorded positive effects while another study recorded no convincing evidence (Insignificant). Similarly, there is scarce evidence for studies who consider Sub-Sahan African countries as a whole (only one unpublished study was found). The direction of effect in this case was no convincing evidence.

Table 2.11: Categorisation of Effects By Region

	Categorisation of Effect					
Region	Positive	Mixed	Insignificant	Negative	No. of Studies	No. of Estimates
North Africa	0	0	1	0	1	30
South Africa	5	0	0	0	5	22
East Africa	10	6	4	0	20	295
Central Africa	1	0	1	0	2	54
West Africa	11	4	1	1	17	165
SSA	0	0	1	0	1	10
Total	27	10	8	1	46	576

Notes: Categorisation of effects was made using authors conclusion and the defined threshold in section 2.5

There are more studies available for both the East Africa and West Africa regions, and to a lesser degree the South African regions. For East Africa, the direction of effect is mixed as out of a total of 20 studies found, 10 recorded positive effect, 6 recorded a mixed impact while 4 recorded no convincing evidence. For the West African regions, the bulk of studies (11) recorded positive effect compared to the remaining 6. In the South African region, all recorded a positive significant effect (a total of 5 studies).

In Table 2.12, the bulk of the evidence on the impact of micro-credit on welfare measures were conducted either before the Covid-19 period or used data collected and covering the period before the pandemic for their analysis (a total of 44 studies). Only 2 were conducted after the Covid-19 pandemic and used data for this period. However, irrespective of the period (before or after the pandemic), the categorisation of effect from the bulk of the studies included shows positive impacts (a total of 27 studies).

Table 2.12: Categorisation of Effects By Period Before and After the Covid-19

Period	Categorisation of Effect					
	Positive	Mixed	Insignificant	Negative	No. of Studies	No. of Estimates
Before Covid-19	25	10	8	1	44	559
After Covid-19	2	0	0	0	2	17
Total	27	10	8	1	46	576

Notes: Categorisation of effects was made using authors conclusion and the defined threshold in section 2.5

Next, Table 2.13 show the categorisation of effects by the various outcome measures used by the studies. The major outcome measures are household assets, total consumption, education, food expenditure, food security, health, income, poverty index, savings and yield. Outcome measures like income (33 counts), household assets (14 counts) and consumption (13 counts) are the most popular outcome measures used by studies. The consumption measure used by most studies is in terms of total consumption of households and not consumption per capita which is still very scarce. Outcome measures like food security, savings, health and education are unpopular. The poverty index is an unpopular measure of welfare, this may be because authors prefer more dis-aggregated measures of welfare to access direct impacts of credit. Furthermore, studies who are more centred on agricultural households may prefer to include yield as a welfare measure compared to those that are not.

Table 2.13: Effect by Outcome measures of Studies

Author	Outcome Measures										Effect
	Assets	Cons	Education	Food Exp.	Food Sec	Health	Income	Poverty Index	Savings	Yield	
Adjei et al. (2009)	√						√				Positive
Akotey and Adjasi (2016)	√										Mixed
Alcino das Felicidades FabHio	√						√				Mixed
Alemu and Genowo (2023)							√				Positive
Ali and Awade (2019)		√				√					Positive
Anne (2012)							√				Mixed
Annim and Frimpong (2018)				√							Positive
Asraf et al 2009	√						√				No
Atamja and Yoo (2021)		√					√				Positive
Baiyegunhi et al (2010)							√				Positive
Barnes et al. (2001)	√						√		√		Positive
Buchenrieder et al (2019)							√				Positive
Bocher et al (2017)				√	√						Positive
Brannen Corner (2010)			√	√		√	√				Mixed
Copestake et al (2010)	√	√					√				Mixed
Crepon et al (2011)	√	√					√				No
Dimova and Adebowale (2017)		√									Positive
Doocy et al (2005)					√						No
Fafona et al (2015)	√						√				Positive
Fasanya (2012)							√				Positive
Ganle et al (2015)							√				Mixed
Gebru and Paul (2011)			√			√	√		√		Mixed
Haddad and Maluccio (2003)		√					√				Positive
Idrissu et al 2018							√			√	No
Karlan and Zinman (2010)		√				√	√				Positive
Lastarria-Cornhiel and Shimamura (2008)		√	√				√				Mixed
Magezi and Nakano (2020)							√				No
Manja and Badjie (2022)		√					√				Mixed
Mejaha et al (2010)		√	√								Positive
Mensah et al (2022)	√	√	√			√	√				Positive
Merra et al (2019)	√						√				Positive
Metrine and Omoro (2019)							√				Positive
Mwansakilwa et al (2017)		√									Positive
Nakano and Megazi (2020)							√			√	No
Nanor (2008)			√				√				Mixed
Nicholas (2010)	√			√			√				Positive
Nwanesi (2006)											Positive
Ogundeji et al (2018)	√										Positive
Okafor et al (2016)								√			Negative
Okoyo et al. (2021)				√			√				Positive
Owuor (2009)							√				Positive
Ozoh et al (2022)							√				Positive
Salia (2014)	√										Positive
Tekana and Oladele (2011)		√									Positive
Tita (2017)	√						√				No
Torazzi et al (2015)			√	√			√				No
Total Count from Studies	14	13	7	6	2	5	33	1	2	2	

Notes: Cons in the table is defined as total consumption, Food .Exp as food expenditure and Food Sec as food security.

2.8 Discussion and Conclusion

This chapter attempts to understand and provide important conclusions from the micro finance literature concerning the impact of financial credit on welfare for Africa, which is believed to be the poorest region of the world and characterised by higher levels of market failures, financial illiteracy and inequality. Categorisation of effects from this study considers both the number of studies that recorded significant effects and the number of individual estimates that show significant effects.

The available evidence from African countries favours a positive direction of impact of micro-credit on welfare, however, I highlight certain factors for discussion. First, the direction of impact depends on the methodological procedure through which the problem of endogeneity is addressed. For studies who employ Randomized Control Trials, the direction of impact was no convincing evidence. This could be as a result of addressing selection endogeneity problems where households self-select into receiving micro-credit through various attributes like productivity, location, social status, interest rates, and so on. On the other hand, the selection problem may arise from credit givers through credit rationing, financial literacy tests, distance to commercial banks, previous loan repayment status, etc.

Randomization as an experimental approach circumvents these problems which is lacking in other methodologies especially the OLS. Although regression studies like the Heckman Selection model, the Endogeneity Switching models, and Propensity Score Matching attempt to address this problem, the extent to which the endogeneity is addressed depends on the level to which treatment exogeneity of obtaining micro-credit or the Conditional Independence Assumption (CIA) is satisfied. The CIA assumption, however in theory, is non-testable. Furthermore, these methods on their own do not address problems of endogeneity which may relate to time variant or invariant unobservables. Also, there is scarcity of panel evidence (long-term effects) for the regression studies. The RCT methods deals with some of these problems but is still limited to short-term impacts due to the short-term data collection (expensive to run over long periods). In addition, there are problems of external validity, as a result obtained in one country may be different from another country (Rodrik 1999, Rodrik 1996). Important for policy would be to provide evidence that draws conclusions on the effects of micro-credit on welfare addressing the issues of endogeneity from both selection problems and unobservable heterogeneity problems.

Furthermore, there is scarce panel data evidence for Africa as shown by the included studies. Most of the analysis for Africa employs cross-sectional data, which could be the reason why micro-credit could either show an immediate impact or no impact depending on the length of period or welfare measure concerned. Moreso, the level of inequality or income level of countries could also be another reason why most of the cross-sectional studies have either a positive impact or a mixed impact. While policy makers seek evidence on short-term impacts of the funds they spend on welfare, lasting impacts as well as long-term impacts are also very important to them. Hence, while the evidence from most of the regression and descriptive studies included favour the direction of positive impact from micro-credit on welfare, questions as to whether similar conclusions are realisable for longer periods in Africa still remains.

Generally, the evidence from this study indicates that more studies (27) show a positive significant effect of financial credit on welfare, however, there is a less clear picture if one considers the individual estimates as fewer find a positive significant effect compared to the number that show insignificant effect. An explanation for this could be the rating of journal and the number of estimates included in intervention studies like RCTs which tend to show no convincing evidence. Articles with higher SJR quality tend to include more estimates compared to those with lower SJR and among articles of high quality are the RCTs. It would be interesting to check if the same conclusion persists if further intervention programmes available in the future are included. Moreso, the focus of studies could be another reason for mixed evidence in terms of number of estimates. Studies that focus on journals relating to applied micro-economics, development and finance show a higher number of estimates on average compared to studies in the social sciences and agriculture.

The categorisation of effect from all regions shows a positive impact however the scarcity of evidence in the North, Central and Sub-Saharan African regions are quite mixed and inconclusive. Possible reasons for the scarcity of evidence might be due to violence, varying religious beliefs, youth restiveness that may prevent successful credit intervention programmes on welfare. I do not rule out the fact that some unpublished articles may also be unavailable to the public. However, a good conclusion to draw from here is that regions with a more stable political system show more evidence and intervention programmes on the effect of credit on welfare. In addition, the fact that after the Covid-19 pandemic, only two studies showing positive impact are available leaves an opening for further research on Covid-19 pandemic, micro-credit and welfare as well as the use of either experimental or quasi-experimental approaches to provide evidence different from the approach employed by the two studies available.

Chapter 3 Does Financial Credit Really Improve Household Welfare?: A Causal Empirical Evidence from A Lower-Middle Income Country

3.1 Introduction

Nigeria, a lower-middle income country is raked among the first thirty world poorest countries as 65% of her populace live below the poverty line of $2 per day (World Bank 2016) and only about 12.6% maternal mortality rate reduction between 2000 to 2020 compared to other countries (World Health Organization 2023) while the mortality rate per 1000 male adults is 378 (World Bank 2022). Although, the country is massively endowed with many resources, with agriculture amongst the top (Central Bank of Nigeria Statistical Bulletin 2015), the Nigerian economy is plagued by developmental and poverty problems as a result of shallow developmental research programmes, poor planning and implementation of economic policies (Ngozi et al. 2021).

From the early 1980s, the Nigerian economy has placed reliance on donor support as well as a handful of intervention programmes aimed towards the provision of financial credit and directed at raising agricultural productivity to tackle degrading welfare levels. For example, Central Bank of Nigeria has employed schemes like the Agricultural Credit Guarantee Scheme Fund (ACGSF) to improve agricultural productivity. Notwithstanding, a massive concern about this credit from the government is the difficulty in extending to farmers in local cooperative farming associations. Consequently, the impact of such funds on improvement in agriculture is difficult to measure. Moreso, intervention programmes are rarely regular. Consequently, the exigency to take on economic research works/programmes aimed at developing economic strategies and policies targeted at improving household welfare for lower-middle income countries as well as to provide answers on whether financial credit policy is sufficient to improve welfare levels gives a great motivation for this study. The contribution of this study to address this vital question is crucial for policy following the approach of combating poverty through financial credit channels by some developing economies.

Arguments on the effects of credit on welfare is quite mixed and still on-going in the economics finance literature as I show in the next section. Many studies have used time series regressions to establish correlation between financial credit and poverty reduction or economic growth, while others find contrasting results (see chapter two). Other studies have also used the channels of private borrowings to show the relationship between the two. Nevertheless, does this correlation genuinely indicate causation? Economic policies should not be formulated solely on the basis of correlation, and to date, there has been no study that comprehensively explores the causal relationship between the two factors in the context of Nigeria. This chapter extends the prvious analysis of James (2020) and adds to the current body of literature by investigating the impact of financial credit on diverse household welfare indicators across different periods for farm households in Nigeria, a lower-middle-income country. In other words, this chapter aims to address the inquiry of whether there are discernible causal effects stemming from financial credit to household welfare among agricultural households in Nigeria using different welfare indicators at different time periods. To my knowledge, this is the first work to investigate the effects of financial credit access on various household welfare indicators using panel datasets in different periods and addressing the issues of selection bias and unobserved heterogeneity for a lower-middle income country.

In 2015, the Central Bank of Nigeria (CBN) implemented an intervention programmeme designed to provide financial credit to farm households across the country's six geopolitical zones. The initiative aimed to enhance farm productivity and household welfare, ultimately contributing to poverty reduction in Nigeria. Farm households have the option to apply for these funds (loans) directly through commercial banks or via farmers' cooperatives and micro-finance institutions. The impact assessment of these credits on various welfare indicators, such as consumption per capita, income, food expenditure, non-food expenditure, and education expenditure, relies on informal information from the CBN and data from the World Bank's Living Standard Measurement Survey (LSMS). This dataset includes information on farm households that applied for and received loans in 2015, as well as their welfare levels before (2012) and after (2016 and 2018) obtaining the loans.

The study employed a quasi-experimental approach of combining the Propensity Score Matching (PSM) with the Difference-In-Difference econometric techniques to address endogeneity problems. The PSM methodology was employed to eliminate potential endogeneity issues arising from selection bias, given that the allocation of these funds to farm households is non-random (Heckman et al. 1997, 1998). This method aims to recreate the conditions of a random experiment by constructing new samples. This is achieved by selecting households from the group that did not receive financial credit but have similar probabilities to those that did. The probability, known as the propensity score (Rosenbaum and Rubin 1983), is a function of observable pre-treatment characteristics of households. Consequently, the chosen households that did not receive credit form the ideal counterfactual group necessary for constructing hypothetical welfare trajectories. This process allows for the measurement of the causal effect of financial credit on household welfare, accurately reflecting what the welfare paths of treated households would have been if they had not received the treatment. Moreover, the empirical findings of the study were enhanced by integrating the PSM model with the Difference-In-Difference econometric approach. This combination allowed for the control of additional unobservable time-invariant characteristics, aligning with the methodologies employed by Blundell and Costa Dias (2000, 2002), Hirano and Imbens (2001, 2003) and Robins et al. (1994). Hirano and Imbens (2001, 2003) demonstrate that the combination of the matching technique with the Difference-In-Difference approach yields more reliable results compared to the instrumental variable approach. The reliability of the instrumental variable approach hinges on the degree to which the exclusive restriction criterion of instruments is met. To the best of my knowledge, this study represents the initial causal analysis of the effects of credit on household welfare for a lower-middle-income country such as Nigeria.

Leveraging a dataset encompassing 4,611 households, of which 773 received financial credit treatment and the remaining 3,838 did not. Households who applied and obtained loans during the 2015 financial credit intervention period were grouped as those who received financial credit treatment while those who did not apply or applied and did not receive the loans were grouped as those without the financial credit treatment. The justification for this choice is to capture both demand side and supply side factors that may play a role in applying for (not applying) financial credit and receiving (not receiving) financial credit. For instance, households eligible for loans may choose not to apply (demand side factors) and excluding them from the sample may constitute bias in the results. This study employed two matching estimators: nearest neighbour matching and inverse probability weighting. The objective was to identify the appropriate counterfactual group for the treated households based on observable characteristics in the dataset. Subsequently, the study estimated the impact of receiving financial credit on household welfare indicators across different periods. This evaluation was conducted using both matching and a matched Difference-In-Difference estimator, following the approach outlined by Blundell and Costa Dias (2000, 2002). The methodology takes into account periods before and after the intervention using available panel data. Additionally, inverse probability weighting was employed to amalgamate the Propensity Score Matching model with a standard Difference-In-Difference model. This approach facilitated the control of more exogenous variables, allowing for the estimation of the effects of financial credit on household welfare in accordance with the framework proposed by Hirano and Imbens (2001, 2003). The results from the study show that only the most productive and informed poor households receive financial credit. The findings of the study also show significant effect only when consumption per capita is considered as a welfare measure in the short-run and only when selection bias and unobserved heterogeneity (i.e., time fixed effects and household/group or feedback) are jointly controlled for. For other welfare measures, I find no significant evidence that obtaining financial credit improves the welfare levels of households in both short-run and long-run periods no matter the level of welfare been used. The results are robust to various specifications.

Proceeding sections of this chapter are as follows. Section 3.2 gives the literature review, while Section 3.3 details the methodological approach utilised in this study, specifically focusing on the Propensity Score Matching and the combined matched Difference-In-Difference estimation methods. Moving to Section 3.4, the discussion delves into the dataset employed, outlining the process of selecting the appropriate counterfactual group through matching techniques and assessing the reliability of the matching. Subsequently, Section 3.5 presents the empirical findings of the study, while Section 3.6 engages in a discussion based on these results. Finally, Section 3.7 offers the conclusions drawn from the study's outcomes and discusses their policy implications.

3.2 Literature Review

First, I refer to the systematic evidence on the impact of financial credit on welfare for African countries in chapter two of this study. Subsequently, this chapter goes beyond the literature for Africa to establish several inputs. The chapter builds from the Agricultural Household Model (AHM) with non-separable decision making as regards production (investment) and consumption due to credit market failure as a theoretical framework to guild this study. The AHM operates under the assumption that households make simultaneous and non-separable decisions regarding both their production and consumption, which are contingent upon the availability of capital (credit) and the initial endowment of households. This implies that households facing credit constraints may struggle to afford the optimal levels of input necessary for farm production. Additionally, low credit availability also impacts consumption decisions. Hence, the failure in the credit market could translate to low productivity of households which could have dampening effects on their welfare levels. This contrasts with earlier literatures of the AHM by Barnum and Squire (1979) that assumes a perfect market condition with funds available to farm households to borrow from, thus, their production decision is independent of their consumption. However Lopez's (1984) empirical findings for Canadian agricultural households lend support to the AHM model, highlighting imperfect substitution between on and off-farm labour due to market failure. The study indicates that market failure, stemming from insufficient skills and credit, can impact the labour supply of farm households, subsequently affecting their production and consumption levels. This contrasts with the perspective of Barnum and Squire (1979), emphasising the dependency of household utility and profit maximisation. Similarly, Jacoby (1993) presents evidence that the labour supply for self-employed farm households, not engaged in wage labour, is strongly influenced by a concave budget constraint, drawing on data from households in Peru. The budget constraint also plays a crucial role in determining the production and consumption levels of households, suggesting that those without adequate credit may engage in sub-optimal farm activities, impacting productivity. Skoufias (1994) supports the prediction of non-separable consumption and production decisions resulting from market failure, using agricultural households in India. He argues that constraints on off-farm work time, imperfect substitution between family and hired labour for production, and household preferences for on or off-farm labour necessitate a dependent decision process. labour supply is determined by shadow wages, which, in turn, depends on the availability of capital in households. Consequently, credit market failure can compel households to restrict their production, employment, or consumption to fit within their budget constraints. De Janvry et al. (1996) demonstrate that farm households in Mexico, with varying asset positions, influence the supply of farm labour based on different levels of endowment or skill, as well as labour demand depending on available capital. Transaction costs come into play when hiring or selling farm labour, indicating that credit market failure can impact the quantity of farm labour hired or sold. This, in turn, can hinder production and consumption, thereby affecting overall welfare.

While early literature on the AHM suggests that an imperfect credit market can impact the production and consumption levels of households, potentially leading to a decline in labour supply or output productivity, ongoing debates revolve around whether the availability of credit enhances welfare or reduces poverty. This uncertainty persists because a decrease in productivity alone may not necessarily translate to a reduction in welfare levels. Consequently, the focus of this study is to assess whether credit improves the welfare of agricultural households in the context of credit market failures. In this context, credit market failures refer to the insufficient availability of credit due to market imperfections. Additionally, households may face challenges in borrowing all the funds needed for agricultural activities, as fund suppliers can restrict disbursement based on the creditworthiness of households.

From the macro perspective, Baktiari (2006) contends that finance has the potential to drive economic growth and indirectly reduce poverty by enhancing the efficiency of resource allocation, fostering a conducive market environment, and expediting the adoption of new technologies. Formal credit sources are identified as influential in urban sectors for poverty reduction, while informal credit sources play a complementary role in developing rural and agricultural areas. On an aggregate level, finance emerges as a viable strategy for poverty alleviation and economic development, as demonstrated by positive effects observed in Thailand, Indonesia, and Bangladesh. Jalilian and Kirkpatrick (2002, 2005) corroborate the idea that the supply of financial credit can elevate welfare levels, particularly when addressing inequality issues in both urban and rural areas. They establish a linkage between financial credit, inequality, and economic growth, suggesting that finance indirectly stimulates economic growth by reducing inequality. Dollar and Kraay (2004) introduce the dimension of financial credit's impact on trade and its subsequent influence on economic growth. Their cross-country regression results indicate that the availability of financial credit can facilitate international trade, leading to economic growth for trading countries. However, it is acknowledged that the relationship is based on correlations, and debates persist regarding the causal effects of trade on economic growth. Parallelly, Beck et al. (2004) investigate the influence of finance on business start-ups in Finland. Their findings indicate that the provision of financial credit can stimulate the establishment of more businesses, ultimately contributing to poverty reduction in the economy over the long term. Similarly, Jeanneney and Kpodar (2011) and Akhter and Daly (2009) analyse the impact of financial development on welfare through economic growth and income distribution, highlighting a positive role in promoting poverty alleviation.

However, counterarguments challenge the notion that financial credit can enhance welfare levels. These opposing perspectives arise from conflicting findings in various studies, suggesting that credit may have detrimental effects on the poor when considered at the aggregate level. Lloyd-Ellis and Bernhardt (2000) demonstrate that the provision of credit in an imperfect credit market can redistribute wealth by fostering the creation of more businesses, encompassing both agricultural and non-farm enterprises. However, their findings indicate that this redistribution does not lead to a significant increase in wealth at the aggregate level. Despite their analysis accounting for positive or negative shocks, the results from their cross-country regression reveal that cyclical fluctuations in income distribution do not significantly contribute to overall growth. Ravallion and Chen (2007) demonstrate that providing credit does not alleviate poverty due to elevated levels of inequality among the poor, especially when compared to urban centres. Their findings suggest that the supply of credit results in uneven development, contributing to short-term improvements in welfare levels but leading to a deterioration of welfare levels in the long-run. This is mainly as a result of inflationary shocks which affect some key output prices that determine wages. They argue that tackling issues of inflation and inequality through effective tax policies, rather than a direct supply of credit, can stimulate growth in rural areas. This, in turn, has the potential to contribute to overall economic growth. Ravallion (2001), also provide conflicting results that credit has worsening effects on the poor mainly because of inflation and inequality issues. Through cross-country regressions, they illustrate that analyzing the impacts of credit, growth, and inequality on welfare requires looking beyond averages and aggregate statistics. Their findings reveal that the well-being of the poor is more compromised than suggested by overall statistics. They demonstrate that access to financial credit can contribute to disparities in trade participation, resulting in increased inequality among the poor, ultimately adversely affecting overall growth.

On a micro level, there is a shortage of conclusive evidence regarding the causal impact of credit on household welfare in low-income countries within the context of an imperfect credit market. This scarcity stems from the unavailability of dependable micro panel data over several decades. The available micro evidence is quite mixed due to the econometric problems of endogeneity and the approach of several studies to address this issue. Studies frequently depend on either single-period cross-sectional data for quantile regressions, illustrating how financial credit induces heterogeneity in various welfare levels, or correlation analyses to elucidate the relationship between the two. Jalan and Ravallion (2000), employing quantile regressions, demonstrate that elevating the wealth level of households can positively impact household welfare for specific poverty levels in China during that period. Their analysis indicates that while increasing household wealth levels can address both chronic and transitory poverty, shocks may raise the likelihood of individuals transitioning from transitory poverty to chronic poverty. Consequently, for certain poverty levels, relying solely on financial credit might be inadequate, and addressing diverse poverty levels necessitates employing various instruments. This aligns with the findings of Hong et al. (2020), who, through quantile regressions, also observe that farm households' vulnerability to poverty differs when considering folk loans compared to private and bank credit. Additionally, Townsend and Ueda (2003, 2006) illustrate through time series analysis that financial credit contributes to increased income inequality, ultimately negatively impacting the poverty levels of households.

Hung and Tuan (2019) investigate the determinants of household welfare in Vietnam. They show that education and non-farm self-employment play an important role in improving the welfare levels of households. However, these results are based on correlation evidence. Their result is very similar to Glewwe (1991) who also show that the availability of medical services positively impacts welfare levels of households.

Kumar et al. (2013) uses a more qualitative and comparative approach to investigate the effects of credit constraints on the well-being of households in India and China using survey data collected between 2008-2009. The analytical outcomes and data reveal that constraining credit has detrimental effects on a wide spectrum of production and livelihood decisions. The findings indicate that credit constraints have negative impacts on food consumption, the application of farm inputs, as well as health and educational achievements. The cross-sectional investigation conducted by Liqiong et al. (2019) also presents findings that highlight the significant impact of credit on the welfare (consumption) of 960 rural households in China in 2017. This aligns with the earlier study by Asad et al. (2015), which indicates that micro-credit can enhance household welfare in Pakistan, utilising cross-sectional data from 2008. However, it is crucial to note that these results are confined to a single cross-sectional period and solely focus on welfare improvements during the treatment period. This may not fully capture the impact on household welfare levels beyond the treatment period, as required in causal analysis. Additionally, the study by Asad et al. (2015) does not address the issue of unobserved heterogeneity, both time-variant and time-invariant.

Alternative efforts to discern the influence of financial credit on household welfare involve Randomized Control Trials (RCT) studies, which yield varied outcomes. Attanasio et al. (2015) present findings from a randomized field experiment in rural Mongolia, evaluating the poverty impacts of a joint-liability micro-credit programmeme targeted at women. The study reveals a positive effect of access to group loans on entrepreneurship for women and household food consumption, but no significant impact on total working hours or household income. The introduction of an individual-liability micro-credit programmeme simultaneously shows no significant poverty impacts. Additionally, the study indicates that the presence of joint liability may discourage borrowers from utilising loans for noninvestment purposes, resulting in stronger impacts. Similarly, Angelucci et al. (2015) employ a clustered randomized trial and conduct over 16,000 household surveys to estimate community-level impacts arising from a group lending expansion at 110 percent APR by Mexico's largest micro-lender. Their study finds no evidence of transformative impacts on 37 outcomes, measured at a mean of 27 months post-expansion, across six domains: micro-entrepreneurship, income, labour supply, expenditures, social status, and subjective well-being. Other RCT studies like, Augsburg et al. (2015), Banerjee et al. (2015), Crépon et al. (2015), and the Ethiopian study of Tarozzi et al. (2015) also find little or no effect of financial credit on household welfare. Although RCT studies are very widely accepted by economists, there are very strong arguments against making predictions from the results of RCTs due to the issue of internal and external validity (Pritchett and Sandefur 2014, Rodrik 1999, Rodrik 2006). This is because their results are unique to specific areas or countries and therefore cannot be generalised for other countries because of the differences in culture, terrain, GDP etc. For example, results unique to high income countries cannot be used to make generalisation for low-income countries and vice versa. Secondly the issue of the long-run impact as RCTs are verily known to give predictions about the present.

For simplicity, I have summarised the studies discussed above in addition to other foreign studies in Table 3.1. Studies already covered in the systematic review are excluded.

Table 3.1: Foreign evidence on the effects of financial credit on welfare

Authors	Country(s)	Year of Data	Level	Methodology	Significant?	Weakness
Attanasio et al (2015)	Mongolia	cross-sectional (2015)	Micro	RCT	Mixed	External validity, One period data
Angeluci et al (2015)	Mexico	cross-sectional (2015)	Micro	RCT	No	External validity, One period data
Augsburg et al (2015)	Bosnia	cross-sectional (2009)	Micro	RCT	No	External validity, One period data
Liqion (2019)	China	cross-sectional (2017)	Micro	Switching Regression	Yes	One period data
Bakhtiari et al (2006)	Cross-country	Time series	Macro	CC-Regression	Yes	Endogeneity
Dollar and Kray(2001)	Cross-country	Time series	Macro	CC-Regression	Yes	Endogeneity
Banerjee et al (2015)	India	Cross-sectional (2005)	Micro	RCT	Mixed	External validity, One period data

Notes: CC= cross-country, RCT= Randomized Control Trial, FEVD= Fixed Effects Vector Decomposition
OLS= Ordinary Least Squares, GMM=generalised Method of Moments.

Table 3.1 Continued: Foreign evidence on the effects of financial credit on welfare

Authors	Country(s)	Year of Data	Level	Methodology	Significant?	Weakness
Beck et al (2004)	Finland	Time series	Macro	Correlation	Yes	Endogeneity
Jeanneney and Kpodar (2010)	cross-country	Time series	Macro	correlation	Yes	Endogeneity
Daly and Ahkter (2010)	cross-country	Panel	Macro	FEVD	Yes	endogeneity
Asad et al (2015)	Pakistan	cross-sectional (2008)	Micro	Probit	Yes	Unobserved Het, One period data
Lloyd-Elliss and Bernhardt(2000)	cross-country	cros-country	Macro	CC-Resgression	No	Endogeneity, correlation
Chen and Ravellion (2010)	cross-country	Time series	Macro	correlation(OLS)	No	Endogeneity
Ravellion (2001, 1997)	Cross-country	time series	Macro	OLS	No	Endogeneity
Jallan and Ravellion (2000)	China	mixed	Micro	Quantile Reg	No	Endogeneity
Hong et al (2020)	China	cross-sectional	Micro	Quantile Reg	No	Endogeneity

Notes: CC= cross-country, RCT= Randomized Control Trial, FEVD= Fixed Effects Vector Decomposition
OLS= Ordinary Least Squares, GMM=generalised Method of Moments.

Table 3.1 continued:Foreign evidence on the effects of financial credit on welfare

Authors	Country(s)	Year of Data	Level	Methodology	Significant?	Weekness
Townsend and Ueda (2003, 2006)	Thialand	Time series	Macro	DSGE	No	Endogeneity
Hung and Tuan (2019)	Vietnam	Time series	Micro	Regression (OLS)	Yes	Correlation
Kuang et al (2019)	China	Panel	Micro	PSTR	Yes	Endogeneity
Cepparulo et al (2017)	cross-country	Panel	Micro	OLS+GMM	Yes	Endogeneity
Compton and Giedeman (2011)	cross-country	Panel/Cross-section	micro	OLS+GMM	Yes	Endogeneity
Masih and Khan(2011)	cross-country	Time Series	Macro	OLS	Mixed	Not Causal
King and Levine (1993)	cross-country	cros-country	Macro	CC-Resgression	No	Endogeneity

Notes: CC= cross-country, RCT= Randomized Control Trial, FEVD= Fixed Effects Vector Decomposition
OLS= Ordinary Least Squares, GMM=generalised Method of Moments.

3.2.1 Contribution of the Study

One major cause of the mixed results on the effects of financial credit on welfare shown by both micro and macro evidence as discussed above is the failure (sometimes weakness) to address the issue of endogeneity. Also, it will be more appropriate to use a panel data set if future predictions are to be drawn from the conclusions of causal studies. This study helps to address this gap and add to the literature in different ways. First, the proposed methodology (a mixture of the Propensity Score Matching and the Difference-In-Difference econometric techniques) would effectively address the issues of endogeneity from both selection bias and unobserved heterogeneity using panel data for a lower-middle income country which is still a gap in literature on the effects of credit on household welfare. While the PSM addresses endogeneity stemming from selection bias, the DID econometric technique deals with the problem of unobserved heterogeneity. Thus, following James (2020), I resolve this problem using various welfare level indicators with a more extended panel dataset for comparison at various post treatment periods. A panel dataset is necessary to address endogeneity stemming from selection bias and time invariant unobservables on the effects of financial credit on welfare for longer periods as compared to cross-sectional data that accounts for a one period impact. Secondly, I estimate the effects of financial credit on welfare levels for Nigeria using various welfare indicators at different periods to assess the degree of robustness of the evidence of financial credit on welfare levels.

3.3 Empirical Methodology

To answer the research question on whether the effects of financial credit on welfare vary by welfare measures and by different time periods, I employ the combination of Propensity Score Matching (PSM) and Difference-In-Difference (DID) methodologies following James (2020), as they are best suited to capture the causal effects. First, I deal with the issue of selection bias using the PSM model to identify ideal treatment and counterfactual groups because the release of credit is non-random. Once these ideal groups have been identified, I employ the DID methodology controlling for fixed effects (through differencing) to determine the Average Treatment Effect on the Treated (ATT) of financial credit on various welfare measures in Nigeria on these ideal groups. Internal validity of obtained results will be validated using these methodologies.

Considering that the credit intervention programmeme takes place in period t, the observed welfare levels for household i in post treatment period $(t+s)$ is denoted by $m_{i,t+s}$ where with $s > 0$. Consequently, the causal impact of financial credit on welfare is expressed as:

$$g_{i,t+s} = m^1_{i,t+s} - m^0_{i,t+s} \tag{3.1}$$

The term $m^1_{i,t+s}$ denote the welfare level of i households who obtained the financial credit treatment at the post-treament period (t+s) while the term $m^0_{i,t+s}$ is given to the same households if they did not receive the treatment. Nevertheless, this causal impact of credit on welfare in equation (3.1) is stated in terms of potential outcomes which is quite arduous to measure owing to the problem of missing data because $m^1_{i,t+s}$ and $m^0_{i,t+s}$ are not observed concurrently [1]. To circumvent this issue, I adopt the approach introduced by Heckman et al. (1997) to define the ATT of receiving financial credit on the households that underwent the credit treatment as

$$\begin{aligned} ATT = E(g_{i,t+s}|FC_i = 1) &= E(m^1_{i,t+s} - m^0_{i,t+s}|FC_i = 1) \\ &= E(m^1_{i,t+s}|FC_i = 1) - E(m^0_{i,t+s}|FC_i = 1) \end{aligned} \tag{3.2}$$

In the equation above, FC_i=1 if households i obtained the financial credit treatment at period t and 0 otherwise. The term E($m^0_{i,t+s}|FC_i = 1$) in equation (3.2)[2] denotes the hypothetical mean welfare of the households who obtained financial credit if they had not received treatment and constructing an ideal counterfactual for this term is of major concern. Had this been the case of a natural experiment, then finding the right counterfactual for

[1] $m^1_{i,t+s}$, $m^0_{i,t+s}$ are termed potential outcomes since only one outcome will ultimately be realised and observed: the potential outcome corresponding to the action actually taken ($m^1_{i,t+s}$). Ex-post, the other potential outcome cannot be observed because the corresponding actions that would lead to its realisation were not taken.

[2] Equation (3.2) is written in terms of the average treatment effect on the treated to show that the local average treatment effect from getting financial credit on welfare (ATT) is the difference between the treated [E($m^1_{i,t+s}|FC_i = 1$)] and the counterfactual non-treated group [E($m^0_{i,t+s}|FC_i = 1$)].

$E(m^0_{i,t+s}|C_i = 1)$ will be unchallenging because $E(m^0_{i,t+s}|FC_i = 0)$ which represents households who do not receive the treatment suffices given that treatment selection ($FC_i = 1$) is random and is statistically independent of $m^0_{i,t+s}$

Consequently, I revert to the PSM procedure that aim to re-establish the requirements of a random experiment through constructing new samples from the selection of households without financial credit, households having identical probabilities with the households who obtained credit. I however take into account certain necessary assumptions. The Conditional Independence Assumption (CIA) or the unconfoundedness condition which in simplification require that conditional on observed confounders/covariates, treatment assignment be exogeneous of potential outcomes (no selection bias) [3]. Hence, the Conditional Independence Assumption (CIA) posits that the distinctions between households that received the credit treatment and those that did not can be explained by observable pre-treatment characteristics. By controlling for these characteristics, it implies that the treatment is essentially random, indicating no systematic difference between the treated and untreated households (absence of selection bias). This assumption is crucial for treating the treatment variable as exogenous, simplifying the estimation process. The CIA assumption, being non-testable, relies on the assumption that all necessary characteristics for treatment assignment are included in the list of observable covariates, with no missing variables. This is presented as

$$(m^1_{i,t+s}, m^0_{i,t+s}) \perp FC_i | X_{i,t-n} \tag{3.3}$$

The $\perp$ in equation (3.3) denotes independence. Also, I consider the common support assumption/condition (also called the overlap condition) that necessitates that the pairs of matched treated and non-treated households be within the distribution of observable covariates thus ensuring the random assignment of treatment and their counterfactuals as

[3] This assumption has been called several names in the econometric evaluation literature like the Unconfoundedness Assumption (Imben and Rubin 2015), Ignorability Assumption (Rubin 1977, Wooldridge 2010, 2020, Wooldridge et al. 2016). The assumption thus imply that there are no omitted variable bias given that some set of observable characteristics x, are contained in the model. This assumption is thus equivalent to the treatment assignment which ignores outcomes; hence the reason it is referred to as the Ignorability Assumption.

ideal control groups[4]. The condition necessitates that the probability of receiving financial credit is positive but bounded away from 0 and 1, eliminating the possibility of perfect predictability of receiving financial credit based on the covariates. I present this below as:

$$0 < Prob(FC_i = 1|X_{i,t-n}) < 1 \tag{3.4}$$

Furthermore, I consider the balancing condition which necessitates that the households who have identical probabilities should have identical distribution of features. Though the CIA is non-testable, this condition can serve as it's testable implication because it verifies the covariates balance used. Consequently, treated and non-treated households are matched with identical propensity scores (see Rosenbaum and Rubin 1983) and the propensity scores defined as household(s) i probability of obtaining financial credit in period t conditional on certain observable pre-treatment features/covariates in period $t-n$ given as;[5] (Hirano and Imbens 2001, 2003)

$$Propscore = Prob(FC_i = 1) = F(X_{i,t-n}) \tag{3.5}$$

The results from matching helps in the construction of ideal counterfactual groups *(C)* for individual who obtained credit *(FC)* using the available features of the individuals who did not get the credit. Hence, I estimate the ATT of the matched pairs as the differ-

[4]The common support condition necessitates that in every value of $X_{i,t-n}$ there are treated and untreated scenarios. Thus, for every treated household there are other matched non-treated household(s) having identical $X_{i,t-n}$. In cases where the assumption was invalid, one could potentially have a case where households having $X_{i,t-n}$ vectors are all treated and households having non-identical $X_{i,t-n}$ are also all untreated. The assumption is not however necessary to identify any treatment parameter(s) for the treated households. To identify treatment effects on household(s) which are randomly selected, then we need for each participant household, an analogous non-participant household for which case the condition prob(FC_i=1 $|X_{i,t-n}$) suffices.

[5]The PSM is an attractive and persuasive econometric methodology to use given that one can control for a rich set of potential controls and x characteristics, and that the parameter of interest is either the ATET or ATE. The methodology also relies on the "No General Equilibrium Effects" condition, also known as the Stable Unit Treatment Value Assumption (SUTVA), which verifies that obtaining treatment doesn't influence the non-treated observations indirectly.

ence between the average welfare levels of those who received the financial credit and the counterfactual household group j below as

$$A\hat{TT}_M = \sum_{i \in FC} (m_{i,t+s} - \sum_{j \in C} (V_{ij} m_{j,t+s}) v_i \tag{3.6}$$

V_{ij} represent the weights placed on household j, a counterfactual for household i , while v_i indicates any re-weighting that reconstructs the treatment category distribution[6].

The PSM estimate causal effects conditional on observables, nevertheless, I do not neglect the possibility where the outcome welfare could be influenced by unobservable factors not captured in the equation above. To circumvent this problem, I combine the matched sample with the Difference in Difference estimator of Blundell and Costa Dias (2000, 2002). I present the ATT for the matched-DID as

$$A\hat{TT}_M^{DID} = \sum_{i \in FC} ((m_{i,t+s} - m_{i,t-n} - \sum_{j \in C} V_{ij} (m_{j,t+s} - m_{j,t-n})) v_i \tag{3.7}$$

Equation 3.7, depicted above, calculates the disparity in household welfare before and after receiving the credit treatment for the matched samples, subsequently estimating the ATT. This approach assists in addressing unobservable factors influencing welfare levels.

Again, to improve the reliability of the result, I now combine the PSM model in equation (3.7) with a standard Difference in Difference model using the inverse propensity weight following Guo and Fraser (2014), Willianson and Forbes (2013), Hirano and Imbens 2001, Hirano et al. 2003) who show that the PSM model can be combined with other regression models using the inverse propensity weights obtained from the known propensity scores from the matching technique where the weight 1/p is assigned to households who obtain treatment and 1/1-p is the weight assigned to their counterfactual, with p denoting propensity score from matching. The weight is calculated as IPW = FC/p + 1-FC/1-p. Using these weights, I estimate the difference in difference model below. I also control for

[6]The matching model in equation (3.6) estimates causal treatment effects of receiving financial credit on welfare using the right counterfactual constructed from similar characteristics with the treatment group. Thus matching estimates causal effects based on observable characteristics.

further exogeneous factors as depicted by z_{it} in our model below

$$LogM_{it} = \alpha_1 + \alpha_2 FC_i + \alpha_3 after_t + \alpha_4 after_t * FC_i + z_{it} + \epsilon_{it} \tag{3.8}$$

where α_4 represents the ATT of the combined PSM and DID model [7] and z_{it} depicts other exogeneous controls.

3.4 Data

I employ panel dataset from the World Bank Living Standard Measurement Survey (LSMS) panel dataset for Nigeria for 2012, 2015, 2016 and 2018 alongside informal information from the Central Bank of Nigeria for the analysis. The data includes 4611 households among which 773 households have applied for and received financial credit during the Central Bank of Nigeria credit intervention programmeme of 2015 and the remainder of 3838 households did not receive this credit. The 3838 households who did not receive credit are a mix of those who did not apply or applied and did not receive the loans and hence were grouped as those without the financial credit treatment. This is important to capture both demand side and supply side factors that may play a role in applying for (not applying) financial credit and receiving (not receiving) financial credit. Supply side factors could result from credit supplier driven requirements like productivity, income, assets of households, etc, which could facilitate self-selection of households into receiving financial credit. On the demand side, households eligible for loans may choose not to apply (due to several reasons, e.g, risk of not been able to pay back) and excluding them from the sample may constitute bias in the results. Features of these households like demographics, computer access, their social class, their asset, farm produce, consumption, on farm labour (men and women farm workers employed), wage for farm labourers, family and labourers work period, health-shock, distance to closest; market, capital, population centre, road, border, and welfare measures as, consumption per capita, income, food, non-food and education expenditure, etc are also included. These features are included to show households social status, information assess, labour supply, labour participation, distances to trade centres and commercialisation centre as contained in the literature (See Chapter 2, James 2020, Asad et al. 2015).

[7] I estimate the DID model here using the inverse probability weight from matching.

Appendix A show the description of the variables used for this chapter. However, I limit the scope of the data to periods before the Covid-19 shocks i.e 2012, 2015, 2016 and 2018.[8] The welfare level of each household is proxied by consumption per capita, income, food expenditure, non-food expenditure and education expenditure (standard of welfares level by the world bank) while households who have received financial credit are defined as the treatment households below. Additional variables encompass pre-treatment characteristics of households aimed at addressing the concern of selection bias. These variables are household demographics, computer accessibility, social status, assets (monetary value of owned farm land), farm production (yield), on-farm labour supply (the number of hired farm workers, both male and female), remuneration for farm workers, distance from the farm to the nearest market, nearest border, population centre, capital, and road. Although, differencing the results from the PSM will help control the issue of unobserved heterogeneity, I also control for other variables like shocks, rainfall, etc.

Tables 3.2, 3.3, 3.4, and 3.5 provide the summary statistics of the variables, with Tables 3.3 and 3.4 displaying the mean and standard deviation of some observable characteristics before and after the treatment period.[9] Table 3.2 indicates that among financed households, a notable percentage (18.77%) do not own assets. This is further corroborated in column 4, where a significant portion of those who own assets did not receive financing. Moreso, more of the households who were financed had basic information access tools such as phone, computer access which implies that the intervention programme targeted households who have information access.

Moreover, households lacking the means to afford TVs for information access received the credit treatment compared to wealthier households. Those facing shocks in the form of poor health also experienced the treatment more. In summary, Table 3.2 indicates that the programme specifically targeted impoverished households with limited access to basic information, which aligns with the common observation that economically disadvantaged

[8] This is for two reasons, first to circumvent the problem of ascribing the resultant effect of the Covid-19 shocks to financial credit policies. This is essential so as not to overestimate/underestimate the effects of credit on welfare due to the covid-19 shocks. Secondly, due to so much missing data for the Covid-19 period in the LSMS dataset.

[9] The variables employed in the combined matched difference-in-difference model are basically for the 4611 households. However, they have a higher number of observations because they were collected for both pre and post treatment periods.

Table 3.2: Description of binary variables by Credit Status

Variable	Obs(n)	Financed(%)	Non-Financed (%)	Total(%)
Asset	4611			
Asset Owned		17.18	82.82	100
Not-Owned		18.77	81.23	100
Computer Access	4611			
Access		19.76	80.24	100
No Access		17.94	82.06	100
TV	4611			
TV-Access		11.02	88.98	100
No Access		13.05	86.95	100
Phone	4611			
Own Phone		19.22	80.78	100
No Phone		10.42	89.58	100
Health Shocks	13833			
Faced Shocks		18.50	81.50	100
No Shocks		17.48	82.52	100

households tend to face more constraints in obtaining credit.

Table 3.3 reveals disparities in the welfare levels of households that received credit and those that did not, evident even before the treatment period (although statistical significance is not established) across all the welfare indicators.

Table 3.3: Household Observable Features Before Treatment

	Financed			Non Financed		
Variables	Observations	Mean	SD	Observations	Mean	SD
Tot. Cons(2012)	773	120782.6	152213.9	3838	145827.5	442019.9
Income (2012)	773	35029.51	107704.1	3838	34059.02	86670.08
Fd. Exp (2012)	773	119079.4	149342	3838	144692.6	443848.5
Nfd Exp (2012)	773	1430.901	2579.12	3838	1463.309	4942.21
Edt Exp (2012)	773	8526.54	22542.74	3838	7237.58	21210.62

Notes: The Full description of all the variables are reported in Appendix A. All monetary values for this chapter were retained at original their original Nigerian Naira values at the time of this estimation in 2020

Interestingly, in Table 3.4, the welfare level of treated households increases for all measures of welfare after the treatment period. However, caution must be exercised when interpreting this increase as a direct outcome of the credit intervention, as untreated households also exhibit improved welfare levels. Post-intervention, households that received treatment are now wealthier than their untreated counterparts.

Table 3.4: Household Observable Features After Treatment

	Financed			Non Financed		
Variables	Observations	Mean	SD	Observations	Mean	SD
Tot. Cons (2016)	773	165149.2	170614.63	3838	164580.9	23219.9
Income (2016)	773	60567.03	246318.86	3838	52823.98	166649.7
Fd. Exp (2016)	773	163049.9	172541.7	3838	163614.1	234751
Nfd Exp (2016)	773	2099.34	4028.598	3838	2320.94	11376.91
Edt. Exp (2016)	773	8884.7	21646.602	3838	7451.09	23376.43
Income (2018)	773	37783.71	89123.2	3838	32144.6	56496.83
Fd Exp (2018)	773	29156.15	36402.49	3838	37631.16	44750.35
Nfd. Exp (2018)	773	23521.25	31360.45	3838	23217.28	35293.3

Notes: The Full description of all the variables are reported in Appendix A. All monetary values for this chapter were retained at original their original Nigerian Naira values at the time of this estimation in 2020

Table 3.5 provides a summary of the remaining variables utilised in the study. The variables used in the combined matched Difference-In-Difference model have a higher number of observations because they were collected for periods both before and after the programme. Meanwhile, the covariates (pre-treatment characteristics) were gathered before the treatment period. Examples of such variables include welfare, shocks, rainfall, dist-capital, and latitude. Howerver, these higher number of observations are just an period for the 4611 households. The average number of male workers hired by households for farm work is around 2.6 workers. Poorer households tend to employ fewer or zero workers, while wealthier households may hire up to a maximum of 100 workers.

Table 3.5: **Summarising the Continuous Variables Used**

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Yield	4611	741.324	2400.608	0.667	40259.5
No. Menhired	4611	2.62	3.74	0	100
No. Womenhired	4611	0.86	2.19	0	50
Women-Pay	4611	259369.53	169.96373	0	1150000
Dist-road	4611	5.936	7.931	0	67.88
Dist-capital	13833	63.83	54.98	0.18	291.6
Dist-market	4611	67.727	43.63	0.37	214.36
Dist-popcentre	4611	18.091	25.78	0.54	101.76
Dist-border	4611	318.477	178.639	5.2	671.25
Rainfall	13833	1290.296	429.2	434	2574
Wetness	13833	459.22	323.62	11	1147
Latitute	13833	8.351716	2.540931	4.315786	13.71425
Longitude	13833	7.293477	2.315955	2.879477	13.63072

The disparity in the employment of women is notable, with a mean of approximately one female worker and a maximum of 50 female workers per annum. The average pay for female workers indicates that many of these households are economically disadvantaged. Wealthier households can afford higher payments for female workers, while those not employing any female workers provide zero pay. The mean pay for a female worker is 259,369.5 Naira ($632), with a maximum of about 1.15 million Naira ($2,804.88) per annum. This observation aligns with the common trend in agricultural households in developing countries, where males are often perceived as physically stronger and more suitable for extended farm work. Nunn (2008) has demonstrated that proximity to borders, population centres, markets, and urban areas can positively impact households, leading to improved welfare levels. Interestingly, there is considerable variation in the distance of each household to the border, with a mean distance of 318 km. Some households are close to the border (minimum of 5.2 km), suggesting potential access to additional markets for their products. Similarly, the mean distance from each household to the nearest market is 67.7 km, with some households in close proximity (0.37 km), potentially enhancing opportunities for product sales and the hiring of farm labour. In comparison, the mean distance from each household to the nearest population centre is shorter (18 km) than the proximity to the market. The mean distance from households' farmlands to the road is approximately 6 km, a crucial factor influencing the accessibility of agricultural outputs to the market. These distances, however, exhibit large variations, as indicated by their sizable standard errors. Additionally, the variation in land latitude among households is significant, and it plays a crucial role in determining the agricultural production levels, with better land latitude potentially leading to increased yields for each household..

3.4.1 Finding the right counterfactual group

As specified in equation 3.5, the matching of treated and untreated households is conducted based on observable pre-treatment characteristics.[10] Initially, a probit model is estimated to identify the determinants of financial credit, utilising observable pre-treatment characteristics, as illustrated in Table 3.6. The results highlight the effects of various covariates on the financial credit treatment across all welfare indicators.

Households who are more distant from the market, road and border are more likely to receive financial credit indicating that the intervention programmeme targets poor households. Also, households who employ more women to work on their farm have greater probability of receiving the credit implying that the programmeme targets farm households with more on-farm labour supply as this will improve the productivity of farm produce. Furthermore, as we shall soon see in later chapters of this study, given that women are also farm household heads, one can expect that the issue of gender bias (if any) as regards the employment of female workers as compared to the male workers will be minimal.

Households who own basic assets like TV sets and Phone which are used for information access are more likely to receive the credit but not computer owners who are perceived to be richer households. Although not statistically significant, the results from the probit models in both Table 3.6 show signs that households with previous better welfare level (landed farm

[10] Propensity scores were generated adhering to the previously defined Conditional Independence Assumption (CIA), common support, and balancing condition. It's worth noting that this technique is not confined to STATA 16, as R-Studio software also offers similar capabilities through its diverse classification functions.

Table 3.6: Determining factors for Obtaining Credit: Effects from the Probit Model

Response variable FC=1 **Tot. Cons**	Effect	**Income**	Effect	**Fd Exp**	Effect
log Tot. Cons (2012)	$-.0279$	Income (2012)	-6.95e-08	Food Exp 2012	$-2e-07^{*}$
	(.031)		(2.35e-07)		(1.16e-07)
Value	-2.06e-09	Value	-2.49e-09	Value	-2.05e-09
	(4.31e-09)		(4.07e-09)		(4.08e-09)
Yield	-0.0001	Yield	-0.00001	Yield	-9.61e-06
	(0.0000106)		(0.00001)		(0.00001)
No. MenHired	0.0118	No. MenHired	0.0116	No. MenHired	0.0119
	(0.0116)		(0.0116)		(0.0117)
Asset	-0.0289	Asset	-0.024	Asset	-0.027
	(0.0511)		(0.050)		(0.051)
Women Hired	0.025^{**}	Women Hired	0.0258^{**}	Women Hired	0.025^{*}
	(0.0137)		(0.0137)		(0.014)
Women-Pay	1.46e-08	Women-Pay	1.43e-08	Women-Pay	1.45e-09
	(1.23e-08)		(1.23e-08)		(1.23e-09)
TV	0.219^{***}	TV	0.211^{***}	TV	0.215^{***}
	(0.052)		(0.051)		(0.051)
Phone	0.266^{***}	Phone	0.250^{***}	Phone	0.250^{***}
	(0.080)		(0.080)		(0.080)
Computer	-0.052	Computer	-0.062	Computer	-0.049
	(0.067)		(0.066)		(0.066)
Dist-Road	0.009^{***}	Dist-Road	0.009^{***}	Dist-Road	0.009^{***}
	(0.003)		(0.003)		(0.003)
Dist-Popcenter	-0.002	Dist-Popcenter	-0.002	Dist-Popcenter	-0.002
	(0.002)		(0.002)		(0.002)
Dist-Market	0.001^{**}	Dist-Market	0.001^{**}	Dist-Market	0.001^{**}
	(0.0005)		(0.0005)		(0.001)
Dist-Border	0.0003^{***}	Dist-Border	0.0003^{***}	Dist-Border	$.00042^{***}$
	(0.00014)		(0.00014)		(0.00014)
Constant	-1.171^{***}	Constant	-1.486^{***}	Constant	-1.46^{**}
	(0.369)		(0.105)		(0.105)
No. Observations	4611		4611		4611

Notes: Robust Standard errors in parentheses. Significance levels are denoted as follows $^{***}p < 0.01$,$^{**}p < 0.05$,$^{*}p < 0.1$. It is important to note that all the variables in Table 3.6 represent pre-treatment characteristics observed before the treatment period.

property), households who own more computer are less likely to receive the credit treatment indicating that richer households are less likely to receive the credit treatment. Those with previous better food welfare levels are less likely to receive the credit treatment.

Subsequently, I employ two matching estimators, namely nearest neighbour matching and inverse probability weighting, to align each treated household with comparable untreated households based on their propensity scores. In particular, I utilise the nearest neighbour (NN) matching technique, which pairs each treated unit with at least one untreated unit possessing similar propensity scores to form the appropriate control group. In this study, each treated unit is matched with 2 and 5 untreated units sharing similar

Table 3.6 Continued: Determining factors for Obtaining Credit: Effects from the Probit Model

Dependent variable FC=1 Nfd Exp	Effect	Edt Exp	Effect
Nfd Exp (2012)	-5.76e-06	Edt Exp (2012)	1.13e-06
	(6.63e-06)		(1.04e-06)
Value	-2.37e-09	Value	$-3.34e-09$
	(4.08e-09)		(4.16e-09)
Yield	-0.0000105	Yield	-0.0000104
	(.0000106)		(0.0000104)
No. MenHired	0.0115	No. MenHired	0.0117
	(0.0117)		(0.0116)
Asset	-0.026	Asset	-0.027
	(0.051)		(0.051)
Women Hired	0.026^{*}	Women Hired	-0.026^{**}
	(0.014)		(0.014)
Women-Pay	1.55e-08	Women-Pay	1.47e-08
	(1.23e-08)		(1.23e-08)
TV	0.213^{***}	TV	0.204^{***}
	(0.051)		(0.051)
Phone	0.249^{***}	Phone	0.250^{***}
	(0.080)		(0.079)
Computer	-0.059	Computer	-0.078
	(0.067)		(0.067)
Dist-Road	0.009^{***}	Dist-Road	0.009^{***}
	(0.003)		(0.003)
Dist-Popcenter	-0.002	Dist-Popcenter	-0.002
	(0.002)		(0.002)
Dist-Market	0.001^{**}	Dist-Market	0.001^{***}
	(0.0005)		(0.005)
Dist-Border	0.003^{***}	Dist-Border	0.0003^{***}
	(0.0001)		(.0001)
Constant	-1.482^{***}	Constant	-1.49^{***}
	(0.105)		(0.105)
No. Observations	4611		4611

Notes: Robust Standard errors in parentheses. Significance levels are denoted as follows $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$. It is important to note that all the variables in Table 3.6 represent pre-treatment characteristics observed before the treatment period propensity scores. This process, known as nearest neighbour oversampling Smith (1997), is valuable as it balances reduced variances resulting from additional information to construct counterfactual groups for the treated. The weights used for matching are drawn from the propensity scores (probability values) of the probit regression from equation (3.3) following the works of Smith (1997). This means that weights are placed for both the treated group and control groups with similar probabilities to identify control groups (untreated units) with similar characteristics as the treated groups. However, various variants of the nearest neighbour matching exist, including matching with replacement and without replacement. In the former, an untreated household can be utilised more than once for matching, while the latter implies that an untreated household is used only once for matching. Smith and Todd (2005) demonstrate that matching with replacement can enhance the average quality of matching and reduce bias. This approach is particularly useful in datasets where the propensity score differs significantly between treated and untreated units. Using nearest neighbour matching, all 773 treated units were matched with untreated units having similar propensity scores, and no observations were excluded from the matching process.

Figure 3.1 displays the histogram of the propensity scores, revealing that the matching process generates suitable comparison groups for all treated units. In particular, the histogram illustrates that all treated units were successfully matched with untreated units possessing comparable propensity scores. The treated group is depicted in the right panel of each histogram *FC=1*, while the left panel *FC=0* represent the control group.

Figure 3.1: Histogram of Propensity Scores

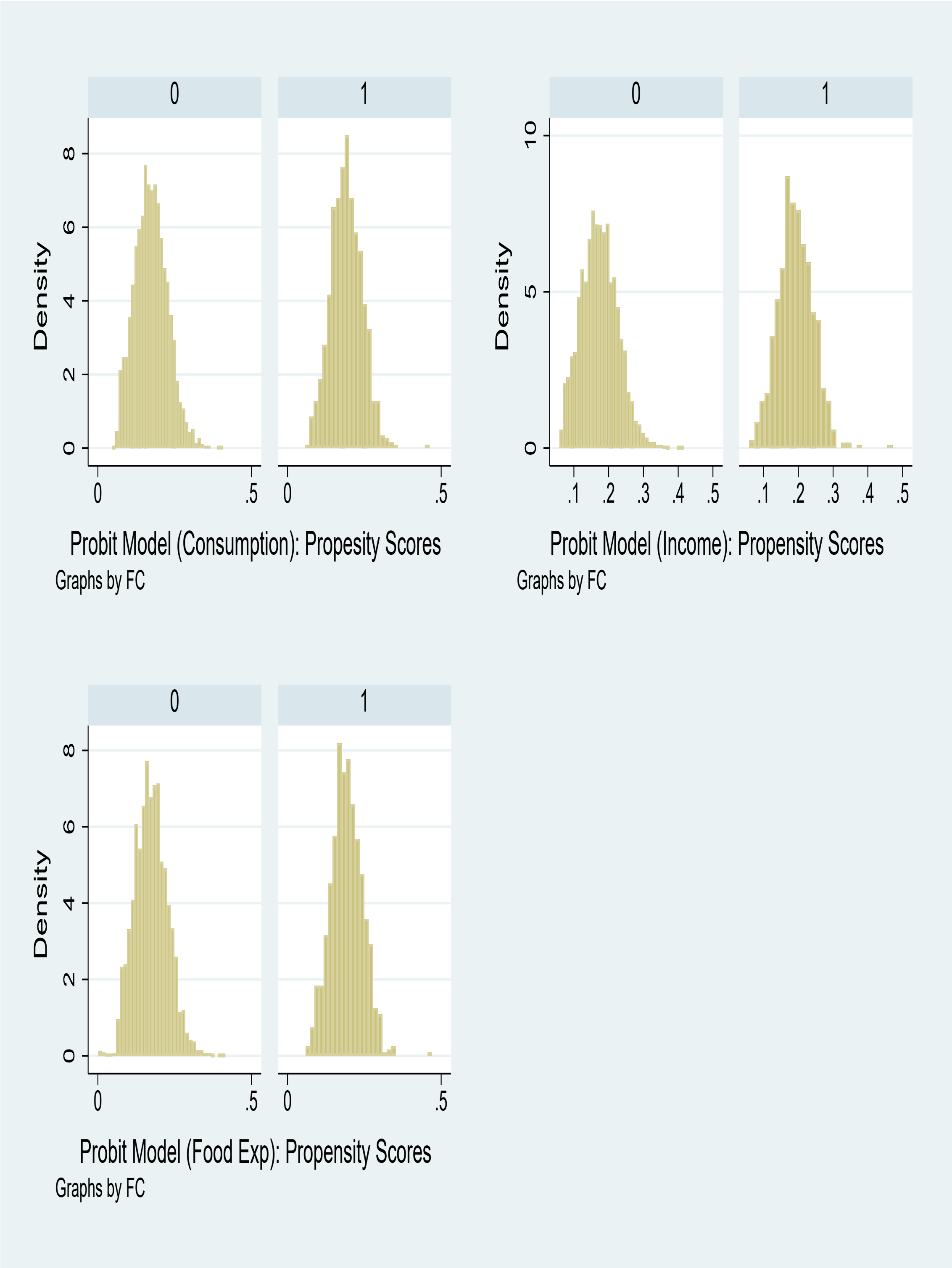
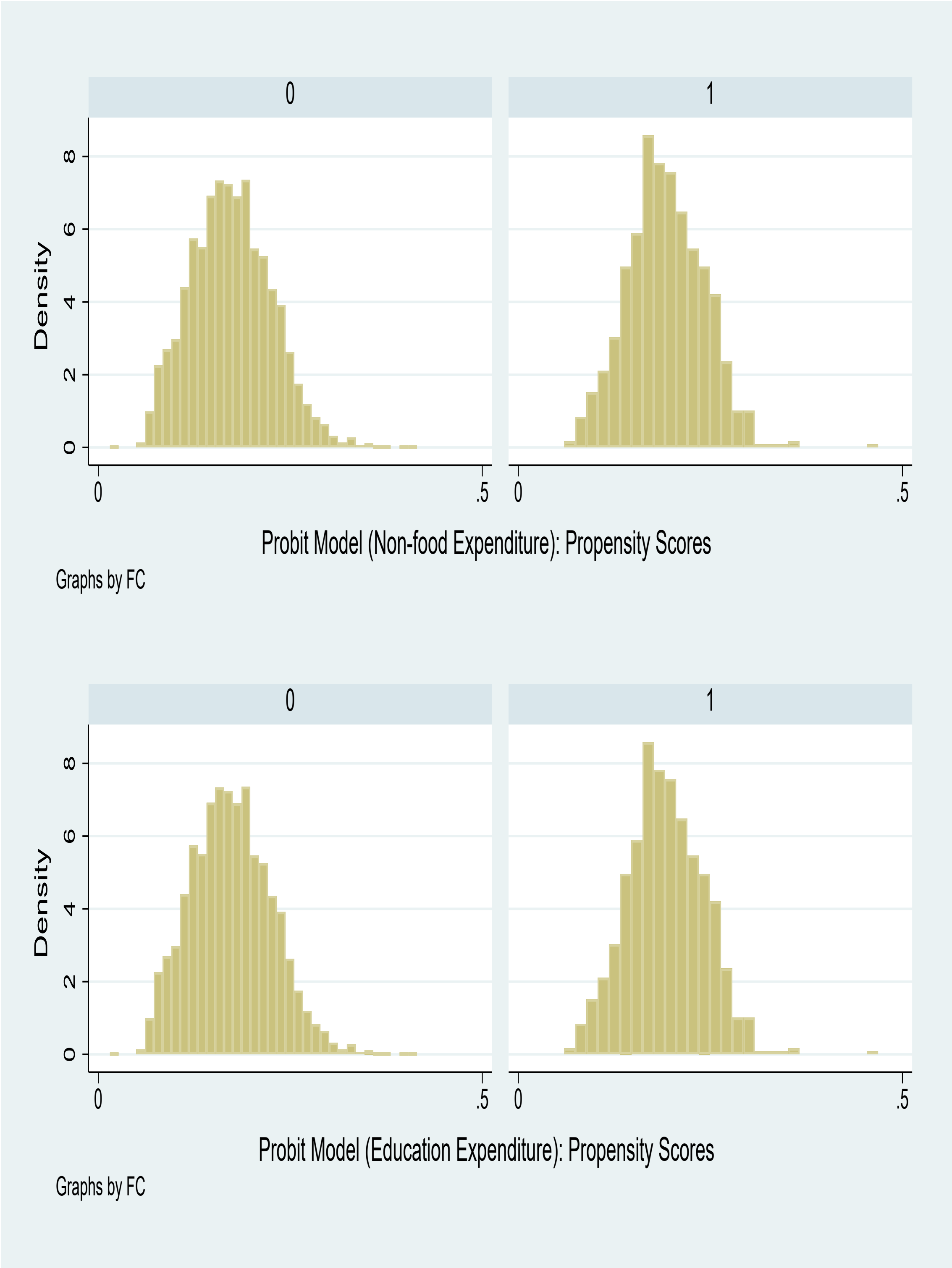


Figure 3.1 Continued. Histogram of Propensity Scores



I also utilise the inverse probability weighting, as discussed in section 4.3, to match treated and untreated units with similar propensity scores. Imbens (2004) suggests that the propensity score can serve as weights to achieve a balanced sample of treated and untreated units. Additionally, studies by Zhao (2004),Willianson and Forbes (2013), Hirano and Imbens (2001), Hirano et al. (2003), Guo and Fraser (2014) demonstrate that Propensity Score Matching can be integrated with other regression models using inverse probability weights derived from known propensity scores obtained through matching. Therefore, I apply the inverse probability weight to combine Propensity Score Matching with a Difference-In-Difference model, estimating the average treatment effect on the treated through this combined approach.

3.4.2 Testing the reliability of the matched samples

Next, to see how good the matching is, I use a battery of tests, commonly used in the evaluation literature, to examine the quality of the matching (e.g., Guo and Fraser 2014, Smith and Todd 2005, Girma and Gorg 2007, Rubin 2008, Arnold and Javorcik 2005). I plot a bias graph for both the matched (M) and unmatched (UnM) samples. Figure 3.2 show that the matching does a great job as on average, bias is greatly reduced in the matched sample. Hence the result from the Propensity Score Matching can be said to be reliable to reduce endogeneity that may arise from selection bias as compared to the UnM sample which is conversant in the literature.

Similarly, I plot the overlap graph to determine how good the matching is as shown in Figure 3.3. Remember that the overlap condition necessitates finding matched pairs for treated (*FC=1*) and untreated (*FC=0*) households across the distribution of covariates. This also implies that the probability of receiving the financial credit treatment must be constrained within the range of zero to one, as outlined in section 4.3. Figure 3.3 shows that the matching used produced a very good overlap confirming that histogram of the Propensity Score Matching.

Figure 3.2: Reduction in Bias after Matching

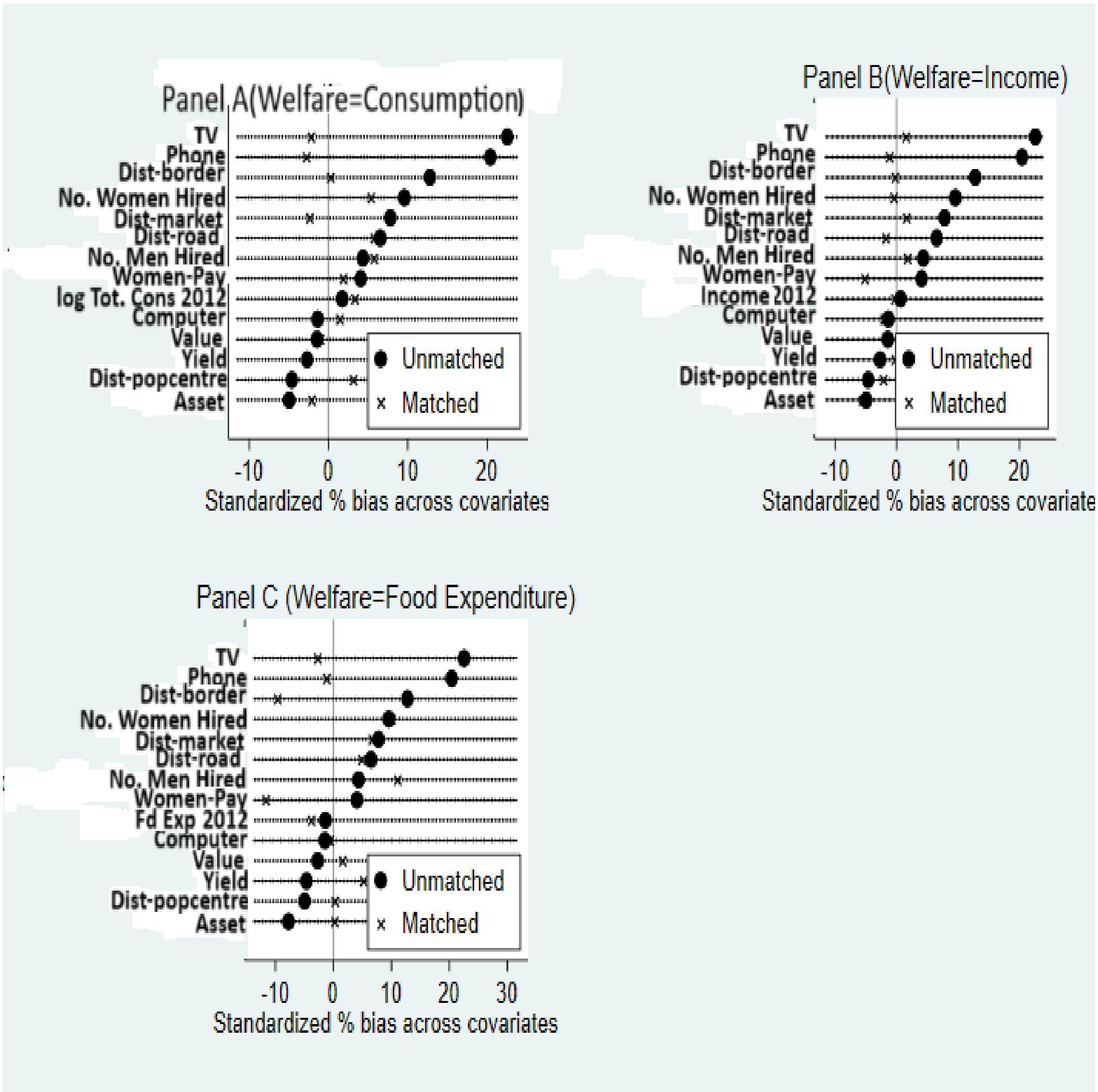


Figure 3.2 Continued Reduction in Bias after Matching

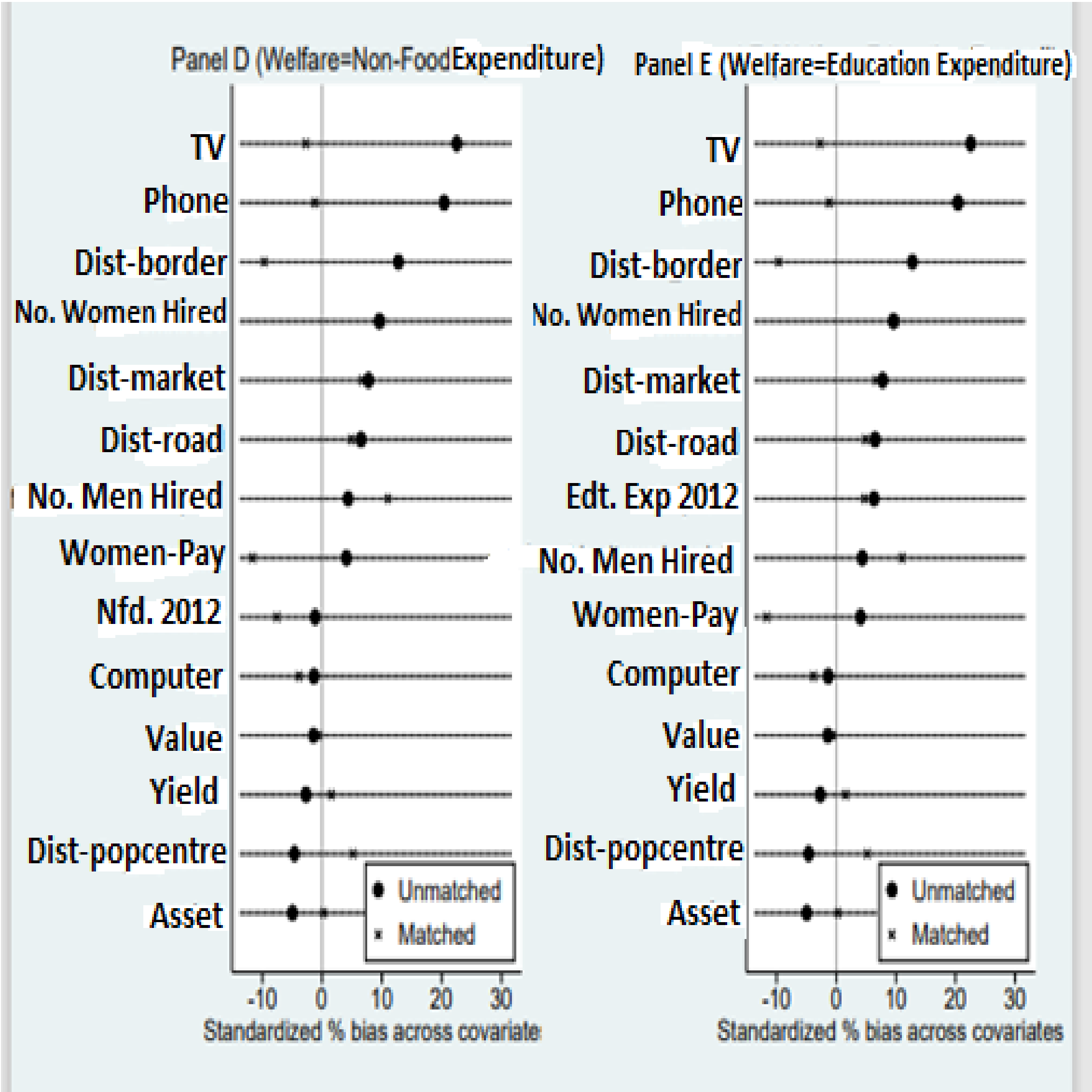


Figure 3.3: Overlap Distribution for the Matched Samples

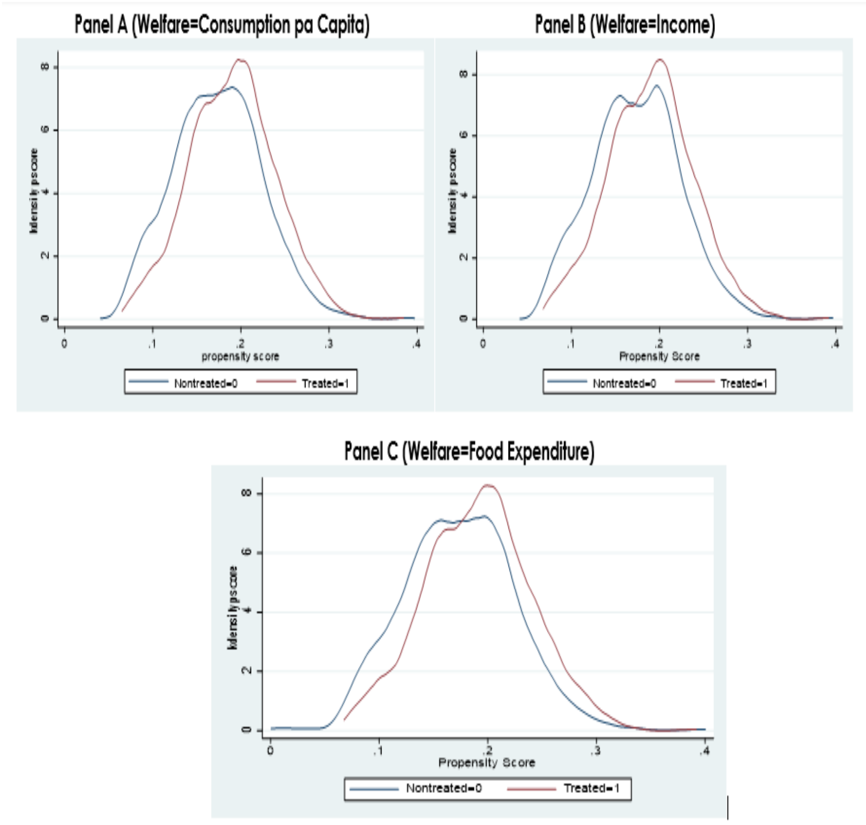
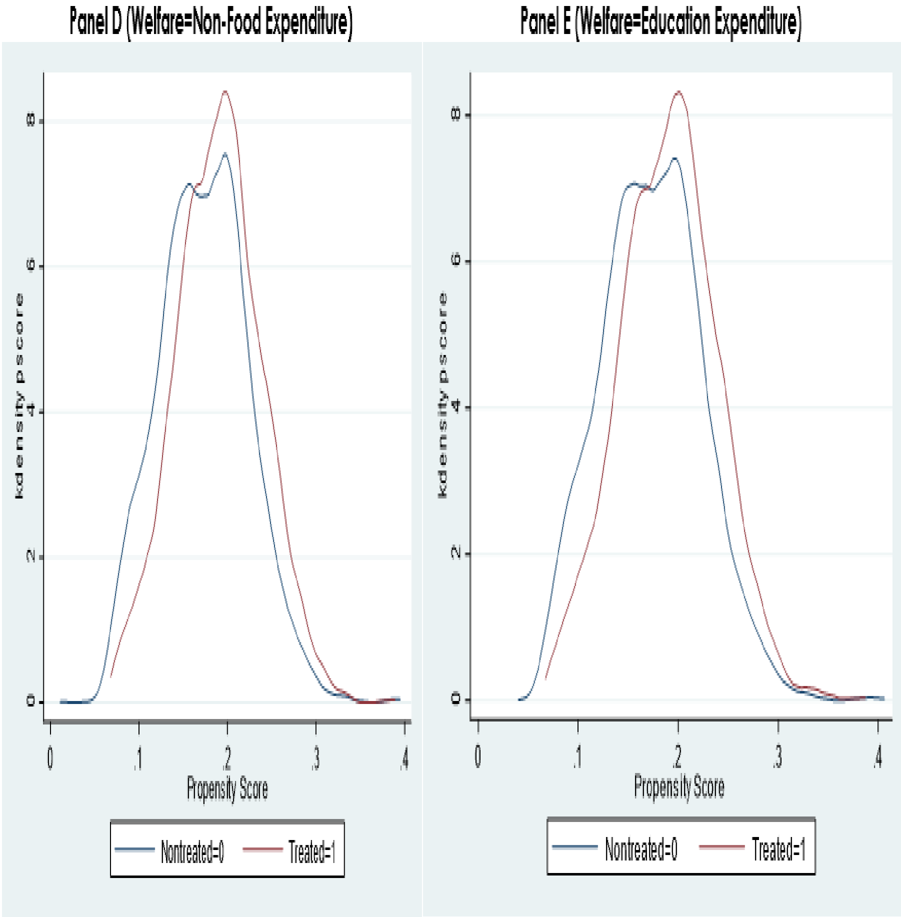


Figure 3 Continued: Overlap Distribution of the Matched Samples



Finally, following Girma and Gorg (2007), Rubin (2008), I report the balancing test results from all the matching used (nearest neighbour and Inverse propensity weighting) to show that covariates are balanced after matching

Tables 3.7-3.9 reveal the balancing property of covariates using the five nearest neighbours, NN(5) and Propensity Score Matching, affirming the covariate balance. The standardized differences in the matched households' covariates are very close, in some cases, reaching 0, while their variance ratio is close to 1, in accordance with Rubin (2008). Similarly, Tables 3.10-3.12 exhibit the balancing property of covariates using the two nearest neighbours NN(2) and Propensity Score Matching. The result just like the five partner nearest neighbour matching satisfies the balancing condition discussed in section 3.3 of this chapter of about zero mean and variance of one across all the covariates. This is corroborated by the *t-test* result (refer to Appendix E) comparing the differences between the treated and control groups in the matched samples across all covariates, as recommended by Arnold and Javorcik (2005). In this context, all differences are minimal and statistically insignificant, indicating balanced covariates across all groups. Standardized bias for each covariate is also calculated (Appendix E)) using the formulae $SB_{Before} = 100 \times \frac{(\bar{X^1} - \bar{X^0})}{\sqrt{0.5[V^1(X) + V^0(X)]}}$ and $SB_{After} = 100 \times \frac{(\bar{X}^{1,M} - \bar{X}^{0,M})}{\sqrt{0.5[(\bar{V}^{1,M} + \bar{V}^{0,M})]}}$ where $\bar{X^1}(V^1)$ is the mean(variance) in the treatment group before matching and $\bar{X^0}(V^0)$ is the analog for the counterfactual group, $\bar{X}^{1,M}(\bar{V}^{1,M})$ and $\bar{X}^{0,M}(\bar{V}^{0,M})$ are the corresponding values for the matched samples, used to estimate the resulting change in before-and-after biases (see Girma and Gorg 2007, Rubin 2008, Sianesi 2004, Caliendo and Kopeinig 2008). The standardized bias for nearly all matched variables is below 5 percent, while column 6 illustrates the percentage fall in bias.

Moreover, I examine the balancing conditions using the inverse probability weight. For all models presented in Table 3.6, I perform over-identification tests for covariate balance in the matching using the inverse probability weight, as suggested by Guo and Fraser (2014). The null hypothesis that the covariates are balanced is not rejected (the $p - values$ are 0.341, 0.452, 0.261, 0.384 and 0.184). Tables 3.13-3.14 display the balancing property of the covariates from the inverse probability weight. Clearly, the standardized differences of the matched households are also very close, with some cases being 0, while their variance ratio is close to 1, similar to what is observed in the case of the five-partner nearest neighbour, NN(5), matching.

Table 3.7: Testing for Balancing of the Covariates Used, NN(5)

Tot Cons					Income				
	Standardized difference		Variance ratio			Standardized difference		Variance ratio	
Variables	Raw	Matched	Raw	Matched		Raw	Matched	Raw	Matched
log Tot. Cons (2012)	0.017	-0.011	0.790	0.880	Income (2012)	0.009	-0.002	1.544	1.832
Value	-0.002	-0.020	0.667	0.773	Value	-0.002	0.001	0.667	0.737
Yield	-0.031	-0.008	0.559	0.727	Yield	-0.031	0.005	0.558	0.726
No Men Hired	0.046	0.061	1.097	1.158	No Men Hired	0.046	0.043	1.098	1.063
Asset	-0.046	0.041	1.041	0.969	Asset	-0.046	0.021	1.041	0.984
No. Women Hired	0.096	0.055	1.275	1.130	No. Women Hired	0.096	0.059	1.275	1.200
Women-Pay	0.053408	-0.028	1.277	0.809	Women-Pay	0.054	-0.013	1.279	0.886
TV	0.225	-0.021	0.959	1.009	TV	0.225	-0.007	0.959	1.003
Phone	0.196	0.018	0.595	0.944	Phone	0.196	-0.026	0.595	1.091
Computer	-0.028	0.007	0.944	1.016	Computer	-0.028	0.004	0.944	1.008
Dist-Road	0.069	0.016	1.191	0.953	Dist-Road	0.0686378	0.001	1.192	0.950
Dist-Popcenter	-0.044	0.041	0.872	0.949	Dist-Popcenter	-0.044	-0.000	0.872	0.898
Dist-Market	0.083	-0.004	1.011	0.941	Dist-Market	0.083	0.020	1.010	0.974
Dist-Border	0.129	-0.029	0.813	0.842	Dist-Border	0.129	-0.025	0.813	0.853

Table 3.8: Testing for Balancing of the Covariates Used, NN(5)

Fd Exp					Nfd Exp				
	Standardized difference		Variance ratio			Standardized difference		Variance ratio	
Variables	Raw	Matched	Raw	Matched		Raw	Matched	Raw	Matched
Fd Exp (2012)	-0.076	0.024	0.118	1.321	Nfd Exp (2012)	-0.008	-0.009	0.272	0.620
Value	-0.002	-0.011	0.667	0.797	Value	-0.002	-0.009	0.667	0.791
Yield	-0.031	0.000	0.559	0.996	Yield	-0.031	0.007	0.559	0.935
No. MenHired	0.046	0.018	1.098	0.988	No. MenHired	0.046	0.051	1.098	1.128
Asset	-0.046	-9.019	1.041	1.016	Asset	-0.046	0.011	1.041	0.992
No. Women Hired	0.096	0.036	1.275	1.094	No. Women Hired	0.096	0.054	1.275	1.139
Women-Pay	0.053	-0.015	1.277	0.871	Women-Pay	0.053	-0.009	1.277	0.887
TV	0.225	-0.020	0.959	1.01	TV	0.225	-0.009	0.959	1.004
Phone	0.196	0.001	0.595	0.997	Phone	0.196	-0.009	0.595	1.029
Computer	-0.028	-0.003	0.944	0.994	Computer	-0.0281	-0.002	0.944	0.997
Dist-Road	0.068	0.030	1.192	1.013	Dist-Road	0.069	0.008	1.192	1.019
Dist-Popcenter	-0.044	0.025	0.872	0.928	Dist-Popcenter	-0.044	0.034	0.872	0.960
Dist-market	0.083	0.039	1.011	0.993	Dist-market	0.083	0.021	1.011	0.983
Dist-Border	0.129	-0.046	0.813	0.866	Dist-Border	0.129	-0.038	0.813	0.840

Table 3.9: Testing for Balancing of the Covariates Used, NN(5).

Education	Standardized difference		Variance ratio	
Variables	Raw	Matched	Raw	Matched
Edt Exp (2012)	0.059	0.034	1.130	1.207
Value	-0.002	-0.021	0.667	0.657
Yield	-0.031	-0.020	0.559	0.799
No. Men Hired	0.046	0.064	1.098	1.241
Asset	-0.046	-0.038	1.041	1.033
No. Women Hired	0.096	0.056	1.275	1.156
Women-Pay	0.053	0.012	1.277	1.006
TV	0.225	-0.021	0.959	1.009
Phone	0.196	-0.004	0.595	1.013
Computer	-0.028	0.042	0.944	1.097
Dist-Road	0.069	-0.010	1.192	0.974
Dist-Popcenter	-0.044	0.003	0.872	0.898
Dist-Market	0.083	-0.009	1.011	0.978
Dist-Border	0.129	-0.032	0.813	0.863

Table 3.10: Testing for Balancing of the Covariates Used, NN(2)

Tot. Cons						Income				
	Standardized difference			Variance ratio			Standardized difference		Variance ratio	
Variables	Raw	Matched		Raw	Matched		Raw	Matched	Raw	Matched
Tot Cons. 2012	-0.076	0.008		0.119	1.405	Income (2012)	0.010	0.014	1.544	3.725
Value	-0.002	-0.027		0.667	0.785	Value	-0.002	0.008	0.667	0.698
Yield	-0.031	-0.031		0.559	0.686	Yield	-0.031	0.041	0.559	0.960
No. Men Hired	0.046	0.016		1.098	0.975	No. Men Hired	0.046	0.081	1.0978	1.23
Asset	-0.046	0.028		1.041	0.979	Asset	-0.045	0.044	1.041	0.967
No. Women Hired	0.096	0.050		1.275	1.133	No. Women Hired	0.096	0.043	1.275	1.013
Women-Pay	0.053	-0.015		1.277	0.849	Women-Pay	0.053	0.002	1.277	1.025
TV	0.225	-0.026		0.959	1.011	TV	0.225	-0.003	0.959	1.001
Phone	0.196	-0.010		0.595	1.032	Phone	0.196	-0.012	0.595	1.041
Computer	-0.028	0.003		0.944	1.00	Computer	-0.028	0.021	0.944	1.047
Dist-Road	0.069	0.035		1.192	1.001	Dist-Road	0.069	-0.012	1.191	0.940
Dist-Popcenter	-0.044	-0.004		0.872	0.892	Dist-Popcenter	-0.044	-0.012	0.872	0.881
Dist-Market	0.083	0.022		1.011	1.002	Dist-Market	0.083	0.009	1.011	0.937
Dist-Border	0.129	-0.055	0.813	0.857	Dist-Border	0.129	-0.018	0.813	0.872	0.978

Table 3.11: Testing for Balancing of the Covariates Used, NN(2)

Fd Exp					Nfd Exp				
	Standardized difference		Variance ratio			Standardized difference		Variance ratio	
Variables	Raw	Matched	Raw	Matched		Raw	Matched	Raw	Matched
Fd Exp (2012)	-0.077	0.028	0.113	1.56	Nfd Exp (2012)	-0.012	0.033	0.260	0.950
Value	-0.014	0.033	0.638	0.91	Value	-0.014	-0.042	0.638	0.616
Yield	-0.027	0.025	0.536	1.14	Yield	-0.027	-0.018	0.536	0.967
No. Men Hired	0.043	0.051	1.01	0.845	No. Men Hired	0.043	0.046	1.076	0.984
Asset	-0.050	-0.003	1.044	1.00	Asset	-0.050	-0.001	1.044	1.00
No. Women Hired	-0.045	-0.001	0.965	0.894	No. Women Hired	0.0955	-0.075	0.965	1.032
Women-Pay	0.096	0.063	1.213	1.103	Women-Pay	0.041	-0.026	1.213	0.829
TV	0.225	-0.041	0.960	1.019	TV	0.225	-0.030	0.960	1.01
Phone	0.204	-0.0139	0.582	0.956	Phone	0.204	-0.007	0.582	1.023
Computer	-0.014	0.025	0.973	1.05	Computer	-0.014	0.026	0.973	1.06
Dist-Road	0.065	0.047	1.194	1.05	Dist-Road	0.065	0.045	1.194	1.09
Dist-Popcenter	-0.046	0.036	0.964	0.961	Dist-Popcenter	-0.046	0.034	0.891	0.981
Dist-Market	0.078	0.027	0.997	0.971	Dist-Market	0.078	-0.039	0.997	0.916
Dist-Border	0.128	-0.022	0.802	0.889	Dist-Border	0.128	-0.026	0.802	0.859

Table 3.12: Testing for Balancing of the Covariates Used, NN(2)

Education	Standardized difference		Variance ratio	
Variables	Raw	Matched	Raw	Matched
Edt Exp (2012)	0.063	0.012	1.149	0.925
Value	-0.014	-0.013	0.638	0.761
Yield	-0.027	0.017	0.536	1.63
No. Men Hired	0.043	0.025	1.076	1.111
Asset	-0.050	0.046	1.044	0.966
No. Women Hired	0.0956	0.069	1.239	1.13
Women-Pay	0.041	0.061	1.213	1.23
TV	0.225	-0.0251	0.960	1.011
Phone	0.204	-0.002	0.582	1.000
Computer	-0.014	-0.001	0.973	0.966
Dist-Road	0.065	-0.009	1.194	0.999
Dist-Popcenter	-0.046	0.005	0.891	0.903
Dist-Market	0.078	0.026	0.997	0.983
Dist-Border	0.128	-0.039	0.802	0.841

Table 3.13: Testing for Balancing of the Covariates Used, (IPW)

Tot Cons					Income				
	Standardized difference		Variance ratio			Standardized difference		Variance ratio	
Variables	Raw	Matched	Raw	Matched		Raw	Matched	Raw	Matched
Log Tot. Cons (2012)	0.017	0.004	0.787	0.839	Income (2012)	0.006	-0.007	1.462	1.385
Value	-0.014	-0.002	0.638	0.769	Value	-0.014	-0.002	0.638	0.773
Yield	-0.027	0.000	0.536	0.849	Yield	-0.027	-0.001	0.536	0.857
No. Men Hired	0.043	-0.013	1.076	0.747	No. Men Hired	0.043	-0.014	1.076	0.742
Asset	-0.050	-0.005	1.044	1.004	Asset	-0.050	-0.005	1.044	1.005
No. Women Hired	0.0956	-0.028	1.238	0.549	No. Women Hired	0.0956	0.028	1.236	0.540
Women-Pay	0.041	-0.002	1.213	0.922	Women-Pay	0.041	-0.002	1.213	0.921
TV	0.225	0.000	0.960	0.999	TV	0.225	0.001	0.960	0.999
Phone	0.204	0.001	0.582	1.000	Phone	0.204	0.002	0.582	0.993
Computer	-0.014	0.001	0.973	1.000	Computer	-0.014	0.001	0.973	1.000
Dist-Road	0.065	0.003	1.194	0.969	Dist-Road	0.065	0.003	1.194	0.970
Dist-Popcenter	-0.046	0.0009	0.891	0.914	Dist-Popcenter	-0.046	0.001	0.891	0.911
Dist-Market	0.078	-0.004	0.997	0.951	Dist-Market	0.078	0.005	0.997	0.951
Dist-Border	0.128	-0.014	0.802	0.841	Dist-Border	0.128	-0.015	0.802	0.842

Table 3.14: Testing for Balancing of the Covariates Used, (IPW)

Fd Exp					Nfd Exp				
	Standardized difference		Variance ratio			Standardized difference		Variance ratio	
Variables	Raw	Matched	Raw	Matched		Raw	Matched	Raw	Matched
Fd Exp (2012)	-0.077	0.038	0.113	0.920	Nfd Exp (2012)	-0.012	0.005	0.260	0.646
Value	-0.014	-0.0030	0.638	0.768	Value	-0.014	-0.002	0.638	0.773
Yield	-0.027	-0.0001	0.536	0.831	Yield	-0.027	-0.001	0.536	0.856
No. MenHired	0.043	0.013	1.076	0.742	No. MenHired	0.043	-0.014	1.076	0.745
Asset	-0.050	-0.006	1.044	1.00	Asset	-0.050	-0.006	1.044	1.00
No. Women Hired	0.0955	0.028	1.238	0.550	No. Women Hired	0.040	-0.028	1.21	0.546
Women-Pay	0.041	-0.003	1.213	0.922	Women-Pay	0.041	-0.002	1.213	0.925
TV	0.225	0.001	0.960	1.00	TV	0.225	0.000	0.960	0.999
Phone	0.204	0.002	0.582	0.992	Phone	0.204	0.002	0.582	0.993
Computer	-0.014	0.001	0.973	1.00	Computer	-0.014	0.001	0.973	1
Dist-Road	0.065	0.003	1.194	0.965	Dist-Road	0.065	0.003	1.194	0.966
Dist-Popcenter	-0.046	0.000	0.891	0.914	Dist-Popcenter	-0.046	0.000	0.891	0.911
Dist-market	0.078	-0.005	0.997	0.949	Dist-market	0.078	-0.005	0.997	0.951
Dist-Border	0.128	0.014	0.802	0.842	Dist-Border	0.128	-0.015	0.802	0.9132

3.5 Empirical Results

The average treatment effect from equation 4.6 (the ATT from the Propensity Score Matching model) is reported in Table 3.15 using the two matching estimators (nearest neighbour and inverse probability weighting). The ATT been interpreted using (($\exp^B$-1)*100) show that on average, receiving financial credit has a positive but insignificant effect on welfare across all the welfare indicators used in the study. However, for reflection of the size and the signs on the coefficients of the welfare variables, I still report the results although insignificant.

For consumption per capita as a measure of welfare , the ATT in Table 3.15 from the 2 partner nearest neighbour matching is 1.31% (($\exp^{0.013}$-1)*100=1.308). Similarly, the ATT in Table 3.15 from the 5 partner nearest neighbour matching is 3.56% (($\exp^{0.035}$-1)*100=3.562) while that of the inverse probability weighting is 3.98% (($\exp^{0.039}$-1)*100=3.98). Using Income as a welfare measure, the ATT from the 5 partner nearest neighbour matching is 3.67% (($\exp^{0.036}$-1)*100=3.67) while that of the 2 partner nearest neighbour is 3.87% (($\exp^{0.038}$-1)*100=3.87). The ATT from the inverse probability weighting gives 2.94%.

Furthermore, when food expenditure is considered as a welfare indicator, the ATT from the 5 partner nearest neighbour matching is 1.41% while the 2 partner nearest neighbour matching is 1.82%. Similarly, the ATT of the inverse probability weighting is 3.67%. Moreso, I move on to the next welfare proxy which is non-food expenditure. The results are also reported in their natural form due to convergence issues from the Log forms.

For non-food expenditure, interestingly, the ATT from both the 2 partner and 5 partner nearest neighbour matching and the inverse probability weighting turns negative, however, with no statistical significant effect. The ATT from the 5 and 2 partner nearest neighbour matching are 449 and 349.65 Nairas in negative respectively ($1.1 and $0.85) while the ATT from the IPW matching in negative is about 420 Naira ($1.02) [11]. Finally, I use education expenditure as the last measure of welfare as some households are more educationally inclined than others. The ATT reported Table 3.15 from the 5 partner near-

[11] The official exchange rate of Naira to Dollar at the time of this estimation is 410 Naira=1 Dollar

Table 3.15: The ATT Estimates from the Matched Samples

	NN		IPW
	$\hat{ATT}_M$		$\hat{ATT}_M$
Outcome	NN(5)	NN(2)	
First Welfare Indicator			
Log Tot. Cons (2016)	0.035	0.013	0.039
	(0.029)	(0.033)	(0.024)
Second Welfare Indicator			
Log Income (2016)	0.036	0.038	0.029
	(0.043)	(0.048)	(0.04)
Third Welfare Indicator			
Log Fd Exp (2016)	0.014	0.018	0.036
	(0.030)	(0.034)	(0.027)
Fourth Welfare Indicator			
Nfd Exp (2016)	-449.883	-349.6503	-420.2245
	(341.544)	(252.839)	(291.185)
Fifth Welfare Indicator			
Edt Exp (2016)	1122.665		
	(912.804)		
No. Observation	4611	4611	4611

- **Notes:** Standard errors are reported in brackets.
- Variables were not logged where either convergence was not attainable in Logs or specific partner matches could not be found using logs.

est neighbour matching is about 1122.665 Naira ($2.738) while the matches for the 2 and inverse probability weighting were not found.

The results reported from Table 3.15 show that the average treatment effect on the treated of receiving financial credit on welfare levels show no statistical significance across all levels of welfare. These results are robust across the various specifications of models and matching estimators used. Thus, I conclude that controlling for selection bias alone, on the average, financial credit show no convincing/statistically significant effects on various welfare indicators of households in Nigeria. Thus, the welfare levels of those who received financial credit is not statistically different from those who do not.

I also calculate the difference between the welfare levels of households (both treated and counterfactual) before and after the financial credit intervention. I then estimate the average treatment effect on the treated, as defined in equation 3.7, using the nearest neighbour and inverse probability weighting matching estimators, respectively. This approach creates a matched Difference-In-Difference estimator following Blundell and Costa Dias (2000, 2002) and addresses unobservable factors that could influence the outcome welfare level.

The results like Table 3.15 are still positive in sign for most of the welfare indicators; however, the results still show no statistical significance even after controlling for unobservable. While I make no claims for insignificant results, for reflection of the size and the signs on the coefficients of the welfare variable, I have reported the results. For consumption per capita as a measure of welfare, the ATT in Table 3.16 from the 5 partner nearest neighbour matching is 4.39% . Similarly, the ATT in Table 3.16 from the 2 partner nearest neighbour matching and the inverse probability weighting are both 3.67% . Using Income as a welfare measure, the ATT from the 5 and 2 partner nearest neighbour matching are 6809.134 Naira ($16.61) and 4711.55 Naira ($11.49) respectively. Moreso only the 2 and the IPW partner matches were found for food expenditure with the ATT of 0.2% and 2% (using Logs) for both welfare indicators respectively.

Furthermore, when non-food expenditure is considered as a welfare indicator, the ATT from the 5 partner nearest neighbour matching is negative 421.16 Naira ($1.03) while the

2 partner nearest neighbour matching is negative 302.766 Naira ($0.74) and 431.72 Naira ($1.05). For education as a welfare measure, the ATT for both the 5 and 2 partner matches are 393.27 and 5.084 Naira ($0.96 and $0.012) respectively which still show no statistical significance. As earlier stated, all the treatment effects are not statistically significant even after differencing to control for both selection bias and some form of unobserved heterogeneity (in the outcome variable).

Table 3.16: The ATT Estimates from the Matched Samples

	NN		IPW
	$\hat{ATT}_M^{DID}$		$\hat{ATT}_M^{DID}$
Outcome	NN(5)	NN(2)	
First Welfare Indicator			
△Log Tot Cons (2016)	0.043	0.036	0.036
	(0.029)	(0.031)	(0.024)
Second Welfare Indicator			
△Income (2016)	6809.134	4711.546	
	(10248.31)	(10652.45)	
Third Welfare Indicator			
△Log Fd Exp (2016)		0.002	0.0199
		(0.033)	(0.026)
Fourth Welfare Indicator			
△Nfd Exp (2016)	-421.163	-302.766	-431.718
	(354.151)	(271.435)	(290.450)
Fifth Welfare Indicator			
△Edt Exp (2016)	393.279	5.084	
	(803.663)	(818.848)	
No. Observation	4611	4611	4611

- **Notes:** Standard errors are reported in brackets.
- Variables were not logged where either convergence was not attainable in Logs or specific partner matches could not be found using logs.
- △ is the difference in the welfare level before and after the treatment.

Utilising the available panel data, I merge the matched sample employing inverse propensity weights with a standard Difference-In-Difference model, incorporating additional exogenous variables. This approach aims to validate the findings of the Propensity Score Matching detailed earlier. The results are summarised in Table 3.17 and Table 3.18.

The ATT results of the combined matching and difference in difference model (coefficient of after*FC) confirms the ATT of the Propensity Score Matching at all the levels of welfare used as the results still show no statistically significant effect except for consumption per capita in the short-run. The PSM+DID models below controls for selection bias by including all the variables in Table 3.6 and also controls for unobserved time invariant heterogeneity through differencing (that is time fixed effects through differencing). However, I also include household/group fixed effects to control for various feedback effects among households that may affect the welfare levels of households. This is important because sharing of individual household information/ideas, loan status, individual risks, etc among households may also affect the use of credit obtained and in turn welfare as these are also unobserved factors. Thus, the inclusion of the household/group fixed effects circumvents this problem.

Table 3.17: The ATT Estimates from the Combined Models

	Log Tot Cons		Income		Income
	PSM+DID 2012-2016	PSM+DID 2012-2016	PSM+DID 2012-2016	PSM+DID 2012-2016	PSM+DID 2012-2018
after	0.237***	0.199***	19611.117***	19657.372***	8889.25**
	(0.016)	(0.019)	(4512.187)	(5474.634)	(3377.148)
FC	−1.337***	−1.738***	13999.192	14847.932	11084.336
	(0.541)	(0.547)	(146934.22)	(148911.86)	(103708)
after*FC	0.061***	0.05**	3501.616	4914.44	3623.495
	(0.022)	(0.023)	(6455.105)	(6448.054)	(4831.325)
Dist-Capital		−0.002*		−794.469***	
		(0.001)		(301.859)	
Rainfall		0.001***		67.232	
		(0.0004)		(114.836)	
Wetness of Land		−0.004***		-157.406	
		(0.001)		(242.939)	
Healthshock		−0.001		8785.92	
		(0.023)		(6683.918)	
Latitude		0.021		1772.037	
		(0.042)		(11939.72)	
Longitude		0.048*		3483.109	
		(0.026)		(7557.748)	
Constant	12.433***	13.013***	64444.44	47475.403	83573.816
	(0.483)	(0.703)	(134407)	(196191.27)	(97679)
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
HH Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	0.766	0.771	0.511	0.527	0.342
No. Observation	9222	9149	9222	9149	13833

- **Notes:** Standard errors are reported in brackets and Superscripts *, **, *** indicates significance levels at 10% and 5% and 1% respectively. The PSM+DID models above control for selection bias by including all the variables in Table 3.6 during matching. This is done through the inverse propensity weight.
- Variables were not logged where either convergence was not attainable in Logs or specific partner matches could not be found using logs.

For the first welfare indicator which is consumption per capita, the ATT of financial credit on the logs of consumption per capita 6.29% ((exp$^{0.061}$-1)*100=6.29)) from column

2 of Table 3.17 [12]. However, this result is statistically significant at 5% at the short-run and after controlling for group fixed effects (exclusion of the group fixed effects makes the ATT statistically insignificant). I also control for other variables that may affect welfare levels of agricultural households like rainfall, land demographics like latitude, longitude and wetness of land, distance from household to capital and health dummy. The ATT remains statistically significant that is financial credit increases consumption per capita by 5.13% on average. The welfare level of poorer household who are more distant from capital cities reduces by 0.2% as expected while rainfall increases the welfare level of households by 0.1% in reverse to land wetness which affects welfare negatively by 0.4%. Other controls like health dummy and latitude of households show no statistical significance while longitude improves consumption by nearly 5%.

Furthermore the ATTs for income as a welfare indicator are 3501.616 Naira (without other controls) and 4914.44 Naira (with other controls) at 2016, and 3623.5 Naira at 2018 respectively. These treatment effects are without any statistical significance. However, been distant from capital reduces income levels by 794.469 Naira ($1.93) while other controls show no statistical significance. For food expenditure Table 3.18 although the sign of the ATT is positive (12830.66 and 11484.53 Naira), I find no statistical significance of the effects of financial credit on welfare.

Interestingly, for Non-food expenditure as a measure of welfare, the sign of the ATT is negative and although statistically insignificant. Also, the effect of been unhealthy increases non-food expenditure significantly by 1330.722 Naira ($3.24).

Finally, when education is considered as a welfare indicator, the ATT from Table 3.18 is about 339.8 and 764 Naira ($0.82 and $1.86 respectively) still show no significance for the models with and without other controls. For this measure however, rainfall is seen to reduce education expenditure slightly by 22.61 Naira ($0.056) while latitude of area also reduces education expenditure by 5605.641 ($13.67). This may be because only few households from such areas can afford education fees.

From the results presented in Table 3.17 and Table 3.18, combining the Propensity Score Matching and a standard Difference-In-Difference model to control for endogeneity

[12] The weight used for the difference in difference model corrects for large standard errors.

steming from selection bias and unobserved heterogeneity, only the ATT from consumption per capita shows significant effects in a lower-middle income country like Nigeria and this effect is in the short-run. I however, find no convincing evidence that receiving financial credit improves welfare for other welfare indicators used in the study.

Table 3.18: The ATT Estimates from the Combined Models

	Fd Exp		Nfd Exp		Nfd Exp	Edu-Exp	Edu-Exp
	PSM+DID		PSM+DID		PSM+DID		
	2012-2016	2012-2016	2012-2016	2012-2016	2012-2018	2012-2016	2012-2016
after	24007.543***	767.538***	897.707***	11280.795***	11813.006***	78.599	58.044
	(7266.115)	(9057.861)	(183.942)	(217.566)	(624.445)	(507.607)	(578.082)
FC	−204666.42	−191013.35	-5380.386	−5069.772	113330.74***	-3487	7005.729
	(245083.7)	(247199)	(5974.003)	(6210.69)	(19125.294)	(17109)	(16612)
after*FC	12830.66	11484.526	-300.24	-270.408	-29.572	339.836	764.305
	(10397.183)	(10583.427)	(263.176)	(267.735)	(939.428)	(726)	(710.771)
Dist-Capital		−224.177		−1.125			2.007
		(494.306)		(12.537)			(33.256)
Rainfall		389.565**		6.326			−22.608*
		(187.764)		(4.735)			(12.597)
Wetness of Land		−1251.059***		-16.203			24.327
		(400.583)		(10.102)			(26.867)
Healthshock		1452.644		1330.722***			-582.453
		(10944.259)		(293.004)			(778.07)
Latitude		−5323.523		561.079			−5605.641***
		(19589.708)		(494.966)			(1318)
Longitude		13669.841		425.592			-409.469
		(12426.776)		(314.52)			(836)
Constant	265077.78	558068.97*	5081.603	1062.329	5081.603	4502.367	60146***
	(221963.08)	(323348)	(263.176)	(8137.976)	(5617.839)	(15548)	(21739)
HH Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.557	0.559	0.548	0.3276	0.548	0.683	0.691
No. Observation	9222	9149	9222	9149	13833	9222	9149

- **Notes:** Standard errors are reported in brackets and Superscripts *, **, *** indicates significance levels at 10%, 5% and 1% respectively.
  The PSM+DID models above control for selection bias by including all the variables in **??** during matching. This is done through the inverse propensity weight.
- Variables were not logged where either convergence was not attainable in Logs or specific partner matches could not be found using logs.

3.5.1 Robustness

Although the various matching estimators serve as robustness for the matching models, I go beyond the matching estimators to check for robustness of the results using two other estimations. First, the PSM+DID model is re-estimated for all households who received credit (773) and those whose loan are pending (41) in case they later received the loan that year which was not captured in the data. This gives a total of 814 households who applied for loan. Next, of the 773 households who have received credit, I use only 532 households who applied for and received credit through formal means (banks). The results are reported in Appendix G and Appendix H respectively

The results still remain the same as earlier reported in tables 3.17-3.18 for both cases. The only significant difference is that the income measure of welfare now becomes significant in the short-run for the PSM+DID model when only 532 households who applied for and received credit through formal means (banks) are used. However, all other results still remain the same in this chapter.

3.6 Discussion of Findings

Evidence from the study shows that the effects of financial credit on welfare using consumption per capita is positive and statistically significant in the short-run. The result suggest that for Nigeria, a positive impact on welfare from financial credit cannot be ruled out when consumption per capita is considered. However, the impact of financial credit on consumption per capita does not extend to longer periods in other measures. Studies with similar conclusions on the effects of financial credit on consumption per capita are Crepon et al. (2015), Baiyegunhi et al. (2010), Dimiova and Adebowale (2017), Karlan and Zinman (2010), Mwansakilwa et al. (2017). One possible reason for the insignificant effect of financial credit for longer periods may be that households in Nigeria are more interested in smoothing their immediate consumption needs than investing the financial credit obtained. For these households, once their immediate consumption needs are satisfied, obtaining financial credit today becomes less important on their future welfare needs. This result is only present if selection bias and unobserved heterogeneity (time fixed effects and household/group or feedback effects) are jointly controlled for as excluding household/group fixed effects produces an insignificant effect.

In contrast however, I find no significant effect of receiving financial credit on the income of households as a welfare measure similar to the RCT study of Crepon et al. (2015) for Morroco. Thus, the conclusion is consistent for both short-run and long-run periods for this chapter. This finding is not inconsistent with expectation as it suggests that while credit might seem to improve the productivity of agricultural households (Asad et al. 2015), the immediate impact of the sales of agricultural products might not be sufficient to increase the income level of households. Thus, for income as a welfare measure, financial credit alone is not sufficient to trigger significant increases in the welfare level of households. Probing further, however, shows that this insignificant impact in the short-run still remains even for a longer period of time. This study thus resolves clearly that the reason why various studies find conflicting results is not farfetched from the issues of unresolved endogeneity and inadequate panel dataset for longer periods as most studies have often relied on cross-sectional data for their analysis (see chapter 2). Secondly, the reason why other studies find a positive effect using this measure might be due to the problems of getting appropriate proxies for financial credit for lower-middle income countries. While other control variables in the study are insignificant when income is considered, been distant from capital still affects the income level of households negatively as expected as proximity to capital cities may also determine the types of jobs that households do and hence the income they earn. The insignificance of other control variables to the income measure may be explained by the volatile nature of income as a welfare measure.

For food expenditure as a measure of welfare, the effect of financial credit is insignificant. This is similar to the RCT conclusions of Banerjee et al. (2015) for India. Of course, the expectation is that as financial credit improves, welfare (using food expenditure) should increase at least in the short-run because of increase in productivity (Asad et al. 2015) and income that may result from sale of agricultural produce. However, the lack of statistical significance of the effect of financial credit using this measure might suggest that improvement in productivity as a result of financial credit is transient (not permanent) as well as other demand driven market imperfections that may result in low profitable sales of farm produce of households. Thus, it will be appropriate to consider other demand driven or supply driven market imperfections outside the scope of this study using this measure for future studies and analysis. Moreso, the effect of rainfall and wetness of land on this measure of welfare also follows expectation as rainfall still triggers improvement in welfare and wetness of land reduces welfare improvement. While it is easy to see that the reason for the positive effect of the former can be traceable to increased productivity levels of households, the later may induce issues like transportation problems or high cost of transportation due to inaccessibility of good roads to transport market produce which could translate into low sales and profitability and in-turn lead to a decline in welfare.

Furthermore, the sign of the short-term result of the effects of credit on welfare for the fourth welfare indicator (non-food expenditure) is negative but statistically insignificant. The result is expected as agricultural households here are more concerned with increasing their food expenditure instead of non-food expenditure at the immediate, thus one can see that while the food expenditure measure of welfare stays positive in sign (although insignificant), the non-food expenditure measure is negative in sign. This may not be the case however for very rich households in high-income countries who are more driven towards luxury goods. However, in the long-run, no particular expectation is norm.

The result of the study using the last welfare measure, which is education, also reaffirms the conclusions drawn from the other welfare indicators apart from consumption per capita. That is receiving financial credit shows positive signs but insignificant effects on the welfare levels of households. This is similar to the study by Banerjee et al. (2015) for India. One can relate the conclusion of the result using education as a welfare measure to certain interplay of the other welfare measures discussed. For instance, the result of the study using the education measure conforms to that of both the income measure and the non-food expenditure in some ways. The insignificant effect of financial credit on the income measure of welfare of households will mean that the effect on improving the education level of such households will also be insignificant but could be expected to have similar direction (positive) with the effect of the income level observed from the study. The same can be said when non-food expenditure is considered. In other words, the education welfare level may not be expected to improve significantly if other welfare measures do not.

3.7 Conclusion and Policy Implication

The conclusions drawn from this study are important for policy, especially for many developing countries who aim to improve welfare levels through credit policy programmes. The study provides answers to the question on whether financial credit significantly affects welfare and examines if any effects of financial credit on welfare improvement is present using various welfare indicators across various time periods.

The result of the study shows that financial credit can indeed affect welfare of households for Nigeria . However, this conclusion depends on two justifications. First, the target welfare indicator that the government would seek to improve. The findings from this study shows that although there are various welfare indicators in Nigeria, financial credit policies alone can only affect significantly consumption per capita all else been equal. However, this conclusion is not realisable for other welfare indicators. In other words, financial credit policies alone can only improve consumption per capita and no other welfare measures in Nigeria Ceteris Paribus. Thus, if the target of policy makers is to improve the welfare of households stemming from income, non-food expenditure, food expenditure and education expenditure, then financial credit policies alone will not be sufficient to trigger significant increases in these welfare indicators. The government or policy makers in this case might need to combine/interact credit policies to other policies to achieve this target. The provision of financial credit alone by governments to increase these welfare measures for Nigeria on average could be a waste of resources.

The second justification relates to the period for which policy makers target to improve welfare levels of households with financial credit policies. The findings of this study show that financial credit policies only affect consumption per capita in the short-run. However, due to current data limitations, the study does not address this issue in the long-run for consumption per capita. In contrast however, the results of the study show that whether in the short-run or long-run, financial credit policies alone do not significantly affect other welfare measures. These results are robust to various specifications as presented in the empirical results section.

Thus, if the target of policy makers in Nigeria is to improve the consumption per capita of households for a short period of time, then financial credit policies alone can suffice. However, this target is not realisable with other welfare measures both in the short-run and long-run. The results of the study show that although credit improves welfare (consumption per capita), this effect is not present for the other welfare measures and at various time periods. Hence, the need for governments to consider combining/interacting financial credit policies with other policies to improve the welfare levels of households across various welfare measures and in both short-run and long-run periods.

A potential area for expanding this study is to integrate various policy measures, such as financial credit, education, agricultural extension services focusing on enhanced farm seeds, equipment, and planting chemicals, as well as skill development for farm labour. This comprehensive approach could be explored to assess the collective impact on the welfare of households in low-income countries.

However, the result of the study necessitates questions as is there variation in the relationship between financial credit and welfare by the nature of the household?, who benefits most from financial credit for both low and for lower-middle income countries?. The answers to these questions are the major focus of later research objectives in the study.

Chapter 4 Where Should Governments Divert Finance: Who Benefits Most?

4.1 Introduction

Evidence on the impact of micro-credit has spanned from deciding whether micro-credit has positive effect on welfare (Attanasio et al. 2015, Banerjee et al. 2015, Van Rooyen et al. 2012), to whether credit has a dampening effect instead (Chen and Ravallion 2010) and if credit possess any significant effect at all on welfare (Banerjee et al. 2015, Angelucci et al. 2015). Other studies focus on different outcome measures and the impact of micro-credit on either aggregate measures or sub-aggregate measures (see chapter 2). Also, chapter 3 of this thesis focused on issues concerning endogeneity and whether micro-credit has a long-term or short-term effect on important measures. While the divide on the results exists for both developing and developed economies, an important gap yet to be answered is to whom or where should policy makers and development organisations divert finance on critical welfare measures? Should governments restrict credit to certain households and improve the proportion of credit provided to others?, and what could be the aftermath of these diversions on welfare.

The principal contribution of this chapter is to attempt to provide answers to the question regarding who should receive micro-credit in relation to the effects of micro-credit on the poor?. Put differently, this work attempts to answer the question on whom among the poor does micro-credit impact most? Micro-credit in this case is obtained from formal and semi-formal sources. I take into consideration the credit market in both low and lower-middle income countries characterised by imperfect credit market environments and then evaluate the effect of obtaining credit on various welfare levels across the distribution of household welfare levels using different welfare indicators. This is because the effect of credit on one welfare distribution might not be the same for others and thus heterogeneity within households might lead to heterogeneous effects of micro-credit on welfare. This study thus provides new arguments in the micro-finance literature to answer the question on whom/where should governments divert finance to and the implication on welfare for both low (Ethiopia and Malawi) and lower-middle income (Nigeria and Tanzania) countries.

Although arguments have also broadened in the subject area on the issues relating to gender discrimination in terms of loan accrual, (Salgado and Aires 2018) and types of projects engaged by both the male and female gender (Brana 2013) and risk aversion in terms of obtaining loans (Dawson and Henley 2015). Expanding the literature beyond discrimination, risks and quality of projects to encompass the effect of the credit obtained on various welfare measures both in the short-term and long-term is an interesting area that I propose to cover in later sections of this research. Specifically, this problem is addressed in the next chapter. In this chapter however, first, a probe into the idea of what welfare/poverty level in terms of distribution should be considered by governments and development organisations in obtaining micro-credit and the consequent effect on welfare across both gender for low and lower-middle income African countries.

The chapter employs the quantile regression econometric framework that enables one to examine the effects of obtaining credit on various distributions of welfare across several panel dataset spanning a period from 2010 to 2019 for lower-middle and low income countries in Africa. Specifically, the procedure of Canay (2011) for quantile regression is adopted as it accounts for the intersection of unobserved heterogeneity and diverse covariate effects, and the presence of panel data potentially enables the incorporation of fixed effects to account for certain unobserved covariates to address potential endogeneity issues. Results obtained were also subjected to several battery of tests using other estimators.

The results show that obtaining micro-credit possesses positive implications for households below certain welfare levels for both low and lower-middle income countries. For richer households, however, there are minimal impacts of obtaining financial credit, hence other household groups should be targeted. In detail, the results suggest that there are inequalities in welfare outcomes because of obtaining credit. I find these significant effects to be particular to households that are at the low to median quantiles of the distribution for the most part. The impact of credit exhibits significant heterogeneity, showing substantial effects in countries with lower welfare levels compared to those with similar characteristics, while being negligible in countries with higher welfare levels relative to counterparts with similar characteristics. This conclusion is consistent when I combine the low income and lower-middle income countries, as well as the low-income countries in isolation. However, for lower-middle income countries in isolation, these significant effects are found across median welfare to households slightly below the median level for the most part. In addition, for low-income countries, households tend to smooth their obtained credit towards welfare measures that are obtainable in the short-term, e.g. consumption per capita, food and non-food measures, instead of measures that they rather see as investments for the long-run. In lower-middle income countries however, for welfare indicators that are more realisable over a longer period, like education, only the median and slightly below median welfare level households in lower-middle income countries show a positive effect. These results are robust across several welfare indicators in both low and lower-middle income countries. This analysis provides arguments on identifying who the poor really are and the need for governments and developmental organisations to target these households instead of relying only on the usual trend of selecting those who should get credit based on credit metrics of commercial banks alone. This is because not everyone who applies for micro-credit really needs credit and previous studies as shown in the literature concentrate on the impact of credit at mean levels for households showing no evidence on this effect across the various depth of poverty level on those who apply or obtain credit. Furthermore, the analysis shows where the most productive investments of households from micro-credit are channeled for low and lower-middle income countries. Thus, the chapter shows that credit could have heterogeneous effects depending on the welfare level of those who apply and identify those who really need the credit from the evidence of these effects.

Further sections of this chapter are structured as follows. Section 4.2 gives the literature review on micro-credit and welfare, while section 4.3 gives an overview of how unequal Africa is compared to the rest of the World. Section 4.4 explains the methodological procedure employed in the study, while section 4.5 provides insights on the data used.

Next, section 4.6 presents the empirical results with discussion. Finally, section 4.7 presents conclusions drawn from the results and the policy implications.

4.2 Literature Review

The focus of the micro-finance literature has seen controversy on the impact of micro-credit on various welfare measures, with differences also found in association with context diversion, and short-term or long-term impacts. However, there is no evidence, that I know of, that has outrightly focused on who should get micro-credit and the consequent effect on welfare as well as the implication of restricting credit on distributional basis for certain households while improving the same for others. At best, studies have focused on certain observable characteristics of households who get micro-credit from suppliers (supply side issues) or features of households who either apply or stalled their application for micro-credit due to certain risk factors which are basically demand side issues (see Chapters 2 and 3, Asad et al. 2015).

One trend of literature has argued that micro-credit possess a significant impact on the poor (Liqiong et al. 2019, Asad et al. 2015, Attanasio et al. 2015) as compared to whether credit has a dampening effect instead and if credit possess any significance at all on welfare (e.g., Copestake et al. 2001, Hulme and Mosley 1996, Morduch 1998, Mosley and Hulme 1998, Zaman 2001); or does not significantly raise income, or has a mixed effect (Banerjee et al. 2015), or does not empower women (e.g., Husain et al. 2010, Mayoux 1999, Rahman 1998). Some argue that a single financial credit intervention is not enough (Lipton 1996) and others portend the negative effects of financial credit showing evidence that financial credit does more harm because it raises inequality, increases financial services discrimination, increases workload and child labour, raises dependency, etc (Adams and Von Pischke 1992, Bateman and Chang 2009, Copestake 2002, Rogaly 1996). Other studies focus on different outcome measures and the impact of micro-credit (see Chapters 2 and 3) on either aggregate measures or sub-aggregate measures. A question that has been left unanswered is what level of poverty should be considered if poor households are to receive credit? and in what kind of countries are these arguments valid?.

Moreso, other studies focus on the relevance of who supplies the credit and show that micro-credit from Non-Governmental Organisations could be relevant depending on the economic conditions of households as compared to micro-credit intervention from government (Chavan and Ramakumar 2002). The argument was premised on the evidence of Yunus (1999) that formal lenders often ignore the unbanked due to high transactional cost of monitoring loan usage and determining the credit worthiness of households. A shift in literature has also focused on gender and discrimination in terms of obtaining loans. The literature has been how gender influences the accessibility of credit (Mazumder et al. 2017, Wahidi 2017, Bahta et al. 2017, Ghosh and Vinod 2017, Salgado and Aires 2018), some scholars contend that women face credit supply discrimination not solely based on gender but rather due to the perceived less robust nature of their projects (Leach and Sitaram 2002, Bellucci et al. 2010, Brana 2013). Further research backing the loan-demand premise suggests that debt aversion mostly characterises female entrepreneurs because of their higher risk aversion compared with males (Carter et al. 2007, Dawson and Henley 2015).

Another direction of argument is schemed to answer the question on whether micro-credit can lead to long-run development in the establishment of business start-up rather than the anti-poverty tool as argued by other authors. Ahlin and Jiang (2008) present findings on the enduring impacts of micro-credit within a model of occupational choice, similar to Banerjee and Newman (1993). They argue that the sustained effects of micro-credit are influenced by the simultaneous facilitation of micro-saving and the eventual graduation of the average borrower. They propose that the emphasis should be on accumulating sufficient wealth for full business start-ups, rather than indefinite retention. This, they suggest, should be the goal of micro-banks for micro-credit to serve as a steppingstone to broad-based development, rather than merely an anti-poverty tool. Furthermore, studies such as Matsuyama (2007) offer evidence that enhancements in the credit market, which increase access to non-frontier technologies, may reduce long-run efficiency Matsuyama (2006) explores the impact of introducing a moderately productive self-employment technology on a range of potential steady states and concludes that self-employment may either raise or lower long-run income levels.

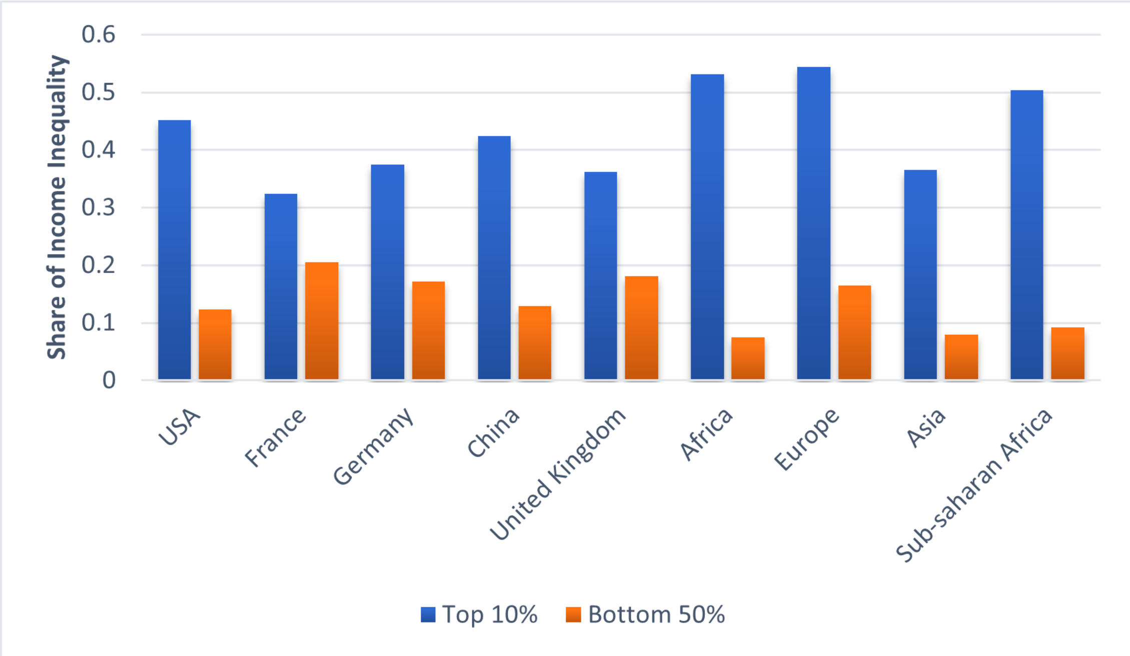
Furthermore, Aitken (2013) provides an argument on the financialisation of micro-credit. The study argues that financialisation techniques such as valuation, intermediation and securitisation are used to turn micro-credit into a commercial process. Moreso, credit suppliers especially banks, follow a credit rational criterion to link credit score, interest rates and other risk factors to decide who gets loans. Although Waller and Woodworth (2001) show that micro-credit can be identified as a grassroot policy for third world countries at the inception of the arguments on the impact of credit on economic indicators, a few other studies have also argued in favour of protecting borrowers. For instance, Fernando (2006) argues that imposing ceilings on micro-credit interest rates could hurt both the poor and credit suppliers.

Following the trend of arguments in the economics-finance literature on the impact of credit on welfare, I deem it necessary to go beyond the impact of micro-credit on the welfare levels of the poor on general basis as well as mean effects level. I propose that greater evidence on who really should get finance suffices to provide evidence for governmental and developmental agencies as regards micro-credit and welfare improvement. This is because not everyone who applies for credit really needs credit or may not be able to use it in the best way and the effects of credit on improving welfare may vary depending on the welfare level of those who apply for credit. It is on this basis that I attempt to provide answers on who should really get micro-credit from formal and informal institutions. This analysis deviates from the usual mean effect regressions in literature to provide evidence on who benefits most from micro-credit.

4.3 How Unequal is Sub-Saharan Africa Compared with the Rest of The World?

Using the World Inequality Database (WID) from 2010-2021, I report the wealth inequality across Africa compared to other regions of the World as presented in Figure 4.1. The report indicates In Africa, there exists a substantial disparity between the average incomes of the top 10% and the incomes of the bottom 50%. The average incomes of the top 10% are approximately 30 times higher than those of the bottom 50%, surpassing the disparity observed in other regions characterised by extreme inequality. For instance, in countries known for extreme inequality like China and the United States, as well as in regions such as Asia and Europe, the income gap is around 20 times.

Figure 4.1: Wealth Inequality across the World.



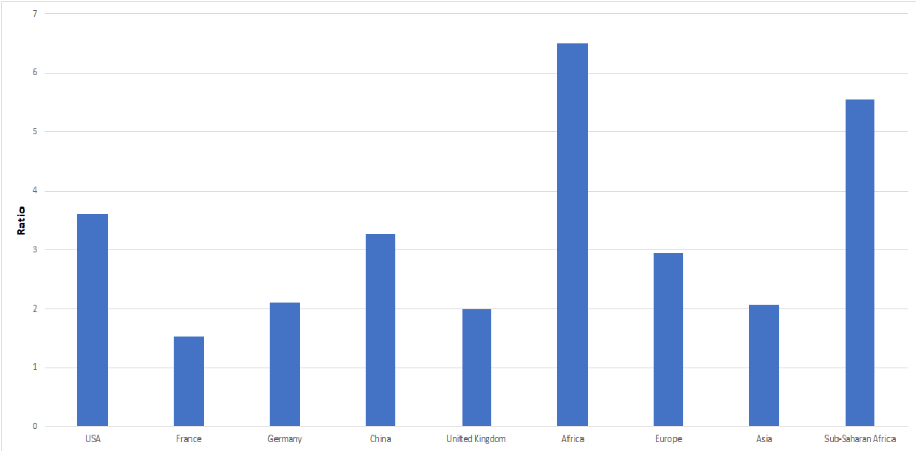
Data obtained from: World Inequality Database 2023.

This highlights the dual nature of the income distribution in Africa, characterised by extremely low incomes at the bottom and relatively high incomes at the top. It emphasises the importance of moving beyond synthetic indicators, such as the Gini coefficient[1], which may not fully capture the nuanced structure of inequality. In this study, I consider additional welfare measures to provide a more comprehensive analysis.

To highlight the differences in income inequalities around the world, I construct a Kuznet's ratio defined as the income share of the top 10% divided by the income share of the bottom 50% from Figure 4.1. The Kuznet's graph is reported in Figure 4.1.2 which confirms the discussion above of high-income inequalities in Africa and Sub-Saharan Africa.

[1]The Gini coefficient is a measure of a county's inequality. It is mostly constructed through the aggregation of income levels of a country and can also be used as an index for measuring a country's wealth, see Chandy and Seidel (2017). The values of the Gini coefficient range from 0 to 1 with values close to 0 depicting low levels of income inequality while values close to 1 represents high levels of income inequality.

Figure 4.1.2: Kuznet's Ratio of Inequality around the World.



Data obtained from: World Inequality Database 2023.

An essential question arises: What contributes to inequality in Africa? Is it predominantly inequality within African countries or disparities in average national income levels? Chandy and Seidel (2017) propose that, upon decomposing overall inequality, the majority of African inequalities can be attributed to inequality within countries. As illustrated in Figure 4.2, some of the world's most unequal countries are located in Sub-Saharan Africa, including Nigeria, South Africa, Ethiopia, Malawi, Tanzania, Mozambique, Botswana, Angola, and the Central African Republic.

Figure 4.2: 20 Most unequal Countries

Data obtained from: World Inequality Database 2023

4.4 Methodology

To answer the research question in this chapter which considers whether there is variation in the relationship between financial credit and welfare by the nature of the household, this chapter adopts quantile regression methodological approaches. The idea here is to identify the various depth of welfare/poverty level across households[2] to see if financial credit policies has any effect across these different depths and through this determine who benefits most from financial credit in terms of welfare. Endogeneity is controlled by using fixed effects. The quantile regression methodology enables one to account for endogeneity stemming from unobserved heterogeneity and the effects of heterogeneous covariates is cru-

[2]This is done through assessing the various distribution of welfare levels across the various welfare indicators used in this chapter.

cial. The presence of panel data offers the opportunity to introduce fixed effects, aiding in the control of certain unobserved covariates. Currently, a burgeoning body of evidence is emerging at the intersection of these two methodologies (e.g. Koenker 2004, Geraci and Bottai 2007, Abrevaya and Dahl 2008, Galvao 2011, Rosen 2012, Lamarche 2010, Canay 2011, Machado and Silver 2019), however, this chapter follows the Canay (2011) approach as it accounts for the intersection of unobserved heterogeneity and heterogeneous covariates effects as compared to others, and refers to the Machado and Silver (2019) approach as a robustness check following the ongoing works in the area. The Machado and Silver (2019) approach of quantiles via moments allows for robust estimation of quantile treatment effects and fixed effects to address potential endogeneity issue

Following Canay (2011), I specify the following model

$$y_{ict} = x'_{ict}\beta(u_{ict}) + \eta_i \tag{4.1}$$

for $i = 1..., n$ households, $c = 1, 2, 3, 4$ countries, $t = 1..., T$ years and $(y_{ict},\, x_{ict}) \in R \times R^k$ are observable variables with y_{ict} depicting the welfare indicators while x_{ict} represents the controls among which includes the main dependent variable of interest (financial credit) and the unobservable components are $(u_{ict},\, \eta_i) \in \mathrm{R} \times \mathrm{R}$. The vector x_{ict} is assumed to include a constant term, i.e., x'_{ict}=$(1,\, x^{s\prime}_{ict})$ with $x^s_{ict} \in {}^{k-1}$. The function $\tau \mapsto x'\beta(\tau)$ is assumed to be strictly increasing in $\tau \in (0,\, 1)$ and the parameter under consideration is assumed to be $\beta(\tau)$ which denotes the conditional quantile effect of an independent variable on an outcome variable of interest at τ-quantile, given some covariates. If η_i were observable it would follow that

$$P[y_{ict} \leq x'_{ict}\beta(\tau) + \eta_i | x_i, \eta_i] = \tau_i \tag{4.2}$$

under the assumption that $u_{ict} \sim$ u[0, 1] conditional on $x_i = (x'_{i1},....x'_{iT})$ and η_i. Particularly, this representation has been extensively used in the literature (e.g. Chernozhukov and Hansen 2006, 2008). However, the notable distinction between the model specified in equation (4.1) and the conventional quantile regression model introduced by Koenker and

Bassett (1978) is in the inclusion of the unobserved η_i. This variable which is random may be arbitrarily related to other random variables in equation (4.2) (i.e. $\eta_i = \eta_i(u_{it},\ x_i,\ \gamma_i)$ for some i.i.d. sequence (γ_i) rendering condition (4.2) as not particularly useful in terms of identification.

Consequently, a critical question what answering is under what additional conditions the unobservable variables $(u_{ict},\ \eta_i)$ with the parameter $\beta(\tau)$ can be identified and consistently estimated from the data, as Rosen (2012) demonstrated that conditional on covariates, quantile restriction in isolation will not identify $\beta(\tau)$. For Instance, if one represents $Q_Z(\tau — \text{A})$ as the τ-quantile of a random variable Z conditional on another random variable A, let $e_{ict}\ (\tau) \equiv x_{ict}[\beta(u_{ict})\ \text{-}\ \beta(\tau)]$, where the model in equation (4.1) can be re-written as

$$y_{ict} = x'_{ict}\beta(\tau) + \eta_i + e_{ict}(\tau), \quad Q_{e_{ict}(\tau)}(\tau|x_i) = 0 \tag{4.3}$$

Rosen (2012) show that the conditional quantile restriction $Q_{e_{ict}}(\tau)(\tau — x_i) = 0$ does not have sufficient identification power. Various authors have explored options around this problem,[3] however, I follow the Canay (2011) method that accounts for endogeneity from un-observed heterogeneity and heterogeneous covariates effects and fixed effects to control for some unobserved covariates through the availability of panel data. I follow this approach because it best suites the data available and also improves on some of the approaches explored earlier.

Canay (2011) resolves this problems by following a simple data transformation that eliminates the fixed effects η_i as T $\Rightarrow \infty$ (as time increases). The transformation leads to an extremely simple asymptotically normal estimator for $\beta(\tau)$ that can be easily computed even for very large values of n-observations. To address this identification issue, I follow the 2-step estimator approach of Canay (2011) similar to the GMM estimation method. The two-step estimator exploits two direct implications and the fact that η_i is a location shift. The first implication is in equation (4.3), where only $\beta(\tau)$ and $e_{ict}(\tau)$ depend on τ. The

[3]Some of the approaches explored in the literature are dyanamic panels with individual fixed effects Galvao (2011), instrumental variabe approach Anderson and Hsiao (1981, 1982) and Arellano and Bond (1991), Chernozhukov and Hansen 2006, 2008 and Galvao 2011, fixed effect penalizer of Koenker (2004), non-additive fixed effects of Powell (2022), quantiles via moments Machado and Silver 2019, etc.

second implication arises by letting $u_{ict} \equiv x'_{ict}[\beta(u_{ict})$- $\beta_u]$ and writing a conditional mean equation for y_{ict} below as

$$y_{ict} = x'_{ict}\beta_\mu + \eta_i + U_{ict}, \quad E[U_{ict}|x_i, \eta_i] = 0 \tag{4.4}$$

Equation (4.4) implies that η_i is also present in the conditional mean of y_{ict}. Consequently, from equation (4.4), Canay (2011) computes a $\sqrt{T}$ -consistent estimator of η_i by using a $\sqrt{nT}$ -consistent estimator of β_μ. Then, using equation (4.3) one can estimate $\beta(\tau)$ by a quantile regression of the random variable

$$\hat{y_{ict}} \equiv y_{ict} - \hat{\eta_i} \quad on \quad x_{ict}$$

In more simplier terms, the 2-step estimator is defined as follows.

Step 1. Let $\hat{\beta_\mu}$ be a $\sqrt{nT}$ - consistent estimator of β_μ. Where the parameter $\hat{\eta_i}$ is defined as $\hat{\eta_i} \equiv E_T[\hat{y_{ict}}$ - x'_{ict} $\hat{\beta_\mu}]$.

Step 2. Let $\hat{y_{ict}} \equiv y_{ict}$ - $\hat{\eta_i}$ and the two-step estimator $\beta(\hat{\tau})$ as:

$$\beta(\hat{\tau}) \equiv \arg\min_{\beta \in \mathcal{B}} E_{nT}[\rho_\tau(\hat{y_{ict}} - x'_{ict}\hat{\beta})] \tag{4.5}$$

The definitions in step one and two can be simply summarised as estimating a fixed effects regression model of independent variables on the outcome variable of interest. After which a control function approach is used to account for unobservable factors by generating the predicted value of the outcome variable from the estimated model and subtracting the predicted from the actual value of the outcome variable. After which a conditional quantile regression in estimated.

4.5 Data Analysis

This study employs the World Bank General Household Survey (GHS) panel dataset from 2010 to 2019 for four countries, grouped into low-income and lower-middle income countries. The countries are Nigeria and Tanzania which are classified as lower-middle income countries while Ethiopia and Malawi are classified as low income countries according to the World Bank classification of different economies and lending group for 2022 (World Bank 2022). [4] My intuition for selecting these countries is to capture African countries with large credit markets as well as the availability of data. Moreso, as earlier explained in section 4.3, these four countries are characterised with high levels of inequality. I thus use this fact to show that credit could have different impacts on welfare depending on the welfare levels of those who apply, instead of assuming average welfare levels for all households and estimating mean effects.

The World Bank GHS dataset contains about 4900 households for Nigeria, 3,969 for Ethiopia, 3000 households for Malawi and for 1200 households for Tanzania and across a panel period from 2010 to 2019. Welfare indicators in terms of consumption per capita, education, food and non-food expenditures are included in the dataset[5]. I use a proxy for micro-credit for households who have applied for loans and actually received the loans. The definition here is thus restricted to only households who have received credit and not those whose applications are pending as the data shows no evidence as to whether the loans were received at later periods in that year. Furthermore, this is done to assess the true impact of those who really obtained credit as well as those who did not. From the dataset across the four countries, 6,670 households indicated that they obtained loans, while 28,199 indicated that they did not.

The data also contains information on the sex of the head of households, employment status, religion, distance to market, distance to population centers, distance to capital, distance to border, terrain and climatic factors as latitude, wetness of land, rainfall to indicate

[4]World Bank recent ranking for economies classify countries whose per capita income is 12,376 or above US Dollars as High income countries, countries with per capita income between US 1,026 to 3995 US Dollars as lower-middle income economies and countries with per capita income below 1,025 US Dollars as low income countries.

[5]I also included other country specific welfare measures available in the dataset for some particular countries but absent in others in the supplementary material.

the location of households and wetness of land for accessibility of households to road or transportation. Other controls are marital status and, whether the household head interviewed can read and write. Appendix A provides description for all the variables included in the study. However, these features are included to show households social status (e.g religion), employment status (employed), basic literacy (read), distances to trade centers and commercialisation center (dist-population center, distance to market, dist-border, dist-popcenter, dist-capital), terrain and climatic factors as latitude, wetness of land, rainfall to indicate the location of households and wetness of land for accessibility of households to road or transportation as contained in the literature (See Chapter 2, James 2020, Asad et al. 2015).

4.5.1 Summary Statistics of Variables

Table 4.1: Household observable features for continuous variables

All Countries								
				Quartiles				
Variables	Obs	Mean	Std.Dev.	10	25	50	75	90.
Tot. Cons	21719	282.417	385.646	1.870	67.462	195.355	379.403	630.571
Edt. Exp	26363	41.063	136.214	0	0.323	6.986	35.644	100.51
Nfd. Exp	26309	128.009	327.225	14.526	32.739	74.862	148.318	262.357
Fdt. Exp	27493	220.301	415.906	0.01	0.018	107.695	272.367	528.596
Latitude	33164	4.24	9.639	-14.208	1.875	7.276	10.0245	12.420
Dist-popcentre	33164	41.198	39.356	4.1	13	30.4	55.3	92
Dist-market	34139	258.839	463.139	4	12.9	62	183.8	1032
Dist-border	33164	257.192	225.03	26	65.7	203.8	394.6	588
Dist-capital	33164	256.507	452.507	10	18	68.4	210.6	1008
Rainfall	33164	966.404	376.647	563	718	848	1179	1488
Wetness	33165	181.646	443.184	9	13	17	18	913

Notes: All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models. The exchange rates to US Dollars of each country was at the time of estimation 2023. The distances are reported in kilometers.

Table 4.1 above presents the summary statistics of some of the variables used in the study. At this stage, basic statistics in quartiles are reported while justification for the inclusion of these variables and others in the chapter are provided at later sections. The table provides information of the distribution of the variables contained in the dataset and shows the difference between the mean welfare indicators across the entire distribution in the dataset. I do not infer any causality at this stage but show clear information to highlight what the distribution holds for all the continuous variables contained in the dataset.

For consumption per capita, although the average value for households is about $282, very poor households in the distribution only constitute close to $2 while households at the 90th quartile constitute about $630.6. It is noteworthy that amongst all the welfare indicators, households spend less on education expenditure and this I do not suppose is as a result of scholarships which are rarely given or either difficult to justify in poor countries. This follows expectations as households in poor or lower-middle income countries see education as rather an investment when compared to other measures. Moreso, apart from total consumption per capita which is computed in relation to GDP, households spend most on food which again follows expectation for low and lower-middle income countries. The mean level of food expenditure is about $220 with households at higher quartiles spending above $528.6. Next to food is the non-food expenditure in terms of how households prioritise their welfare. The information contained in Table 4.1 says much on what each welfare indicator means for households in low and lower-middle income countries and how households smooth their spending across the most important welfare indicators.

The summary statistics of terrain and climatic factors including latitude, wetness of land, rainfall to indicate the location of households and wetness of land for accessibility of households to road or transportation as well as access to commercialisation indicators such as distances to market, population centre, capital, and the border are also reported. I refer to chapter 3 on the relevance of these variables. The quantile reports in Table 4.1 help me to show in detail the dispersion from the mean in these variables across households which is important in the methodology used in this study.

Next, Table 4.2 below presents details of households who obtained credit and those who do not. Given that the dataset contains other binary variables, I show in detail the summary statistics of the binary variables contained in the study which are basically credit status, sex, employment, an indicator variable of whether household member can read and write at least in English and religion. I categorise sex, employment, an indicator variable of whether household member can read and write at least in English and religion by credit status to provide richer information on the contents of the data and thus, I present the summary in percentages (%).

The Table 4.2 indicates that more households are headed by the male gender, of those that obtained loans, males constitute nearly 20% while about 19% of women got the loans. Although, several literatures have argued about the risk averse nature in borrowing by women, I, at this point, make no claims on this argument as the data does not show why women did not receive or apply for loans. Probing further into the data, show that nearly an equal percent of both employed and unemployed households in low (Ethiopia and Malawi) and lower-middle (Nigeria and Tanzania) income countries obtain financial credit, approximately (20%). Moreso, as expected, more of those who can read and write obtained credit (20.66%) while more Christians applied for and obtained loans (22.28%).

Table 4.2: Summary Statistics for binary variables by Credit Status

Variable	Non-Financed(%)	Financed (%)	Total(%)
Male			
Female	81.42	18.58	100
Male	80.27	19.73	100
Employed			
Not Employed	80.50	19.50	100
Employed	80.09	19.91	100
Read and Write			
Unable	81.56	18.44	100
Read	79.34	20.66	100
Religion			
Others	85.96	14.04	100
Christian	77.72	22.28	100

4.5.2 Selecting some Important Controls

I draw from evidence some controls and variables that affect welfare (Asad et al. 2015, Chapters 2 and 3)[6]. Specifically, these controls are important factors to consider especially for rural or poor households in developing countries. They include the sex of head of households, employment status, religion, distances to market, population centre, capital, border, terrain and climatic factors as latitude, wetness of land, rainfall to indicate the location of households and wetness of land for accessibility of households to road or transportation. Other controls are marital status and whether the household head interviewed can read and write. While there are other individual country specific factors that are prevalent in the different countries, I include only factors that are consistent and available in the dataset for all countries. Notwithstanding, I control for these factors in the regression using country fixed effects in addition to group and time fixed effects.

As seen in the panel regression with fixed effects for all the countries used in Table 4.3, all the controls stated above are statistically significant determinants of welfare, except wetness of land when a fixed effects regression for all the variables are estimated. However, this variable is statistically significant when regressed alone on all the welfare indicators or at least some of the variables in Table 4.3 are excluded as shown in Appendix I. These results are consistent for the panel regressions at the mean level. Whether the same results are realisable for quantile regressions which address effects at various levels of the distribution of welfare is what the empirical section also provides answer to. Table 4.3 thus summarises that these controls can't be overlooked when assessing effects on welfare

[6]See the papers by Asad et al. (2015) and the literature in Chapters 2 and Chapter 3. They include factors that proxy distance of households to market, primary form of education, terrain of households, sex, religion, employment status.

Table 4.3: Some Important Controls and Determinants of Welfare

	Tot Con	Edt. Exp	Fd Exp	Nfd. Exp
Male	21.17	2.551	39.26***	3.247
	(11.12)	(2.615)	(8.393)	(5.748)
Religion	19.17	1.818	1.350	17.27*
	(12.82)	(3.102)	(9.956)	(6.818)
Employed	2.352	-17.42***	3.828	-8.284*
	(8.025)	(1.595)	(5.119)	(3.506)
Married	173.8***	-2.092	117.5***	27.05***
	(11.13)	(2.523)	(8.097)	(5.545)
Latitude	1.942	0.648**	0.506	0.0558
	(1.080)	(0.228)	(0.731)	(0.501)
Read	57.04***	3.226	18.05***	25.18***
	(7.252)	(1.646)	(5.283)	(3.618)
Wetness	2.316	-0.0117	-0.0172	-0.0573
	(3.536)	(0.0148)	(0.0474)	(0.0324)
Dist-market	-0.0729**	0.0222***	-0.0258	-0.0545***
	(0.0259)	(0.00513)	(0.0165)	(0.0113)
Dist-border	0.0382	0.0396**	0.0163	-0.0391
	(0.0677)	(0.0132)	(0.0425)	(0.0291)
Dist-popcenter	0.337*	-0.0372	0.115	0.0839
	(0.146)	(0.0260)	(0.0834)	(0.0571)
Rainfall	-0.139***	-0.0166	-0.0568*	-0.0515**
	(0.0405)	(0.00879)	(0.0282)	(0.0193)
Dist-capital	0.265*	0.0917***	-0.0360	0.114***
	(0.117)	(0.0156)	(0.0501)	(0.0343)
GroupFE	Yes	Yes	Yes	Yes
CountryFE	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes
Obs	20238	24307	24265	24265
R-sq	0.072	0.161	0.057	0.109

Notes: Standard errors are reported in brackets and *, **, *** represents 10, 5 and 1 percents significance levels respectively. All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models. The exchange rates to US Dollars of each country was at the time of our estimation been 2023.

4.6 Empirical Results and Discussion

For simplicity, Table 4.4 and Table 4.5 summarises the empirical quantile regression results of the impact of obtaining credit on the various distribution of the welfare levels of households at different quantiles with all the controls shown in Table 4.3. Appendix J includes full details of the quantile regression results presenting coefficients for all the controls used. The outcome of analysing the results collectively is to suggest that there are inequalities in welfare outcomes from obtaining credit. Any significant effects are particular to households that are at the low to median quantiles of the distribution for most part. Furthermore, to provide further and clearer explanation as well as clear differences on the conditional quantile regression effects of credit on the various welfare measures, the quantile regression plots first across all countries, followed by lower-middle income countries and then low income countries are also presented. However, I use a shorter spread in quantiles that is every 5th quantile beginning from the 10th to the 90th quantile for clearer explanation allowing the spread of this effect across 15 different quantiles. All the plots contain the controls included in Tables 4.4 and 4.5. These are reported in Figures 4.3-4.5 below

Specifically, the results obtained using the Canay (2011) estimator in Table 4.4 suggest that the effect of credit is very heterogeneous, being large for countries whose welfare levels are low relative to that of countries with similar characteristics, and negligible for countries with high welfare level relative to that of countries with similar characteristics. Generally, what I find is that obtaining credit is more important for households from the low to slightly above median levels of the distribution of welfare as regards consumption per capita and food expenditure. Thus, obtaining micro-credit improves the welfare (consumption per capita and food expenditure) of households at the low and slightly above median quantiles when one considers both low and lower-middle African countries together. As the quantile level increases, the magnitude of the effect of credit on both consumption per capita and food expenditure falls until the median quantile after which there is no statistical significance on the effects of credit when considering both low and lower-middle African countries together.

In detail, the conditional quantile regression effects of credit on consumption per capita first increases at \$19.34 at the 10th quantile but falls to \$11.28 at the median, before losing significance after the 75th quantile. This is also in corollary to the the conditional quantile regression effects of credit on food expenditure which initially increases from \$9.14 at the 10th quantile and then drops to \$4.317 at the median, before losing significance at the 75th to the 90th quantile. Moreso, having a first glance at Figure 4.3, I find that the effects of conditional quantile regression of credit is uniformly positive across all the welfare measures beginning from the low quantiles but these effects falls in magnitude as the quantiles tends towards the median before the loss of significance from the higher quantiles as the confidence intervals clearly depicts. This result is consistent across consumption per capita and food expenditure. These findings strongly confirm the point discussed above that credit has different effects at different points of the welfare distribution and the conditional quantile regression estimates reported in columns two and four of Table 4.4 show that credit shift the location of the conditional welfare distribution for consumption and food expenditures respectively (i.e., positive effect on the median) but also reduces conditional welfare dispersion.

What one can infer from this result is that raising the income level of poorer households and slightly above median welfare level households is very important if policy makers want to improve consumption per capita as it seems rational for these households to smooth their income more towards improving their consumption level compared to higher income level households. In corollary, what the result also suggests is that improving food expenditure seems to be a major concern for households at the lower to median quantiles of the distribution of welfare. Thus, for these households, it is only rational to channel the credit obtained or extra income acquired to improving their food expenditure needs which is expected when considering developing countries as compared to developed ones. Available evidence prior to this study (Banerjee et al. 2015, Chapter 2) tends to focus on the mean impact (mean-effect approach) of micro-credit on welfare and have some similar as well as opposing arguments as a result of the varying endogeneity approach followed. However, the mean-effect approach assumes that all household levels have similar means, but ideally, they do not because even for low-income countries, the distribution of welfare or poverty varies among households. However, the evidence from chapter 3 and Banerjee et al. (2015) show that at mean level, micro-credit matters when consumption per capita and food expenditure is considered respectively, lending support to the results in this study however, at specific

Table 4.4: Estimates across various depth of poverty

All Countries CANAY PQRFE τ	Tot Cons	Edt Exp	Fd Exp	Nfd Exp
0.1	19.34***	1.928	9.145***	6.675**
	(3.646)	(1.357)	(2.520)	(2.185)
0.25	16.13***	0.463	7.871***	5.979***
	(2.812)	(0.389)	(1.800)	(1.136)
0.5	11.28***	0.127	4.317*	5.394***
	(2.706)	(0.351)	(1.747)	(1.048)
0.75	8.602*	0.180	3.260	5.768***
	(4.448)	(0.587)	(2.896)	(1.655)
0.9	11.79	-0.589	2.229	8.532**
	(9.787)	(1.455)	(6.431)	(3.162)
Controls	Yes	Yes	Yes	Yes
GroupFE	Yes	Yes	Yes	Yes
CountryFE	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes
No. Obs	20183	24252	24210	24210

Notes: Standard errors are presented in brackets and *, **, *** at 10, 5 and 1 percent significance levels respectively. All the expenditures have been converted to US Dollars for simplicity using the official nominal exchange rates of each country as at the time of estimation of the models been 2023.

quantiles. The results show that the food needs are quite high at the lowest quantiles.

For education expenditure however, the results show no effect of credit at all quantiles on the welfare distribution when one considers both low and lower-middle income countries together. This result might seem to suggest that households are smoothing their credit obtained across other welfare measures as opposed to education which they may rather see as a long-term investment. This result is also confirmed by Figure 4.4 of the quantile regression plot as the opposing signs of the confidence intervals on education indicates that there are no significant effects of credit on education across low and higher quantiles. Interestingly, Banerjee et al (2015) and chapter 3 find similar results for a developing country like India and a lower-middle income country like Nigeria respectively, although at mean level. This could suggest that generally, for developing countries, policy makers need to consider other policy options in combination with finance to improve education because micro-finance alone might not be a sufficient stand-alone policy. Alternatively, credit in the form of tuition vouchers, tuition receipts and scholarships could be considered rather than giving out loans in monetary forms to poor households. This is because, for these households, meeting immediate needs are prioritised over needs that are rather seen as for the future such as education. However, this result drives me to also probe into the data in considering whether this is the case for low-income countries and lower-middle income countries in isolation. I have presented the results for low and lower-middle income countries separately in Table 4.5 below, but at the moment, the quantile regression results for both the low and lower-middle income countries combined is reported in Table 4.4.

However, I find the exact opposite when I consider non-food expenditure as a welfare indicator compared to that for education. For non-food expenditure, the results show that there is heterogeneity in welfare outcomes because of obtaining credit. I find significant effects at all quantile levels across the welfare distribution which also strongly confirms the point discussed above that credit has different effects at different points of the welfare distribution. However, one can observe some interesting shifts in these effects. At first, the conditional quantile regression effects of credit on non-food expenditure first increases at \$6.67 at the 10th quantile but falls to \$5.39 at the median reducing the conditional welfare dispersion, but reverts at the higher quantiles as the result show an initial increase from \$5.768 at the 75th quantile to \$8.532 at the 90th quantile thus widening the conditional welfare dispersion in non-food expenditure. This twin peak pattern seen for the low and then the high quantiles suggest that credit has different effect on non-food expenditure for the low quantiles in the welfare distribution as opposed to the higher quantiles. For both extreme quantiles (low and high), the conditional quantile regression estimates reported in columns five of Table 4.4 show that credit shift the location of the conditional welfare distribution but reduces conditional welfare dispersion for the lower quantiles as opposed to the increase in the conditional welfare dispersion for richer households. Similarly, Figure 4.3 makes the result easier to understand as one can observe significant effect across all quantiles with first a fall in the magnitude of the effects from the 10th to 50th quantile and then increase in the magnitude of effect from the 75th to 90th quantile with the effect at the extreme higher quantiles larger than the extreme lower quantiles.

Put differently, for non-food expenditure, there is heterogeneity in welfare outcomes as a result of obtaining credit. The results show significant effects at all quantile levels across the welfare distribution which also strongly confirm the point discussed above that credit have different effects at different points of the welfare distribution. Although, due to data limitations, I am not able to show the direction of non-food expenditure that is improved. This is because obtaining credit may trigger commercial activities, business start-ups, further farm production activities and so on. In fact, Ali et al. (2014), show that the removal of credit constraints could improve the likelihood of households expanding their farming activities, which could lead to an increase in yields. However, it is important to highlight and discuss the interesting shifts in these effects. At first, I observe an increase in the conditional quantile regression effects of credit on non-food expenditure at the low quantiles, however, the magnitude of this effect falls towards the median quantile which generally reduces the conditional welfare dispersion. Interestingly, after the median quantile, the direction of dispersion of this effect reverts as I now observe a shift and increase in the conditional welfare dispersion from the median quantiles towards the highest quantiles. If one considers that households could be directing their obtained credit towards farm or non-farm activities which in turn improves welfare, then it is not difficult to see why these shifts are observed. Households who are at the lower quantiles are impacted most because of their needs to either produce more or invest more. On the other hand, richer households care more about investing any extra income that they obtain. While it is also not possible to rule out the argument that households could also be spending their income on leisure, I observe that median welfare level households seem to be affected less as compared to richer and poorer households. Consequently, the two patterns of direction seen for the low and then the high quantiles suggest that credit has different effect on non-food expenditure for the low quantiles in the welfare distribution as opposed to the higher quantiles. For both extreme quantiles (low and high), the conditional quantile regression estimates show that credit shift the location of the conditional welfare distribution but reduces conditional welfare dispersion for the lower quantiles as opposed to the increase in the conditional welfare dispersion for richer households. However, one can observe that the magnitude of this effect is largest for the richer households (at the highest quantiles of the distribution) as compared to the poorer households which follows expectation. This is because richer households might have other non-food priorities and investments which they spend more on.

As stated earlier, I probe further in to the data by separating the data into lower-middle (Nigeria and Tanzania) and low income (Ethiopia and Malawi) countries to see whether each division show similar or different welfare outcomes across the distribution at different quantiles. The quantile regression results for both the lower-middle (Nigeria and Tanzania) and low income (Ethiopia and Malawi) countries in isolation are reported in Table 4.5 while Figure 4.4 shows the quantile regression plots. Both Table 4.5 and Figure 4.4 show that for the Nigeria and Tanzania, credit has significant effects on the welfare measures mainly at the 25th and 50th quartiles. Put differently, financial-credit possess a positive significant implication on welfare for households at the median level as well as households that are not too poor in the distribution. For consumption per capita, the conditional quantile regression effects of credit on consumption per capita only show positive significant effect at the 50th quantile of \$3.209 while other quantiles show no significant effect. This result suggest that when consumption per capita is considered a welfare measure in Nigeria and Tanzania, the effect of credit on welfare at various quantiles (welfare distribution) is not heterogeneous i.e no inequality in welfare outcomes. This could be the case that households in Nigeria and Tanzania are more exposed and are actually smoothing their income on other welfare indicators instead of consumption alone. This could explain why randomized control trial studies like Banerjee et al. (2015) and Angeluci et al. (2015) find no credit effect on consumption, especially since the mean level of welfare in India is higher than that of the countries used in this study. As the result in this study also confirms, credit does not improve the welfare levels of richer households. Using quantile regressions, Angeluci et al. (2015) also finds no heterogeneity although their interest was in a richer country like Mexico.

However, when education and food are considered as welfare measures in Nigeria and Tanzania, there is heterogeneity only between the 25th and 50th quantile. The result in column 3 of Table 4.5 show that the conditional quantile regression effects of credit on education expenditure first increases at \$2.76 at the 25th quantile but falls very slightly to \$2.73 at the median with a very little evidence of a slight reduction on the conditional welfare dispersion. Again, this follows expectations as lower-middle income countries are known to have richer households who are more exposed to education as compared to low-income countries. I find similar pattern of credit impact on food expenditure to that of education as the result in column 4 of Table 4.5 show that the conditional quantile regression effects of credit on food expenditure first increases at \$2.354 at the 25th quantile but falls very slightly to \$2.309 at the median with very slight reduction on the conditional welfare dispersion. For non-food expenditure, similar conclusions to that of consumption per capita is found, however at the 25th quantile. The conditional quantile regression effects of credit on non-food expenditure only show positive significant effect at the 25th quantile of \$4.673 (this effect is larger than that of food expenditure which is a notable sign for slightly richer countries compared to Ethiopia and Malawi) while other quantiles show no significant effect. This result suggest that when non-food expenditure is considered a welfare measure in lower-middle income countries, the effect of credit on welfare at various quantiles (welfare distribution) is not heterogeneous, i.e no inequality in welfare outcomes, as there is no significant effect for all quantiles. Figure 4.4 re-enforces these results explained above in Table 4.5 visually. The result in Figure 4.4, show that the effects of conditional quantile regresion of credit is uniformly positive at mostly between the 25th to 50th quantile (education and food expenditure) or uniquely at the 25th (the case for non-food expenditure) or 50th quantiles (consumption per capita). Beginning from the low quantiles, these effects fall only slightly in magnitude as the quantiles tends towards the median before the loss of significance from the higher quantiles as the confidence intervals clearly depicts.

Table 4.5: Estimates across various depth of poverty

CANAY PQRFE	Lower-middle Income (Nigeria and Tanzania)				Low Income (Ethiopia and Malawi)			
τ	Tot. Cons	Edt Exp	Fd Exp	NFd. Exp	Tot. Cons	Edt Exp	Fd Exp	NFd. Exp
0.1	3.776	3.842	2.152	4.706	29.48***	1.000	15.31**	6.757***
	(3.350)	(2.857)	(1.850)	(4.324)	(6.165)	(0.684)	(4.922)	(1.649)
0.25	3.695	2.764**	2.354*	4.673*	27.48***	0.162	16.97***	6.048***
	(2.696)	(1.070)	(1.166)	(1.932)	(4.458)	(0.143)	(3.592)	(1.097)
0.5	3.209*	2.730**	2.309*	1.614	22.54***	-0.0312	10.35**	6.199***
	(1.389)	(0.892)	(1.045)	(1.775)	(5.192)	(0.115)	(3.953)	(1.302)
0.75	2.051	1.997	1.177	2.923	15.19**	-0.277	15.35*	7.613***
	(1.886)	(1.368)	(1.166)	(2.404)	(8.201)	(0.282)	(6.863)	(2.313)
0.9	0.425	2.185	-0.384	1.705	26.22	-0.940	23.68	12.89**
	(4.032)	(3.067)	(1.853)	(4.925)	(17.33)	(0.955)	(14.38)	(4.961)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GroupFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8741	12768	12768	12768	11442	11484	11442	11442

Notes: Standard errors are presented in brackets and *, **, *** represents 10, 5 and 1 percents significance levels respectively. All the expenditures have been converted to US Dollars for simplicity using the official nominal exchange rates of each country as at the time of estimation of the models been 2023.

The results of the quantile regression on the impact of credit on welfare for Nigeria and Tanzania suggest that heterogeneity in welfare outcomes are only observed in education and food while for consumption and non-food expenditures, the effect of credit on welfare at various quantiles (welfare distribution) is not heterogeneous. Moreso, these effects are only observed in the 25th and 50th quantiles.

The chapter proceeds further by reporting the result for Ethiopia and Malawi also in columns 6-9 of Table 4.5. This was done to compare the similarities/differences with the results of Nigeria and Tanzania as I believe that this is critical and will give a clearer and country specific (in terms of income levels) guide in determining who benefits most from micro-credit according to country income levels. The results for the low-income countries indicate heterogeneity in welfare outcomes as a result of obtaining credit. Furthermore, these results significant effects affect households that are at low to median quantiles of the distribution for most cases.

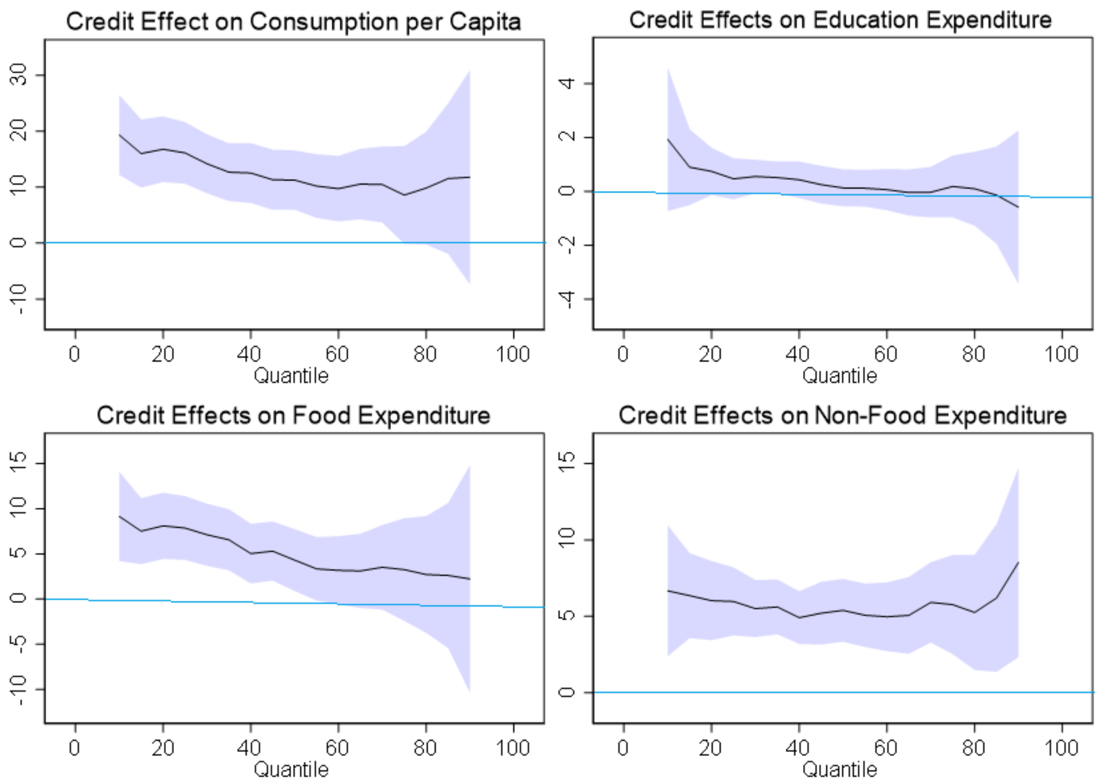
From the results for Ethiopia and Malawi in column 6 in Table 4.5, the conditional quantile regression effects of credit on consumption per capita first increases at \$29.48 at the 10th quantile, this falls to \$22.54 at the median, but loses significance after the 75th quantile. These effects seem to be larger for Ethiopia and Malawi as compared to Nigeria and Tanzania and seem to suggest that credit portents greater effects for poorer countries. The consistency of this result is seen across consumption per capita and food expenditure in Figure 4.5 even with a larger spread across the quantiles. However, the conditional quantile regression effects of credit on food expenditure show some interesting results. The conditional quantile regression effects of credit on food expenditure initially at \$15.31 at the 10th quantile increases to \$16.97 and then drops to \$10.35 at the median. However, this effect then increases to \$15.35 at the 75th quantile before losing significance at the 90th quantile. Again, these findings strongly confirm the point discussed above that credit have different effects at different points of the welfare distribution and the conditional quantile regression estimates reported in columns two and four of Table 4.5 show that credit shift the location of the conditional welfare distribution for consumption and food expenditures respectively (i.e., positive effect on the median) but also reduce conditional welfare dispersion.

On education expenditure, I find no effect of credit at all quantiles on the welfare distribution when I consider only Ethiopia and Malawi together. This is observed in both Table 4.5 and Figure 4.5 as opposing signs of the confidence intervals on education indicates that there are no significant effects of credit on education across low and higher quantiles. This could be because households to are smoothing their credit obtained across other welfare measures as opposed to education which they may rather see as a long-term investment as Table 4.5 generally indicate. Thus, for Ethiopia and Malawi countries, improving other welfare measures as consumption, food and non-food is more important to households as compared to education which follows expectation for the less developed countries.

Furthermore, I find the exact opposite when I consider non-food expenditure as a welfare indicator comparing to education's insignificance. For non-food expenditure, the result indicates heterogeneity in welfare outcomes as a result of obtaining credit. There are significant effects at all quantile levels across the welfare distribution which also strongly confirm the point discussed above that credit have different effects at different points of the welfare distribution. However, one can observe some interesting shifts in these effects. At first, the conditional quantile regression effects of credit on non-food expenditure first increases at \$6.757 at the 10th quantile but falls to \$6.199 at the median reducing the conditional welfare dispersion, after which the effects reverts at the higher quantiles as I find that the initial increase of \$7.613 at the 75th further increases to \$12.80 at the 90th quantile thus widening the conditional welfare dispersion in non-food expenditure. Consequently, the two pattern of direction seen for the low and then the high quantiles suggest that credit has different effect on non food expenditure for the low quantiles in the welfare distribution as opposed to the higher quantiles. For both extreme quantiles (low and high), the conditional quantile regression estimates reported in columns 9 show that credit shift the location of the conditional welfare distribution but reduces conditional welfare dispersion for the lower quantiles as opposed to the increase in the conditional welfare dispersion for richer households. Moreso, while poorer households are more interested on meeting basic needs like food, only richer households can really spend much more on non-food expenditures.

Although the main objective of this chapter is to examine the effects of credit across the various distribution of welfare measures in both low and lower-middle income African countries, I would like to highlight the impact of several of the controls used in the study across the various quantiles. For simplicity, a summary of the results in Tables 4.4 and 4.5 already discussed are reported and then I refer to Appendix J where the full details of the regression results containing all the controls used are reported. The result indicate that sex, being employed, been able to read and write, religion and marital status impact welfare positively at the various quantiles for the most part while distances to market, border, capital and population affects welfare negatively for the most part. However, the signs of these effects especially for the distance to capital and distance to population centre varies when I compare the results by income levels of countries, that is lower-middle income countries (Nigeria and Tanzania) and low income countries (Ethiopia and Malawi). For Nigeria and Tanzania, the effect of distance to population centre on consumption for instance is heterogeneous and ranges from positive to negative effects but for Ethiopia and Malawi, this effect is mostly negative. In addition, the signs of this controls follows expectation,

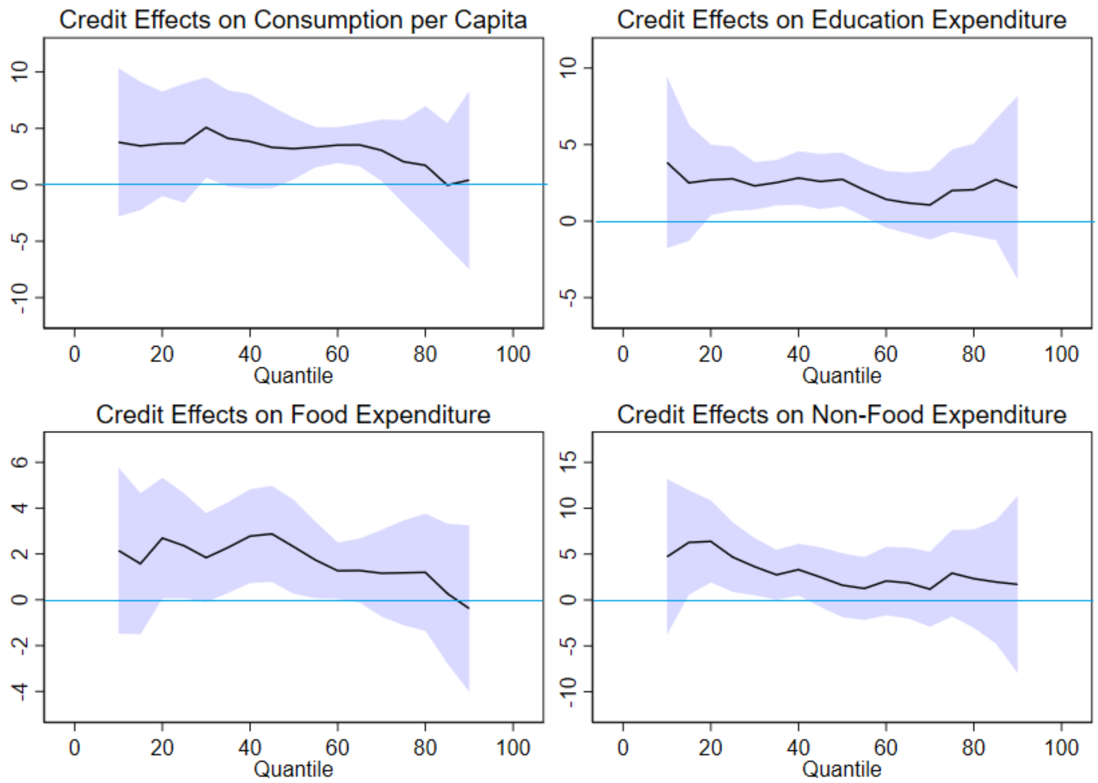
Figure 4.3: Quantile Regression Plots of Credit on Welfare for All Countries



for instance, distance to population centre could increase education expenditure for Nigeria and Tanzania, the reverse is the case for Ethiopia and Malawi.

The effect of rainfall and wetness of land on welfare is heterogeneous across the various quantiles and varies by both the welfare indicator concerned and the income level of the country. Also, the results show positive effect of rainfall and wetness of land on at least food expenditure and consumption per capita for lower-middle income countries, the reverse (negative and significant) is the case for low income countries. Again, this could relate to the fact that richer countries are more productive than the poorer ones with poorer countries having many of their populace concentrated in rural areas were productivity is somewhat low. However, I find negative effects of rainfall and wetness of land on education and non-food expenditure and these effects are consistent across both lower-middle income countries (Nigeria and Tanzania) and low income countries (Ethiopia and Malawi). Interestingly, latitude also show positive effects across the various quantiles for all the countries included.

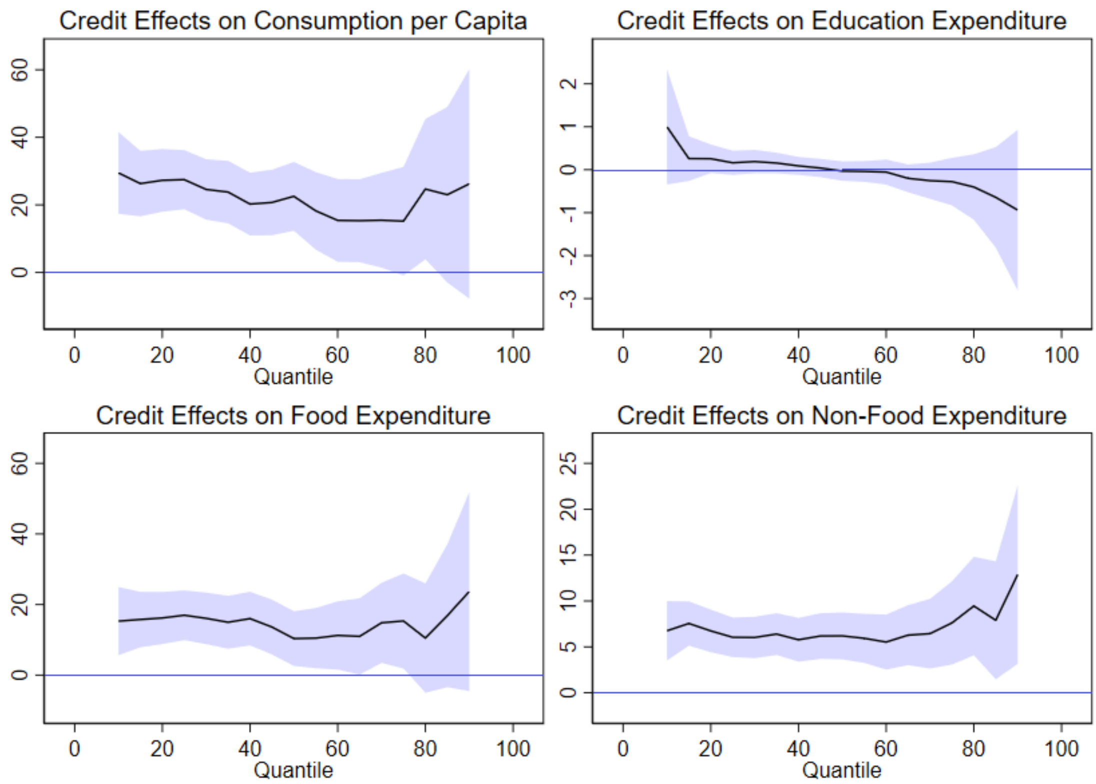
Figure 4.4: Quantile Regression Plots of Credit on Welfare for Lower-middle income Countries



4.6.1 Robustness

To ensure that the results obtained in the study are robust, this chapter uses a variety of checks. First, I change the specification of the model by varying and dropping some of the controls reported in Table 4.3 above to see if the results change. Controls such as distances to border, population centre, capital and rainfall are excluded not because they are less important controls but to see if the effect of credit on welfare in the study is in anyway triggered by the absence or inclusion of the controls. This is also done for several combination of controls but similar outcomes are found. The results of the new specification are reported in Appendix J. I find that the results do not change and are still consistent with the results reported in Tables 4.4 and 4.5. Like those results reported in Tables 4.4 and 4.5, the robustness checks of Appendix J also suggest that the effect of credit is very is heterogeneous, exhibiting substantial effects in countries where the welfare level is low compared to those with similar characteristics. In contrast, the impact is minimal in

Figure 4.5: Quantile Regression Plots of Credit on Welfare for Low income Countries



countries with a high welfare level relative to those with similar characteristics..

What the results suggest is that, obtaining credit is crucial for households from the low to slightly above median levels of the distribution of welfare as regards consumption per capita and food expenditure. Thus, obtaining micro-credit improves the welfare (consumption per capita and food expenditure) of households at the low and median quantiles when I consider both low and lower-middle African countries together. However, one can observe a shift in location from the low to median quantiles of this effect. That is as the quantile level increases, the magnitude of the effect of credit on both consumption per capita and food expenditure falls until the median quantile after which there is no statistical significance on the effects of credit. For education and non-food expenditures, I find similar results and reported in Tables 4.4 and 4.5. On education expenditure, there are no significant effect of credit at all quantiles on the welfare distribution when one consider only the low countries together while for non-food expenditure. For non-food expenditure, the results show heterogeneity in welfare outcomes as a result of obtaining credit. I find significant effect at all quantile levels across the welfare distribution which also strongly confirm the point discussed above that credit has different effects at different points of the welfare distribution. These effects also show a mixed pattern of reduction in the conditional welfare dispersion from low to median quantiles and then reverts to increase in the conditional welfare dispersion at the higher quantiles which have been clearly noted in Tables 4.4 and 4.5.

Next, I follow the Machado and Silver (2019) quantiles via moments approach to see if there are significant differences in the results. Although, it is important to highlight that the Machado and Silver (2019) approach has different assumptions which are beyond the scope of this study, however, this is used to improve the reliability of the results found. Using the Machado and Silver (2019), the quantile regression on the effects of credit on the various distribution of welfare used in the study with and without controls was estimated. These results are reported in Appendix J. The implications of the results again are no different from what I have already reported in Tables 4.4 and 4.5 although using different estimators show different estimate coefficients.

4.7 Conclusions and Policy Implication

The results from the conditional quantiles estimation of credit on welfare suggest that there is heterogeneity in the welfare outcomes as a result of obtaining credit. However, the significant effects are particular to households that are at the low to median quantiles of the distribution for the most part. This conclusion is consistent across the combination of low income (Ethiopia and Malawi) and lower-middle income countries (Nigeria and Tanzania) as well as the low-income countries (Ethiopia and Malawi) in isolation. Thus, an important implication to draw from this result is that if governments and development organisations intend to improve the welfare of households through financial credit programmes, then the targets and credit recipients should most likely be the low and median level households with regards to the various welfare measures. Generally, for African countries, financial credit policies are most impactful for poorer households as compared to the richer ones in regards of the welfare level. This conclusion is also persistent if one considers only the low-income countries.

However, for welfare indicators that are more realisable after longer periods, e.g., education, only the median and slightly below median welfare level households in Nigeria and Tanzania show positive effects. This is in line with the findings of Mwansakilwa et al. (2017) who show that micro-credit possess positive impact on education for a lower-middle income country like Zambia. Although, their study focus on mean effects using data for one cross-section. Generally, policy makers can target households at the median or slightly below median level households in Nigeria and Tanzania to raise welfare standards in Nigeria and Tanzania especially as regards consumption per capita, food, education and non-food welfare measures. For Ethiopia and Malawi, poor households tend to smooth their income across other welfare indicators that they consider could raise their standard of living at shorter basis and not the long-term indicators.

In summary, I recommend that for African countries, governments and policy makers should consider low to median level welfare households as regards micro-credit policies aimed at improving welfare levels. For Ethiopia and Malawi in isolation, governments and policy makers should consider for the most part low to median level households to raise welfare levels especially for welfare indicators that are most realisable on the short-run e.g., consumption per capita, food and non-food welfare indicators. For Nigeria and Tanzania alone, policy makers can consider households at median welfare level and slightly below median welfare levels to raise welfare. Credit policies also improve the welfare levels of these households for indicators as education because they are more exposed to development and the need for education as compared to Ethiopia and Malawi. Alternatively, credit in the form of tuition vouchers, tuition receipts and scholarships could be considered rather than giving out loans in monetary forms to poor households. This is because, for these households, meeting immediate needs is prioritised over needs that are rather seen as for the future such as education. These needs are more towards improving other welfare measures as consumption, food and non-food which they perceive to be more immediate and short-termed than education.

Future directions from this chapter could be to identify how financial credit policies affect the welfare distribution of males and females, modeling various welfare thresholds from the various distributions identified in this chapter and then examine the effect of financial credit on these thresholds for both low and lower-middle income countries. The next chapter of this thesis examines the first gap highlighted here.

Chapter 5 Gender, Micro-Finance and Welfare: Heterogeneity and Effects Gap?

5.1 Introduction

A major call that has gained prominence in terms of micro-finance is female participation in micro-credit programmes. The literature has spanned from the influence of gender in terms of obtaining credit (Mazumder et al. 2017), to discrimination in obtaining credit (Brana 2013), size of projects operated by entrepreneurs of different gender (Leach and Sitaram 2002) and then arguments on the effectiveness in the use of financial services (Leach and Sitaram 2002).

However, there is no study, in my knowledge, that has presented evidence on the heterogeneous effects of credit on various welfare distribution for both genders using a panel dataset for low and lower-middle income countries. Previous studies have relied on mean effect regression models to assess the impact of micro-finance programmes for either of the gender groups (see Chapters 2 and 3, Asad et al. 2015). However, beyond the mean level effects of credit on welfare, this chapter shows that credit could have heterogeneous effects on the welfare outcomes for each gender depending on the welfare level of those who obtain credit. The effects of credit as captured in the literature assumes that households have the same average welfare levels, and thus the impact of obtaining micro-credit is examined on the mean welfare level. However, this may not to be true as households who apply for credit have varying welfare levels and obtaining credit can lead to heterogeneous outcomes for these households depending on their welfare level especially across gender (Hong et al. 2020, Angelucci et al. 2015, Jalan and Ravallion 2000). In this study, I thus go beyond the usual mean effect regression on welfare for both gender categories.

Evidence from the WID (2023) has shown that there is inequality in wage distribution across the male and female genders. Although there has been some improvement in female income share around the world generally, the African and MENA regions still show gender inequalities in female income share as compared to the total adult income share. While this study does not include the scope for wage determination, this chapter focuses on financial credit programmes that aim at improving various welfare measures other than income.

The contribution of this study is in attempting to answer to the research question regarding: Is there any evidence that any relationship between financial credit and welfare may be operating through an empowerment effect?. For simplicity, this research question was further broken down into questions such as: what factors determine the acquisition of loans across male and female applicants?, what level of welfare does credit impact most across each gender and how large are the effect gaps?, and which of the two genders does obtaining micro-finance empower?. The answers to these questions play an important role in policy as it will provide clear suggestions to policy makers on what kind of financial credit policies to employ for the different genders in order to get the optimal response needed to improve welfare for households.

The chapter thus contributes to literature in three ways. Using a panel dataset for both low (Ethiopia and Malawi) and lower-middle (Nigeria and Tanzania) income countries, first, I compare the determinants of micro-credit across each gender. Next, I determine the heterogeneous outcomes in welfare as a result of obtaining micro-credit across the two genders and show how large their effect gaps are. Finally, I provide evidence for the effects of micro-finance on job empowerment across the two genders.

Put differently, this is an attempt to provide a direction on who benefit most from financial credit. To achieve this, the chapter provide analysis on how gender can also play a crucial role in using credit to achieve welfare improvements and where would be more appropriate for governments to channel or provide financial credit if they aim to improve the welfare of households. This is indeed crucial for ensuring finance optimisation in respect to improving living conditions in low and lower-middle income countries.

The results from this study show that suppliers of credit consider more factors in determining who receives micro-finance for males. However, this is not the same with females who apply for loans as I find that more factors account for obtaining loans for males as compared to females. Next, there are some interesting results on the heterogeneity outcomes of obtaining credit for both genders. In terms of the effect of credit on males, I find that obtaining micro-credit significantly improves the welfare of the poor males (low quantiles). On the female part, the impact is more heterogeneous and spreads across low to quantiles slightly above median but not the rich. Moreso, the effect of credit is significantly larger for females who received credit compared to the males who do receive credit. Finally, the results show that among the two genders, obtaining micro-credit empowers women in participation in non-farm enterprises. This is however not the case for males.

Further sections of this chapter are structured as follows. Section 5.2 gives the literature review on gender, micro-credit and welfare until date, while section 5.3 gives an overview of female income shares in regions of the world. Section 5.4 explains the methodological procedure employed in the study, while section 5.5 provides insights on the data used. Next, section 5.6 presents the empirical results with discussion. Finally, section 5.7 concludes on the results found in the study stating valid policy implications.

5.2 Literature Review

The focus of much literature has been how gender influences the accessibility of these credit (Mazumder et al. 2017, Wahidi 2017, Bahta et al. 2017, Gosh and Vinods 2017, Salgado and Aires 2018). Some authors contend that the discrimination against women in credit supply is not solely due to gender but is attributed to the perceived less robust nature of their projects (Leach and Sitaram 2002, Bellucci et al. 2010, Brana 2013). Leach and Sitaram (2002) go on to argue that women-managed businesses are perceived as less attractive to banks due to their smaller scale, which is perceived as riskier. This perspective is supported by Bellucci et al. (2010), who assert that female business owners encounter stringent loan application processes. Research backing the loan-demand premise suggests that debt aversion mostly characterises female entrepreneurs because of their higher risk aversion compared with males (Carter et al. 2007, Dawson and Henley 2015)

The second theoretical explanation in the literature for a possible gender-welfare gap using financial credit access relates to the effective use of finance by both women and men. Some studies argue that women lack the financial skills or know-how required to choose and make effective use of financial services or products (Lusardi and Mitchel 2014, Xu and Bilal 2012). For these studies, women face limitations of obtaining financial credit because they do not have the know-how that financial services providers may require but this is however less profound in their male counterparts. For those obtaining finance, the welfare effects may be uncertain as only the best female applicants may get financial credit, so they use it better, or if this doesn't happen, lower skills applicants will mean that credit is used less effectively.

It is also noteworthy that most finance institutions and governments of developing economies recently targeted women to help them earn income, gain financial independence and strengthen their decision-making power within the household and society (Zhang and Posso 2017). Also, women have lower levels of default in micro-credit participation indicating that women have lesser credit risks when compared to men (Alves and Camargos 2014, Soares et al. 2011).

Other emerging studies recently focus on whether financial credit could reduce gender inequality. Ohiomu and Ogbeide-Osaretin (2020) provide evidence to show that access to financial services can indeed reduce gender inequality more than the usage of financial services in Sub-Saharan Africa. Surprisingly however, they find that raising the educational levels of females had a negative impact on gender inequality. This they attribute to the high level of educational gap as this will increase inequality (gender) with increased financial inclusion. According to them, there are low levels of female tertiary education in most Sub-Saharan Africa countries. Although the interest of this chapter is not on reducing gender inequality, it is necessary to state that available evidence have also established some direction between finance and gender. My interest extends beyond this relationship as I probe more into the role of gender on the effects of financial credit on welfare levels.

Nanziri (2016) provides evidence on whether there are gender gaps in terms of financial inclusion and welfare for an emerging economy like South Africa. Using quantile regression analysis and probit models, the study relied on pooled data to establish that there are no significant differences between the average welfare levels of male and female users of financial services. However, for the female gender, they show that there are significant differences between the welfare levels of females who use financial services and their counterparts who do not. Their study is, however, limited in certain areas. First, the arguments are not verifiable for a panel dataset. The pooled dataset used by the study relies on data for different households coming from different sources in different periods. This means that random samples of different individuals are taken at different periods and at different units, that is, each sample is populated by different individuals. Hence, the heterogeneity of the dataset could trigger bias in the results found. An appropriate dataset to use in this kind of analysis will be a sample of the same individuals over an extended period of time as is the case for panel data analysis. Secondly, probit models alone are still very limited in handling the problems of endogeneity as have established in the second and third chapters of this study.

The recent study by Delis et al (2020) investigates the role of owners' gender (entrepreneurs) in bank credit decisions and post-credit-decision firm outcomes for small and micro-enterprises. They also investigate whether male entrepreneurs are more aggressive loan applicants than females. They show that, all else equal, women entrepreneurs are more prudent loan applicants than the men because they are less likely to apply for credit or to default after loan origination. However, the study finds that in terms of higher average firm performance after loan origination, the men are better off. However, the analysis and conclusions from the study focus on European entrepreneurs. Hence it is important to check whether the same realisation from the study is obtainable for lower-middle income countries and why. Secondly, the study concentrates on addressing endogeneity from selection bias and fails to capture issues relating to endogeneity originating from unobserved heterogeneity.

Asiedu et al. (2012) conducts an analysis on access to credit by small businesses: how relevant are race, ethnicity, and gender? The main contribution of their study is to examine if differences in loan denial rates and interest rates charged on approved loans between White male firms and other groups can be explained by variations in creditworthiness, firm characteristics, and other observable factors influencing loan decisions. The findings reveal that Black-owned firms encountered increased discrimination in obtaining credit in 2003 compared to 1998. In contrast, Hispanic firms faced discrimination in 1998 but not in 2003, although both Black and Hispanic-owned businesses experienced discrimination in loan renewals in 2003. While their contribution is relevant to literature, it still lies on the discrimination premise and credit access with no scope to probe the welfare performance of these loans as they could on the other hand trigger biases if lower welfare performance increases the probability of obtaining loans. Moreso, Beck et al. (2018) resent findings that align with the presence of gender bias and learning effects, resulting in the eventual elimination of gender bias in accessing credit over time.

Andres et al. (2019) investigate the gender gap in acquiring bank credit. They use Spanish companies owned by sole entrepreneurs and show the distinction between female and male business owners' demand for credit, credit approval rates and performance. They show that female business owners who start-up businesses are less likely to display demand for loans; but for those who do ask for loan, the probability of obtaining a loan in the start-up year is significantly lower than their male counterparts. However, this disappears with longer periods. Moreso, female entrepreneurs who receive loans are less likely to default as compared to the males in their founding year. However, this better performance disappears with longer periods coinciding with the disappearance of lower credit access. Their contribution is basically the possibility of the presence of double standards in credit access and performance of loans which may be because of implicit (unconscious) discrimination. It will be interesting to extend beyond the level of loan performance and investigate the effects of credit access on welfare for both genders using a panel data set and also check for double standards in developing countries.

Over the decade, with the absence of micro-level panel data especially on access to finance and the resultant use of the finance obtained, there has been limited research on welfare disparities between the two gender triggered by finance. It is however important to note that the purpose of this section is not to compare the effects of financial credit on welfare for the male and female gender because there will be a bias in such comparison. For instance, most male headed households in Africa still have females as wives or children, however, this is not the same for female headed households as they are seen as households headed by widows who may not have grown up male children.

Using the 2016/2017 Ghana living standard survey, Danquah et al. (2021) explore the impact of gender wage disparities within households on women's empowerment and welfare in Ghana. The study employs methods that address unconfoundedness in the selection of observables and unobservables to examine the structural effects of gender wage differences on women's empowerment and well-being. Their findings indicate that a decrease in the household gender wage gap significantly enhances women's empowerment. Furthermore, a reduction in the household gender wage gap leads to meaningful improvements in both household and women's welfare.

Despite the generally assumed positive effects of micro-credit on women's empowerment and household well-being, recent studies have revealed varying impacts, ranging from positive to mixed and even negative outcomes. For instance, a quantitative study in Vietnam found no significant impact of micro-credit on borrowers' income and expenditure (Nghiem et al. 2012). Similarly, evidence suggests that micro-credit programmes may lead to marital violence as men may coerce their spouses into obtaining loans for the household, perpetuating gender-based disparities and reinforcing specific roles (Haile et al. 2012). Furthermore, a quantitative study on micro-finance in Ghana indicates a potential negative impact, where women losing control over their loans could result in difficulties repaying them on time (Ganle et al. 2015).

The inconsistent conclusions within the micro-credit literature may be attributed, in part, to the insufficient focus of studies on changes in community dynamics, cultural norms, and gender roles and how these changes interact with micro-credit programmes (Singh 2018). Additionally, variations in findings may arise from inadequate consideration of certain dimensions of welfare or empowerment (Kabeer 2001a, 2001b) or the use of different measurements in empowerment assessments. For example, studies that utilised metrics related to management, such as "loan use and control" (Haile et al. 2012), reported negative impacts on women, while those employing measurements of household decision-making (Kabeer 2005a, 2005b) indicated positive effects. The study's geographical context is also crucial, as the impact of micro-credit may differ across locations with distinct communities, gender norms (Johnson 2005, Kabeer 2005a, 2005b), or different economic settings

(Van Rooyen et al. 2012, Verrest 2013). Furthermore, the rules governing micro-credit programmes can play a significant role in influencing their impact (Hulme 2000).

Consequently, are there heterogeneities in welfare outcomes that are considered important across both genders if the impact of credit is examined beyond the usual mean level for both low and lower-middle income countries? Are the results from the low and lower-middle countries any different from the earlier results discussed? In an effort to investigate how financial credit works best, this study is the first to my knowledge to investigate whether the effects of financial credit on household welfare is sensitive to gender, that is which gender welfare level responds best to financial credit policies for low and lower-middle countries and why this is the case. An answer to this question will help guide decision makers on what gender as well as their welfare distribution to target in implementing financial policies to improve welfare. Hence, with the available micro panel data for both low and lower-middle income countries, this chapter goes beyond mean effect regressions and attempt to answer to the research questions as, what level of welfare does credit impact most across both genders and how large is the effect gaps?, and which among the two gender does obtaining micro-finance empower?. I incorporate welfare measures that can be categorised as economic and social and management indicators of welfare.

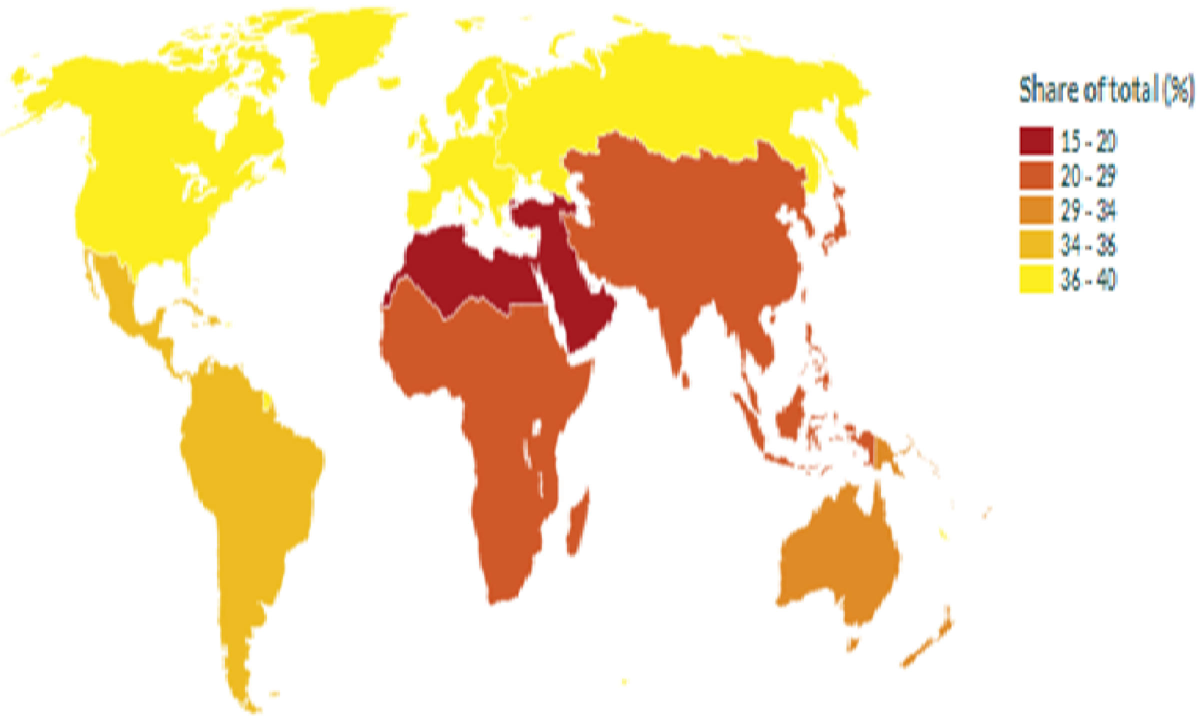
The answer to this research question plays an important role in designing relevant policy as it will provide clear suggestions to policy makers on what kind of financial credit policies to employ for the different genders in order to get the optimal response needed on welfare for households. This will assist in improving living conditions in low and lower-middle income countries.

5.3 Female Income Share in World Regions

Figure 5.1 presents a map of the income shares of females in the major regions of the world like Africa, Europe, Oceania, Americas, MENA and Asia. The data is sourced from the World Inequality Database using the last updated dataset for income participation been 2019.

Figure 5.1 shows that in general, female income share is larger in other regions of the world apart from Sub-Saharan Africa and the Middle East and North African (MENA) regions[1]. Specifically, the MENA, regions show about 14.6% female income share while the Sub-Saharan African region show 28.9% . I delve further into the data and find that in African countries such as Nigeria, Ghana, Tanzania, Malawi and Ethiopia, the female income share ranged from 28% to 36%.

Figure 5.1: Female Income Share



Source: World Inequality Database 2023

The data from the map might suggest that the African and MENA regions still fall below in gender equality and sensitisation programmes. Although, this study does not include the scope for sensitisation in female income share, I show that proper financial credit policies targeted at both the male and female genders could lead to welfare improvements across the various distribution of welfare in both genders.

[1] I do not rule out the possibility that this may be due to the number of women in work. This is because advanced economies have higher number of females in the work force than developing countries and could have higher incomes, see Chandy and Seidel (2017).

5.4 Methodology

To answer to the research question, is there any evidence that any relationship between financial credit and welfare may be operating through an empowerment effect?, I divide the question into three parts for simplicity. First, what factors determine the acquisition of loans across male and female applicants?, next what level of welfare does credit impact most across each gender and how large are the effect gaps?, and which of the two genders does obtaining micro-finance empower?[2].

For the first part, what factors determine the acquisition of loans across male and female applicants?, I estimate a probit model on the determinants of obtaining credit across both gender. I specify a panel probit regression model below as

$$Pr(Loan_{ict} = 1)_g = \zeta + \gamma * Controls_{ict} + \nu_i + \eta_t + \mu_c + \xi_{ict} \tag{5.1}$$

$$where \quad g = \{ \begin{smallmatrix} m & when & male \\ f & when & female \end{smallmatrix}$$

for $i = 1...,n$ households, $t = 1,...T$ years and $c = 1,2,3,4$ for the four countries in the data set. Also, ζ is the constant term, the $Controls$ are a list of covariates that affect the likelihood of obtaining loan, ν_i, η_t and μ_c are the household, time and country fixed effects respectively, while ξ_{ict} represents the disturbance error term. The m and f represents the male headed and female headed households respectively. The model specified above in equation (5.1), indicates that the probability of obtaining a loan across both gender, $Pr(Loan_{ict} = 1)_g$, is dependent on a vector of several variables which I categorise under controls. The fixed effects ensures that any endogeneity[3] from unobservables from the households, across countries over time are accounted for.

[2] I focus on economic empowerment which relates to engaging in non-farm activities as a means to improving welfare. The choice of this measure relates to the fact that agricultural households could engage in non-farm businesses or start-ups that could improve their welfare or decision making (Garikipati 2008).

[3] I include household, country and time fixed effects to account for unobservables across these panels. However, I do not make claims that the unobservables are time varying.

To improve the robustness of the model in equation (5.1) and show some forms of heterogeneity, I include interaction of covariates following the approach of Ai and Norton (2003), Mello et al. (2002) and DeLeire (2000). These are meant to capture any significant interactions between the included variables (social and economic). Hence, the model in equation (5.1) is re-specified as

$$Pr(Loan_{ict} = 1)_g = \zeta + \gamma * Controls_{ict} + \delta * Controls_{ict} * W + \nu_i + \eta_t + \mu_c + \xi_{ict} \quad (5.2)$$

$$where \quad g = \{ {}^{m}_{f} \quad {}^{when}_{when} \quad {}^{male}_{female}$$

Every other parameter remains the same as already defined above. However, $\delta * Controls_{ict} * W$ captures the interaction between the included variables with the main parameter of interest as δ, which captures the coefficient of the interaction of the variables.

Next, to determine what level of welfare does credit impact most across each gender and how large are the effect gaps (whether there are heterogeneous outcomes as a result of obtaining credit for each gender), I specify a quantile regression model. The idea here is to identify the various distributions of welfare across households for both genders and see if financial credit have any effect across these different distributions. Also, it is used to identify if there are differences between the effects of financial credit across the genders at the various quantiles or distribution of welfare. The quantile regression methodology enables me to account for endogeneity stemming from unobserved heterogeneity and heterogeneous covariates effects, while the availability of panel data potentially allows me to include fixed effects to control for some unobserved covariates. Currently, there is still growing evidence of the intersection of these two methodologies (e.g., Koenker 2004, Geraci and Bottai 2007, Abrevaya and Dahl 2008, Galvao 2011, Rosen 2012, Lamarche 2010, Canay 2011, Machado and Silver 2019), however, I follow the Canay (2011) approach as it accounts for the intersection of unobserved heterogeneity and heterogeneous covariates effects as compared to others.

Specifying the quantile regression below in terms of quantiles for the τth conditional function of the response of the tth observation on the ith individual in the cth country,

$y_{ict/g}$ is given by

$$Qy_{ict}(\tau|z_{ict}, x_{ict})_g = z_{ict}\eta_i + x_{ict/g}\beta(\tau) \tag{5.3}$$

$$g = \{^{m}_{f} \quad ^{when}_{when} \quad ^{male}_{female}$$

Where $y_{ict/g}$ denotes the outcome welfare measure of interest for each male or female headed household across time, $x_{ict/g}$ depicts a vector of exogeneous variables for both male and female headed households, z_{ict}[4] captures the fixed effects and $\eta = (\eta_1 ... \eta_N)$ is a $N * 1$ individual specific effects or intercept term.

Finally, to answer the question on which among the two gender does obtaining microfinance empower?, I specify a binary outcome Extended Regression Model (ERM). The model adequately accounts for any combination of endogenous covariates, nonrandom treatment assignment, and endogenous sample selection (Imbens and Newey 2009, Wooldridge 2010, Wooldridge et al. 2016, Wooldridge 2020). However, part of the analysis, I consider only the mean level effect of credit on empowerment for both gender.

Consequently, I specify a panel probit model, for x_{ict} exogenous covariates and w_{ict} endogeneous covariates below as

$$Emp_{ict/g} = 1(x_{ict}\beta + w_{ict}\beta_2 + \xi_{ict} > 0) \tag{5.4}$$

$$Again \quad for \quad g = \{^{m}_{f} \quad ^{when}_{when} \quad ^{male}_{female}$$

Where $Emp_{ict/g} = 1$ depicts the probability that a household is empowered across both gender, and ϵ_{it} is a standard normal error with the independent parts

$$\xi_{ict} = \alpha_i + \epsilon_{ict} \tag{5.5}$$

[4] Again like equation (5.1) $i = 1, ..., n$ households, $t = 1, ...T$ years and $c = 1, 2, 3, 4$ for the four countries in the dataset.

$\alpha_i = \gamma\xi_{2ict}$ is the unobserved heterogeneity that gives rise to the endogeneity and the variance of the error ϵ_{ict}, is σ^2_ϵ. Hence, conditional on the covariates and unobserved heterogeneity for the endogenous covariate, the probability that a household is empowered, $Emp_{ict/g} = 1$ is given by

$$Prob(Emp_{ict/g} = 1/x_{ict}, w_{ict}, \alpha_i) = \phi(\frac{x_{ict}\beta + w_{ict}\beta_2 + \alpha_i}{\sigma_\epsilon}) \tag{5.6}$$

Again here, there are N panels with $i = 1..., n$ households, $t = 1, ...T$ years, c= the number of countries and one can observe $Emp_{ict/g}$.

5.5 Data

I refer to chapter 4 for the data used in this chapter. Basically, this chapter employs the World Bank General Household Survey (GHS) panel dataset from 2010 to 2019 for the four countries in the previous chapter, grouped into low-income and lower-middle income countries. The countries are Nigeria and Tanzania which are classified as lower-middle income countries while Ethiopia and Malawi are classified as low-income countries according to the World Bank country and lending group classification of different economies for 2022 (World Bank 2022). My intuition for selecting these countries is first due to data availability and then to capture African countries with large credit markets. I use this fact to provide evidence on the determinants of credit across both gender show that credit could possess different impact on welfare depending on the welfare levels of those who apply, instead of assuming average welfare levels for all households and estimating mean effects.

The World Bank GHS datset contains about 4900 households for Nigeria, 3,969 for Ethiopia, 3000 households for Malawi and for 1200 households for Tanzania and across a panel period from 2010 to 2019. Welfare indicators in terms of consumption per capita, education, food and non-food expenditures are included in the dataset. I use a proxy for micro-credit for households who have applied for loans and actually received the loans. The definition here is restricted to only households who have received credit and not those whose applications are pending as the data shows no evidence as to whether the loans were received at later periods that year. Furthermore, I do this to access the true impact of those who really obtained credit as well as those who did not. From the dataset across the four countries, 6,670 households indicated that they obtained loans, while 28,199 indicated that they did not.

The data in Table 5.1 show the mean and standard deviation values of the continuous variables in the data by gender. Also, a *t-test* is included on the continuous variables by gender to see if there are significant differences between the male headed and female headed households respectively. Table 5.1 is necessary to highlight and explain any dispersion (mean and standard deviations, and *t-test*) observed among the gender category. Although, I do not make any inferential claim at this point, Table 5.1 show some preliminary statistical differences between the male headed and female headed households. The table also show the focus of households in terms of welfare for both gender categories, the structure and size of households. The table show that for some variables, there are significant differences between households for both gender, however, I highlight a few. There are significant differences in household size, total consumption per capita, and location of households like distances to; population centres, market, border, and capital for the households headed by both gender. However, at this point, I do not attach much importance to these differences but highlight that determining factors for obtaining loans across both gender could be different given the observed differences across households for both gender.

Table 5.1: Household observable features for continuous variables

	Male Headed			Female Headed	
	Mean	Standard Deviation	T-Test	Mean	Standard Deviation
HH Size	5.634	2.8	-2.017***	3.618	2.25
Latitute	4.393	9.568	-0.822***	3.571	9.916
Dist-popcentre	42.398	39.356	-6.183***	36.209	34.92
Dist-market	269.049	465.59	-49.03***	220.018	453.041
Dist-border	257.192	225.030	-3.629	254.01	217.683
Dist-capital	263.668	456	-30.15***	233.516	444.169
Rainfall	967.451	374.92	-2.688	964.762	384.977
Wetness	190.12	446.38	-35.38***	154.737	435.847
Tot Cons	285.75	409.302	-17.76***	267.990	286.986
Edt Exp	41.31	133.922	-0.389	40.923	146.282
Nfd Exp	129	335.71	-4.170	124.912	296.252
Fdt Exp	220.265	432.61	-1.017	219.248	349.012
N	34407				

Notes: All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models. The exchange rates to US Dollars of each country was at the time of estimation 2023. The distances are reported in kilometers.

Table 5.1 also verifies that the households contained in the dataset are relatively poor given by the low values of the welfare measures, (total consumption per capita, education expenditure, food and non-food expenditure). However, apart from the total consumption per capita which is on the average, \$285.75 for males and \$267.99 form females, the most important welfare indicator for poor households is food expenditure which is \$220.27 for males and $219.25 for females, followed by non-food and education respectively. In addition, the average values across both gender of the distances to market, border and capital show that the households are located in remote areas.

Table 5.2 show that there are no large differences in terms of the proportion of males and females who obtained loans (19.7% and 18.58% for males and females respectively). However, in terms of employment, been able to read and write, the male headed households dominate. Furthermore, females are more religious in terms of Christianity with a large proportion of the data showing that there are differences between the married and unmarried for both gender.

Table 5.2: Summary statistics for binary variables by Gender of household-head

Variable	Obs(n)	Male Headed(%)	Female Headed (%)
Credit Status	34,055		
Obtained		19.73	18.58
Did not		80.27	81.42
Employed	23,806		
Employed		29.53	20.79
Not Employed		70.47	79.21
Read and Write	25,968		
Read		64.70	39.88
Unable		35.30	60.12
Religion	32,467		
Christian		61.05	75.58
Others		38.95	24.42
Marital Status	33052		
Married		91.06	24.31
Unmarried		8.94	75.69
Non-farm Business	32530		
Engaged		33.98	28.67
Did not Engage		66.02	71.33

Additionally, the proportion of males and females that participate in non-farm businesses are quite close (nearly one-third for both gender category). About 33.98% males engaged in non-farm businesses in comparison to 28.67% females who also do.

5.6 Empirical Results and Discussion

Table 5.3 presents the results from three panel probit regression models on the determinants of obtaining financial credit as modelled in equation (5.2). First, I show the determinants of credit across all households which are a combination of male headed and female headed households. Next, I then estimate the panel probit regression models on the determinants of financial credit for male headed and female headed households in isolation. To improve the robustness of the models and show some forms of heterogeneity, I include the interaction of covariates following Ai and Norton (2003), Mello et al. (2002) and DeLeire (2000) as earlier stated in the methodology section. The results of the model with interaction is presented in Table 5.3, however, I also, present the results of the model without interaction in Table 5.3.1. To account for endogeneity, I include household, country and time fixed effects to account for unobservables across the panels. These fixed effects ensure that any endogeneity from unobservables from the households, across countries over time are adequately accounted for.

Column two of Table 5.3 shows that generally, factors such as religion, married, distance to market, household size, households that can read and write but are far from population centres, households who are employed but are located far from population centres, increases the likelihood of obtaining financial credit. These factors are some of the features that characterise poor households and lend support to evidence such as Ali et al. (2015), Chapter 3. Interestingly, factors such as distance to population centres, married but located far from the market decrease the likelihood of obtaining financial credit. This may suggest that except households which can at least read and write, suppliers of credit consider distance to population centres in terms of giving out loans because households may not be financially inclusive. On the demand side, households who are far from population centres (where banks are located) might be risk averse in terms of applying for loans and following up their loan applications. For households who can read but are located far from markets, suppliers of credit may not be convinced as to how such loans may help, especially for agricultural households. I also check that the results are consistent, however without interactions. Again, variables such as religion, married, distance to market, household size, employed, households that can read and write are important determinants of obtaining credit across all groups. The model without interaction in Table 5.3.1 replicates the results of the interaction model in Table 5.3 but is not robust to include cases of significance for interacted variables as contained in Table 5.3.

However, when I estimate the panel probit regression model for only the male headed households, some slight changes from the model for all households become evident. This is reported in column three of Table 5.3. For the male headed households, factors such as religion, being employed, being married, the latitude of household location, distance to market, household size, households can read and write but are far from population centres, households who are employed but are located far from population centres, increases the likelihood of obtaining financial credit. Similarly, for the model without interaction in Table 5.3.1, factors such as religion, being employed, being married, the latitude of household location, distance to market, distance to border and household size are important determinants of obtaining credit for male headed households. It is not difficult to understand why this is the case for male headed households. This is because, for the male headed households, suppliers of credit may consider characteristics for being poor (latitude of household location, distance to market, household size, households can read and write but are far from population centres, households who are employed but are located far from population centres) before they give out loans but also, they consider responsibilities as being married, household size and whether the household can at least handle other financial responsibilities through their employment status. In terms of religion, being Christian may increase the likelihood of obtaining loans if religious beliefs in Christianity make Christians more open to loan applications than other religious.

Conversely, only being distant from population centres reduces the likelihood of obtaining financial credit. This again reinforces the results shown in column two that from the supply side, credit givers consider distance to population centres when giving out loans because they may not be financially inclusive and financially literate. On the demand side, households who are far from population centres may be financially excluded or risk averse in terms of applying for loans and following up their loan applications.

For females however, the result is slightly different. Fewer factors are statistically significant in regard to obtaining loans as compared to the male headed households. The results at this point does not imply any discrimination (or not), one reason for this difference

Table 5.3: Determinants of Credit Across both Gender

Outcome=Credit	All	Male Headed	Female Headed
Religion	0.189***	0.177***	0.211**
	(0.0352)	(0.0362)	(0.0668)
Employed	0.0389	0.0686*	-0.0406
	(0.0325)	(0.0364)	(0.0890)
Married	0.109***	0.140**	-0.0322
	(0.0360)	(0.0594)	(0.0733)
Latitude	0.00472	0.00670**	0.00749
	(0.00310)	(0.00334)	(0.00715)
Read	0.00254	-0.000701	-0.0121
	(0.0341)	(0.0372)	(0.0655)
Dist-market	0.000324***	0.000217*	-0.000126
	(0.0000859)	(0.000128)	(0.000193)
Dist-borderpost	0.000194	0.000358*	-0.000163
	(0.000154)	(0.000168)	(0.000247)
Dist-popcentre	-0.00245**	-0.00262*	-0.00203*
	(0.000788)	(0.00123)	(0.00107)
Rainfall	0.0000984	0.0000660	-0.0000286
	(0.0000665)	(0.0000717)	(0.000114)
Dist-capital	0.000199	0.000114	-0.0000388
	(0.000184)	(0.000211)	(0.000296)
Wetness	-0.0000991	-0.0000237	-0.000147
	(0.000180)	(0.000195)	(0.000305)
HH Size	0.0351***	0.0286***	0.0635***
	(0.00426)	(0.00455)	(0.00967)
Married#Dist-market	-0.000118*	-0.0000257	0.0000191
	(0.0000505)	(0.0000862)	(0.000152)
Married#Dist-popcentre	-0.000149	0.000118	0.000959
	(0.000740)	(0.00125)	(0.00133)
Married#Dist-capital	0.0000387	0.0000887	0.0000504
	(0.0000520)	(0.0000932)	(0.000156)
Read#Dist-market	-0.0000231	0.0000589	-0.0000959
	(0.0000562)	(0.0000743)	(0.0000872)
Read#Dist-popcentre	0.00244**	0.00233*	0.00220*
	(0.000902)	(0.000959)	(0.00127)
Read#Dist-capital	0.0000144	0.0000135	0.0000615
	(0.0000579)	(0.0000692)	(0.0000973)
Employed#Dist-market	-0.0000613	-0.0000705	-0.0000759
	(0.0000430)	(0.0000492)	(0.0000929)
Employed#Dist-popcentre	0.00135**	0.00136**	0.00181*
	(0.000536)	(0.000607)	(0.00129)
Employed#Dist-capital	-0.0000184	-0.0000683	0.000207*
	(0.0000437)	(0.0000490)	(0.000102)
GroupFE	Yes	Yes	Yes
CountryFE	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes
N	28968	22908	6060

Notes: Standard errors are reported in brackets and *, **, *** represents 10, 5 and 1 percents significance levels respectively . I include the group, country and time fixed effects to control for other group, country and time invariant unobservable factors in the estimation . All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models. The exchange rates are in nominal values.

Table 5.3.1: Determinants of Credit Across both Gender (Model Without Interactions)

Outcome=Credit	All	Male Headed	Female Headed
Religion	0.192***	0.180***	0.216***
	(0.0271)	(0.0301)	(0.0591)
Employed	0.0658**	0.0788***	0.0515
	(0.0214)	(0.0236)	(0.0529)
Married	0.0829***	0.156***	0.0141
	(0.0247)	(0.0401)	(0.0519)
Latitude	0.00482	0.00663*	0.00831
	(0.00304)	(0.00331)	(0.00705)
Read	0.100***	0.114***	0.0451
	(0.0201)	(0.0229)	(0.0459)
Dist-market	0.000190**	0.000208**	-0.000224
	(0.0000706)	(0.0000766)	(0.000195)
Dist-borderpost	0.000208	0.000365*	-0.000144
	(0.000139)	(0.000149)	(0.000273)
Dist-popcenter	-0.000502	-0.000429	-0.000269
	(0.000322)	(0.000350)	(0.000761)
Rainfall	0.0000986	0.0000636	-0.0000265
	(0.0000589)	(0.0000632)	(0.000117)
Dist-admctr	0.000238	0.000183	0.0000583
	(0.000161)	(0.000173)	(0.000308)
Wetness	-0.0000968	-0.0000156	0.0000383
	(0.000166)	(0.000180)	(0.000331)
HH Size	0.0356***	0.0292***	0.0650***
	(0.00378)	(0.00417)	(0.00947)
GroupFE	Yes	Yes	Yes
CountryFE	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes
N	28968	22908	6060

Notes: Standard errors are reported in brackets and *, **, *** represents 10, 5 and 1 percents significance levels respectively . I include the group, country and time fixed effects to control for other group, country and time invariant unobservable factors in the estimation . All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models.The exchange rates are in nominal values.

in the results for females as compared to males as regards the insignificance of more factors required for obtaining loans for females could be as a result of sensitisation programmes directed at reducing discrimination and promoting participation for females in economic activities. Although suppliers of credit consider features that suggest that households are poor, only factors such as religion, household size, households can read and write but are far from population centres, households who are employed but are located far from population centres and employed females who are distant from capital cities, increase the likelihood of obtaining loans for female headed households. Similar to that of the males, being distant from population centres exerts a negative influence on the likelihood of receiving loans. Furthermore, although I do not report marginal effects because the aim of the study at this point is to provide evidence on the determinants of credit across both gender and not how large the effects are, one can observe that the magnitude of the effects of these factors is larger for the female headed households as compared to the males[5].

The results from Table 5.3 show that less factors are considered when females apply for credit. Consequently, I categorise the determinants of obtaining credit into social and economic factors and an interaction between them. The social factors are religious beliefs, marital status, family size, been able to read and write. The economic factors are mainly been employed, location of households from markets, centres of commercialisation and trade such as capital cities, borders and population centres.

Next, Table 5.4 presents the results from the conditional quantile regression models specified in equation (5.3). This is done to determine whether there are heterogeneous outcomes as a result of obtaining credit for each gender. The results help to identify the various distributions of welfare across households for both genders and the consequent effects of financial credit across these different distributions. Also, they help to identify if there are differences in magnitude between the effects of financial credit across both genders at the various quantiles or distribution of welfare. For simplicity, I summarise the empirical quantile regression results of the impact of obtaining credit on the various distribution of the welfare levels of households at different quantiles for both genders in Table 5.4. Appendix K includes the full details of the quantile regression results presenting coefficients for all the

[5]This is also consistent for the model without interactions.

controls used.

Table 5.4 show some interesting results and suggests that the effect of credit is very heterogeneous in both genders, being large for households whose welfare levels are low, and negligible for households with high welfare levels except for education and non-food expenditure. In terms of the magnitude of the effects of micro-credit on the various welfare distributions for both genders, the effects of micro-credit on female headed households are larger.

For the male headed households, credit is more important for households from the low to median levels of the distribution of welfare as regards consumption per capita and food expenditure. Thus, obtaining micro-credit improves the welfare (consumption per capita and food expenditure) of households at the low and median quantiles. However, I observe a shift in location from the low to median quantiles of this effect. That is as the quantile level increases, the magnitude of the effect of credit on both consumption per capita and food expenditure falls until the median quantile after which there is no statistical significance on the effects of credit. In detail, the conditional quantile regression effects of credit on consumption per capita first increases at \$17.97 at the 10th quantile but falls drastically to \$5.4 at the median, before losing significance from the 75th to the 90th quantile. This is also in corollary to the the conditional quantile regression effects of credit on food expenditure which initially increases from \$10.97 at the 10th quantile and then drops to \$3.5 at the median, before losing significance at the 75th to the 90th quantile.

However, I observe a different pattern for the female headed households with regards to the effect of credit on consumption per capita and food expenditure. First, the magnitude of the effects of credit on consumption per capita and food expenditure is larger for the females compared to the males. This could be because because the males are diverting the funds received to other non-food expenses, as column six reveals, or that female headed households are more focused on household responsibilities directed at maintaining their homes especially with households where husbands are deceased (single parents), hence, obtaining credit depicts more responsibilities for these households and the aftermath effects on welfare becomes larger compared to the males.

Next, the spread of impact of obtaining micro-credit on consumption per capita and food expenditure begins from the low quantiles to the higher quantiles of the distribution for females. That is micro-credit is very important to nearly all the households from the low to high levels of the distribution of welfare as regards consumption per capita and food expenditure. Thus while richer males may prioritise their obtained credit on other investments or non-food expenditure, both the poor and richer households for female headed households are interested in raising consumption and food welfare levels in their home. Furthermore, the direction of the shift in location of the effect of micro-credit from the low to higher quantiles is the reverse of the male headed households. That is as the quantile level increases, the magnitude of the effect of credit on both consumption per capita and food expenditure increases. Thus, for females, the richer the household, the more their responsibilities and obtaining credit is channelled towards these responsibilities. This is observed from the conditional quantile regression effects of credit on consumption per capita which increases at \$30.41 at the 10th quantile and then rises drastically to \$42.05 at the 90th quantile. Also, the the conditional quantile regression effects of credit on food expenditure initially increases from \$13.66 at the 10th quantile to \$14.51 at the 75th quantile, before losing significance at the 90th quantile.

Although there is no study that I know of that has examined at a panel level the effects of credit on welfare for both gender in quantiles for low and lower-middle income countries, the results from the female headed households in this study conforms to studies as Al-shami et al. (2018), who show that micro-credit improves expenditure for women borrowers in Malasia and Fofana et al. (2015) who show that micro-credit improve welfare levels for females using cross sectional data in Ivory Coast. However, their results are at mean levels.

For education and non-food expenditures, there are similar results for both male and female headed households. On education expenditure, there are no effect of credit at all quantiles on the welfare distribution when one considers both gender in isolation. This result is very similar to chapter 4 which show no significant effect on education for low and lower-middle income countries in combination. Other studies that do not find positive effects are Fernandez (2011), who argue that micro-credit does not work likewise there is little or no

Table 5.4: **Estimates across various depth of welfare for both gender**

CANAY PQRFE	Male Headed				Female Headed			
τ	Tot Cons	Edt Exp	Fd Exp	NFd. Exp	Tot Cons	Edt Exp	Fd Exp	NFd. Exp
0.1	17.97***	1.186	10.97***	8.056***	30.41***	1.821	13.66***	8.683*
	(4.158)	(1.263)	(2.838)	(2.275)	(8.381)	(3.331)	(5.278)	(4.722)
0.25	13.57***	0.687	7.139***	5.534***	33.64***	0.699	12.20***	9.459***
	(3.205)	(0.446)	(1.937)	(1.196)	(5.772)	(1.007)	(3.761)	(2.487)
0.5	5.423*	0.331	3.5*	4.628***	36.33***	1.117	13.50***	10.43***
	(3.061)	(0.392)	(2.024)	(1.128)	(6.121)	(0.932)	(4.117)	(2.661)
0.75	1.667	0.241	1.724	4.278**	38.15***	-0.0206	14.51**	8.634*
	(5.063)	(0.637)	(3.140)	(1.704)	(10.42)	(1.462)	(6.240)	(3.813)
0.9	4.221	-0.511	2.141	7.224*	42.05**	-0.309	17.80	13.09
	(10.09)	(1.646)	(6.895)	(3.813)	(20.47)	(3.697)	(12.02)	(8.102)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
GroupFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15824	19290	19256	19256	4359	4962	4954	4954

Notes: Standard errors are reported in brackets and *, **, *** represents 10, 5 and 1 percents significance levels respectively . I include the group, country and time fixed effects to control for other group, country and time invariant unobservable factors in the estimation . All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models. The exchange rates are in nominal values.

impact in Vietnam (Nghiem et al. 2012), Thailand (Cull et al. 2009), mixed impact between positive to no impact in the Sub-Sahara Africa countries (Van Rooyen et al. 2012). This could be because households to are smoothing their credit obtained across other welfare measures as opposed to education which they may rather see as a long-term investment as Table 5.4 generally indicate. Thus, male headed and female headed households when considered in isolation, for low and lower-middle income countries in combination, sees credit improving other welfare measures such as consumption, food and non-food expenditure. These welfare measures are possibly perceived to be more important to households when compared to education, which follows expectation for the less developed countries.

The results show significant effects at nearly all quantile levels across the welfare distribution for non-food expenditure. However, I find opposite directions in the shift pattern of significance on impacts across the distribution for each gender. For males, At first, the conditional quantile regression effects of credit on non-food expenditure first increases at \$8.056 at the 10th quantile but falls to \$4.628 at the median reducing the conditional welfare dispersion, after which the effects reverts to \$7.224 at the higher quantile (90th) widening the conditional welfare dispersion in non-food expenditure again. Consequently, the two pattern of direction seen for the low and then the high quantiles suggest that credit has different effect on non-food expenditure for the low quantiles in the welfare distribution as opposed to the higher quantiles. For both extreme quantiles (low and high), the conditional quantile regression estimates reported in column 5 show that credit shift the location of the conditional welfare distribution but reduces conditional welfare dispersion for the lower quantiles as opposed to the increase in the conditional welfare dispersion for richer households. Moreso, while poorer households are more interested on meeting basic needs like food, only richer households can really spend much more on non-food expenditures. For the females however, I observe the reverse in the directions of the shift in pattern of significance. At first, the conditional quantile regression effects of credit on non-food expenditure first increases at \$8.683 at the 10th quantile and further increases to \$10.43 at the median widening the conditional welfare dispersion, after which the effects reverts to \$8.634 at the higher 75th quantile before losing significance (see column 9 of Table 5.4). The results suggest that for females, richer households spend more on non-food expenditure but not the extremely rich.

While there are changes in the magnitude of significance across the distribution of non-food expenditure, these changes are smaller compared to the males. However, the magnitude of significance on the various distribution for both the male and female headed households are quite similar. Generally, by considering that households could be directing their obtained credit towards farm or non-farm activities which in turn improves welfare, then it is not difficult to see why these shifts are observed. Households who are at the lower quantiles are impacted most because of their needs to either produce more or invest more. On the other hand, richer households care more about investing any extra income that they obtain while it is also not possible to rule out the argument that households could also be spending their income on leisure. In addition, richer households might have other non-food priorities and investments which they spend more on. However, for male headed households generally, the richer the household, the less they spend on non-food expenditure which could be to take care of their home. For female headed households, richer households spend more on non-food expenditure but not the extremely rich. I thus extend my analysis to see if obtaining credit empowers female headed households to embark on non-farm activities which could provide further evidence in support of the results discussed on the spread and magnitude of significance on the various distribution for both the male and female headed households.

Table 5.5 presents the results of the model on the effects of obtaining credit on the likelihood that households will engage in non-farm business. Due to data limitations and unavailability, I use a variable that indicate if households have engaged in non-farm businesses instead of business start-ups. To address the issues of endogeneity between credit and engagement in non-farm businesses, I estimate the probit version of an Extended Regression Model (ERM). The model adequately accounts for any combination of endogenous covariates[6], nonrandom treatment assignment, and endogenous sample selection (Imbens and Newey 2009, Wooldridge 2010, Wooldridge et al. 2016, Wooldridge 2020) as stated in section 5.4.

[6]The correlation report in Table 5.5 show that non-farm business engagement and credit are indeed endogeneous, hence, estimating the model significantly dealt with endogeneity.

The results from Table 5.5 show that obtaining credit increases the likelihood that female headed households will engage in non-farm businesses. This is however the reverse for the male headed households. This result is robust to several specifications. For robustness checks, first, I estimate a mean ERM model (reported) in Appendix L, where I find that the results do not change. The ERM model can be estimated for both a binary outcome model (as specified in equation 5.6) and a mean extended regression model. Thus, while the results from binary outcome model are discussed, the mean extended regression model was used to test the reliability of the binary outcome model. Next, a panel probit regression model on the effects of obtaining credit on the likelihood that households will engage in non-farm business was estimated. The results still show that for female headed households, obtaining credit increases the likelihood that that female headed households will engage in non-farm businesses. For the males, the sign of the coefficient remains negative but insignificant.

Although, the results presented are mean effects, it is not difficult to see why credit has larger effect on the various welfare measures for female headed households as compared to the males. However, I do not rule out the fact that credit may empower male headed households to start up businesses but in terms of non-farm business participation, financial credit possess positive implications for female headed households. This may be because, female headed households engage in further income activities to fend for their homes especially for single parents, while the men may engage in business start-ups which may or may not have immediate impacts on their home. Studies like Garikipati (2008), show that micro-credit increases income for females which support the result from this study.

The results from the study might also suggest that receiving credit can be used to determine how households allocate their time differently. The results show that financial credit increases women's empowerment by allowing them to engage more or increase their work time participation. If credit is intended to increase the value of women's work time, it follows that the use of loans then matters. Whereas for males, while obtaining financial credit might not improve their participation in non-farm businesses, they may be engaging in non-farm business start-up. The evidence from this study conforms to that of Garikipati (2012) in India who argue that loans to women helps their husbands move away from wage work (associated with bad pay and low status) to self-employment.

Table 5.5: ERM on the effects of Credit on Empowerment

Outcome=Non-farm Business	Male Headed	Female Headed
HH Size	-0.0012	0.0017
	(0.0018)	(0.0023)
Credit	-2.3629***	2.5316***
	(0.1021)	(0.04667)
Credit		
Religion	0.0307***	0.0060
	(0.0004)	(0.0057)
Employed	0.0474***	-0.0137**
	(0.0058)	(0.0054)
Married	0.0233***	0.0058
	(0.0084)	(0.0051)
Latitude	-0.0017***	0.0002
	(0.000337)	(0.0004)
Read	-0.0110***	0.00089*
	(0.0036)	(0.00046)
Dist-market	-0.000037***	0.000056***
	(8.08e-06)	(0.000015)
Dist-borderpost	0.0000297	-0.00011***
	(0.0000198)	(0.000031)
Dist-popcentre	0.0000199	-0.00014*
	(0.0000488)	(0.00007)
Rainfall	-2.83e-06	-0.000032*
	(0.0000717)	(0.000011)
Dist-capital	0.00013***	-0.000069**
	(0.00003)	(0.000027)
Wetness	-0.00015***	0.00002
	(0.0000308)	(0.00003)
GroupFE	Yes	Yes
CountryFE	Yes	Yes
TimeFE	Yes	Yes
N	22095	5862
var(e.credit,e.non.farm business)	0.9031***	-0.9745***
	(0.0382)	(0.0135)

Notes: Standard errors are reported in brackets and *, **, *** represents 10, 5 and 1 percents significance levels respectively . I include the group, country and time fixed effects to control for other group, country and time invariant unobservable factors in the estimation .

5.7 Conclusion and Policy Implication

This study highlights the fact that there could be effect gaps from the impact of micro-credit on the male and female gender and that micro-credit could possess empowerment effect. Specifically, the findings from this chapter show that economic and social factors and the interactions between them are important determinants of obtaining financial for each gender. Furthermore, there are effect gaps from financial credit and an empowerment effect on the female gender.

The results from this study has several implications for policy. First, economic and social factors and the interaction between them are important determinants of obtaining financial credit in low and lower-middle income countries for both male headed and female headed households. However, these factors also have significant effects on the various distribution of welfare for both gender. Hence financial credit policies that improves the economic and social conditions of households can indirectly improve their welfare.

Furthermore, an important contribution of the study is the evidence on the effect gaps on the impact of micro-credit on the various distribution of welfare for both male and female headed households. Policies that drive participation of females in micro-credit interventions and programmes are encouraged. From the results of the study, qualified females should be provided with the needed support and finance, because this has a significant increase in their welfare outcomes. Whereas for the males, governments could target low to median level households if welfare improvements are considered from financial credit policies. However, if education is considered as a welfare indicator in Africa as a whole, financial credit alone may not be a sufficient stand-alone policy. Alternatively, a policy mix or credit in the form of tuition vouchers, tuition receipts and scholarships could be considered rather than giving out loans in monetary forms to poor households. This is because, for these households, meeting immediate needs is prioritised over needs that are rather seen as for the future such as education. These needs relate more towards other welfare measures, such as, consumption, food and non-food which they perceive to be more immediate and short-termed imperatives rather than education.

In addition, the analysis of this study show that financial credit possess positive implications for female households as regards to empowerment to engage in non-farm enterprises. This was however the reverse for the males. Governments can encourage female headed households to allocate more time to income generating activities through financial credit policies which in turn have direct effect on distribution of welfare for these households cutting across various welfare measures.

Future research will be to consider if there are credit effect gaps for business start-ups across both gender? and what welfare threshold are affected most from financial credit for both gender?.

Chapter 6 Conclusions

The prior chapters of this thesis have included four pieces of analysis on the relationship between financial credit and household welfare in the African context. This chapter presents the summary of the main contributions of the thesis and policy recommendations.

6.1 Main Theoretical and Empirical Contributions

The first analysis examined the existing evidence on the effect of financial credit on welfare for Africa. The analysis indicated that 59% of the total studies included in African countries favours a positive relationship between micro-credit and welfare. However, the number of individual estimates that reflect a significant positive relationship is low compared to the number of estimates that find no significant relationship. From the evidence of the included studies, the relationship found depends on the analytical approach adopted. Problems of endogeneity (selection bias and unobserved heterogeneity) were frequently not addressed by the studies. For studies who employ the Randomized Control Trials (RCT), and therefore account for these issues to a greater degree, the categorisation of impact was that no convincing evidence was present. This contrasts with the much more numerous descriptive and regression studies which find a positive relationships more frequently, but given these issues of endogeneity, were rarely able to provide convincing robust evidence of a significant positive causal effect. This reflects the dangers of households self-selecting into receiving micro-credit through various attributes like productivity, location, social status, interest rates, and so on. On the other hand, the selection problem may also arise from credit givers through credit rationing, financial literacy tests, distance to commercial banks, previous loan repayment status, etc.

Although the works using RCT methods deals with these problems, their insights are limited to short-term impacts due to the length of period of data collection, which are generally curtailed due to the expense of running them over long periods. Problems of external validity are also present where a result obtained in one country (or even one area of a country) may be different from another country (or another part of the country). The chapter also highlights the scarcity of panel evidence (long-term effects) for the regression studies. This is in addition to the scarcity of research on the effects of financial credit on welfare for North African countries. It also becomes apparent that studies either consider the population as a whole, or specific individual groups in the population, rather than systematically exploring the relationship's nature over different important groups in the population. Further research could consider credit intervention programmes and the effect on welfare for North African countries.

These gaps in knowledge, identified through the systematic review of the literature, inspired the empirical analyses undertaken in the remainder of the thesis. In the analysis in chapter three, I combined the Propensity Score Matching (PSM) model with a standard Difference-In-Difference (DID) model to address endogeneity problems and used a longer period panel dataset. While the PSM addressed the issues of endogeneity stemming from selection bias, the DID model addressed the issue of endogeneity stemming from unobserved heterogeneity. The result of the analysis shows significant effect only when consumption per capita is considered as a welfare measure in the short-run and only when selection bias and unobserved heterogeneity (time fixed effects and household/group or feedback) are jointly controlled for. For other welfare measures, I find no sufficient evidence that obtaining financial credit improves the welfare levels of households in both short-run and long-run periods no matter whether the level of welfare been used. Future areas for research of this chapter are to combine a diverse set of policy measures, including financial credit, education, agricultural extension services focusing on enhanced farm seeds, equipment, and planting chemicals, as well as skill acquisition for farm labour. Also, to examine the resulting effects on the welfare levels of households in low (Ethiopia and Malawi) and lower-middle (Nigeria and Tanzania) income countries. The combination of financial credit with other policies will help determine the best policy mix targeted at improving welfare levels where only financial credit policies alone are insufficient.

Although the impact of financial credit on welfare, when considering all households in a country, appears limited and temporary, this may not be an issue if those most in need still benefit. To explore this, the analysis in chapter four deviates from the usual mean effect regressions, in order to provide arguments on identifying who really benefits from micro-credit and the need for governments and developmental organisations to target these households. This would be a move away from the usual trend of selecting those who should get credit based on credit metrics of commercial banks alone. The results suggest that there is heterogeneity in the welfare outcomes associated of obtaining credit. Specifically, financial credit significantly affects households that are at the low to median quantiles of the distribution for the most part.

Given those with lower welfare are likely to benefit more, and existing work noting the benefits of micro-credit for women (Garikipati 2012), but the limited existing work on this in an African context as revealed in chapter two, this led to the final piece of analysis. Using a panel dataset for both low (Ethiopia and Malawi) and lower-middle income (Nigeria and Tanzania) countries, first, I provide evidence on the determinants of micro-credit across both genders in comparison. Next, I determine the heterogeneous outcomes in welfare from obtaining micro-credit across the two genders and present evidence on their effect gap. Lastly, I provide evidence for the effects of micro-finance on job empowerment across gender. The result from this chapter has several implications for policy. First, economic and social factors and the interaction between them are important determinants of obtaining financial credit in low (Ethiopia and Malawi) and lower-middle income (Nigeria and Tanzania) countries for both male headed and female headed households. Furthermore, the result from the study show that the effect of financial credit is heterogeneous across gender and that there are positive effect gaps from the impact of micro-credit on the various distribution of welfare for both gender with larger impacts on the females. Micro-credit empowers the female headed households as the results from the study show that female headed households to allocate more time to income generating activities having obtained micro-credit.

6.2 Policy Recommendations

Important for policy was the need to provide evidence that draws conclusion on the causal effects of micro-credit on welfare addressing the issues of endogeneity from both selection problems and unobservable heterogeneity problems for a longer period of time. From the analyses of this thesis, if the target of policy makers in Nigeria is to improve the consumption per capita of households for a short period of time, then financial credit policies alone can suffice. This means that financial credit policies can be used by households to smooth short-term shocks or financial credit have a transient effect on households consumption per capita in Nigeria. However, realising improvements for other welfare measures both in the short-run and long-run is not achievable.

Additionally, for Ethiopia and Malawi, governments and policy makers should consider for the most part low to median level households, to raise welfare levels, especially for welfare indicators that are most realisable on the short-run, e.g., low to 50th quantiles of the distribution for consumption per capita, food and non-food welfare indicators for the most part. For Nigeria and Tanzania, policy makers can consider households at median welfare level and slightly below median welfare levels to raise welfare (within the 25th to 50th quantiles). Credit policies also improve the welfare levels of these households for indicators such as education because they are more exposed to development and the need for education as compared to Ethiopia and Malawi.

Policies that drive participation of females in micro-credit interventions and programmes should therefore be encouraged. Qualified females should be provided with the needed support and finance, because this significantly increases their welfare outcomes. Whereas for males, governments could target low to median level households if welfare improvements are considered from financial credit policies. However, future research could be to investigate whether there are credit effect gaps for business start-ups across both gender and to find out the welfare threshold mostly affected from financial credit for both gender.

Appendix A Variables used and their definition

Table A.1: Variables and their description

Variable Name	Description
Credit	Dummy for households who have applied for and obtained loans where credit=1 if households obtained the credit and credit=0, if they do not.
FC	Proxy for the treatment variable in 2015 where FC=1 if households received financial credit and FC=0, otherwise
Tot Cons	Households total consumption per capita (in US Dollars) . One indicator for the welfare of households. Measured in Naira for chapter 3
Fdt Exp	Household food expenditure (in US Dollars) . Another indicator for the welfare of households.
Non Fd. Exp	Household non-Food expenditure (in US Dollars). Another indicator for the welfare of households used in this study.
Edt Exp	Household education expenditure (in US Dollars) for learned households. Indicator for the welfare of households used in this study.
Income	Income (Nigerian Naira) for different households. a proxy for a measure of household welfare
Wetness	Average start of wettest quarter. A measure of topography and to good roads and transportation of households
Religion	A Dummy that equals one if households members are Christians and zero otherwise
Male	A Dummy that equals one if household respondent is male are and zero otherwise
Latitude	Latitude of households, measured by GPS. A measure of household location.
Longitude	Longitude of households, measured by GPS. A measure of household location.
Dist-Popcentre	The distance in kilometres from household to nearest population centre
Dist-Market	The distance in kilometres from household to the nearest market.
Dist-Border	The distance in kilometres from household to the nearest border.
Dist-Capital	The distance in kilometres from household to the capital of state of residence
Rainfall	The average yearly rainfall in different household areas
Employed	A dummy variable that equals one if household has a paid employment and zero otherwise
Read	A Dummy that equals one if households members can at least read and write and zero otherwise
Married	A Dummy that equals one if household respondent is married and zero otherwise
TV	Dummy for households who own television sets a measure of both poverty level and information of households.
Asset	A dummy variable that equals one if households' own the landed property used for cultivation and 0, otherwise.
Net-Access	A dummy variable that indicate one for households who have access to internet facilities and zero otherwise.
Yield	Output per plot produced (kg), a measure of productivity.
Asset Value	The monetary value of farm land used by individual households
Phone	Dummy where Phone=1 for households who own phones for accessing information/communication and 0 otherwise.
HH Size	The number of members in a household.
No. Men hired	The number of men hired to work on farm plots by households
Healthshock	A dummy variable that equals one if households' have faced health problems and 0, otherwise.
No. Women Hired	The number of women households employ to work on their farms.
Women-Pay	The amount paid to women hired to work on the farm in Naira
Non-farm Business	A dummy that equals 1 if households engage in non-farm businesses different from their employment and 0, otherwise

Notes: The dataset is sourced from the World Bank Living Standard Measurement Survey (LSMS) Dataset

Appendix B Description of Included Studies for Systematic Review

Table B.1: Description of Regression Studies

Author	Year	Source	Country	Data Type	Technique	Published	Effect
Akotey and Adjasi	2016	World Development	Ghana	cross-section	Heckman Selection/IV	Yes	Mixed
Alemu and Genowo	2023	JKE	Ethiopia	cross-section	PSM	Yes	Positive
Ali and Awade	2019	Helyon	Togo	cross-section	Switching	Yes	Positive
Anne	2012	Thesis	Kenya	cross-section	OLS	No	Mixed
Annim	2018	Enterprise	Ghana	cross-section	OLS/Probit	Yes	Positive
Atamja and Yoo	2021	Sustainability	Cameroon	cross-section	Switching	Yes	Positive
Baiyegunhi et al	2010	AJAR	Ethiopia	cross-section	Switching	Yes	Positive
Bocher et al	2017	AJEMS	Ethiopia	cross-section	OLS/Switching	Yes	Positive
Brannen Corner	2009	Disertation	Tanzania	cross-section	OLS/Probit	No	Mixed
Buchenrieder et al	2019	Agr. Fin.Rev	Cameroun	Panel	Probit	Yes	Positive
Copestake et al	2010	Journ. Devt.Std	Zambia	cross-section		Yes	Mixed
Dimova and Adebowale	2017	Devt Studies	Nigeria	cross-section	Mills Ratio	Yes	Positive
Fafona et al	2015	Rev.	Côte d'Ivoire	cross-section	PSM	Yes	Positive
Haddad and Maluccio	2003	Eco Dvt Cul Chag	SA	cross-section	IV	Yes	Positive
Idrissu et al	2017	Agric. Fin.Rev	Ghana	cross-section	PSM	Yes	No
Lastarria-Cornhiel and Shimamura	2008	Economies	Malawi	cross-section	OLS/Probit	Yes	Mixed
Manja and Badjie	2022	SAGE	Gambia	cross-section	PSM	Yes	Mixed
Mejaha et al	2010	Nig Agr Jour	Nigeria	cross-section	OLS	Yes	Positive
Mensah et al	2022	WJEMSD	Ghana	cross-section	PSM	Yes	Positive
Mera et al.	2019	JITLL	Ethiopia	cross-section	PSM	Yes	Positive
Mwansakilwa et al	2017	AJARE	Zambia	cross-section	PSM	Yes	Positive
Nanor	2008	Thesis	Ghana	cross-section	OLS/Heckman	No	Mixed
Ogundeji et al	2018	Agrekon	SA	cross-section	Probit	Yes,	Positive
Okafor et al.	2016	IJMRI	Nigeria	Time -series	OLS	Yes	Negative
Okoyo et al	2021	Afr Fin.Rev	Ethiopia	cross-section	PSM	Yes	Positive
Owuor George	2009	Agr Eco	Kenya	Cross-section	PSM	Yes	Positive
Ozoh et al	2022	IJMS	Nigeria	Cross-section	IV	Yes	Positive
Tekana and Oladele	2011	Jour Hum. Eco	SA	cross-section	OLS	Yes	Positive
Tita	2017	Thesis	SSA	cross-section	OLS	No	No
Salia	2014	IJARBS	Tanzania	cross-section	PCA	Yes	Positive

Notes: Categorisation of effects was made using authors conclusion and the defined threshold in section 2.5. All journal articles as well as unpublished papers are duly referenced in the reference section.

Table B.2: Descriptive Studies

Author	Year	Journal	Country	Data	Technique	Published	Effect
Adjei et al.	2009	BWPI Working Papers	Ghana	cross section	T-Test	No	Positive
Alcino das Felicidades FabHio	2008	Thesis	Mozambique	Cross section	summary stat	No	Mixed
Barnes et al.	2001		Uganda	cross section	ANOVA	No	Positive
Doocy et al	2005	SSM	Ethiopia	cross-section	ANOVA	Yes	No
Ganle et al	2015	World Development	Ghana	Cross section	summary stat	Yes	Mixed
Fasanya NS Onakoya	2012	JSDA	Nigeria	Cross section	Chi-square	Yes	Positive
Gebru and Paul	2011	JSDA	Ethiopia	cross-secton	T-Test	Yes	Mixed
Metrine and Omoro	2019	ADFJ	Kenya	Cross section	summary stat	Yes	Positive
Nicholas Mugabi	2010	Thesis	Uganda	crosssecitonal	Chi-square	No	Yes
Nwanesi Peter Karubi	2006	Thesis	Nigeria	Cross section	summary stat	No	Positive

Notes: Categorisation of effects was made using authors conclusion and the defined threshold in section 2.5. All journal articles as well as unpublished papers are duly referenced in the reference section.

Table B.3: Randomized Control Trials

Author	Year	Journal	Country	Data	Technique	Published	Effect
Asraf et al.	2009	AER	Kenya	Cross-section	RCT	Yes	No
Crepon et al	2015	AER	Morocco	cross-section	RCT	Yes	No
Karlan and Zinman	2011	Rev. Fin. Studies	South Africa	cross-section	RCT	Yes	Positive
Torazzi et al	2015	American Economic Journal	Ethiopia	cross-section	RCT	Yes	No
Magezi and Nakano	2020	Jap.J Agric. Econs	Tanzania	cross-section	RCT	Yes	No
Nakano and Magezi	2020	World Development	Tanzania	cross-section	RCT	Yes	No

Notes: Categorisation of effects was made using authors conclusion and the defined threshold in section 2.5. All journal articles as well as unpublished papers are duly referenced in the reference section.

Table B.4: Excluded Studies

Author	Year	Country	Outcome	Effect
Akalu et al	2010	Ethiopia	Food Security	Positive
Bulte et al	2014	Tanzania	Yield	Positive
Benin and You	2007	Uganda	Income	Positive
Hotz et al	2012	Uganda	Food Security	Positive
Kijima	2014	Uganda	Income	No Sig
Low et al	2007	Mozambique	Food security	Positive
Matsumoto	2014	Uganda	Income	Positive
Todo and Takahashi	2013	Ethiopia	Income	Positive
Waarts et al	2012	Kenya	Income	Positive

Appendix C Bias and efficiency Trade-offs from Matching

Table C.1: Bias and efficiency Trade-offs from Matching

Type	Bias	Variance
NN		
Multiple/Single	(Inc)/(Dec)	(Dec)/(Inc)
	Bias	Variance
Replacement:		
Yes/No	(Decrease)/(Inc)	(Inc)/(Dec)
	Bias	Variance
Choice:		
NN / Radius	(Dec)/(Inc)	(Inc)/(Dec)
Local Linear / NN	(Inc)/(Dec)	(Dec)/(Inc)
Caliper:		
small / large	(Dec)/(Inc)	(Inc)/(Dec)

NN: Nearest Neighbour
Dec: Decrease
Inc: Increase

Appendix D Description of Propensity Scores

Table D.1: Description of estimated Propensity Score for Model 1 (Consumption)

		Estimated	Propensity	Score	
	Percent	least			
1 Percent	0.0733945	0.0406343			
5 Percent	0.0929592	0.0481072			
10 Percent	0.1098986	0.0561776		Observations	4,611
25 Percent	0.1409261	0.0574886		Weight Sum.	4,611
50 Percent	0.1765921			Average	0.1765118
		Largest		Std. Dev.	0.0502398
75 Percent	0.2103451	0.3846922			
90 Percent	0.2421463	0.3886635		Variance	0.002524
95 Percent	0.2587341	0.3905966		Skewness	0.184716
99 Percent	0.2972379	0.3971504		Kurtosis	2.984626

Table D.1 Cont'd: Description of estimated Propensity Score for Model 2 (Income)

		Estimated	Propensity	Score	
	Percent	Least			
1 Percent	0.0732429	0.0414938			
5 Percent	0 .0925176	0.0584446			
10 Percent	0.1094242	0.0592577		Observations	4,611
25 Percent	0.1418467	0.0626676		Weight Sum.	4,611
50 Percent	0.1770406			Average	0.1765159
		Largest		Std.Dev.	0 .0498684
75 Percent	0 .209182	0.3873388			
90 Percent	0.2392987	0.3916251		Variance	0.0024869
95 Percent	0.2584675	0.3919675		Skewness	0.1701347
99 Percent	0 .29408	0.3967158		Kurtosis	3.019334

- Table D.1 above presents the description of the estimated propensity scores from all

Table D.1 Cont'd: Description of Propensity Score for Model 3 (Food Expenditure)

		Estimated	Propensity	Score	
	Percent	Least			
1 Percent	0.0711675	0.0004009			
5 Percent	0.09164	0.0013291			
10 Percent	0.108816	0.0030581		Observations	4,611
25 Percent	0.1410406	0.0035395		Weight Sum	4,611
50 Percent	0.1766132			Average	0.1765143
		Largest		Std. Dev.	0.0512297
75 Percent	0.2106583	0.3915581			
90 Percent	0.2421583	0.3920374		Variance	0.0026245
95 Percent	0.2604203	0.3944652		Skewness	0.1095818
99 Percent	0.2991649	0.4002934		Kurtosis	3.150026

Table D.1 Cont'd: Description of Propensity Score for Model 4 (Non-Food Expenditure)

		Estimated	Propensity	Score	
	Percent	Least			
1 Percent	0.0731846	0.0112085			
5 Percent	0.0921899	0.0426435			
10 Percent	0.1098189	0.0579308		Observations	4,611
25 Percent	0.1413876	0.0595423		Weight Sum	4,611
50 Percent	0.1766264			Average	0.1765107
		Largest		Std. Dev.	0.0501964
75 Percent	0.209667	0.3891289			
90 Percent	0.2405853	0.3903656		Variance	0.0025197
95 Percent	0.2595149	0.3927162		Skewness	0.1740069
99 Percent	0.294947	0.394879		Kurtosis	3.029386

Table D.1 Cont'd: Description of Propensity Score for Model 5 (Education Expenditure)

		Estimated	Propensity	Score	
	Percent	Least			
1 Percent	0.0732283	0.0399925			
5 Percent	0.0922363	0.0590965			
10 Percent	0.1087652	0.0595677		Observations	4,611
25 Percent	0.1410412	0.0601475		Weight Sum	4,611
50 Percent	0.1766046			Average	0.1765085
		Largest		Std. Dev.	0.0504739
75 Percent	0.2098879	0.3894314			
90 Percent	0.2395247	0.3919377		Variance	0.0025476
95 Percent	0.2597193	0.4032709		Skewness	0.2003135
99 Percent	0.2952287	0.4060487		Kurtosis	3.077324

the models using the five welfare indicators which are consumption per capita, income, food expenditure, non-food expenditure and eduction expenditure

- The propensity scores from Table D.1 are broken into percentiles 1 to 100
- The Description confirms the unconfoundedness and common support assumptions the the propensity scores are bounded from zero and one (that is lie between zero and one)

Appendix E Check for Balance with the T-Tests and Standard Bias

Table E.1: Standardised Bias Reduction from Matching (consumption)

		Mean		S.Bias	% fall in Bias	T-test	
Covariate		Treatment	Counterfactual			Stat	P
Log Tot. Cons (2012)	UnM	11.403	11.390	1.7		0.430	0.667
	M	11.403	11.374	3.3	-91.8	0.68	0.498
Value	UnM	2.80e+06	2.90e+06	-1.400		-0.350	0.72
	M	2.80e+06	2.90e+06	-1.1	25.5	-0.23	0.821
Yield	UnM	692.480	751.800	-2.700		-0.640	0.522
	M	692.48	568.21	5.7	109.5	1.64	0.101
No. Men Hired	UnM	1.141	1.049	4.3		1.140	0.256
	M	1.141	1.0202	5.7	-31.6	1.17	0.242
Asset	UnM	0.684	0.707	-5.000		-1.300	0.195
	M	0.684	0.694	-2.1	57.00	-0.43	0.0669
No. Women Hired	UnM	0.620	0.458	9.60		257.150	0.010
	M	0.620	0.530	5.3	44.1	1.04	0.300
Women-Pay	UnM	2.80e+05	2.10e+05	4.1		1.090	0.278
	M	2.80e+05	2.5e+05	1.8	55.0	0.36	0.719
TV	UnM	0.602	0.490	22.500		5.800	0
	Matched	0.602	0.613	-2.2	90.1	-0.46	0.648
Phone	UnM	0.926	0.864	20.400		4.880	0.000
	M	0.926	0.934	-2.8	96.2	0.470	0.642
Computer	UnM	0.140	0.145	-1.400		-0.350	0.723
	M	0.140	0.135	1.4	-2.3	0.29	0.774
Dist-Road	UnM	6.374	5.842	6.5		1.740	0.082
	M	6.374	5.907	5.7	12.2	1.14	0.256
Dist-Popcentre	UnM	17.699	18.396	-4.600		-1.180	0.239
	M	17.699	17.229	3.1	32.7	0.63	0.528
Dist-Market	UnM	70.524	67.127	7.8		2.020	0.044
	M	70.524	71.57	-2.4	69.2	-0.48	0.634
Dist-Border	UnM	336.620	314.590	12.800		3.200	0.001
	M	336.620	336.2	0.2	98.1	0.05	0.961

Table E 1 Cont'd: Standardised Bias Reduction from Matching (Income)

		Mean		S.Bias	% fall in Bias	T-test	
Covariate		Treatment	Counterfactual			Stat	P
Income (2012)	UnM	34732	34112	0.6		0.180	0.859
	M	34732	35053	0.3	48.3	-0.07	0.946
Value	UnM	2.80e+06	2.90e+06	-1.400		-0.350	0.726
	M	2.80e+06	2.60e+06	4.1	-182.7	0.97	0.33
Yield	UnM	692.480	751.800	-2.700		-0.640	0.522
	M	692.480	699.47	-0.300	88.2	-0.08	0.934
No Men Hired	UnM	1.141	1.049	4.3		1.140	0.256
	M	1.141	1.1044	1.7	59.7	0.35	0.724
Asset	UnM	0.684	0.707	-5.000		-1.300	0.195
	M	0.684	0.710	-0.56	-12.8	-1.13	0.258
No. Women Hired	UnM	0.620	0.458	9.6		2.57	0.010
	M	0.620	0.628	-0.5	95.2	-0.08	0.934
Women-Pay	UnM	2.80e+05	2.10e+05	4.1		1.090	0.278
	M	2.80e+05	3.80e+05	-5.2	-28.4	-0.89	0.374
TV	UnM	0.602	0.490	22.500		5.800	0
	M	0.602	0.595	1.5	93.4	0.30	0.762
Phone	UnM	0.926	0.864	20.400		4.880	0.
	M	0.926	0.930	-1.2	94.1	-0.29	0.774
Computer	UnM	0.140	0.145	-1.400		-0.350	0.723
	M	0.140	0.150	-2.1	-53.5	-0.42	0.672
Dist-Road	UnM	6.374	5.842	6.5		1.740	0.082
	M	6.374	6.521	-1.8	72.5	-0.34	0.737
Dist-Popcentre	UnM	17.699	18.396	-4.600		-1.180	0.239
	M	17.699	18.024	-2.2	53.3	-0.44	0.660
Dist-Market	UnM	70.524	67.127	7.8		2.020	0.044
	M	70.524	69.826	1.6	79.5	0.32	0.745
Dist-Border	UnM	336.620	314.590	12.800		3.200	0.001
	M	336.620	337.12	-0.3	97.7	-0.06	0.952

Table E.1 Cont'd: Standardised Bias Reduction from Matching (Food Expenditure)

		Mean		S.Bias	% fall in Bias	T-test	
Covariate		Treatment	Counterfactual			Stat	P
Fd. Exp (2012)	UnM	1.20e+05	1.40e+05	-7.700		-1.630	0.104
	M	1.20e+05	1.10e+05	4	47.900	2.190	0.029
Value	UnM	2.80e+06	2.90e+06	-1.400		-0.350	0.726
	M	2.80e+06	2.80e+06	-0.200	84.400	-0.050	0.961
Yield	UnM	692.480	751.800	-2.700		-0.640	0.522
	M	692.480	575.210	5.3	-97.700	1.510	0.132
No. Men Hired	UnM	1.141	1.049	4.3		1.140	0.256
	M	1.141	1.097	2.1	51.400	0.420	0.676
Asset	UnM	0.684	0.707	-5.000		-1.300	0.195
	M	0.684	0.697	-2.700	46.300	-0.540	0.592
No. Women Hired	UnM	1.692	1.771	-4.500		-1.150	0.250
	M	1.692	1.617	4.3	3.5	0.820	0.410
Women-Pay	UnM	2.80e+05	2.10e+05	4.1		1.090	0.278
	M	2.80e+05	1.30e+05	8.699	-113.700	1.880	0.061
TV	UnM	0.602	0.490	22.500		5.800	0
	M	0.602	0.623	-4.200	81.300	-0.860	0.387
Phone	UnM	0.926	0.864	20.400		4.880	0
	M	0.926	0.930	-1.200	94.100	-0.290	0.774
Computer	UnM	0.140	0.145	-1.400		-0.350	0.723
	M	0.140	0.129	3.2	-130.200	0.650	0.514
Dist-Road	UnM	6.375	5.842	6.5		1.740	0.082
	M	6.374	6.168	2.5	61.200	0.480	0.628
Dist-Popcentre	UnM	17.699	18.396	-4.600		-1.180	0.239
	M	17.699	17.524	1.2	74.900	0.240	0.810
Dist-Market	UnM	70.524	67.127	7.8		2.020	0.044
	M	70.524	68.354	5	36.100	0.990	0.322
Dist-Border	UnM	336.620	314.590	12.800		3.200	0.001
	M	336.620	327.110	5.5	56.900	1.130	0.258

Table E.1 Cont'd: Standardised Bias Reduction from Matching (Non-food expenditure)

		Mean		S.Bias	% fall in Bias	T-test	
Covariate		Treatment	Counterfactual			Stat	P
Nfd Exp (2012)	UnM	1419.200	1466.200	-1.200		-0.260	0.793
	M	1419.200	1306.100	2.9	-141.200	0.940	0.347
Value	UnM	2.80e+06	2.90e+06	-1.400		-0.350	0.726
	M	2.80e+06	2.70e+06	1.4	0.5	0.320	0.746
Yield	UnM	692.480	751.800	-2.700		-0.640	0.522
	M	692.480	680.130	0.6	79.200	0.150	0.880
N0. Men Hired	UnM	1.141	1.049	4.3		1.140	0.256
	M	1.141	1.115	1.2	71.500	0.240	0.807
Asset	UnM	0.684	0.707	-5.000		-1.300	0.195
	M	0.684	0.688	-0.800	83.900	-0.160	0.873
Men-Pay	UnM	8.50e+05	6.80e+05	3.5		0.950	0.344
	M	8.50e+05	9.60e+05	-2.400	32.600	-0.440	0.659
Log No. Women Hired	UnM	1.692	1.771	-4.500		-1.150	0.250
	M	1.692	1.758	-3.700	16.500	-0.760	0.450
Women-Pay	UnM	2.80e+05	2.10e+05	4.1		1.090	0.278
	M	2.80e+05	3.30e+05	-2.600	35.400	-0.490	0.623
TV	UnM	0.602	0.490	22.500		5.800	0
	M	0.602	0.593	1.7	92.300	0.350	0.724
Phone	UnM	0.926	0.864	20.400		4.880	0
	M	0.926	0.934	-2.400	88.100	-0.580	0.560
Computer	UnM	0.140	0.145	-1.400		-0.350	0.732
	M	0.140	0.127	3.9	-181.400	0.800	0.423
Dist-Road	UnM	6.374	5.842	6.5		1.740	0.082
	M	6.374	6.479	-1.300	80.300	-0.250	0.802
Dist-Popcentre	UnM	17.699	18.396	-4.600		-1.180	0.239
	M	17.699	17.697	0	99.800	0.000	0.998
Dist-Market	UnM	70.524	67.127	7.8		2.020	0.044
	M	70.524	70.052	1.1	86.100	0.220	0.829
Dist-Border	UnM	336.620	314.590	12.800		3.200	0.001
	M	336.620	332.590	2.3	81.700	0.480	0.632

Table E.1 Cont'd: Standardised Bias Reduction from Matching (Education)

		Mean		S.Bias	% fall in Bias	T-test	
Covariate		Treatment	Counterfactual			Stat	P
Edt Exp (2012)	UnM	8599.500	7208	6.3		1.680	0.093
	M	8599.500	8478.100	0.6	91.300	0.110	0.913
Value	UnM	2.80e+06	2.90e+06	-1.400		-0.350	0.726
	M	2.80e+06	3.20e+06	-6.000	-316.300	-1.170	0.241
Yield	UnM	692.480	751.800	-2.700		-0.640	0.522
	M	692.480	591.580	4.6	-70.100	1.320	0.188
No. Men Hired	UnM	1.141	1.049	4.3		1.140	0.256
	M	1.141	1.054	4.1	5.5	0.850	0.394
Asset	UnM	0.684	0.707	-5.000		-1.300	0.195
	M	0.684	0.725	-8.800	-77.300	-1.790	0.073
Log No. Women Hired	UnM	1.692	1.771	-4.500		-1.150	0.250
	M	1.692	1.743	-2.900	35.000	-0.580	0.559
Women-Pay	UnM	2.80e+05	2.10e+05	4.1		1.090	0.278
	M	2.80e+05	4.30e+05	-7.900	-93.800	-1.400	0.162
TV	UnM	0.602	0.490	22.500		5.800	0
	M	0.602	0.591	2.2	90.100	0.450	0.650
Phone	UnM	0.926	0.864	20.400		4.880	0
	M	0.926	0.923	1.2	94.100	0.280	0.779
Computer	UnM	0.140	0.145	-1.400		-0.350	0.723
	M	0.140	0.138	0.7	48.800	0.140	0.886
Dist-Road	UnM	6.374	5.842	6.5		1.740	0.082
	M	6.374	6.019	4.3	33.300	0.870	0.386
Dist-Popcentre	UnM	17.699	18.396	-4.600		-1.180	0.239
	M	17.699	17.030	4.4	4.1	0.930	0.350
Dist-Market	UnM	70.524	67.127	7.8		2.020	0.044
	M	70.524	71.166	-1.500	81.100	-0.290	0.771
Dist-Border	UnM	336.620	314.590	12.800		3.200	0.001
	M	336.620	349.290	-7.400	42.400	-1.490	0.137

Appendix F Matrices of Correlation

Table F.1: Correlation Matrix for Chapter 3

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Log Tot. Cons 2012	1.000												
(2) Log Tot. Cons 2016	0.496	1.000											
(3) Income 2012	0.074	0.068	1.000										
(4) Income 2016	0.036	0.053	0.024	1.000									
(5) Income 2018	0.078	0.124	0.027	-0.007	1.000								
(6) Fd Exp 2012	0.539	0.102	0.012	0.005	0.002	1.000							
(7) Fd Exp 2016	0.313	0.718	0.047	0.036	0.055	0.089	1.000						
(8) Fd Exp 2018	-0.030	-0.108	-0.006	-0.037	0.082	0.072	-0.046	1.000					
(9) Nfd Exp 2012	0.227	0.212	0.034	-0.003	0.031	0.085	0.201	-0.051	1.000				
(10) Nfd Exp Exp2016	0.098	0.151	0.017	0.025	0.029	0.017	0.210	-0.026	0.122	1.000			
(11)Nfd Exp Exp2018	0.101	0.151	-0.020	0.006	0.160	0.003	0.080	-0.044	0.026	0.024	1.000		
(12) Nfd Exp 2012	0.292	0.242	0.062	0.032	0.139	0.083	0.163	-0.021	0.071	0.041	0.142	1.000	
(13) Edt Exp 2016	0.196	0.202	0.068	0.036	0.102	0.040	0.136	-0.012	0.037	0.023	0.144	0.370	1.000

	(14)	(15)	(16)	(17)	(18)	(19)
(14) Value	1.0000					
(15) Yield	-0.0339	1.0000				
(16) No. Men Hired	-0.1129	-0.0324	1.0000			
(17) Asset	-0.2099	0.0047	0.1110	1.0000		
(18) No. Women Hired	-0.0709	-0.0343	0.4332	0.0754	1.0000	
(19) Women-Pay	-0.0180	-0.0484	-0.0714	-0.0287	-0.0376	1.0000

	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)
(20) FC	1.0000								
(21) TV	0.0797	1.0000							
(22) Phone	0.0780	0.3774	1.0000						
(23) Computer	0.0272	0.2280	0.1086	1.0000					
(24) Dist-Road	0.0261	-0.2132	-0.0855	-0.0881	1.0000				
(25) Dist-Popcenter	-0.0151	-0.3238	-0.1352	-0.1319	0.4718	1.0000			
(26) Dist-Market	0.0307	-0.1201	-0.0496	-0.0329	0.1554	0.2380	1.0000		
(27) Dist-Border	0.0544	0.1865	0.0786	0.0549	-0.1021	-0.1020	0.1014	1.0000	
(28) Dist-Capital	-0.0347	-0.3167	-0.1672	-0.0992	0.2314	0.3085	0.3010	-0.1151	1.0000

Table F.2: Correlation Matrix for Other Chapters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) latitute	1.000							
(2) Dist-market	0.111	1.000						
(3) Dist-border	0.299	0.713	1.000					
(4) Dist-popcenter	0.181	0.259	0.037	1.000				
(5) Rainfall	0.006	0.455	0.647	-0.159	1.000			
(6) Dist-capital	0.188	0.026	-0.353	0.257	-0.305	1.000		
(7) Wetness	0.131	0.071	-0.337	0.237	-0.283	0.970	1.000	
(8) HH Size	0.056	0.061	0.0250	0.104	-0.028	0.038	0.041	1.000

	(9)	(10)	(11)	(12)
(9) Tot Cons	1.000			
(10) Edt Exp	0.023	1.000		
(11) Fd EXp	0.942	-0.047	1.000	
(12) Nfd Exp	0.139	0.169	0.031	1.000

	(13)	(14)	(15)	(16)	(17)	(18)
(13) Read	1.000					
(14) Credit	0.032	1.000				
(15) Male	0.221	0.014	1.000			
(16) Religion	0.129	0.099	-0.120	1.000		
(17)Employed	0.090	0.010	0.080	-0.008	1.000	
(18) Married	0.173	0.033	0.648	-0.130	0.032	1.000

Appendix G Robustness using all 814 households who applied for loan

Table G.1: The ATT Estimates from the Matched Samples

	NN		IPW
	$\hat{ATT}_M$		$\hat{ATT}_M$
Outcome	NN(5)	NN(2)	
First Welfare Indicator			
Log Tot Cons (2016)	0.021	0.016	0.035
	(0.028)	(0.033)	(0.024)
Second Welfare Indicator			
Log Income (2016)	0.042	0.014	0.021
	(0.042)	(0.047)	(0.040)
Income (2018)	4284.12	3782.77	
	(3212.566)	(3392.917)	
Third Welfare Indicator			
Log Fd Exp (2016)	0.012	0.003	0.032
	(0.029)	(0.034)	(0.026)
Fourth Welfare Indicator			
Nfd Exp (2016)	-497.3048		-374.2072
	(469.713)		(278.174)
Non-Food Exp 2018	999.720	1938.146	
	(1408.445)	(1510.238)	
Fifth Welfare Indicator			
Edt Exp (2016)	958.1348	1370.599	
	(885.952)	(985.353)	
No. Observation	4611	4611	4611

- **Notes:** Standard errors are reported in brackets.
- Variables were not logged where either convergence was not attainable in Logs or specific partner matches could not be found using logs

Table G.2: **The ATT Estimates from the Matched Samples**

	NN		IPW
	$\hat{ATT}_M^{DID}$		$\hat{ATT}_M^{DID}$
Outcome	NN(5)	NN(2)	
First Welfare Indicator			
△Log Tot. Cons (2016)	0.034	0.014	0.031
	(0.029)	(0.033)	(0.024)
Second Welfare Indicator			
△Income (2016)	10116.84	6402.401	
	(9725.971)	(10740.17)	
△Income (2018)	3516.209	4821.378	
	(5011.014)	(5332.142)	
Third Welfare Indicator			
△Log Fd Exp (2016)	0.001		0.0145
	(0.028)		(0.025)
Fourth Welfare Indicator			
△Nfd Exp (2016)	-550.869	-66.683	
	(473.119)	(230.806)	
△Nfd Exp (2018)	946.155	1851.886	
	(1408.864)	(1513.119)	
Fifth Welfare Indicator			
△Edt Exp (2016)	821.474	1090.754	
	(862.233)	(993.939)	
No. Observation	4611	4611	4611

- **Notes:** Standard errors are reported in brackets.
- Variables were not logged where either convergence was not attainable in Logs or specific partner matches could not be found using logs.
- △ is the difference in the welfare level before and after the treatment.

Table G.3: **The ATT Estimates from the Combined Models**

	Log Tot Cons		Income		Income
	PSM+DID		PSM+DID		PSM+DID
	2012-2016		2012-2016	2012-2016	2012-2018
after	0.241***	0.199***	18209.923***	18369.765***	8103.848**
	(0.016)	(0.019)	(4572.802)	(5518.934)	(3420.437)
FC	−1.823***	−1.738***	-40098.128	-19175.71	-20875.53
	(0.540)	(0.547)	(145408)	(147319.63)	(102569)
after*FC	0.05**	0.05**	5446.255	6967.525	4438.295
	(0.023)	(0.023)	(6469.808)	(6460.362)	(4839.39)
Dist-Capital		−0.002*		−794.469***	
		(0.001)		(301.859)	
Rainfall		0.001***		67.232	
		(0.0004)		(114.836)	
Wetness of Land		−0.004***		-157.406	
		(0.001)		(242.939)	
Healthshock		−0.001		8785.92	
		(0.023)		(6683.918)	
Latitude		0.021		1772.037	
		(0.042)		(11939.72)	
Longitude		0.048*		3483.109	
		(0.026)		(7557.748)	
Constant	12.431***	13.013***	65145	47475.403	84097.435
	(0.509)	(0.703)	(137100)	(196191.27)	(96699)
HH Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	0.766	0.771	0.511	0.527	0.342
No. Observation	9222	9149	9222	9149	13833

- **Notes:** Standard errors are reported in brackets and Superscripts *, **, *** indicates significance levels at 10% and 5% and 1% respectively.
  The PSM+DID models above control for selection bias by including all the variables in **??** during matching. This is done through the inverse propensity weight.
- Variables were not logged where either convergence was not attainable in Logs or specific partner matches could not be found using logs.

Table G.4: The ATT Estimates from the Combined Models

	Fd Exp		Nfd Exp		Nfd Exp	Edu-Exp	Edu-Exp
	PSM+DID 2012-2016		PSM+DID 2012-2016	2012-2016	PSM+DID 2012-2018		
after	24461.065***	767.538***	849.465***	11280.795***	11280.795***	83.345	56.044
	(7400.568)	(9057.861)	(187.925)	(217.566)	(603.319)	(510.81)	(538.082)
FC	−236149.69	−191013.35	-4089.977	−5069.772	131971***	-4707.3	7000.119
	(241467.34)	(247190)	(6084.87)	(6210.69)	(18422)	(16663.92)	(16612)
after*FC	11008.840	11671.526	-280.96	-270.408	613.011	331.267	764.305
	(0.023)	(10583.427)	(265.943)	(267.735)	(853.792)	(722.848)	(710.771)
Dist-Capital		−224.177		−1.125			2.007
		(494.306)		(12.537)			(33.256)
Rainfall		389.565**		6.326			−22.608*
		(187.764)		(4.735)			(12.597)
Wetness of Land		−1251.059***		-16.203			24.327
		(400.583)		(10.102)			(26.867)
Healthshock		1452.644		1330.722***			-582.453
		(10944.259)		(293.004)			(778.07)
Latitude		−5323.523		561.079			−5302.811***
		(19589.708)		(494.966)			(1320)
Longitude		13669.841		425.592			-409.469
		(12426.776)		(314.52)			(836)
Constant	264851.02	558068.97*	5083.224	1062.329	4833.108	4499.994	60146***
	(221281.15)	(323348)	(5579.903)	(8137.976)	(16391)	(15318)	(21739)
HH Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.557	0.559	0.548	0.556	0.327	0.683	0.691
No. Observation	9222	9149	9222	9149	13833	9222	9149

Notes: Standard errors are reported in brackets and Superscripts *, **, *** indicates significance levels at 10%, 5% and 1% respectively. The PSM+DID models above control for selection bias by including all the variables in **??** during matching. This is done through the inverse propensity weight. Variables were not logged where either convergence was not attainable in Logs or specific partner matches could not be found using logs.

Appendix H Robustness using households who applied for formal loans

Table H.1: The ATT Estimates from the Matched Samples

	NN		IPW
	$\hat{ATT}_M$		$\hat{ATT}_M$
Outcome	NN(5)	NN(2)	
First Welfare Indicator			
Log Tot Cons (2016)	0.013	0.012	0.043
	(0.034)	(0.039)	(0.029)
Second Welfare Indicator			
Log Income (2016)	0.048	0.017	0.042
	(0.055)	(0.061)	(0.051)
Third Welfare Indicator			
Log Fd Exp (2016)	0.037	0.047	0.041
	(0.036)	(0.040)	(0.030)
Fourth Welfare Indicator			
Nfd Exp (2016)	44.616	3.69	-254.822
	(235.195)	(261.217)	(261.342)
Fifth Welfare Indicator			
Edt Exp (2016)	943.561	123.273	
	(1235.365)	(1315.209)	
No. Observation	4611	4611	4611

- **Notes:** Standard errors are reported in brackets and Superscripts *, **, *** indicates significance levels at 10% and 5% and 1% respectively.
- Variables were not logged where either convergence was not attainable in Logs or specific partner matches could not be found using logs

Table H.2: The ATT Estimates from the Matched Samples

	NN		IPW
	$\hat{ATT}_M^{DID}$		$\hat{ATT}_M^{DID}$
Outcome	NN(5)	NN(2)	
First Welfare Indicator			
△Log Tot Cons (2016)	0.005	0.006	0.049
	(0.034)	(0.040)	(0.029)
Second Welfare Indicator			
△Income (2016)	13108.5		
	(15067.83)		
Third Welfare Indicator			
△Log Fd Exp (2016)	0.017	0.047	0.047
	(0.043)	(0.036)	(0.029)
Fourth Welfare Indicator			
△Nfd Exp (2016)	-22.307	-20.862	-264.097
	(243.461)	(275.006)	(260.742)
Fifth Welfare Indicator			
△Edt Exp (2016)	585.215	531.356	
	(1205.029)	(1316.181)	
No. Observation	4611	4611	4611

- **Notes:** Standard errors are reported in brackets.
- Variables were not logged where either convergence was not attainable in Logs or specific partner matches could not be found using logs.
- △ is the difference in the welfare level before and after the treatment.

Table H.3: The ATT Estimates from the Combined Models

	Log Tot Cons		Income		Income
	PSM+DID		PSM+DID		PSM+DID
	2012-2016		2012-2016	2012-2016	2012-2018
after	0.241^{***}	0.199^{***}	17851.457^{***}	19657.372^{***}	8162.602^{**}
	(0.016)	(0.019)	(4928.024)	(5474.634)	(3649.329)
FC	-1.341^{**}	-1.738^{***}	9516.296	14847.932	8749.013
	(0.53)	(0.547)	(165313.33)	(148911.86)	(115443.32)
after*FC	0.068^{***}	0.05^{**}	12667.408^{*}	4914.44	7126.481
	(0.022)	(0.023)	(6985.943)	(6448.054)	(5173.275)
Dist-Capital		-0.002^{*}		-794.469^{***}	
		(0.001)		(301.859)	
Rainfall		0.001^{***}		67.232	
		(0.0004)		(114.836)	
Wetness of Land		-0.004^{***}		-157.406	
		(0.001)		(242.939)	
Healthshock		-0.001		8785.92	
		(0.023)		(6683.918)	
Latitude		0.021		1772.037	
		(0.042)		(11939.72)	
Longitude		0.048^{*}		3483.109	
		(0.026)		(7557.748)	
Constant	12.431^{***}	13.013^{***}	65324.272	47475.403	84058.266
	(0.505)	(0.703)	(157012.75)	(196191.27)	(109635.8)
HH Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	0.761	0.771	0.509	0.527	0.340
No. Observation	9222	9149	9222	9149	13833

- **Notes:** Standard errors are reported in brackets and Superscripts *, **, *** indicates significance levels at 10% and 5% and 1% respectively.
  The PSM+DID models above control for selection bias by including all the variables in **??** during matching. This is done through the inverse propensity weight.
- Variables were not logged where either convergence was not attainable in Logs or specific partner matches could not be found using logs.

Table H.4: The ATT Estimates from the Combined Models

	Fd Exp		Nfd Exp		Nfd Exp	Edu-Exp	Edu-Exp
	PSM+DID 2012-2016		PSM+DID 2012-2016	2012-2016	PSM+DID 2012-2018		
after	24171.502***	756.724***	856.425***	11280.795***	11419.903***	117.129	67.124
	(7470.501)	(9040.011)	(180.862)	(217.566)	(565.996)	(524.463)	(500.012)
FC	−202818.06	−191013.35	-446.21	−5069.772	113474.84***	-3434.892	7005.729
	(258308.97)	(247199)	(6234.038)	(6210.69)	(18397.143)	(18129)	(16612)
after*FC	9133.944	10484.526	-168.493	-270.408	-248.709	236.451	764.305
	(10593.307)	(10570.400)	(256.473)	(267.735)	(802.614)	(743.71)	(710.771)
Dist-Capital		−224.177		−1.125			2.007
		(494.306)		(12.537)			(33.256)
Rainfall		389.565**		6.326			−22.608*
		(187.764)		(4.735)			(12.597)
Wetness of Land		−1251.059***		-16.203			24.327
		(400.583)		(10.102)			(26.867)
Healthshock		1452.644		1330.722***			-582.453
		(10944.259)		(293.004)			(778.07)
Latitude		−5323.523		561.079			−5522.234***
		(19589.708)		(494.966)			(1300)
Longitude		13669.841		425.592			-409.469
		(12426.776)		(314.52)			(836)
Constant	264995.8	558068.97*	5102.244	1062.329	4740.369	4483.102	60146***
	(237109.35)	(323348)	(5720.229)	(8137.976)	(16879.39)	(16676)	(21739)
HH Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.552	0.559	0.550	0.3276	0.328	0.665	0.691
No. Observation	9222	9149	9222	9149	13833	9222	9149

- **Notes:** Standard errors are reported in brackets and Superscripts *, **, *** indicates significance levels at 10%, 5% and 1% respectively.
  The PSM+DID models above control for selection bias by including all the variables in **??** during matching. This is done through the inverse propensity weight.
- Variables were not logged where either convergence was not attainable in Logs or specific partner matches could not be found using logs.

Appendix I Important Controls and Determinants of Welfare

Table I.1: Some Important Controls and Determinants of Welfare

	tot	Edt. Exp	Fdt. Exp	Non. Fd. Exp
Male	7.708	2.515	14.41*	11.81*
	(8.540)	(2.510)	(6.228)	(5.079)
Employed	23.60***	-17.75***	5.903	-11.02***
	(6.132)	(1.551)	(4.146)	(3.274)
Married	64.98***	-5.160*	48.03***	-17.83***
	(8.163)	(2.408)	(5.906)	(4.823)
Christian	-8.192	9.092***	-19.80***	25.34***
	(5.447)	(2.583)	(3.965)	(4.256)
Latitude	-2.214***	-0.0102	-1.436**	-1.726***
	(0.634)	(0.212)	(0.461)	(0.416)
Read	88.71***	7.258***	34.02***	32.08***
	(5.288)	(1.572)	(3.770)	(3.138)
Dist-market	-0.0262	0.0290***	-0.00693	-0.0446***
	(0.0148)	(0.00435)	(0.0104)	(0.00858)
Wetness	0.0562	0.0792***	0.0160	0.113***
	(1.072)	(0.00415)	(0.0110)	(0.00866)
Constant	98.22***	-919.8***	75.20***	40.93***
	(20.18)	(57.05)	(7.390)	(6.569)
GroupFE	Yes	Yes	Yes	Yes
CountryFE	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes
Obs	20238	24307	24265	24265

Notes: Standard errors are presented in brackets and Superscripts *, **, *** indicates significance levels at 10% and 5% and 1% respectively. All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models.

Table I.2: Estimates across various depth of poverty

All Countries PQRFE CANAY	Consumption pa Capita					Education Expenditure				
Variable	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
credit	19.34***	16.13***	11.28***	8.602*	11.79	1.928	0.463	0.127	0.180	-0.589
	(3.646)	(2.812)	(2.706)	(4.448)	(9.787)	(1.357)	(0.389)	(0.351)	(0.587)	(1.455)
sex	16.05**	18.73***	19.27***	27.01***	31.25*	1.566	0.0716	-0.0772	-0.703	-1.505
	(4.995)	(3.852)	(3.707)	(6.095)	(13.41)	(1.902)	(0.545)	(0.492)	(0.823)	(2.039)
religion	25.47***	22.05***	17.29***	15.53***	14.81	-0.925	1.224**	1.976***	3.048***	4.131**
	(3.545)	(2.734)	(2.631)	(4.325)	(9.516)	(1.326)	(0.380)	(0.343)	(0.573)	(1.421)
employed	0.592	3.779	5.192	6.029	8.875	-8.577***	-6.118***	-4.373***	-4.429***	-6.103***
	(3.589)	(2.768)	(2.664)	(4.380)	(9.636)	(1.267)	(0.363)	(0.328)	(0.548)	(1.359)
married	167.4***	156.0***	164.7***	161.2***	166.7***	4.441*	1.956***	0.878	-0.249	-2.107
	(4.776)	(3.684)	(3.545)	(5.828)	(12.82)	(1.805)	(0.517)	(0.467)	(0.780)	(1.934)
latitude	2.181***	1.755***	1.696***	1.307**	1.113	1.150***	0.688***	0.500***	0.266***	-0.0531
	(0.385)	(0.297)	(0.286)	(0.470)	(1.035)	(0.148)	(0.0424)	(0.0382)	(0.0640)	(0.159)
read	33.19***	41.79***	51.05***	57.24***	60.83***	-3.984***	-0.609	0.891**	3.130***	8.989***
	(3.114)	(2.402)	(2.312)	(3.800)	(8.361)	(1.161)	(0.333)	(0.300)	(0.502)	(1.245)
dist-market	-0.0761***	-0.0674***	-0.0598***	-0.0695***	-0.0851***	0.0108**	0.0150***	0.0230***	0.0223***	0.0235***
	(0.00918)	(0.00708)	(0.00682)	(0.0112)	(0.0247)	(0.00341)	(0.000976)	(0.000881)	(0.00147)	(0.00365)
dist-border	-0.0457***	-0.0360***	-0.00108	0.0522**	0.102**	0.0356***	0.0419***	0.0440***	0.0497***	0.0543***
	(0.0132)	(0.0102)	(0.00979)	(0.0161)	(0.0354)	(0.00515)	(0.00148)	(0.00133)	(0.00223)	(0.00552)
dist-popcenter	0.483***	0.476***	0.382***	0.334***	0.335**	0.00855	-0.00105	0.00124	-0.00118	-0.0128
	(0.0433)	(0.0334)	(0.0321)	(0.0528)	(0.116)	(0.0151)	(0.00432)	(0.00390)	(0.00652)	(0.0162)
rainfall	-0.118***	-0.120***	-0.125***	-0.137***	-0.138***	-0.0180***	-0.0156***	-0.0145***	-0.0108***	-0.00660**
	(0.00551)	(0.00425)	(0.00409)	(0.00673)	(0.0148)	(0.00218)	(0.000625)	(0.000564)	(0.000944)	(0.00234)
dist-capital	0.357***	0.316***	0.279***	0.256***	0.160***	0.0992***	0.0940***	0.0919***	0.0890***	0.0831***
	(0.0149)	(0.0115)	(0.0110)	(0.0181)	(0.0399)	(0.00540)	(0.00155)	(0.00140)	(0.00234)	(0.00579)
wetness	3.164***	3.724***	2.808***	1.167	-0.890	-0.0567***	-0.0506***	-0.0358***	0.00256	0.0745***
	(0.643)	(0.496)	(0.478)	(0.785)	(1.728)	(0.00615)	(0.00176)	(0.00159)	(0.00266)	(0.00659)
constant	125.3***	151.7***	189.2***	231.5***	305.1***	-37.34	-0.0517	24.98***	49.56***	73.00*
	(14.20)	(10.95)	(10.54)	(17.32)	(38.12)	(27.25)	(7.805)	(7.047)	(11.79)	(29.21)
GroupFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	20183	20183	20183	20183	20183	24252	24252	24252	24252	24252
pseudo R-sq	0.307	0.284	0.253	0.215	0.227	0.212	0.287	0.365	0.391	0.371

Notes: Standard errors are presented in brackets and Superscripts *, **, *** indicates significance levels at 10% and 5% and 1% respectively. All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models.

Appendix J Effects of credit across various depth of poverty for all countries

Table J.1: Estimates across various depth of poverty

All Countries PQRFE CANAY	Food Expenditure					Non. Food Expenditure				
Variable	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	9.145***	7.871***	4.317*	3.260	2.229	6.675**	5.979***	5.394***	5.768***	8.532**
	(2.520)	(1.800)	(1.747)	(2.896)	(6.431)	(2.185)	(1.136)	(1.048)	(1.655)	(3.162)
Male	41.80***	42.74***	42.67***	57.87***	67.18***	1.893	4.120**	2.507	2.452	7.867
	(3.535)	(2.526)	(2.452)	(4.064)	(9.024)	(3.065)	(1.594)	(1.471)	(2.322)	(4.437)
Religion	0.131	-0.0619	-1.143	-1.476	0.814	13.80***	14.20***	13.23***	16.94***	23.47***
	(2.460)	(1.758)	(1.706)	(2.828)	(6.280)	(2.133)	(1.109)	(1.023)	(1.616)	(3.088)
Employed	7.720**	6.682***	7.857***	6.246*	5.094	-7.870***	-6.464***	-5.998***	-6.312***	-10.26***
	(2.353)	(1.681)	(1.632)	(2.705)	(6.006)	(2.040)	(1.061)	(0.979)	(1.546)	(2.953)
Married	111.2***	104.9***	104.5***	95.87***	85.79***	34.13***	26.90***	21.51***	16.77***	7.315
	(3.354)	(2.396)	(2.326)	(3.856)	(8.561)	(2.908)	(1.513)	(1.395)	(2.203)	(4.210)
Latitude	0.742**	0.677***	0.533**	0.319	0.316	0.861***	0.400**	0.0819	0.0121	-0.296
	(0.274)	(0.196)	(0.190)	(0.315)	(0.700)	(0.238)	(0.124)	(0.114)	(0.180)	(0.344)
Read	7.528***	10.88***	14.01***	15.63***	15.44**	4.790*	11.60***	19.72***	29.19***	43.13***
	(2.155)	(1.539)	(1.494)	(2.477)	(5.499)	(1.868)	(0.972)	(0.896)	(1.415)	(2.704)
Dist-market	-0.0234***	-0.0267***	-0.0281***	-0.0292***	-0.0346*	-0.0425***	-0.0312***	-0.0262***	-0.0302***	-0.0518***
	(0.00632)	(0.00451)	(0.00438)	(0.00726)	(0.0161)	(0.00548)	(0.00285)	(0.00263)	(0.00415)	(0.00793)
Dist-border	-0.0398***	-0.0370***	-0.0156*	0.0186	0.0472	-0.0386***	-0.0315***	-0.0319***	-0.0281***	-0.0393**
	(0.00956)	(0.00683)	(0.00663)	(0.0110)	(0.0244)	(0.00829)	(0.00431)	(0.00398)	(0.00628)	(0.0120)
Dist-popcenter	0.175***	0.146***	0.104***	0.0677*	0.0519	0.128***	0.0913***	0.0770***	0.0462*	0.0363
	(0.0280)	(0.0200)	(0.0194)	(0.0322)	(0.0714)	(0.0243)	(0.0126)	(0.0116)	(0.0184)	(0.0351)
Rainfall	-0.0346***	-0.0361***	-0.0376***	-0.0460***	-0.0498***	-0.0451***	-0.0491***	-0.0499***	-0.0492***	-0.0512***
	(0.00405)	(0.00289)	(0.00281)	(0.00465)	(0.0103)	(0.00351)	(0.00183)	(0.00168)	(0.00266)	(0.00508)
Dist-capital	0.00345	-0.0193**	-0.0220**	-0.0245*	-0.0338	0.146***	0.127***	0.107***	0.0951***	0.0882***
	(0.0100)	(0.00716)	(0.00695)	(0.0115)	(0.0256)	(0.00869)	(0.00452)	(0.00417)	(0.00658)	(0.0126)
Wetness	-0.0765***	-0.0445***	-0.0312***	-0.0204	-0.00749	-0.148***	-0.123***	-0.0896***	-0.0411***	0.0196
	(0.0114)	(0.00814)	(0.00791)	(0.0131)	(0.0291)	(0.00988)	(0.00514)	(0.00474)	(0.00749)	(0.0143)
Constant	90.23***	115.5***	138.3***	162.7***	207.4***	-1.355	71.76***	110.3***	140.7***	169.2***
	(6.613)	(4.724)	(4.585)	(7.602)	(16.88)	(5.733)	(2.982)	(2.751)	(4.343)	(8.299)
GroupFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	24210	24210	24210	24210	24210	24210	24210	24210	24210	24210
Pseudo R-sq	0.290	0.279	0.235	0.213	0.234	0.206	0.280	0.328	0.287	0.209

Notes: Standard errors are presented in brackets and Superscripts *, **, *** indicates significance levels at 10% and 5% and 1% respectively. All the expenditures have been converted to US

Effects of credit across various depth of poverty for Lower-middle income countries

Table J.2: Estimates across various depth of poverty

Lower-middle PQRFE CANAY	Consumption per Capita					Education Expenditure				
Variable	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	3.776	3.695	3.209*	2.051	0.425	3.842	2.764**	2.730**	1.997	2.185
	(3.350)	(2.696)	(1.389)	(1.886)	(4.032)	(2.857)	(1.070)	(0.892)	(1.368)	(3.067)
Male	34.31***	50.77***	56.28***	61.83***	80.57***	-32.55***	-32.07***	-28.83***	-22.27***	-19.30***
	(4.943)	(3.979)	(2.049)	(2.783)	(5.950)	(4.355)	(1.630)	(1.359)	(2.086)	(4.676)
Religion	-0.934	-1.001	0.748	1.141	5.544	-11.60***	-4.464***	-1.287	2.510	7.626*
	(3.320)	(2.672)	(1.376)	(1.869)	(3.996)	(2.819)	(1.055)	(0.880)	(1.350)	(3.027)
Employed	18.49***	18.96***	21.87***	19.02***	17.82***	-16.01***	-18.17***	-18.06***	-19.97***	-22.92***
	(2.664)	(2.144)	(1.104)	(1.500)	(3.206)	(2.228)	(0.834)	(0.695)	(1.067)	(2.392)
Married	24.94***	9.307**	-0.319	-9.336***	-32.30***	-14.42***	-22.65***	-29.84***	-39.93***	-43.99***
	(4.306)	(3.465)	(1.785)	(2.424)	(5.182)	(3.836)	(1.436)	(1.198)	(1.837)	(4.119)
Latitude	0.871***	0.850***	0.811***	0.546***	0.391	0.874***	0.629***	0.451***	0.384***	0.272
	(0.223)	(0.180)	(0.0925)	(0.126)	(0.269)	(0.231)	(0.0866)	(0.0722)	(0.111)	(0.248)
Read	13.42***	14.74***	15.50***	16.81***	17.98***	-16.19***	-10.01***	-5.727***	-2.915**	2.133
	(2.657)	(2.139)	(1.102)	(1.496)	(3.198)	(2.327)	(0.871)	(0.726)	(1.114)	(2.498)
Dist-market	-0.0285***	-0.0175**	-0.0163***	-0.0165***	-0.0384***	0.0349***	0.0189***	0.0159***	0.0104***	0.0170**
	(0.00680)	(0.00547)	(0.00282)	(0.00383)	(0.00819)	(0.00519)	(0.00194)	(0.00162)	(0.00249)	(0.00557)
Dist-borderpost	-0.0434**	-0.0601***	-0.0498***	-0.0145	0.0142	0.0516***	0.0360***	0.0273***	0.0146*	0.004
	(0.0152)	(0.0122)	(0.00630)	(0.00855)	(0.0183)	(0.0135)	(0.00505)	(0.00421)	(0.00647)	(0.0145)
Dist-popcenter	0.117***	-0.0344	-0.108***	-0.182***	-0.191***	0.0245	0.0238*	0.0228**	0.0258	-0.00756
	(0.0342)	(0.0275)	(0.0142)	(0.0193)	(0.0412)	(0.0277)	(0.0104)	(0.00864)	(0.0133)	(0.0297)
Rainfall	0.0315***	0.0445***	0.0459***	0.0362***	0.0402***	-0.0592***	-0.0221***	-0.00742***	0.00838**	0.0141*
	(0.00648)	(0.00522)	(0.00269)	(0.00365)	(0.00780)	(0.00607)	(0.00227)	(0.00190)	(0.00291)	(0.00652)
Dist-capital	-0.364***	-0.383***	-0.462***	-0.424***	-0.548***	0.0662***	0.0604***	0.0694***	0.0730***	0.0779***
	(0.0303)	(0.0244)	(0.0126)	(0.0171)	(0.0365)	(0.0149)	(0.00559)	(0.00467)	(0.00716)	(0.0160)
Wetness	2.089*	2.890***	2.010***	0.948	-0.923	-0.0132	-0.0178**	-0.0211***	0.00385	0.0572***
	(0.955)	(0.768)	(0.396)	(0.538)	(1.149)	(0.0153)	(0.00572)	(0.00477)	(0.00732)	(0.0164)
Constant	21.29	18.85	72.41***	106.8***	186.3***	73.18***	74.15***	77.58***	79.00***	84.29***
	(18.60)	(14.97)	(7.711)	(10.47)	(22.39)	(6.870)	(2.572)	(2.145)	(3.290)	(7.377)
GroupFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	8741	8741	8741	8741	8741	12768	12768	12768	12768	12768
Pseudo R-sq	0.465	0.485	0.529	0.494	0.430	0.221	0.262	0.301	0.327	0.325

Notes: Standard errors are presented in brackets and Superscripts *, **, *** indicates significance levels at 10% and 5% and 1% respectively. All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models.

Table J.3: Estimates across various depth of poverty

Lower-middle PQRFE CANAY	Food Expenditure					Non. Food Expenditure				
Variable	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	2.152	2.354*	2.309*	1.177	-0.384	4.706	4.673*	1.614	2.923	1.705
	(1.850)	(1.166)	(1.045)	(1.166)	(1.853)	(4.324)	(1.932)	(1.775)	(2.404)	(4.925)
Male	-11.22***	-1.614	2.290	5.872***	12.01***	-72.32***	-68.59***	-60.64***	-49.00***	-36.09***
	(2.821)	(1.777)	(1.593)	(1.777)	(2.825)	(6.591)	(2.945)	(2.706)	(3.665)	(7.508)
Religion	-3.487	-2.362*	-0.169	1.703	4.366*	-13.90**	-8.071***	-3.928*	3.130	6.969
	(1.826)	(1.150)	(1.031)	(1.150)	(1.829)	(4.266)	(1.906)	(1.752)	(2.372)	(4.860)
Employed	13.17***	11.61***	11.29***	9.714***	8.777***	-10.04**	-10.65***	-10.46***	-12.48***	-16.54***
	(1.443)	(0.909)	(0.815)	(0.909)	(1.445)	(3.372)	(1.506)	(1.384)	(1.875)	(3.841)
Married	7.649**	-6.930***	-14.64***	-21.15***	-29.65***	21.25***	-0.158	-17.23***	-44.16***	-73.23***
	(2.485)	(1.566)	(1.403)	(1.565)	(2.489)	(5.806)	(2.594)	(2.384)	(3.228)	(6.614)
Latitude	0.363*	0.400***	0.370***	0.350***	0.276	0.730*	0.316*	0.218	0.130	-0.611
	(0.150)	(0.0943)	(0.0846)	(0.0943)	(0.150)	(0.350)	(0.156)	(0.144)	(0.195)	(0.399)
Read	3.985**	4.949***	5.611***	5.497***	5.340***	-22.36***	-13.23***	-9.896***	-4.831*	0.987
	(1.507)	(0.949)	(0.851)	(0.949)	(1.509)	(3.522)	(1.573)	(1.446)	(1.958)	(4.012)
Dist-market	-0.00337	-0.00470*	-0.00763***	-0.0105***	-0.0208***	-0.0243**	-0.0241***	-0.0237***	-0.0288***	-0.0537***
	(0.00336)	(0.00212)	(0.00190)	(0.00212)	(0.00337)	(0.00786)	(0.00351)	(0.00323)	(0.00437)	(0.00895)
Dist-borderpost	-0.0173*	-0.0174**	-0.00794	0.00287	0.0222*	-0.00685	-0.0470***	-0.0400***	-0.0591***	-0.0852***
	(0.00874)	(0.00551)	(0.00494)	(0.00551)	(0.00876)	(0.0204)	(0.00913)	(0.00839)	(0.0114)	(0.0233)
Dist-popcenter	0.158***	0.118***	0.0791***	0.0643***	0.0704***	0.0666	0.0913***	0.0782***	0.0832***	0.0815
	(0.0179)	(0.0113)	(0.0101)	(0.0113)	(0.0180)	(0.0419)	(0.0187)	(0.0172)	(0.0233)	(0.0477)
Rainfall	0.0266***	0.0288***	0.0316***	0.0306***	0.0330***	-0.0892***	-0.0583***	-0.0577***	-0.0458***	-0.0349***
	(0.00393)	(0.00248)	(0.00222)	(0.00248)	(0.00394)	(0.00919)	(0.00411)	(0.00378)	(0.00511)	(0.0105)
Dist-capital	-0.0593***	-0.0402***	-0.0345***	-0.0209***	-0.0177	0.0644**	0.0413***	0.0631***	0.0654***	0.0838**
	(0.00968)	(0.00610)	(0.00547)	(0.00610)	(0.00969)	(0.0226)	(0.0101)	(0.00929)	(0.0126)	(0.0258)
Wetness	0.0520***	0.0358***	0.0354***	0.0242***	0.0234*	-0.0517*	-0.0374***	-0.0482***	-0.0235	0.00699
	(0.00990)	(0.00624)	(0.00559)	(0.00623)	(0.00991)	(0.0231)	(0.0103)	(0.00950)	(0.0129)	(0.0263)
Constant	35.82***	54.01***	77.58***	101.6***	143.3***	154.1***	197.3***	230.5***	262.1***	296.9***
	(4.450)	(2.803)	(2.513)	(2.803)	(4.457)	(10.40)	(4.645)	(4.269)	(5.781)	(11.84)
GroupFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12768	12768	12768	12768	12768	12768	12768	12768	12768	12768
Pseudo R-sq	0.340	0.388	0.492	0.546	0.531	0.235	0.296	0.307	0.275	0.252

Notes: Standard errors are presented in brackets and Superscripts *, **, *** indicates significance levels at 10% and 5% and 1% respectively. All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models.

Effects of credit across various depth of poverty for Low income countries

Table J.4: Estimates across various depth of poverty

Low Income PQRFE CANAY	Consumption per Capita					Education Expenditure				
Variable	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	29.48***	27.48***	22.54***	15.19	26.22	1.000	0.162	-0.0312	-0.277	-0.940
	(6.165)	(4.458)	(5.192)	(8.201)	(17.33)	(0.684)	(0.143)	(0.115)	(0.282)	(0.955)
Male	18.77*	16.73**	18.35**	13.98	-8.314	1.634	0.360	-0.432**	-1.228***	-2.580*
	(8.141)	(5.888)	(6.857)	(10.83)	(22.88)	(0.903)	(0.189)	(0.152)	(0.372)	(1.259)
Religion	34.20***	28.19***	21.91***	6.285	-9.535	-1.336	0.271	0.770***	1.588***	2.343*
	(6.572)	(4.753)	(5.535)	(8.743)	(18.47)	(0.730)	(0.153)	(0.123)	(0.301)	(1.018)
Employed	-19.67**	-12.35*	-5.318	-0.766	-0.608	-2.483**	-0.407*	-0.126	0.354	1.234
	(7.124)	(5.153)	(6.001)	(9.478)	(20.02)	(0.791)	(0.166)	(0.133)	(0.326)	(1.102)
Married	108.0***	105.3***	118.7***	154.9***	235.1***	1.845*	0.921***	1.187***	1.731***	1.964
	(8.185)	(5.920)	(6.894)	(10.89)	(23.00)	(0.907)	(0.190)	(0.153)	(0.374)	(1.265)
Latitude	72.61***	71.82***	68.78***	65.05***	65.57***	6.433***	5.832***	5.545***	5.047***	4.312***
	(1.922)	(1.390)	(1.619)	(2.558)	(5.403)	(0.213)	(0.0447)	(0.0360)	(0.0880)	(0.298)
Read	10.37	28.16***	52.98***	96.01***	138.5***	-1.784**	-0.343**	0.724***	2.839***	9.164***
	(5.527)	(3.997)	(4.655)	(7.354)	(15.53)	(0.614)	(0.129)	(0.104)	(0.253)	(0.857)
Dist-market	0.960***	0.799***	0.634***	0.399***	0.0701	0.0366***	0.0173***	0.0105***	-0.00331	-0.0264*
	(0.0670)	(0.0485)	(0.0564)	(0.0892)	(0.188)	(0.00745)	(0.00156)	(0.00126)	(0.00307)	(0.0104)
Dist-borderpost	0.230***	0.198***	0.171***	0.206***	0.254***	0.0339***	0.0404***	0.0420***	0.0422***	0.0424***
	(0.0265)	(0.0192)	(0.0223)	(0.0353)	(0.0745)	(0.00295)	(0.000618)	(0.000497)	(0.00122)	(0.00411)
Dist-popcenter	-0.168	-0.347***	-0.466***	-0.546***	-0.455	-0.0343***	-0.0325***	-0.0242***	-0.0195***	-0.0291*
	(0.0934)	(0.0676)	(0.0787)	(0.124)	(0.263)	(0.0104)	(0.00218)	(0.00175)	(0.00428)	(0.0145)
Rainfall	-0.143***	-0.166***	-0.201***	-0.252***	-0.318***	-0.00584***	-0.00594***	-0.00592***	-0.00697***	-0.00899***
	(0.0104)	(0.00754)	(0.00878)	(0.0139)	(0.0293)	(0.00116)	(0.000243)	(0.000195)	(0.000478)	(0.00162)
Dist-capital	0.830***	0.807***	0.776***	0.768***	0.685***	0.0557***	0.0561***	0.0530***	0.0510***	0.0441***
	(0.0226)	(0.0164)	(0.0190)	(0.0301)	(0.0635)	(0.00251)	(0.000527)	(0.000424)	(0.00104)	(0.00351)
Wetness	-0.484	-0.987	-0.283	-0.774	-4.802	-1.163***	-0.716***	-0.670***	-0.443***	-0.114
	(1.437)	(1.039)	(1.210)	(1.911)	(4.037)	(0.160)	(0.0335)	(0.0269)	(0.0658)	(0.223)
Constant	-783.7***	-642.0***	-486.8***	-292.4***	-30.88	-55.64***	-53.99***	-49.90***	-45.19***	-34.81***
	(23.95)	(17.32)	(20.17)	(31.86)	(67.31)	(2.663)	(0.558)	(0.449)	(1.098)	(3.713)
GroupFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11442	11442	11442	11442	11442	11484	11484	11484	11484	11484
Pseudo R-sq	0.303	0.292	0.251	0.179	0.119	0.366	0.431	0.428	0.316	0.167

Notes: Standard errors are presented in brackets and Superscripts *, **, *** indicates significance levels at 10% and 5% and 1% respectively. All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models.

Table J.5: Estimates across various depth of poverty

Low Countries PQRFE CANAY	Food Expenditure					Non. Food Expenditure				
Variable	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	15.31**	16.97***	10.35**	15.35*	23.68	6.757***	6.048***	6.199***	7.613***	12.89**
	(4.922)	(3.592)	(3.953)	(6.863)	(14.38)	(1.649)	(1.097)	(1.302)	(2.313)	(4.961)
Male	22.67***	17.34***	21.58***	21.21*	12.77	2.746	1.313	-3.103	-7.372*	-18.31**
	(6.500)	(4.744)	(5.221)	(9.063)	(18.99)	(2.177)	(1.449)	(1.720)	(3.054)	(6.551)
Religion	15.87**	11.09**	5.766	-13.29	-10.02	14.39***	11.99***	12.17***	14.03***	19.63***
	(5.247)	(3.829)	(4.215)	(7.316)	(15.33)	(1.757)	(1.170)	(1.388)	(2.466)	(5.288)
Employed	-8.386	-5.278	-6.682	-13.68	-21.20	-4.687*	-4.141**	-2.266	-0.139	5.702
	(5.688)	(4.151)	(4.569)	(7.931)	(16.62)	(1.905)	(1.268)	(1.505)	(2.673)	(5.733)
Married	76.73***	80.37***	93.77***	123.3***	194.0***	19.51***	19.14***	21.01***	26.47***	42.66***
	(6.535)	(4.769)	(5.249)	(9.112)	(19.09)	(2.189)	(1.457)	(1.729)	(3.071)	(6.587)
Latitude	36.31***	34.40***	33.46***	29.45***	31.35***	32.19***	32.54***	31.60***	30.45***	29.04***
	(1.535)	(1.120)	(1.233)	(2.140)	(4.484)	(0.514)	(0.342)	(0.406)	(0.721)	(1.547)
Read	-3.913	6.556*	23.47***	44.74***	55.06***	4.394**	12.01***	23.40***	41.79***	72.71***
	(4.413)	(3.221)	(3.545)	(6.153)	(12.89)	(1.478)	(0.984)	(1.168)	(2.074)	(4.448)
Dist-market	0.860***	0.723***	0.519***	0.433***	0.0667	0.131***	0.103***	0.0803***	0.0252	-0.0681
	(0.0535)	(0.0391)	(0.0430)	(0.0746)	(0.156)	(0.0179)	(0.0119)	(0.0142)	(0.0251)	(0.0539)
Dist-borderpost	0.0318	-0.0281	-0.0499**	-0.0227	0.0676	0.175***	0.202***	0.189***	0.181***	0.157***
	(0.0212)	(0.0155)	(0.0170)	(0.0295)	(0.0619)	(0.00709)	(0.00472)	(0.00560)	(0.00995)	(0.0213)
Dist-popcenter	-0.203**	-0.243***	-0.276***	-0.343***	-0.163	-0.0747**	-0.0690***	-0.112***	-0.155***	-0.181*
	(0.0746)	(0.0544)	(0.0599)	(0.104)	(0.218)	(0.0250)	(0.0166)	(0.0197)	(0.0351)	(0.0752)
Rainfall	-0.0965***	-0.117***	-0.156***	-0.190***	-0.261***	-0.0287***	-0.0319***	-0.0366***	-0.0441***	-0.0583***
	(0.00832)	(0.00607)	(0.00668)	(0.0116)	(0.0243)	(0.00279)	(0.00185)	(0.00220)	(0.00391)	(0.00838)
Dist-capital	0.408***	0.394***	0.406***	0.375***	0.355***	0.383***	0.371***	0.342***	0.325***	0.319***
	(0.0181)	(0.0132)	(0.0145)	(0.0252)	(0.0527)	(0.00605)	(0.00403)	(0.00478)	(0.00848)	(0.0182)
Wetness	2.979**	2.257**	0.786	0.412	-4.722	-2.304***	-2.580***	-2.190***	-1.361*	0.124
	(1.147)	(0.837)	(0.921)	(1.599)	(3.351)	(0.384)	(0.256)	(0.304)	(0.539)	(1.156)
Constant	-406.0***	-268.0***	-120.8***	45.67	256.4***	-369.6***	-349.9***	-312.7***	-278.4***	-238.9***
	(19.12)	(13.96)	(15.36)	(26.66)	(55.86)	(6.405)	(4.264)	(5.060)	(8.985)	(19.27)
GroupFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	11442	11442	11442	11442	11442	11442	11442	11442	11442	11442
Pseudo R-sq	0.224	0.200	0.157	0.110	0.080	0.424	0.432	0.403	0.310	0.211

Notes: Standard errors are presented in brackets and Superscripts *, **, *** indicates significance levels at 10% and 5% and 1% respectively. All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models.

Canay (2011) robustness checks on estimates across various depth of poverty

Table J.6: Robustness Checks on Estimates across various depth of poverty

All Countries PQRFE CANAY	Consumption pa Capita					Education Expenditure				
Variable	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	17.14***	12.77***	10.58***	8.229	11.21	1.204	0.534	0.323	0.427	-0.302
	(4.080)	(2.971)	(2.732)	(4.309)	(9.701)	(1.357)	(0.374)	(0.347)	(0.579)	(1.455)
Male	21.71***	23.24***	21.22***	26.14***	26.54*	1.425	0.267	-0.276	-0.502	-1.055
	(5.591)	(4.071)	(3.743)	(5.904)	(13.29)	(1.902)	(0.524)	(0.487)	(0.812)	(2.039)
Religion	18.82***	16.61***	16.02***	15.80***	17.14*	-1.460	0.761*	1.741***	3.750***	6.989***
	(3.582)	(2.608)	(2.398)	(3.783)	(8.516)	(1.217)	(0.335)	(0.312)	(0.519)	(1.305)
Employed	1.533	1.197	5.576*	5.792	6.493	-8.330***	-6.655***	-4.202***	-4.334***	-5.356***
	(4.013)	(2.922)	(2.686)	(4.238)	(9.541)	(1.267)	(0.349)	(0.324)	(0.541)	(1.358)
Married	167.5***	155.1***	163.7***	161.4***	166.5***	3.835*	1.500**	0.903	-0.322	-3.617
	(5.346)	(3.892)	(3.579)	(5.645)	(12.71)	(1.804)	(0.497)	(0.462)	(0.770)	(1.934)
Latitude	2.668***	1.890***	1.422***	1.041*	0.706	1.045***	0.493***	0.262***	-0.0362	-0.375*
	(0.415)	(0.302)	(0.278)	(0.438)	(0.987)	(0.141)	(0.0388)	(0.0361)	(0.0602)	(0.151)
Read	31.69***	39.35***	48.86***	55.52***	61.38***	-3.664**	-0.622	0.848**	3.151***	10.21***
	(3.461)	(2.520)	(2.317)	(3.654)	(8.228)	(1.153)	(0.317)	(0.295)	(0.492)	(1.236)
Dist-market	-0.0472***	-0.0384***	-0.0328***	-0.0340***	-0.0335	0.0194***	0.0227***	0.0307***	0.0321***	0.0326***
	(0.00969)	(0.00706)	(0.00649)	(0.0102)	(0.0230)	(0.00318)	(0.000876)	(0.000814)	(0.00136)	(0.00341)
Wetness	2.814***	3.257***	2.138***	1.062	0.884	0.0420***	0.0425***	0.0552***	0.0898***	0.159***
	(0.702)	(0.511)	(0.470)	(0.741)	(1.668)	(0.00337)	(0.000927)	(0.000862)	(0.00144)	(0.00361)
Constant	42.75**	71.34***	116.3***	143.4***	197.0***	-40.68	9.009	36.28***	67.86***	104.2***
	(13.21)	(9.617)	(8.842)	(13.95)	(31.40)	(27.06)	(7.453)	(6.929)	(11.55)	(29.02)
GroupFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	20183	20183	20183	20183	20183	24252	24252	24252	24252	24252
Pseudo R-sq	0.267	0.259	0.220	0.164	0.173	0.161	0.258	0.406	0.435	0.400

Notes: Standard errors are reported in brackets and Superscripts *, **, *** indicates significance levels at 10% and 5% and 1% respectively. All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models.

Table J.7: Robustness Checks on Estimates across various depth of poverty

All Countries PQRFE CANAY	Food Expenditure					Non-Food Expenditure				
Variable	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	8.113**	7.616***	3.730*	2.432	1.017	7.281***	5.659***	4.913***	5.200**	8.600**
	(2.500)	(1.814)	(1.687)	(2.894)	(6.431)	(2.029)	(1.051)	(1.033)	(1.631)	(3.335)
Male	41.13***	42.66***	43.10***	57.81***	70.87***	1.249	3.758*	2.360	3.287	7.377
	(3.507)	(2.545)	(2.367)	(4.060)	(9.021)	(2.846)	(1.474)	(1.449)	(2.287)	(4.678)
Religion	-0.251	-0.180	0.684	0.538	1.210	12.64***	13.53***	13.11***	17.42***	23.11***
	(2.240)	(1.626)	(1.512)	(2.593)	(5.763) (1.818)	(0.942)	(0.926)	(1.461)	(2.989)	
Employed	7.827***	6.093***	6.605***	5.888*	4.202	-8.338***	-7.438***	-5.407***	-6.444***	-9.055**
	(2.334)	(1.693)	(1.575)	(2.701)	(6.003)	(1.894)	(0.981)	(0.964)	(1.522)	(3.113)
Married	113.5***	105.3***	103.6***	95.78***	82.71***	37.28***	26.38***	21.22***	14.91***	5.687
	(3.327)	(2.414)	(2.245)	(3.851)	(8.558)	(2.700)	(1.398)	(1.375)	(2.170)	(4.438)
Latitude	0.958***	0.777***	0.475**	0.259	0.204	0.448*	0.275*	-0.0651	-0.109	-0.289
	(0.259)	(0.188)	(0.175)	(0.300)	(0.667)	(0.211)	(0.109)	(0.107)	(0.169)	(0.346)
Read	6.356**	11.29***	14.41***	15.99***	14.98**	4.498**	11.98***	19.63***	30.11***	44.25***
	(2.122)	(1.540)	(1.432)	(2.457)	(5.459)	(1.722)	(0.892)	(0.877)	(1.384)	(2.831)
Dist-market	-0.0171**	-0.0214***	-0.0183***	-0.0149*	-0.0158	-0.0150**	-0.00746**	-0.00512*	-0.00807*	-0.0369***
	(0.00585)	(0.00425)	(0.00395)	(0.00677)	(0.0151)	(0.00475)	(0.00246)	(0.00242)	(0.00382)	(0.00781)
Wetness	-0.0347***	-0.0248***	-0.0186***	-0.0155*	-0.0137	0.0518***	0.0536***	0.0695***	0.102***	0.165***
	(0.00619)	(0.00449)	(0.00418)	(0.00717)	(0.0159)	(0.00503)	(0.00260)	(0.00256)	(0.00404)	(0.00826)
Constant	44.09***	66.95***	94.79***	116.9***	165.4***	-44.01***	22.82***	59.19***	89.23***	112.6***
	(4.159)	(3.018)	(2.807)	(4.815)	(10.70)	(3.376)	(1.748)	(1.719)	(2.713)	(5.548)
GroupFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	24210	24210	24210	24210	24210	24210	24210	24210	24210	24210
Pseudo R-sq	0.283	0.276	0.213	0.196	0.216	0.203	0.317	0.384	0.335	0.252

Notes: Standard errors are reported in brackets and Superscripts *, **, *** indicates significance levels at 10% and 5% and 1% respectively. All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models.

Machado and Silver (2019) robustness checks on estimates across various depth of poverty

Table J.8: Machado and Silver (2019) Robustness Estimates across various depth of poverty

All Countries PQRFE	Consumption Pa capita				Education Expenditure			
τ	PQR				PQR			
0.1	31.98***	11.31***	19.22***	33.67***	1.188	1.86	2.178	0.692
	(6.247)	(4.91)	(5.94)	(6.54)	(97.55)	(1.23)	(1.619)	(8.815)
0.25	31.50***	13.61***	14.77***	33.06***	1.717	1.965*	1.924*	0.627
	(5.934)	(4.29)	(3.77)	(6.19)	(81.16)	(0.77)	(0.932)	(7.148)
0.5	28.15***	7.101	10.73**	29.45***	2.210	2.045**	1.673**	0.504
	(5.019)	(3.900)	(3.76)	(5.20)	(65.90)	(0.66)	(0.612)	(10.49)
0.75	20.88*	-3.21	1.84	21.84*	3.705	2.337	0.722	0.179
	(10.18)	(8.44)	(8.84)	(10.31)	(19.92)	(1.873)	(3.11)	(30.97)
0.9	20.66*	-17.47	-11.81	21.46*	4.595	2.981	-1.584	0.0470
	(10.40)	(16.49)	(18.66)	(10.67)	(9.515)	(5.55)	(10.28)	(39.88)
GroupFE	Yes	No	No	Yes	Yes	No	No	Yes
CountryFE	No	Yes	No	Yes	No	Yes	No	Yes
TimeFE	No	No	Yes	Yes	No	No	Yes	Yes

Notes: Standard errors are reported in brackets and Superscripts *, **, *** indicates significance levels at 10% and 5% and 1% respectively. All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models.

Table J.9: Robustness: Machado and Silva (2019) Estimates across various depth of poverty

All Countries PQRFE	Food Expenditure				Non Food Expenditure			
τ	PQR				PQR			
0.1	14.60***	6.029	8.115*	(18.30)	6.957	11.47***	9.988***	6.181
	(3.439)	(3.531)	(3.779)	(221.9)	(4.139)	(2.833)	(2.660)	(4.209)
0.25	13.56***	2.791	3.661	17.14	8.190**	9.809***	8.048***	6.518*
	(2.938)	(2.787)	(2.228)	(192.5)	(3.119)	(1.919)	(1.781)	(2.968)
0.5	13.19***	2.786	(-0.985)	(14.31)	10.16***	6.325***	4.426*	7.050
	(2.856)	(2.789)	(3.210)	(139.4)	(2.844)	(1.891)	(1.765)	(3.603)
0.75	7.135	-10.60	-2.146	9.686	13.34*	0.656	-2.103	8.193
	(7.095)	(6.929)	(3.883)	(166.4)	(5.655)	(5.421)	(5.178)	(9.859)
0.9	5.298	-26.04	-13.13	7.672	15.12	-8.628	-12.74	8.925
	(9.038)	(14.61)	(9.854)	(213.7)	(7.724)	(11.88)	(11.45)	(14.33)
GroupFE	Yes	No	No	Yes	Yes	No	No	Yes
CountryFE	No	Yes	No	Yes	No	Yes	No	Yes
TimeFE	No	No	Yes	Yes	No	No	Yes	Yes

Notes: Standard errors are reported in brackets and Superscripts *, **, *** indicates significance levels at 10% and 5% and 1% respectively. All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models.

Table J.10: Estimates across various depth of poverty

All Countries PQRFE	Consumption pa Capita					Education Expenditure				
Variable	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	17.86*	16.63*	12.61	4.279	2.444	1.761	1.553	1.159	0.128	-0.344
	(8.966)	(8.047)	(7.033)	(13.84)	(15.95)	(26.59)	(22.73)	(21.12)	(45.36)	(60.50)
Male	8.877	10.85	17.30	30.66	33.60	1.882	2.044	2.351	3.154	3.521
	(15.32)	(13.75)	(12.02)	(23.65)	(27.26)	(19.97)	(17.07)	(15.86)	(34.06)	(45.43)
Religion	8.314	9.746	14.41	24.08	26.21	1.098	1.193	1.374	1.846	2.062
	(17.42)	(15.64)	(13.67)	(26.90)	(31.00)	(17.35)	(14.83)	(13.78)	(29.60)	(39.48)
Employed	5.651	4.929	2.578	-2.298	-3.372	-19.62	-19.22	-18.47	-16.50	-15.61
	(9.830)	(8.822)	(7.709)	(15.18)	(17.49)	(30.68)	(26.23)	(24.37)	(52.34)	(69.80)
Married	94.86***	107.8***	150.0***	237.6***	256.8***	-1.429	-1.626	-2.000	-2.978	-3.425
	(14.93)	(13.38)	(11.80)	(23.03)	(26.62)	(24.16)	(20.65)	(19.19)	(41.21)	(54.97)
Latitude	1.619***	1.633***	1.676***	1.766**	1.785*	0.388	0.404	0.434	0.514	0.550
	(0.391)	(0.351)	(0.307)	(0.604)	(0.696)	(3.443)	(2.943)	(2.734)	(5.873)	(7.833)
Read	43.52***	45.63***	52.53***	66.83***	69.97***	-1.153	-0.132	1.807	6.876	9.193
	(8.673)	(7.783)	(6.806)	(13.39)	(15.43)	(15.85)	(13.55)	(12.59)	(27.05)	(36.07)
Dist-market	-0.0477**	-0.0462**	-0.0412**	-0.0309	-0.0286	0.0410	0.0382	0.0329	0.0191	0.0127
	(0.0166)	(0.0149)	(0.0130)	(0.0256)	(0.0295)	(0.106)	(0.0904)	(0.0839)	(0.180)	(0.240)
Wetness	1.199	1.353	1.853	2.892	3.120	0.0621	0.0655	0.0719	0.0888	0.0966
	(3.404)	(3.055)	(2.670)	(5.255)	(6.055)	(0.102)	(0.0872)	(0.0810)	(0.174)	(0.232)
GroupFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	20183	20183	20183	20183	20183	24252	24252	24252	24252	24252

Notes: Standard errors are reported in brackets and Superscripts *, **, *** indicates significance levels at 10% and 5% and 1% respectively. All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models.

Appendix K Estimates across various depth of poverty by gender

Table K.1: Estimates across various depth of poverty

Male Headed	Consumption per Capita (Tot Cons)					Education Expenditure (Edt. Exp)				
Variable	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	17.97***	13.57***	5.423*	1.667	4.221	1.186	0.687	0.331	0.241	-0.511
	(4.158)	(3.205)	(3.061)	(5.063)	(10.09)	(1.263)	(0.446)	(0.392)	(0.637)	(1.646)
Religion	30.19***	28.32***	26.55***	22.24***	23.84*	0.945	1.961***	2.977***	4.018***	5.027**
	(4.048)	(3.120)	(2.980)	(4.929)	(9.826)	(1.235)	(0.436)	(0.384)	(0.623)	(1.610)
Employed	4.111	2.758	3.249	5.134	10.25	-7.958***	-6.860***	-5.181***	-5.565***	-7.394***
	(4.054)	(3.125)	(2.984)	(4.937)	(9.841)	(1.166)	(0.412)	(0.362)	(0.588)	(1.520)
Married	243.2***	214.3***	217.5***	199.2***	198.3***	9.692***	2.850***	0.569	-3.636***	-17.51***
	(6.179)	(4.762)	(4.548)	(7.524)	(15.00)	(1.887)	(0.666)	(0.586)	(0.952)	(2.459)
Latitute	2.374***	1.915***	1.858***	1.545**	1.514	0.977***	0.567***	0.412***	0.198**	-0.0630
	(0.424)	(0.327)	(0.312)	(0.516)	(1.028)	(0.134)	(0.0475)	(0.0417)	(0.0678)	(0.175)
Read	33.50***	39.52***	51.26***	54.06***	55.39***	-2.882**	-0.482	0.846*	2.628***	6.587***
	(3.518)	(2.712)	(2.590)	(4.284)	(8.540)	(1.076)	(0.380)	(0.334)	(0.543)	(1.402)
Dist-market	-0.0958***	-0.0804***	-0.0689***	-0.0780***	-0.0834***	0.00966**	0.0166***	0.0263***	0.0251***	0.0253***
	(0.0102)	(0.00785)	(0.00749)	(0.0124)	(0.0247)	(0.00309)	(0.00109)	(0.000959)	(0.00156)	(0.00403)
Dist-borderpost	-0.0376*	-0.0292*	0.00355	0.0681***	0.0905*	0.0321***	0.0349***	0.0362***	0.0439***	0.0505***
	(0.0152)	(0.0117)	(0.0112)	(0.0185)	(0.0368)	(0.00485)	(0.00171)	(0.00151)	(0.00245)	(0.00633)
Dist-popcentre	0.661***	0.621***	0.552***	0.502***	0.506***	0.0263	0.0222***	0.0201***	0.0250***	0.0195
	(0.0488)	(0.0376)	(0.0359)	(0.0594)	(0.118)	(0.0138)	(0.00489)	(0.00430)	(0.00698)	(0.0180)
Rainfall	-0.146***	-0.150***	-0.154***	-0.169***	-0.162***	-0.0158***	-0.0112***	-0.00953***	-0.00498***	0.000910
	(0.00638)	(0.00491)	(0.00469)	(0.00776)	(0.0155)	(0.00207)	(0.000731)	(0.000642)	(0.00104)	(0.00270)
Dist-capital	0.519***	0.470***	0.436***	0.425***	0.308***	0.0904***	0.0863***	0.0839***	0.0808***	0.0780***
	(0.0172)	(0.0133)	(0.0127)	(0.0210)	(0.0418)	(0.00511)	(0.00180)	(0.00159)	(0.00258)	(0.00665)
Wetness	2.326**	3.449***	3.807***	1.471	1.243	-0.0454***	-0.0394***	-0.0248***	0.0157***	0.0875***
	(0.740)	(0.570)	(0.545)	(0.901)	(1.797)	(0.00579)	(0.00204)	(0.00180)	(0.00292)	(0.00754)
Constant	61.42***	103.9***	118.8***	197.5***	240.1***	-44.65	-13.39	16.06*	41.84***	75.99*
	(16.86)	(13.00)	(12.41)	(20.54)	(40.93)	(24.34)	(8.598)	(7.558)	(12.28)	(31.73)
GroupFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15824	15824	15824	15824	15824	19290	19290	19290	19290	19290
pseudo R-sq	0.298	0.276	0.247	0.226	0.246	0.216	0.288	0.369	0.400	0.388

Notes: Standard errors are reported in brackets and *, **, *** represents 10, 5 and 1 percents significance levels respectively . I include the group, country and time fixed effects to control for other group, country and time invariant unobservable factors in the estimation . All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models.

Table K.2: Estimates across various depth of poverty

Male Headed	Food Expenditure (Fd. Exp)					Non-Food Expenditure (Nfd Exp)				
Variable	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	10.97***	7.139***	3.500*	1.724	2.141	8.056***	5.534***	4.628***	4.278**	7.224*
	(2.838)	(1.937)	(2.024)	(3.140)	(6.895)	(2.275)	(1.196)	(1.128)	(1.704)	(3.813)
Religion	-0.130	2.106	1.316	0.961	4.262	16.75***	17.27***	15.45***	18.73***	24.41***
	(2.775)	(1.894)	(1.978)	(3.070)	(6.741)	(2.224)	(1.169)	(1.103)	(1.666)	(3.728)
Employed	7.905**	6.568***	7.209***	6.385*	5.310	-8.104***	-6.893***	-5.825***	-5.923***	-9.297**
	(2.622)	(1.789)	(1.869)	(2.901)	(6.370)	(2.101)	(1.105)	(1.042)	(1.575)	(3.522)
Married	161.4***	141.5***	131.2***	109.5***	83.63***	54.00***	31.36***	22.16***	9.989***	-18.70**
	(4.244)	(2.896)	(3.026)	(4.695)	(10.31)	(3.401)	(1.788)	(1.687)	(2.549)	(5.701)
Latitude	0.650*	0.663**	0.568**	0.430	0.480	0.917***	0.325*	0.0739	0.0397	-0.335
	(0.302)	(0.206)	(0.215)	(0.334)	(0.733)	(0.242)	(0.127)	(0.120)	(0.181)	(0.405)
Read	8.008***	11.33***	14.47***	15.91***	15.13**	3.536	9.020***	16.49***	23.58***	37.70***
	(2.416)	(1.649)	(1.723)	(2.673)	(5.870)	(1.936)	(1.018)	(0.960)	(1.451)	(3.246)
Dist-market	-0.0353***	-0.0333***	-0.0325***	-0.0325***	-0.0379*	-0.0459***	-0.0347***	-0.0288***	-0.0343***	-0.0614***
	(0.00694)	(0.00473)	(0.00495)	(0.00768)	(0.0169)	(0.00556)	(0.00292)	(0.00276)	(0.00417)	(0.00932)
Dist-borderpost	-0.0355**	-0.0283***	-0.00740	0.0278*	0.0552*	-0.0560***	-0.0524***	-0.0546***	-0.0557***	-0.0572***
	(0.0109)	(0.00744)	(0.00777)	(0.0121)	(0.0265)	(0.00873)	(0.00459)	(0.00433)	(0.00655)	(0.0146)
Dist-popcentre	0.192***	0.150***	0.120***	0.0804*	0.0712	0.140***	0.0829***	0.0677***	0.0349	0.0206
	(0.0311)	(0.0212)	(0.0222)	(0.0344)	(0.0755)	(0.0249)	(0.0131)	(0.0124)	(0.0187)	(0.0418)
Rainfall	-0.0468***	-0.0502***	-0.0525***	-0.0630***	-0.0659***	-0.0389***	-0.0416***	-0.0408***	-0.0365***	-0.0414***
	(0.00465)	(0.00317)	(0.00331)	(0.00514)	(0.0113)	(0.00372)	(0.00196)	(0.00185)	(0.00279)	(0.00624)
Dist-capital	0.0182	0.00165	-0.0111	-0.0162	-0.0356	0.135***	0.109***	0.0922***	0.0793***	0.0738***
	(0.0115)	(0.00782)	(0.00818)	(0.0127)	(0.0279)	(0.00919)	(0.00483)	(0.00456)	(0.00689)	(0.0154)
Wetness	-0.100***	-0.0725***	-0.0500***	-0.0368*	-0.0151	-0.141***	-0.111***	-0.0807***	-0.0380***	0.0206
	(0.0130)	(0.00887)	(0.00927)	(0.0144)	(0.0316)	(0.0104)	(0.00548)	(0.00517)	(0.00781)	(0.0175)
Constant	73.58***	113.3***	145.5***	196.6***	259.7***	-17.29***	67.45***	103.7***	139.0***	192.4***
	(7.979)	(5.445)	(5.689)	(8.827)	(19.38)	(6.394)	(3.361)	(3.171)	(4.791)	(10.72)
GroupFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	19256	19256	19256	19256	19256	19256	19256	19256	19256	19256
pseudo R-sq	0.247	0.215	0.194	0.195	0.242	0.204	0.280	0.325	0.276	0.197

Notes: Standard errors are reported in brackets and *, **, *** represents 10, 5 and 1 percents significance levels respectively . I include the group, country and time fixed effects to control for other group, country and time invariant unobservable factors in the estimation . All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models.

Table K.3: Estimates across various depth of poverty

Female Headed	Consumption per Capita (Tot Cons)					Education Expenditure (Edt. Exp)				
Variable	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	30.41***	33.64***	36.33***	38.15***	42.05*	1.821	0.699	1.117	-0.0206	-0.309
	(8.381)	(5.772)	(6.121)	(10.42)	(20.47)	(3.331)	(1.007)	(0.932)	(1.462)	(3.697)
Religion	35.76***	35.28***	23.22***	12.02	3.266	-4.199	-2.893**	-1.243	-1.435	-0.706
	(8.265)	(5.692)	(6.036)	(10.28)	(20.18)	(3.311)	(1.001)	(0.926)	(1.453)	(3.675)
Employed	12.55	9.240	17.53**	10.51	21.67	-5.885	-3.258**	-1.965*	-1.203	-0.320
	(8.609)	(5.929)	(6.287)	(10.71)	(21.02)	(3.324)	(1.005)	(0.930)	(1.458)	(3.689)
Married	75.64***	79.19***	91.88***	123.3***	153.0***	2.929	1.670	2.040*	1.914	2.013
	(8.319)	(5.729)	(6.075)	(10.34)	(20.31)	(3.366)	(1.018)	(0.942)	(1.477)	(3.736)
Latitude	1.818	0.948	1.131	0.574	0.580	1.709***	0.995***	0.838***	0.667***	-0.0529
	(1.058)	(0.729)	(0.773)	(1.316)	(2.584)	(0.415)	(0.125)	(0.116)	(0.182)	(0.460)
Read	32.34***	48.90***	71.76***	82.86***	101.4***	-9.385**	-3.256***	0.0688	4.993***	22.38***
	(7.573)	(5.215)	(5.530)	(9.417)	(18.49)	(2.947)	(0.891)	(0.824)	(1.293)	(3.270)
Dist-market	0.0802**	0.0790***	0.0508*	0.0262	0.0217	0.0188	-0.000794	-0.0108***	-0.0154**	-0.0123
	(0.0278)	(0.0191)	(0.0203)	(0.0345)	(0.0678)	(0.0108)	(0.00327)	(0.00303)	(0.00475)	(0.0120)
Dist-borderpost	-0.171***	-0.150***	-0.127***	-0.0504	0.0175	0.0641***	0.0764***	0.0776***	0.0706***	0.0592***
	(0.0304)	(0.0209)	(0.0222)	(0.0378)	(0.0743)	(0.0125)	(0.00377)	(0.00349)	(0.00548)	(0.0139)
Dist-popcentre	-0.121	-0.244***	-0.372***	-0.387**	-0.420	-0.182***	-0.150***	-0.136***	-0.150***	-0.176***
	(0.106)	(0.0731)	(0.0775)	(0.132)	(0.259)	(0.0397)	(0.0120)	(0.0111)	(0.0174)	(0.0441)
Rainfall	0.0150	0.0135	-0.00593	-0.0343*	-0.0527	-0.0138**	-0.0179***	-0.0185***	-0.0198***	-0.0225***
	(0.0125)	(0.00861)	(0.00913)	(0.0155)	(0.0305)	(0.00520)	(0.00157)	(0.00146)	(0.00228)	(0.00578)
Dist-capital	-0.127***	-0.174***	-0.198***	-0.269***	-0.333***	0.0741***	0.0663***	0.0644***	0.0580***	0.0461**
	(0.0326)	(0.0225)	(0.0238)	(0.0406)	(0.0797)	(0.0126)	(0.00382)	(0.00354)	(0.00555)	(0.0140)
Wetness	4.315**	5.152***	2.214*	0.502	-3.687	-0.0656***	-0.0532***	-0.0497***	-0.0598***	-0.0317
	(1.464)	(1.008)	(1.069)	(1.821)	(3.575)	(0.0154)	(0.00467)	(0.00432)	(0.00677)	(0.0171)
Constant	144.2***	161.3***	274.7***	349.2***	489.1***	-65.46***	-0.595	26.17***	56.84***	82.02***
	(33.19)	(22.86)	(24.24)	(41.27)	(81.05)	(9.734)	(2.944)	(2.723)	(4.271)	(10.80)
GroupFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4359	4359	4359	4359	4359	4962	4962	4962	4962	4962
pseudo R-sq	0.163	0.170	0.171	0.171	0.193	0.202	0.281	0.379	0.437	0.400

Notes: Standard errors are reported in brackets and *, **, *** represents 10, 5 and 1 percents significance levels respectively . I include the group, country and time fixed effects to control for other group, country and time invariant unobservable factors in the estimation . All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models been 2023.

Table K.4: Estimates across various depth of poverty

Female Headed										
	Food Expenditure (Fd Exp)					Non-Food Expenditure (Nfd Exp)				
Variable	0.1	0.25	0.5	0.75	0.9	0.1	0.25	0.5	0.75	0.9
Credit	13.66***	12.20***	13.50***	14.51**	17.80	8.683	9.459***	10.43***	8.634**	13.09
	(5.278)	(3.761)	(4.117)	(6.240)	(12.02)	(4.722)	(2.487)	(2.661)	(3.813)	(8.102)
Religion	27.50***	24.25***	13.22**	6.600	1.478	7.997	10.60***	10.23***	14.83***	20.37*
	(5.245)	(3.738)	(4.091)	(6.201)	(11.94)	(4.692)	(2.471)	(2.644)	(3.789)	(8.051)
Employed	10.36*	8.000*	12.42**	8.855	10.94	-6.470	-3.839	-2.238	-0.533	-4.894
	(5.260)	(3.748)	(4.102)	(6.219)	(11.97)	(4.706)	(2.478)	(2.652)	(3.800)	(8.074)
Married	43.79***	47.05***	56.17***	71.78***	107.5***	13.78**	15.76***	17.07***	20.56***	28.94***
	(5.334)	(3.801)	(4.160)	(6.307)	(12.14)	(4.772)	(2.513)	(2.689)	(3.854)	(8.189)
Latitude	0.450	0.549	-0.383	-0.520	-0.127	0.728	-0.189	-0.361	-0.831	0.0556
	(0.657)	(0.468)	(0.512)	(0.776)	(1.495)	(0.587)	(0.309)	(0.331)	(0.474)	(1.008)
Read	7.334	10.56**	21.28***	22.51***	30.08**	8.110	20.51***	36.35***	48.86***	57.42***
	(4.668)	(3.327)	(3.641)	(5.519)	(10.63)	(4.176)	(2.199)	(2.354)	(3.372)	(7.166)
Dist-market	0.0783***	0.0485***	0.0322**	0.0228	0.0347	-0.0267	-0.0331***	-0.0444***	-0.0442***	-0.0125
	(0.0171)	(0.0122)	(0.0134)	(0.0203)	(0.0390)	(0.0153)	(0.00807)	(0.00864)	(0.0124)	(0.0263)
Dist-borderpost	-0.109***	-0.104***	-0.0843***	-0.0270	-0.000448	0.0697***	0.0955***	0.106***	0.110***	0.0767*
	(0.0198)	(0.0141)	(0.0154)	(0.0234)	(0.0450)	(0.0177)	(0.00931)	(0.00996)	(0.0143)	(0.0303)
Dist-popcentre	0.0752	0.0400	-0.0495	-0.0617	-0.0352	0.0588	0.0552	0.0613	0.0305	-0.0566
	(0.0629)	(0.0448)	(0.0491)	(0.0744)	(0.143)	(0.0563)	(0.0296)	(0.0317)	(0.0454)	(0.0966)
Rainfall	0.0296***	0.0364***	0.0300***	0.00878	-0.0180	-0.0771***	-0.0793***	-0.0792***	-0.0939***	-0.0992***
	(0.00824)	(0.00587)	(0.00642)	(0.00974)	(0.0188)	(0.00737)	(0.00388)	(0.00415)	(0.00595)	(0.0126)
Dist-capital	-0.0921***	-0.0733***	-0.0745***	-0.0726**	-0.0668	0.151***	0.140***	0.127***	0.103***	0.106***
	(0.0200)	(0.0143)	(0.0156)	(0.0237)	(0.0455)	(0.0179)	(0.00943)	(0.0101)	(0.0145)	(0.0307)
Wetness	0.0722**	0.0485**	0.0431*	0.0620*	0.0680	-0.170***	-0.160***	-0.141***	-0.118***	-0.116**
	(0.0244)	(0.0174)	(0.0191)	(0.0289)	(0.0556)	(0.0219)	(0.0115)	(0.0123)	(0.0176)	(0.0375)
Constant	110.8***	125.1***	175.8***	222.2***	305.9***	5.416	89.39***	115.9***	187.6***	226.6***
	(15.41)	(10.98)	(12.02)	(18.21)	(35.07)	(13.78)	(7.259)	(7.768)	(11.13)	(23.65)
GroupFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
CountryFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
TimeFE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4954	4954	4954	4954	4954	4954	4954	4954	4954	4954
pseudo R-sq	0.125	0.127	0.162	0.175	0.203	0.192	0.254	0.316	0.334	0.300

Notes: Standard errors are reported in brackets and *, **, *** represents 10, 5 and 1 percents significance levels respectively . I include the group, country and time fixed effects to control for other group, country and time invariant unobservable factors in the estimation . All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models been 2023.

Appendix L Robustness on the Effects of Credit on Empowerment

Table L.1: Robustness on the Effects of Credit on Empowerment

Outcome=Non-farm Business	Male Headed	Female Headed
HH Size	-0.0002	0.0017
	(0.0011)	(0.0023)
Credit	-1.6351***	2.5316***
	(0.4593)	(0.04667)
Credit		
Religion	0.0324***	0.0036
	(0.0118)	(0.0043)
Employed	0.0436***	-0.0124**
	(0.0073)	(0.0045)
Married	0.0182**	0.0041
	(0.0083)	(0.0039)
Latitude	-0.0017***	0.00025
	(0.000337)	(0.0004)
Read	-0.010***	0.0074*
	(0.0031)	(0.0037)
Dist-market	-0.000036***	0.000057***
	(7.54e-06)	(0.000015)
Dist-borderpost	0.000013	-0.00011***
	(0.000017)	(0.000030)
Dist-popcentre	0.00002	-0.00014**
	(0.00004)	(0.00006)
Rainfall	3.5e-06	-0.00003***
	(8.48e-6)	(0.00001)
Dist-capital	0.00011***	-0.000056**
	(0.00003)	(0.000023)
Wetness	-0.00013***	0.00002
	(0.0000303)	(0.00002)
GroupFE	Yes	Yes
CountryFE	Yes	Yes
TimeFE	Yes	Yes
N	22095	5862
var(e.credit,e.non.farm business)	0.8642***	-0.9665***
	(0.0613)	(0.0175)

Notes: Standard errors are reported in brackets and *, **, *** represents 10, 5 and 1 percents significance levels respectively . I include the group, country and time fixed effects to control for other group, country and time invariant unobservable factors in the estimation . All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models.

Table L.2: Robustness on the Effects of Credit on Empowerment

Outcome=Non-farm Business	Male Headed	Female Headed
Credit	-0.00859	0.364*
	(0.0706)	(0.171)
Married	0.595***	0.741*
	(0.128)	(0.312)
Religion	-0.349***	-0.616*
	(0.0916)	(0.267)
Employed	-0.206***	-0.336*
	(0.0573)	(0.161)
Read	0.524***	0.625***
	(0.0621)	(0.157)
Dist-market	0.000222	0.000369
	(0.000136)	(0.000375)
Dist-popcentre	-0.00475***	-0.00522*
	(0.000698)	(0.00243)
Dist-borderpost	-0.000776*	-0.00145
	(0.000321)	(0.000898)
Dist-capital	-0.00480***	-0.00143
	(0.000666)	(0.00230)
Rainfall	-0.000476***	-0.00132**
	(0.000144)	(0.000421)
wetness	-0.0616**	0.0199
	(0.0222)	(0.0533)
hhsize	0.0748***	0.148***
	(0.0112)	(0.0373)
constant	1.435***	1.901
	(0.435)	(1.044)
lnsig2u	0.898***	1.162***
	(0.0806)	(0.195)
N	7884	1398

Notes: Standard errors are reported in brackets and *, **, *** represents 10, 5 and 1 percents significance levels respectively . I include the group, country and time fixed effects to control for other group, country and time invariant unobservable factors in the estimation . All the expenditures have been converted to US Dollars for simplicity using the various official exchange rates of each country as at the time of estimation of the models.

References

Abrevaya, J. and Dahl, C.M. (2008). The effects of birth inputs on birthweight: evidence from quantile estimation on panel data. *Journal of Business and Economic Statistics,* 26(4), 379-397.

Adams, D. and Von Pischke, J. D. (1992). Micro-entreprise credit programmes: Deja vu. *World Development,* 20(10), 1463-1470.

Afrane, S. (2002). Impact assessment of Microfinance interventions in Ghana and South Africa; a synthesis of major impacts and lessons. *Journal of Microfinance,* 4(1), 37-58.

Ahlin, C. and Jiang, N., 2008. Can micro-credit bring development?. *Journal of Development Economics,* 86(1), 1-21.

Ai, C. and Norton, E.C. (2003). Interaction terms in logit and probit models. *Economics letters,* 80(1), 123-129.

Aitken, R. (2013). The financialization of micro-credit. *Development and Change,* 44(3), 473-499.

Akalu, G., Taffesse, S., Gunaratna, N. and De Groote, H. (2010). The effectiveness of quality protein maize in improving the nutritional status of young children in the Ethiopian highlands. *Food and Nutrition Bulletin,* 31(3), 418-430.

Akhter, S. and Daly, K. J. (2009). Finance and Poverty: Evidence from fixed effect vector decompositism. *Emerging Markets Review,* 10, 191-206.

Akotey, O. J. and Ajasi, C. (2016). Does microcredit increase Household welfare in the absence of microinsurance?. *World Development,* 77, 380-394.

Ali, D.A., Deininger, K. and Duponchel, M. (2014). Credit constraints, agricultural productivity, and rural nonfarm participation: evidence from Rwanda. *World Bank Policy Research Working Paper, (6769).*

Ali, E. and Awade, N. E. (2019). Credit constraints and soybean farmers welfare in subsistence agriculture in Togo. *Helyion,* 5(4)

Al-Shami, .A., Razali, R.M. and Rashid, N. (2018). The effect of microcredit on women empowerment in welfare and decisions making in Malaysia. *Social Indicators Research,* 137, 1073-1090.

Alves, C. M. and Camargos, M. A. (2014). Fatores condicionates de inadimplencia em operacões de microcrédito. *Revista de Administração e Contabilidade das UNISINOS,* 11(1), 59-74.

Anderson, T.W. and Hsiao, C., 1982. Formulation and estimation of dynamic models using panel data. *Journal of Econometrics,* 18(1), 47-82.

Anderson, T.W. and Hsiao, C. (1981). Estimation of dynamic models with error components. *Journal of the American Statistical Association,* 76(375), 598-606.

Andres de Pablo., Gineno, R. and Cabo, R. M. (2019). The Gender Gap in Bank Credit Access. *Journal of corporate Finance,* 71, 101782.

Angelucci, M., Karlan, D., and Zinman, J. (2015). "Microcredit impacts: Evidence from a randomized microcredit programme placement experiment by Compartamos Banco". *American Economic Journal: Applied Economics*, 7(1), 151–182.

Annim, K. S. (2018).Ou treach and the poverty reducing effect of Microfinance in Ghana. *Enterprise Development and Microfinance,* 29(2), 145-171.

Antonio, F. G. (2009). Quantile Regression for Dynamic Panel Data with fixed effects.

Apostolakis, G., VanDijk, G. and Drakos P. (2015). Microinsurance performance—a systematic narrrative Literature Review. *Corporate Governance,* 5(1), 116-170.

Armendariz de Aghion, B. and Morduch, J. (2010). The Economics of Microfinance. Cambridge, MA: The MIT Press.

Arnold, M. and Javorcik, S. (2005). Gifted kids or pushy parents? Foreign acquisitions and plant performance in Indonesia.

Arouri, M., Nguyen, C. and Youssef, A. B. (2015). Natural disasters, household welfare and resilience: Evidence from rural Vietnam. *World Development,* 70, 59-77

Arellano, M. and Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies,* 58(2), 277-297.

Arrivillag, M. and Salcedo, J. P. (2014). A systematic review of Microfinance based interventions for HIV/AIDS prevention. *AIDS education and Prevention,* 26(1), 18-27.

Asad, K. G., Issam, M. and Katsushi, S. M. (2015). Microfinance and household poverty reduction: Empirical Evidence from Rural Pakistan. *Oxford Development Studies,* 43(1), 84-104.

Asiedu, E., Freeman, J. and Nti-Addae, A. (2012). Access to credit by small businesses: how relevant are race, Ethnicity and Gender?. *American Economic Review* 102(3), 532-537.

Attanasio, O. Augsburg, B., De Hans, R., Fitzsimmons, E. and Harmgart, H. (2015). The impact of Microfinance: Evidence from joint-liability lending in Mongolia. *American Economic Journal, Applied Economics,* 7(1), 90-122.

Augsburg, B. De Hans, R., Harmgart, H. and Meggie, C. (2015). The impact of micrcredit: Evidence from Bosnia and Herzegovina. *American Economic Journal, Applied Economics,* 7(1), 183-203.

Awaworyi Churchill. S., Dauso, J., and Appan, S. (2016). Microcredit and poverty reduction in Bangladesh: Average effects beyond publication bias. *Enterprise Development and Microfinance,* 87(8), 59-72.

Awaworyi-Churchill. S., Korankyo, D. J., and Appan. S. (2015). Microcredit and poverty reduction in Bangladesh: Beyond publication bias, does genuine effect exist? (Working paper).

Awaworyi-Churchill, S. (2014). Impact of Microfinance interventions: a meta-analysis. *Business and Economics,* 4(1), 3-14.

Bahta, Y. T., Strydom, D. B., and Donkor, E. (2017). Microcredit and gender empowerment: Policy Implications for sustainable Agricultural Development in Eritrea. *Development in Practice,* 27(1), 90-102.

Baiyegunhi, L., Fraser, G. C., Darroch, M. (2010). Credit constraints and household welfare in the Eastern Cape Province, South Africa. *African Journal of Agricultural Research*, 5(16), 2243-2252.

Bakhtiari, S.(2006). Microfinance and Poverty Reduction: Some international Evidence. *Business and Economics Research Journal*, 5(12), 65-70.

Barnes, C., Gaile, G. and Kimbombo, R. (2001). Impact of three microfinance programmes in Uganda.

Barnes, C. (1996). Assets and the impact of micro-enterprise finance programmes . AIMS paper Washington DC Management Systems International.

Barnes. C, and Keogh, E (1999). An assessment of the impact of Zambuko's micro-enterprise programme of Zimbabwe Baseline findings. Washington DC. Management systems international.

Banerjee ,A., Duflo, E., Glemnerstar, R, and Kinnan, C. (2015). The Miracle of Microfinance?. Evidence from a Randomized Evaluation. *American Economic Journal Applied Economics*, 7(1), 22-53.

Banerjee, A. and Newman, A. (1993). Occupational choice and the process of development. *Journal of Political Economy,* 101(2), 274-298.

Barnum, H.N. and Squire, L. (1979). An econometric application of the theory of the farm-household. *Journal of Development Economics,* 6(1), 79-102.

Bateman, M., and Chang, H. (2000). The microfinance illusion (E-text type], http://www.pron.cam.ac.uk/faculty/chang/pubs/Microfinance.pdf . Last accessed June 30, 2023.

Beck, T., Bert, P., Madestam, A. (2018). Sex and Credit: Do gender interaction matter for credit market outcomes?. *Journal of Banking and Finance,* 87, 380-396.

Beck, T., Damirgue-Kunt, A. and Levine, R. (2004). Finance, inequality and poverty: cross-country evidence (World Bank Policy Research Working Paper 3338) Washington DC: World Bank.

Beck,T., Demigue-Kunt, A. and Levine, R. (2007). SMEs, Growth, And Poverty: Cross-Country Evidence. *Journal of Economic Growth,* 27(3), 12-49.

Beck,T., Demigue-Kunt, A. and Levine, R. (2005). SMEs, Growth, And Poverty: Cross-country Evidence. *Journal of Economic Growth,* 10(3), 199-229.

Belloni, A., V. Chernozhukov and Y. Wei. (2016). Post-selection inference for generalised linear models with many controls. *Journal of Business and Economic Statistics,* 34, 608-619.

Bellucci, A., Borisov, A. and Zazzaro, A. (2010). Does Gender matter in bank-firm relationships?: Evidence From Small Business Lending. *Journal of Business Banking and Finance* 34(12), 2968-2984.

Benin, S. and You, L., 2007. Benefit-Cost Analysis of Uganda's Clonal Coffee Replanting programme, An Ex-Ante Analysis (Vol. 744). Intl Food Policy Res Inst.

Bergson, A. (1938). A reformulation of certain aspects of welfare economics. *Quarterly Journal of Economics,* 52(2), 310-340.

Bhageerathy, R., Nair, S. and Bhaskaran, U. (2017). A systematic review of community based health insurance programme in South Asia. *The International Journal of Health Planning and Management,* 32(2), e218-e231.

Blundell, R. and Costa Dias, M. (2002). Alternative Approaches to Evaluation in Empirical Microeconomics. The Institute for Fiscal Studies, Department of Economics, UCI,CEMMAP (Centre for Microdata Methods and Practice) Working Paper n. 10.

Blunndell, R. and Costa Dias, M. (2000). Evaluation Methods for Non-Experimental Data. *Fiscal Studies,* 21(4), 427-468.

Bocher, T., Alemu B. A. and Kelbore, Z. (2017). Does access to credit improve household welfare?. Evidence from Ethiopia using Endogenous regime switching regression. *African Journal of Economic and Management Studies* 8(1), 51-65.

Brana, S. (2013). Microcredit: An Answer to the Gender Problem in Funding?. *Small Business Economics,* 40(1), 87-100.

Brandt, Laura., Natalya, E. and Tatiana Klepikova. (2012). Lending Methodology Module: A U.S. Department of State/NISCUP Funded Partnership with the University of Washington-Evans School of Public Affairs, The Siberian Academy of Public Administration, and the Irkutsk State University http://depts.washington.edu/mlinaade/o curriculum/docs/63,ending Methodology.pdf.

Brannen, C. (2010). An Impact Study of the Village Savings and Loan Association (VSLA) programme in Zanzibar, 'Tanzania'. A Thesis Submitted to Wesleyan University.

Brody, C., De Hoop, T., Vojtkova, M., Warnock, R., Dunbar, M., Murthy, P. and Dworkin, S.L. (2015). Economic Self-Help group programmes for improving women's Empowerment: a systematic review. *Campbell Systematic Reviews,* 11(1), 1-182. Brody et al. 2015

Bulte, E., Beekman, G., di Falco, S., Hella, J. and Lei,P. (2014). Behavioral responses and the impact of new agricultural technologies: evidence from a double-blind field experiment in Tanzania. *American Journal of Agricultural Economics,* 96(3), 813-830.

Caliendo, M. and Kopeinig, S. (2008). Some practical guidance for the implementation of Propensity Score Matching. *Journal of Economic Surveys,* 22(1), 31-72.

Canay, I.A. (2011). A simple approach to quantile regression for panel data. *The Econometrics Journal—,* 14(3), 368-386.

Caplan, M., Birkenmater J., Bae, J. (2021). Financial exclusion in the OECD countries: a Scoping Review. *International Journal of social welfare,* 30, 58-71.

Carter, S. E., Shaw, W., Lam and Wilson, F. (2007). Gender, Entrepreneurship and Bank Lending: The Criteria and Processes Used by Bank loan officers in Assessing Applications". *Entrepreneurship Theory and Practice,* 31, 427-444.

Central Bank of Nigeria (2015). Statistical Bulletin. https://www.cbn.gov.ng/documents/Statbulletin.asp.

Cepparulo, A., Cuetas .J. A., and Intartagia, M. (2017). Financial development, Institution and poverty alleviation: an empirical analysis , *Applied Economics,* 49, 3611-3622.

Seppruio, A. and Gledeman, D.C. (2011). Panel evidence on finance, institutions and economic growth. *Applied Economics,* 43(25):, 523-3547.

Chancel, L., Piketty, T., Saez, E. and Zucman, G. eds. (2022). *World inequality report 2022.* Harvard University Press.

Chandy, L. and Seidel, B. (2017). How much do we really know about inequality within countries around the world? Adjusting Gini coefficients for missing top incomes. *Brookings Institute.*

Chant, S., 2003. Female household headship and the feminisation of poverty: facts, fictions and forward strategies.

Chavan, P. and Ramakumar, R. (2002). Micro-credit and rural poverty: An analysis of empirical evidence. *Economic and Political Weekly*, 955-965.

Chen, S. and Ravallion, M. (2010). The developing World is Poorer than We Thought, But No Less Successful in their fight against poverty. *Quarterly Journal of Economics,* 125(4), 1577-1625.

Chernozhukov, V., Hansen, C. and Spindler, M. (2015). Post Selection and Post-Regularization inference in linear models with many controls and instruments. *American Economic Review,* 105 (5), 486-490.

Chernozhukov, V. and Hansen, C. (2005). An IV Model of Quantile Treatment Effects. *Econometrica,* 73, 245-261.

Chernozhukov, V. and Hansen, C. (2006). Instrumental Quantile Regression inference fir Structural and Treatment Effects Models. *Journal of Econometrics,* 132, 491-525.

Chernozhukov, V. and Hansen, C. (2008). Instrumental Variable Quantile Regression: A Robust Inference approach. *Journal of Econometrics,* 142, 379-398.

Chilova, M., Brinckanann, J. and Rosenbusch, N. (2015). Microcredit a blessing for the poor?: A metaphysical examining development outcomes and contextual considerations. *Journal of Business Venturing,* 30(9), 467-487. Chilova et al. 2015

Cole, S., Bastian, G., Vyas, S., Wendel, C. and Stein, D. (2012). The effectiveness of index-based microinsurance in helping smallholders manage weather related risks. London: EPPI-Centre, Social Science Research Unit, Institute of Education, University of London.

Copestake, J. (2002). Inequality and the polarizing impact of microcredit: Evidence from Zambia's Copperbelt. *Journal of International Development,* 14(6), 743-755.

Copestake. J., Bhalotra, S. and Johnson S. (2001). Assessing the impact of microcredit: A Zambian case study" Journal of Development Studies, 37(4), 81-100.

Crépon, B., Devoto, F., Duflo, E. and Parienté, W. (2015). Estimating the impact of microcredit on those who take it up: Evidence from a randomized experiment in Morocco. *American Economic Journal: Applied Economics,* 7(1), 123-150.

Cull, R., Demirguc-Kunt, A., and Morduch, J. (2009). Microfinance meets the market. *Journal of Economic Perspectives,* 23(1), 167–192.

Danquah, M., Iddrissu, A. M., Boakyec, E. O. and Owusu, S. (2021). Do gender wage differences within households influence women's empowerment and Welfare?.*Journal of Behaviour and Organization,* 188, 916-932.

Dawson, C. and Henley, A.(2015),"Gender, Risk, and Venture Creation Intentions. *Journal of Small Business Management,* 53,501-515.

De Janvry, A., Sadoulet, E., Davis, B. and de Anda, G.G. (1996). Ejido sector reforms: From land reform to rural development. *Randall (ed.),* 71-106.

DeLeire, T. (2000). The wage and employment effects of the Americans with Disabilities Act *Journal of Human Resources,* 35(4), 693-715.

Delis, M. D., Hasan, I., Losifidi, M. and Ongena, S. (2020). Gender, Credit, and Firm Outcomes. *Journal of Financial and Quantitative Analysis,* 1-31.

Demirguc Kunt, A., Klapper, L., Singer, D., Ansar, S., and Hess, J. (2018). The Global Findex Database 2017: Measuring financial inclusion and the fintech revolution. Prepared for The World Bank. Retrieved from http://documents worldbank.org.

DFID (2010). AusAid-DFID-3ie *systematic reviews.* London: DFID.

DFID (2011). Systematic review in international development: An initiative to strengthen evidence-informed policy making [E-text type]. http://www.dfid.gov.uk/r4d/systematic reviewfeature.asp.

Dimova, R., and Adebowale, O. (2017). Does Access to Formal Finance Matter for Welfare and Inequality?. Micro Level Evidence from Nigeria *The Journal of Development Studies,* 64(9), 1534-1680.

Dollar, D. and Kraay, A. (2004). Trade, Growth, and Poverty. *The Economic Journal,* 114(49), 22-49.

Doocy, S., Teffera, S., Norell, D. and Burnham, G. (2005). Credit programme outcomes: Coping capacity and nutritional status in the food insecure context of Ethiopia. *Social Science and Medicine,* 60, 2371-2382.

Duvendack, M. and Mader, P. (2019). Impact of financial Inclusion in low-and middle-income countries: A systematic review of reviews. Campbell Systematic Reviews. 2019, 2.

Duvendack, M., Palmer-Jones, R., Copestake, J. G., Hooper, L., Loke, Y., and Rao, N. (2011). What is the evidence of the impact of microfinance on the well-being of poor people? EPPI-Centre, Social Science Research Unit, Institute of Education. London, UK: University of London.

Fernandez, A. (2011). Why doesn't microfinance work? The destructive rise of local neoliberalism. *European Journal of Development Research,* 23(1), 174–175.

Fofana, N., Antonides, G., Niehof, A. and van Ophem, J.A. (2015). How microfinance empowers women in Côte d'Ivoire. *Review of Economics of the Household,* 13, 1023-1041.

Fernando, J.L. (2006). Microcredit and empowerment. *Microfinance: Perils and Prospects,* 187-238.

Fischer, G and Ghatak, M.(2011). Spanning the chasm ; Uniting the theory and empirics in microfinance research. In B. Armenda riz, and M. Labie(Eds.). The handbook of microfinance (pp. 59-75). Hackensack, N.J: World Scientific.

Ganle, J.K., Afriyie, K. and Segbefia, A.Y. (2015). Microcredit: Empowerment and disempowerment of rural women in Ghana. *World Development,* 66, 335-345.

Galvao, A.F. (2011). Quantile regression for dynamic panel data with fixed effects. *Journal of Econometrics,* 164(1), 142-157.

Gammage, S., Kes, A., Winograd, L., Sultana, N., Hiller, S. and Bourgault, S.(2017).Gender and digital financial inclusion: What do we know and what do we need to know?

Garikipati, S.(2008). The impact of leading woman on household vulnerability and women's empowerment: evidence from India. *World Development,* 36(12), 2620-2642

Garikipati, S.(2012), Microcredit and Women's Empowerment: Through the Lens of Time-Use Data from Rural India. *Development and Change,* 43(3), 719-750.

Gash, M.(2017). Understanding the impact of saving groups. The SEEP network.

Gebru, B. and Paul, I., 2011. Role of microfinance in alleviating urban poverty in Ethiopia. *Journal of sustainable Development in Africa,* 13(6), 165-180.

Geraci, M. and Bottai, M., 2007. Quantile regression for longitudinal data using the asymmetric Laplace distribution. *Biostatistics, 8(1),* 140-154.

Ghosh, S. and Vinod ,D. (2017). What constraints financial inclusion for women? Evidence from Indian micro data. *World Development,* 92, 60-81.

Girma, S. and Görg, H. (2007). Evaluating the foreign ownership wage premium using a difference-in-differences matching approach. *Journal of International Economics,* 72(1), 97-112.

Glewwe, P. (1991). Investigating the determinants of household welfare in Cote. *Journal of Development Economics,* 35(2), 307-337.

Gopalaswamy, A. K., Babu, M.S. and Dash, U.(2016). Systemic review of quantitative evidence on the impact of microfinance on the poor in South Asia. London: EPPI Center, Social Science Research Unit, Institute of Education, University College London. Gopalaswami et al. 2016

Guo, S. and Fraser, M.W. (2014). *Propensity score analysis: Statistical methods and applications (Vol. 11).* SAGE publications.

Habib, S. S., Perveen, S., and Khuwaja, H. M. A. (2016). "The role of micro health insurance in providing financial risk protection in developing countries: A systematic review". *BMC Public Health,* 16(1), 281.

Haddad, L., and May, J. (2003). Social capital and household welfare in South Africa, 1993-1998. In: A. Quisumbing, (Ed.), Household decisions, gender and development: A synthesis of recent research (pp. 145-152). Washington DC: International Food Policy Research Institute.

Haile, H.B., Bock, B. and Folmer, H., 2012, July. Microfinance and female empowerment: Do institutions matter?. In *Women's studies international forum* (Vol. 35, No. 4, pp. 256-265). Pergamon.

Heckman, J., Ichimura, H., and Todd, P. (1997). Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training programmeme.*The Review of Economic Studies*, 64(4), 605-654.

Heckman, J., Ichimura, H., Smith, J. and Todd, P.E. (1998). Characterizing selection bias using experimental data.

Herath, H. (2018). Microfinance as a Strategy of Empowering the Conflict-Affected Communities in Sri Lanka. *Journal of Social and Development Sciences,* 9(2), 6-21. Herath

2018

Hidalgo, D., Pai, M., Carrigan, A., and Bhatt, A. (2013). Toward people's cities through land use and transport integration: A review of India's national urban investment programme. *Transportation Research Record, 2394(1), 10–18.*

Hietalahti, J., and Linden, M. (2006). Socio-economic impacts of microfinance and repayment performance: A case study of the Small Enterprise Foundation, South Africa. *Progress in Development Studies, 6(3), 201–210.*

Higgins, J.P., López-López, J.A., Becker, B.J., Davies, S.R., Dawson, S., Grimshaw, J.M., McGuinness, L.A., Moore, T.H., Rehfuess, E.A., Thomas, J. and Caldwell, D.M. (2019). Synthesising quantitative evidence in systematic reviews of complex health interventions. *BMJ global health, 4(Suppl 1)*, p.e000858.

Hirano, K., and G. Imbens. (2001). Estimation of Causal Effects Using Propensity Score Weighting: An Application of Data on Right Ear Catheterization. *Health Services and Outcomes Research Methodology*, 2(1), 259–278.

Hirano, K., G. Imbens, and G., Ridder. (2003). Efficient Estimation of Average Treatment Effects Using the Estimated Propensity Score." *Econometrica*, 71(4), 1161–1189.

Hong, S., Xiaohong, L. and Wenjing, L. (2020). The Nexus between Credit Channels and Farm Household Vulnerability to Poverty: Evidence from Rural China. *Sustainability*, 12(7), 1-18.

Hossain, F., and Knight, T. (2008). "Financing the poor: Can microcredit make a difference? Empirical observations from Bangladesh (BWPI Working Paper 38)". Manchester: Brooks World Poverty Institute.

Hotz, C., Loechl, C., Lubowa, A. (2012). Introduction of b-Carotene–Rich Orange Sweet Potato in Rural Uganda Resulted in Increased Vitamin A Intakes among Children and Women and Improved Vitamin A Status among Children. *Journal of Nutrition,* 142, 1871–1880.

Howard, N. Barnum and Squire, l. (1979). An econometric application of the theory of the farm-household." *Journal of Development Economics*, 6(1), 79-102.

Hulme, D., and Mosley, P. (1996). Finance against the poor (Vols. 1–2). London: Routledge.

Hulme, D. (2000). Impact assessment methodologies for microfinance: theory, experience and better practice. *World Development,* 28(1), 79-98.

Hung,M.N and Tuan, A.N (2019). Investigating the determinants of household welfare in the Central Highland, Vietnam. *Cogent Economics and Finance* 7(1), 1-11.

Husain, Z., Mukherjee, D., and Dutta, M. (2010). Self-help groups and empowerment of women: Self-selection or actual benefits?.

Iddrisu, A., Ansah, I.G.K. and Nkegbe, P.K. (2018). Effect of input credit on smallholder farmers' output and income: Evidence from Northern Ghana. *Agricultural Finance Review,* 78(1), 98-115.

Imbens, G.W., 2004. Nonparametric estimation of average treatment effects under exogeneity: A review. *Review of Economics and Statistics,* 86(1), 4-29.

Imbens, G.W. and Rubin, D.B. (2015). Causal inference in statistics, social, and biomedical sciences. Cambridge University Press.

Imbens, G.W. and Newey, W.K. (2009). Identification and estimation of triangular simultaneous equations models without additivity. *Econometrica,* 77(5), 1481-1512.

International Network on Financial Education. (2012). Financial education in schools. Prepared for the OECD. Retrieved from https://www.oecd.org/daf/fin/financial-education/FinEdSchool-web.pdf.

Isangula, K. G. (2012). Improving women and family's health through integrated microfinance, health education and promotion in rural areas. *Journal of Sustainable Development, 5(5), 76.*

Ismayilova, L., Ssewamala, F., Mooers, E., Nabunya, P., and Sheshadri, S. (2012). Imagining the future: Community perceptions of a family-based economic empowerment intervention for AIDS orphaned adolescents in Uganda. *Children and Youth Services Review, 34(10), 2042–2051.*

Ismi, A. (2004). Impoverishing a continent: The World Bank and the IMF in Africa. Ottawa: Canadian Centre for Policy Alternatives.

Jacoby, H.G. (1993). "Shadow Wages and Peasant Family labour Supply: An Econometric Application to the Peruvian Sierra." *Review of Economic Studies*, 60(1): 903-921.

Jalan, J. and Ravallion, M. (2000). Is transient poverty different? Evidence for rural China. *The Journal of Development Studies,* 36(6), 82-99.

Jalilian, H. and Kirkpatrick, C. (2002), Financial development and poverty reduction in developing countries: *International Journal of Finance and Economics,* 7(1), 07-108.

Jalilian, H. and Kirkpatrick, C. (2005). Does financial development contribute to poverty reduction?. *Journal of Development Studies,* 41(1), 636-656.

James E. O. (2020). The effects of Financial credit on Household Welfare: Empirical evidence from Nigeria. Masters Dissertation, University of Nottingham.

Jeanneney, S.G. and Kpodar, K. (2011). Financial development and poverty reduction: Can there be a benefit without a cost?. *The Journal of Development Studies,* 47(1), 143-163.

Johnson, S., 2005. Gender relations, empowerment and microcredit: moving on from a lost decade. *The European Journal of Development Research,* 17, 224-248.

Kabeer, N. (2001). Conflicts over credit: Re-evaluating the empowerment potential of loans to women in rural Bangladesh. *World Development,* 29(1), 63-84.

Kabeer, N. (2001). Reflections on the Measurement of Women's Empowerment.

Kabeer, N. (2005). Gender equality and women's empowerment: A critical analysis of the third millennium development goal 1. *Gender and Development,* 13(1), 13-24.

Kabeer, N. (2005). Is microfinance a'magic bullet'for women's empowerment? Analysis of findings from South Asia. *Economic and Political Weekly*, 4709-4718.

Karlan, D. and Zinman, J. (2010). Expanding credit access: Using randomized supply decisions to estimate the impacts. *The Review of Financial Studies,* 23(1), 433-464.

Kaung, X., Liu, H., Guo, G., and Cheng, H. (2019). The nonlinear effect of financial and fiscal policies an poverty alleviation in China: An empirical analysis of Chinese impoverished countries with PSTR models. *PLoS ONE* 14(11), e0224375.

Kempson, E., Perotti, V., and Scott, K. (2013). Measuring financial capability: A new instrument and results from low and middle income countries. Prepared for The World Bank. Retrieved from https://openknowledge.worldbank.org/handle/10986/16296.

Khandker, S. (2001). Does micro-finance really benefit the poor? Evidence from Bangladesh. Paper delivered at the Asia and Pacific Forum on Poverty: Reforming Policies and Institutions for Poverty Reduction.

Kijima, Y. (2014). Enhancing rice production in Uganda: Impact evaluation of a training programmeme and guidebook distribution in Uganda. JICA-RI Working Paper. JICA Research Institute: Tokyo

King R.G., and Levine, R. Finance (1993). Entrepreneurship and Growth: Theory and Evidence. *Journal of Monetary Economics*, 32, 513–54

Koenker, R. (1984). A Note on L-Estimates for Linear Models. *Statistics and Probability Letters,* 2, 323–325.

Koenker, R.(2004). Quantile Regression for Longitudinal Data. *Journal of Multivariate Analysis,* 91, 74–89.

Koenker, R., and Bassett, G.W. (1978). Regression Quantiles. *Econometrica,* 46, 33–49.

Koenker, R., and Bassett, G.W. (1982a). Robust Tests for Heteroscedasticity Based on Regression Quantile. *Econometrica,* 50, 43–61.

Koenker, R., and Bassett, G.W. (1982b). Tests of Linear Hypothesis and Estimation. *Econometrica,* 50, 1577–1584.

Koenker, R., and Hallock, K. (2000). Quantile Regression an Introduction. Manuscript, University of Illinois at Urbana-Champaign.

Koenker, R., and Machado, J.A. (1999). Goodness of Fit and Related Inference Processes for Quantile Regression. *Journal of the American Statistical Association,* 94, 1296–1310.

Koenker, R., and Xiao, Z. (2006). Quantile Autoregression. *Journal of the American Statistical Association,* 101, 980–990

Kpodar, K. and Jeanneney, S.G. (2010). Financial Development and poverty Reduction: Can there be a benefit without a cost?. *Journal of development studies* 1(1), 143-163

Kuang, X., Liu, H., Guo, G., and Cheng, H. (2019). The nonlinear effect of financial and fiscal policies on poverty alleviation in China—An empirical analysis of Chinese impoverished counties with PSTR models". *PLoS ONE* 14(11): e0224375.

Kumar, C.J., Turvey, D., and Kropp, J.D. (2013). The Impact of Credit Constraints on Farm Households: Survey Results from India and China. *Applied Economic Perspectives and Policy*, 35(3), 508-527.

Lamarche, C. (2010). Robust penalized quantile regression estimation for panel data. *Journal of Econometrics, 157(2),* 396-408.

Leach, F. and S. Sitaram. (2002). Microcredit and women's empowerment: A lesson from India. *Development in Practice* 12(5), 575-500.

Lipton, M. (1996). Successes in antipoverty. Geneva: International Institute of labour Studies.

Liqiong, L., Weighzou, W., Christopher, G., and Nguyen, Q.T. (2019). Credit Constraints on Farm Household Welfare in Rural China: Evidence from Fujian Province. *Sustainability,* 11(11), 3221.

Lloyd-Ellis, H. and Bernhardt, D. (2000). Enterprise, Inequality and Economic Development. *Review of Economic Studies,* 6(1), 147-168.

Lopez, R. (1984). Estimating labour supply and production decisions of self-employed farm producers. *European Economic Review,* 24(1), .61-82.

Lorenzetti, L. M., Leatherman, S. and Flax, V. L. (2017). "Evaluating the effect of integrated microfinance and health interventions: An updated review of the evidence". *Health Policy and Planning, 32(5), 732–756.*

Low, J.W., Arimond, M., Osman, N., Cunguara, B., Zano, F. and Tschirley, D. (2007). A food-based approach introducing orange-fleshed sweet potatoes increased vitamin A intake and serum retinol concentrations in young children in rural Mozambique. *The Journal of Nutrition,* 137(5), 1320-1327.

Lusardi, A. and Mitchell, S.O. (2014). The economic importance of financial literacy: Theory and evidence. *Journal of economic literature,* 52(1).

Ma, C.H. and Smith, B.D. (1996). Credit market imperfections and economic development: Theory and evidence. *Journal of Development Economics,* 48(2), 351-387.

Machado, J. A. and Silva, J. S. (2019). Quantiles via moments. *Journal of Econometrics,* 213(1), 145–173.

Madhani, F., Tompkins, C., Jack, S., and Fisher, A. (2015). Participation in micro-finance programmes and women's mental health in South Asia: A modified systematic review. *Journal of Development Studies,* 51(9), 1255–1270. Madhani et al. 2015

Marr, A., Winkel, A., vanAsseldonk, M., Lensink, R., and Bulte, E. (2016). Adoption and impact of index-insurance and credit for smallholder farmers in developing countries: A systematic review. *Agricultural Finance Review,* 76(1), 94–118.

Masih, R. and Khan, S.F. (2011). Is the Finance led Growth Hypothesis robust to alternative measures of Financial Development?. *Applied Financial Economics,* 21(9), 601-623.

Matsumoto, T. (2014). Disseminating new farming practices among small scale farmers: An experimental intervention in Uganda. *Journal of the Japanese and International Economies,* 33, 43-74.

Matsuyama, K. (2007). Credit traps and credit cycles. *American Economic Review,* 97(1), 503-516.

Matsuyama, K. (2006). The 2005 Lawrence R. Klein lecture: emergent class structure. *International Economic Review,* 47(2), 327-360.

Mayoux, L. (1999). "Questioning virtuous spirals: Microfinance and women's empowerment in Africa". *Journal of International Development, 11, 957–984.*

Mazumder,R., Dastidar, S. and Bhandari, A.K. (2017). Access to credit and microentrepreneurship: A gender comparison. In C. Neogi, A.K. Bhandari, and S. Ghosh (Ed's,), women entrepreneurship and microfinance (vol, chap 11, pp, 191-210) Singapore: Springer.

McKinnon, R.I. (2010). Money and capital in economic development. Brookings Institution Press.

Mello, M.M., Stearns, S.C. and Norton, E.C. (2002). Do Medicare HMOs still reduce health services use after controlling for selection bias?. *Health Economics,* 11(4), 323-340.

Mitton, L. (2008). Financial inclusion in the UK: Review of policy and practice. York, UK: Joseph Rowntree Foundation.

MIX (Microfinance Information Exchange) and CGAP (Consultative Group to Assist the Poor) (2011). MIX microfinance world: Sub-Saharan Africa microfinance analysis and benchmarking report 2010. Washington, D.C.: MIX.

Morduch, J. (1998). Does microfinance really help the poor? Evidence from flagship programmes in Bangladesh. Washington DC: World Bank.

Mosley, P. and Hulme, D. (1998). Microenterprise finance: is there a conflict between growth and poverty alleviation?. *World Development,* 26(5), 783-790.

Mwansakilwa, C., Tembo, G., Zulu, M. M., Wamulume, M. (2017). "Village savings and loan associations and household welfare: Evidence from eastern and western Zambia". *African Journal of Agricultural and Resource Economics,* 12(1), 85–97.

Nam, Y., Wikoff, N., and Sherraden, M. (2016). "Economic intervention and parenting: A randomized experiment of statewide Child Development Accounts". *Research on Social Work Practice, 26(4), 339–349.*

Nanziri, E. L. (2016). Financial inclusion and welfare in South Africa: is there a gender gap?. *Journal of African Development,* 18(2), 209-134.

Narayan-Parker, D. ed. (2002). Empowerment and poverty reduction: A sourcebook. World Bank Publications.

Nghiem, S., Coelli, T. and Rao, P. (2012). Assessing the welfare effects of microfinance in Vietnam: Empirical results from a quasi-experimental survey. *Journal of Development Studies,* 48(5), 619-632.

Ngozi, C., Ewah, A. and Chioma, C. (2021). Impact of Natural Resource Earnings and Industrialization in Nigeria.

Nunn, N. (2008). The long-term effects of Africa's slave trades. *The Quarterly Journal of Economics,* 123(1), 139-176.

Odell, K. (2010). Measuring the impact of microfinance: Taking another look. Washington, DC: Grameen Foundation.

O'Grady, M. (2016). All that glitters: A meta-analysis of microfinance in developing world. Essay. The Public Purpose.

Ogundeji, A.A., Donkor, E., Motsoari, C. and Onakuse, S. (2018). Impact of access to credit on farm income: Policy implications for rural agricultural development in Lesotho. *Agrekon,* 57(2), 152-166.

Ohiomu, S. and Ogbeide- Osaretin, E.N. (2020). Financial inclusion and gender inequality reduction: evidence from sub- Saharan Africa. *The Indian Economic Journal,* 67(34), 967-972.

O'Malley, T. L., and Burke, J. G. (2017). "A systematic review of microfinance and women's health literature: Directions for future research". *Global Public Health, 12(11),* 1433–1460.

Omoro, N.O. and Omwange, A.M. (2013). The utilisation of microfinance loans and household welfare in the emerging markets. *European International Journal of Science,* 59-78.

Orton, L., Pennington, A., Nayak, S., Sowden, A., White, M., and Whitehead, M. (2016). "Group-based microfinance for collective empowerment: A systematic review of health impacts". *Bulletin of the World Health Organization,* 94(9), 694.

Palmkvist, F., and Lin, R. P. J. (2015). Women's empowerment through microfinance self-help groups: A systematic literature review (Bachelor thesis). The Netherlands: Aarhus University.

Pande, R., Cole, S., Sivasankaran, A., Bastian, G., and Wendel, C. (2012). Does poor people's access to formal banking services raise their incomes? EPPI-Centre, Social Science Research Unit, Institute of Education, University of London.

Pearce, D. (2011). Financial inclusion in the Middle East and North Africa: Analysis and roadmap recommendations. World Bank Policy Research Working Paper No. 5610.

Peters, M. D. J., Lockwood, C., Munn, Z., Moola, S., and Mishra, R. K. (2016). People's views and experiences of participating in microfinance interventions: A systematic review of qualitative evidence. London: EPPI-Centre, Social Science Research Unit, UCL Institute of Education, University College London. Peters et al. 2014

Petticrew, M., and Roberts, H. (2006). *Systematic reviews in the social sciences: A practical guide.* Oxford: Blackwell.

Powell, D. (2022). Quantile regression with nonadditive fixed effects. *Empirical Economics,* 63(5), 2675-2691.

Pritchett, L. and Sandefur, J. (2014). Context matters for size: why external validity claims and development practice do not mix. *Journal of Globalization and Development,* 4(2), 161-197. Pritchett and Sandefur 2014

Rahman, A. (1998). A micro-credit initiative for equitable and sustainable development: Who pays?". *World Development,* 26(1), 67–82.

Ravallion, M. (2001). Growth, Inequality and Poverty: Looking beyond Averages." *Journal of World Development*, 29(1), 1803–1815.

Ravallion, M. and Chen, S. (2007). China's uneven progress against poverty. *Journal of Development Economics,* 82(1), 1–42.

Reed, L.R., Marsden, J., Ortega, A., Rivera, C. and Rogers, S. (2011). State of the microcredit summit campaign report 2011. *Microcredit Summit Campaign. Washington DC.*.

Robert, M. Townsend. and Kenichi Ueda.(2006). Financial Deepening, Inequality, and Growth: A Model-Based Quantitative Evaluation. *Review of Economic Studies*, 73(1), 251-293.

Rodrik, D. (1999) Where did all the growth go? External shocks, social conflict and growth collapses. *Journal of Economic Growth,* 4 (4), 385-412.

Rodrik, D. (2006). Goodbye Washington consensus, hello Washington confusion? A review of the World Bank's economic growth in the 1990s: learning from a decade of reform. *Journal of Economic literature,* 44(4), 973-987.

Rogaly, B. (1996). Micro-finance evangelism, destitute women and the hard selling of a new anti-poverty formula. *Development in Practice,* 6(2), 100–112

Robins, J.M., Rotnitzky, A. and Zhao, L.P. (1994). Estimation of Regression Coeficients When Some Regressors Are Not Always Observed. *Journal of the American Statistical Association*, 89(1): 846-866.

Rosen, A.M. (2012). Set identification via quantile restrictions in short panels. *Journal of Econometrics,* 166(1), 127-137.

Rosenbaum, P. R. and D. B. Rubin (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1), 41-55.

Rubin, D. B. (2008). For objective causal inference, design trumps analysis. *The Annals of Applied Statistics,* 2(3), 808-840

Rubin, D.B. (1977). Assignment to Treatment Group on the Basis of a Covariate." *Journal of Educational Statistics*, 2(1): 1–26.

Sadoulet, E., A., De Janvry. and Catherine, B. (1996). Household Behavior with Imperfect labour Markets Household Behavior with Imperfect labour Markets. *Journal of economy and society*, 1(1), 85-108.

Salgado, C.R., and Aires, R.F., (2018). Microcredit and Gender: Are there differences in credit conditions? *Brazilian Administration Review*, 15(2), 1-19.

Salia, P. J. (2014). The Effect of Microcredit on the Household Welfare (Empirical Evidences from Women Micro-entrepreneurs in Tanzania). *International Journal of Academic Research in Business and Social Sciences,* 4(5)

Samuelson, P. A. (1947). Foundations of Economic Analysis. Cambridge, Mass.: Harvard University Press.

Sarma, M. (2008). Index of financial inclusion. New Delhi, India: Indian Council for Research on International Economics Relations.

Schuler, S. R., Hashemi, S. M., and Riley, A. P. (1997). The influence of women's changing roles and status in Bangladesh's fertility transition: Evidence from a study of credit programmes and contraceptive use. *World Development,* 25(4), 563–576.

Shaw, E.S. (1973). Financial deepening in economic development. New York: Oxford University Press.

Sianesi, B. (2004). An evaluation of the Swedish system of active labour market programmes in the 1990s. *Review of Economics and statistics,* 86(1), 133-155.

Singh, S. (2018). Microfinance and the Mirage of Women's Empowerment. *E-International Relations.*

Skoufias, E. (1994). Using Shadow Wages to Estimate labour Supply of Agricultural Households. *American Journal of Agricultural Economics*, 76(2), 215–227.

Skimmyhorn, W. (2016). Assessing financial education: Evidence from boot camp. *American Economic Journal:Economic Policy, 8(2),* 322–43.

Smith, H.L. (1997). Matching with multiple controls to estimate treatment effects in observational studies. *Sociological Methodology,* 27(1), 325-353.

Smith, J.A. and Todd, P.E. (2005). Does matching overcome LaLonde's critique of nonexperimental estimators?. *Journal of Econometrics,* 125(1-2), 305-353.

Soares, R. B., Barreto, F. A., and Azevedo, M. T. (2011). Condicionantes da saída da pobreza com microcrédito: O caso dos clientes do Crediamigo. *Estudos Econômicos*, 41(1), 119-142.

Tarozzi, A., Desai, J., and Johnson, K. (2015). The impacts of microcredit: Evidence from Ethiopia. *American Economic Journal. Applied Economics*, 7(1), 54–89.

Townsend, M. and Ueda, K. (2003). Financial Deepening, Inequality, and Growth: A Model-Based Quantitative Evaluation (EPub) (No. 3-193). International Monetary Fund.

Todo, Y. and Takahashi, R. (2013). Impact of farmer field schools on agricultural income and skills: evidence from an aid-funded project in rural Ethiopia. *Journal of International Development,* 25(3), 362-381.

Townsend, M. and Ueda, K. (2006). Financial deepening, inequality, and growth: a model-based quantitative evaluation. *The Review of Economic Studies,* 73(1), 251-293.

UNICEF (1997). Give us credit. Geneva: Division of Evaluation, Policy and Planning, UNICEF.

Van Rooyen, C., Stewart, R. and De Wet, T. (2012). The Impact of Microfinance in Sub-Saharan Africa: A Systematic Review of the Evidence. *World Development,* 40(11), 2249–2262.

Vaessen, J., Rivas, A., Duvendack, M., Palmer Jones, R., Leeuw, F., VanGils, G., and Bastiaensen, J. (2014). The Effects of microcredit on women's control over household spending in developing countries. Campbell Systematic Review. Retrieved from http://www.campbellcollabouration.org/lib/project/178/

Verrest, H. (2013). Rethinking microentrepreneurship and business development programmes: Vulnerability and ambition in low-income urban Caribbean households. *World Development,* 47, 58-70.

Waarts, Y.R., Ge, L., Ton, G. and Jansen, D.M. (2012). Sustainable Tea Production in Kenya; Impact Assessment of Rainforest Alliance and Farmer Field School Training.

LEI, part of Wageningen UR.

Wahidi, I. (2017). Microcredit in Lebanon: First data on its beneficiaries. *International Business Research*, 10(4), 32-41.

Waller, G. and Woodworth, W. (2001). Microcredit as a grass-roots policy for international development. *Policy Studies Journal,* 29(2), 267-282.

Williamson, E.J. and Forbes, A. (2013). Introduction to Propensity Score Matching. *Respirology*, 19(5): 625-635.

Wooldridge, J.M., (2010). Econometric analysis of cross section and panel data. MIT press.

Wooldridge, J.M., Wadud, M. and Lye, J., 2016. Introductory econometrics: Asia pacific edition with online study tools 12 months. Cengage AU.

Wooldridge, J.M. (2020). Introductory Econometrics, A Modern Approach (7th edt). Cengage Learning

World Bank Group. (2016). World development report 2016: Digital dividends. World Bank Publications.

World Bank Group. (2022). Mortality rate, adult, male (per 1,000 male adults). https://data.worldbank.org/indicator/SP.DYN.AMRT.MA

World Bank Group. (2022). World Bank Country and Lending Group. https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups.

World Inequalitity Database. (2023). World Inequality Index 2023. https:wid.world/world.

World Health Organization (2023). Trends in maternal mortality 2000 to 2020: estimates by WHO, UNICEF, UNFPA, World Bank Group and UNDESA/Population Division: executive summary.

Wright, G. A. (2000). Microfinance systems: Designing quality financial services for the poor. London: Zed Books.

Xu, L. and Bilal, Z. (2012). Financial literacy around the world: An overview of the Evidence with practical suggestions for the way forward". The world bank, Development research group, finance and private sector development team, June 2012, policy research working paper 6107.

Yang, M., and Stanley, T.D. (2013). Micro-Credit and Income: A Literature Review and Meta-analysis. Yang and Stanley 2013

Yunus, M. (1999). The grameen bank. *Scientific American,* 281(5), 114-119.

Yunus, M. (1998). Poverty alleviation: Is economics any help? Lessons from the Grameen Bank experience. *Journal of International Affairs,* 47-65.

Yunus, M. (2007). The Nobel peace prize 2006-Nobel lecture. *Law and Business Review America,* 13, 267.

Yunus, M. and Heiden, C., (2019). The future of microfinance. Brown J. *World Affairs,* 26, 119.

Zaman, H. (2001). Assessing the poverty and vulnerability impact of micro-credit in Bangladesh: A case study of BRAC. Unpublished background paper for World Development Report 2000/2001. Washington, DC: World Bank.

Zhang, Q. and Posso, A. (2017). Microfinance and gender inequality: Cross-country evidence. *Applied Economics Letters*, 24(20), 1494-1498.

Zhao, Z. (2004). Using matching to estimate treatment effects: Data requirements, matching metrics, and Monte Carlo evidence. *Review of Economics and Statistics,* 86(1), 91-107.