Access to Credit and Household Welfare in Rural Rwanda

Edouard Musabanganji

Research Paper 562

AFRICANECONOMICRESEARCHCONSORTIUM
CONSORTIUM POUR LA RECHERCHE ÉCONOMIQUE EN AFRIQUE

Bringing Rigour and Evidence to Economic Policy Making in Africa

Access to Credit and Household Welfare in Rural Rwanda

BY
Edouard Musabanganji
School of Economics
University of Rwanda

AERC Research Paper 562
African Economic Research Consortium, Nairobi
February 2025

THIS RESEARCH STUDY was supported by a grant from the African Economic Research Consortium. The findings, opinions and recommendations are, however, those of the author and do not necessarily reflect the views of the Consortium, its individual members or the AERC Secretariat.

Published by: The African Economic Research Consortium
P.O. Box 62882 - City Square
Nairobi 00200, Kenya

ISBN 978-9966-61-267-0

Abstract

Rwanda is a densely populated developing country where many people depend on agriculture but lack access to credit. The country has low agricultural productivity, along with high levels of income inequality and food insecurity. Studies have shown that credit access can improve rural agricultural household welfare. Over the years, the government's policies have substantially improved financial inclusion. However, poverty levels remain high particularly in rural areas. This study investigates the drivers of participation in the credit market and the effect of credit access on dietary and food diversity scores, as well as household spending. It utilizes data from 6,183 rural households obtained from the 2015 National Comprehensive Food Security and Vulnerability Analysis survey. It analyzes the effect and drivers of access to credit on rural household total monthly expenditure, food consumption score and dietary diversity score as the outcome variables. The study applied the Endogenous Switching Regression, Propensity Score Matching, and Coarsened Exact Matching techniques. The estimation yields consistent results and reveals that access to credit is positively affecting the welfare of rural households as it induces an increase of the household consumption expenditure of borrowing households. The study does not reveal a significant linkage between access to credit and the household food consumption score. The findings suggest increasing sensitization sessions and awareness on the importance of credits.

Key words: Access to credit, endogenous switching regression, and propensity score, Coarsened Exact matching, welfare, Rwanda.

1. Introduction

Background information

Rwanda is a landlocked country with an area of 26,338 km^2 and an estimated average population density of 501 inhabitants per km^2 in 2022 (NISR, 2023). It is ranked among the most densely populated countries in the world with a poverty incidence estimated at 37.3% of the population in 2022 (NISR, 2023) and a food insecurity rate of 20.6% at country level (NISR, 2022a). The economy of Rwanda is highly depending on agriculture sector which employs about 72% of economically active population, provides more than 50% of exports revenues and accounts for 24% of the Gross Domestic Product (NISR, 2022b). This economic context, in which agriculture contributes significantly to the country's economic growth, is a peculiarity of many developing economies characterized by a low level of industrialization.

For many years, Rwanda has recognized the importance of the primary sector and rural development initiatives in addressing poverty and enhancing the livelihoods of its population. In alignment with global and regional agricultural commitments, the country has developed a robust policy and strategic framework to promote agricultural development and improve household welfare. Since the 2000s, policymakers and development partners have increasingly acknowledged the need to improve socio-economic conditions and living standards in rural areas by addressing the limited access to rural finance. In response, various strategies and programs have been introduced, including the establishment of local Saving and Credit Cooperatives (SACCOs), which are available in each of the country's 416 administrative sectors, part of Rwanda's administrative structure that consist of 5 provinces—City of Kigali, Northern, Southern, Western, and Eastern—further subdivided into 30 districts and 416 sectors.

Besides all the endeavors mentioned above, Rwanda set up in 2008 a flagship anti-poverty and social protection programme named Vision 2020 Umurenge Programme (VUP) as one of the policy interventions to tackle the increasing economic shocks, disasters, and poverty levels in rural areas. This programme targets resource-constrained people estimated at about 46% of the population and has three main components: (i) public works offering short-term employment to poor rural households, (ii) the credit package which is designed

to release productive capacities of beneficiaries, (iii) and the direct financial support allowing vulnerable people engage in appropriate skill acquisition activities, handicraft, and social activities.

In parallel with the forgoing rural development-prone policy initiatives, all rural households are encouraged to join local farmer cooperatives and associations which enable disadvantaged rural residents to meet daily needs or invest in various income-generating activities such as petty trading, small businesses, and handicrafts through group loans where there is no collateral requirement and other group members acting as guarantors. In addition, banks have been urged to explore new and inclusive innovative products and services, develop links with informal providers of financial services for a better service to rural inhabitants, increase access to finance, and then enhance welfare outcomes in rural areas. Despite significant progress in financial inclusion for the adult population, which rose from 93% in 2020 to 96% in 2024, farmers' access to finance remains relatively low compared to other sectors (AFR, 2024). Moreover, poverty and food insecurity levels remain high in regions with limited access to finance.

The Financial Sector, Loan Patterns, and Credit Usage in Rwanda

The Rwandan financial sector is aligned with international standards and is composed of the banking sector, which includes commercial banks, microfinance institutions (MFIs), and savings and credit cooperatives (SACCOs), as well as the non-banking sector, which encompasses pension funds and insurance companies. Additionally, the sector includes the capital market, funds management, and is overseen by regulatory and supervisory public entities (MINECOFIN, 2018). The dual structure of Rwanda' banking sector is marked by the simultaneous operation of formal and informal financial institutions, both providing financial services to various segments of the population. Formal financial institutions refer to entities that are registered and licensed by the Central Bank to offer a wide range of financial products and services (Awotide et al., 2015). In contrast, informal financial institutions are unregistered financial bodies that cater primarily to resource-constrained rural populations, offering small and short-term loans for immediate needs (Thomas, 1992; Aredo, 1993). Formal financial institutions are predominantly accessible to wealthier

individuals and groups; however, their stringent eligibility criteria often render them inaccessible to many low-income households. Individual loan conditions require a feasibility study, technical capacity, market potential, and minimum participation from the applicant, along with adequate collateral such as mortgage with title deeds, pledge of receivables, joint guarantees from spouse or business partners, pledge of resources, and required insurance. In rural areas, group lending in formal institutions allows members to collectively apply for and repay loans, with the group acting as a guarantor. If one member defaults, others are liable for repayment. This approach increases access to financial services, lowers borrowing costs, and ensures that applicants are trustworthy individuals with strong community integrity. The system is particularly beneficial for individuals who may not meet individual lending requirements. In informal financial institutions, accessing small loans does not require many conditions. The applicant has only to be a group member with regular savings in the joint fund. Such a member is entitled to a loan amount approved in proportion to their total savings, with repayment terms and interest rates commonly agreed upon by the group members. In formal institutions, applicants are mainly household heads, and lending conditions vary depending on whether the loan is individual, or group based.

Regarding the proportion of formal approved loans by sector of activities, Tables 1 and 2 below illustrate the share (as a percentage of total) of approved loans over a 10-year period, from 2012 to 2021, and the total approved loans, respectively. A detailed analysis of Table 1 reveals that the commerce, restaurants and hotels sector have the highest borrowing rate, with an average of 38.4% of total approved loans over the last 10 years, compared to other sectors. This is followed by the public sector and construction, with an average of 24.4%. Next in rank are non-classified activities, manufacturing, transport, warehousing and communication, services provided to the community, and water and energy activities, with an average share of 12.1%, 8.9%, 7.7%, 3.9% and 2.2% of total approved loans, respectively, over the 10-year period. Other financial institutions (OFIs), insurance, and other non-financial services have an average share of 0.9%, while mining activities account for only 0.1%. Loans contracted for investment in agriculture, fisheries, and livestock—sectors expected to positively impact rural household welfare—represent just 1.5% of total approved loans from 2012 to 2021.

In terms of credit usage at the household level, significant differences exist between rural and urban populations. According to NISR surveys that have examined household borrowing patterns, rural households in 2022 primarily used credit to finance food purchases (29%) and agricultural or livestock inputs (29%). Smaller proportions were allocated to education (12%) and healthcare (11%) (NISR, 2022a). Furthermore, NISR (2022a) highlights that poorer households are more likely to use credit for immediate consumption needs, such as food purchases, whereas wealthier households tend to invest in productive activities, including agriculture and off-farm businesses.

Financial inclusion and credit access in Rwanda

Financial inclusion refers to the availability and accessibility of financial services, such as transactions, savings accounts, payment and remittance facilities, insurance, and investment opportunities, to individuals and businesses (Sanderson et al., 2018; Mahendra, 2006). It aims to ensure that all segments of society, particularly underserved and resource-constrained individuals, have access to financial services from formal financial institutions. This access supports poverty alleviation, reduces income disparities, enhances overall well-being, and contributes to the achievement of various sustainable development goals (Persaud & Thaffe, 2023). It plays a key role in empowering people by providing access to formal financial services, thereby stimulating economic and social development (Demirgüç-Kunt et al., 2018). In contrast, credit access is a more specific concept that pertains to the ability of individuals or businesses to secure loans. Since merely having a bank account does not guarantee access to credit, credit access emphasizes the availability of loan products, the terms under which they are provided—such as collateral requirements and interest rates—and the borrower's financial credibility. In essence, while financial inclusion encompasses a wide range of services, credit access specifically focuses on providing capital to allow adults to address their financial needs and invest in education, business, and other productive activities (Demirgüç-Kunt et al., 2017).

In Rwanda, financial inclusion has been a key priority, and the country has made significant strides in this area. Today, 96% of the adult population, equivalent to 7.8 million adults have access to some form of financial service (AFR, 2024). Rwanda's significant progress in financial inclusion can be attributed to

government initiatives promoting digital financial services, such as mobile money, alongside the expansion of pension and insurance products and efforts by financial institutions to reach underserved communities. The 2024 Fins cope Rwanda Report highlights the pivotal role of mobile money in improving financial access, particularly in rural areas. In contrast, urban financial inclusion is primarily driven by the widespread use of banking services and mobile money platforms (AFR, 2024). While Rwanda boasts a high financial inclusion rate, access to credit remains a significant challenge, particularly in rural areas. The percentage of banked individuals has stagnated at 22% between 2020 and 2024, and the proportion of credit-active consumers has declined from 76% in 2020 to 63% in 2024 (AFR, 2024). In rural areas, stringent collateral requirements, poverty and limited financial literacy, coupled with formal financial institutions' preference for more affluent borrowers, significantly hinder access to credit (Diop et al., 2023). In this regard, a study by Diop et al. (2023) revealed that while 56% of individuals save through SACCOs, fewer than half can access loans due to challenges like repayment issues, collateral requirements, and high interest rates. Limited geographical access further exacerbates this issue, with only 23% of rural dwellers able to reach a SACCO within 30 minutes compared to 84% of urban dwellers (Diop et al., 2023). This limited access forces many rural residents to rely on high-interest, unregulated lenders, hindering their ability to save and access affordable credit.

Table 1: Total share (in % of total) of approved formal loans by sector of activities from 2012 to 2021

Sector of activity	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Average of last 10 years
Non classified activities	16.6	12.0	9.6	9.0	9.9	11.0	11.0	12.7	14.1	15.2	12.1
Agricultural, fisheries and livestock	2.1	1.9	1.3	1.9	1.5	1.1	1.2	1.5	1.4	1.0	1.5
Mining activities	0.0	0.0	0.0	0.0	0.2	0.1	0.0	0.0	0.0	0.0	0.1
Manufacturing activities	7.4	9.3	11.1	6.9	8.1	7.3	7.3	12.4	9.5	9.8	8.9
Water and energy activities	0.8	1.2	3.9	0.2	3.1	2.4	1.6	5.2	1.8	1.5	2.2
Public works and building	22.4	19.7	21.2	32.0	24.7	28.0	26.2	25.6	23.0	21.6	24.4
Commerce, restaurants, and hotels	40.7	45.8	41.7	37.7	44.2	37.7	34.6	29.4	37.6	34.3	38.4
Transport, warehousing, and communication	6.1	6.2	6.5	7.3	4.8	8.9	14.6	7.7	5.5	9.3	7.7
OFI and Insurances and other non-financial services	0.9	1.3	0.7	2.0	0.7	1.1	0.5	1.1	0.3	0.3	0.9
Services provided to the community	2.9	2.7	4.0	3.0	2.8	2.4	3.1	4.5	6.9	7.0	3.9
Total	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**	**100.0**

Source: Calculated based on data from the National Bank of Rwanda, May 2022

Table 2: Total approved formal loans (in Billion Rwf) by sector of activities from 2012 to 2021

Sector of activity	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Non classified activities	83.0	56.5	62.6	67.1	77.7	90.6	106.6	146.8	149.9	187.0
Agricultural, fisheries and livestock	10.6	8.8	8.8	13.9	11.5	8.8	11.2	17.1	14.8	12.7
Mining activities	0.0	0.2	0.2	0.3	1.8	0.8	0.4	0.4	0.1	0.0
Manufacturing activities	37.0	43.9	72.5	51.2	63.9	60.3	70.6	143.6	101.8	120.7
Water and energy activities	3.9	5.6	25.6	1.3	24.7	20.2	15.5	59.9	18.7	17.9
Public works and building	111.9	93.2	138.4	237.3	195.1	230.8	252.9	297.6	244.8	265.3
Commerce, restaurants, and hotels	203.1	216.2	272.1	279.7	348.3	310.9	333.9	341.0	400.8	422.0
Transport, warehousing, and communication	30.4	29.5	42.2	53.8	37.7	73.6	141.1	89.8	58.3	114.8
OFI and Insurances and other non-financial services	4.6	6.1	4.5	14.8	5.8	9.4	4.7	12.4	3.3	3.2
Services provided to the community	14.4	12.5	26.1	22.6	21.8	19.5	29.5	51.9	73.3	86.6
Total	**498.9**	**472.5**	**653.0**	**742.1**	**788.3**	**824.9**	**966.5**	**1160.4**	**1065.8**	**1230.2**

Source: Data from the National Bank of Rwanda, May 2022

Problem statement and research questions

In rural areas of developing countries, access to finance is one of the pillars of socio-economic development. It allows the poor to start new activities, set up small businesses, and thus promotes inclusive economic growth and contributes to poverty reduction. Most rural people derive their livelihoods from subsistence farming or wages in the informal sector and do not have secured reliable income. Savings, credits, and new investments are almost non-existent, and leading therefore to uncertain living conditions. Limited credit availability in rural areas has been reported in many developing countries as preventing farmer households to diversify income and smooth their consumption (Okoyo et al., 2021). This problem is mainly due to the inability of the rural household to cope with the conventional lenders' requirements in terms of collaterals and high interest rates. Poor savings, low financial literacy, and low incomes are other challenges leading the potential rural borrower to self-select out of the formal schemes, and then not to benefit from the contribution of microcredit to poverty reduction.

Evidence on the effect of credit in rural households is mixed. The literature is replete of diverging points of view and empirical results have been characterizing the scientific debate on the effect of microcredit. On the one hand, some scholars have clearly shown that improving the access to loans by the rural households has a direct and indirect effect on their living conditions (see for instance, Bocher et al., 2017; Hossain & Knight, 2008; Petrick, 2004). The increase in capital at household level may not have direct effect on household living standards but it could have a positive and significant indirect effect through its positive influence on access to agricultural inputs (fertilizers, improved seeds, and external labour), post-harvest technologies, and service delivery in off-farm activities, which improve the household off-farm and farm productivity. Microfinance makes households wealthier through an income effect that improves accessibility to food, family health, children's education, as well as leisure (Armendariz & Morduch, 2005; Temesgen et al., 2017). On the other hand, authors have shown that access to credit does not positively affect household welfare. To Quach (2016), the credit effect depends on the poverty status of borrowing households as those of the richest quintile have a larger positive response than the poorest. The study by Diagne and Zeller (2011) showed that participating in credit did not statistically affect both acute and chronic malnutrition for children in pre-school age in Malawi. Similarly, the empirical study by Frohberg and Müller (2007) revealed that incomes of households involved in joint liability borrowing in Kenya were lower than those of their non-borrowing counterparts.

With these controversial views on the effect of credit on welfare highlighted in the literature, there is much need to have a thorough understanding and determine at what extent the provision of agricultural credit induces benefits in the improvement of household food and nutrition security. Hence, rigorous impact assessments are more needed for decision making in rural areas of developing countries and particularly in sub-Saharan Africa (Van Rooyen, Stewart & De Wet, 2012), where food insecurity and malnutrition are seen as the main challenges in the short and long run, and rural credit has been put forward as one of the major strategies for poverty alleviation.

Besides the contentious debate on the real contribution of credit on rural household welfare requiring further appraisals in developing countries, empirical research on the impact of access to credit on rural

household welfare using econometric analysis is almost non-existant in Rwanda. Some studies (mainly undergraduate dissertations) which attempted to evaluate the above-mentioned impact used small samples and relied on descriptive measures, correlational analysis, and statistical comparison techniques to draw their conclusions (see for instance, Calderon et al., 2008; Muyombano & Mbabazize, 2016; Ntuite, 2020). None of these has used matching techniques on the covariates to ensure a fair comparison between the treated and untreated, and novel econometric techniques addressing the selectivity bias often encountered when analyzing the causal effect of access to credit. Although they all found that microcredit affect positively the socio-economic status of rural households, it is inevitable to realize that, as contended by Quach (2016), differences in research methods may lead to disparities in study findings.

Therefore, this study seeks to fill in this methodological gap in the case of Rwanda and contribute to the existing debate in the literature on the impact of access to credit on rural household welfare in developing countries. Specifically, this research aimed to answer the following questions: (i) What drives the access to credit by rural households of Rwanda; (ii) To what extent is the access to credit affecting Rwandan rural household monthly expenditure, food consumption score, and dietary diversity score?

3. Literature review

Theories and factors affecting household consumption

A wide range of theories have been developed to describe the individual or household behavior about consumption. According to economic theory, the consumers' income is the primary determinant of consumption (Muellbauer, 2016), but at microeconomic level, other factors may influence the demand for goods and services such as the price and availability of the good or service, the prices of the related commodities, consumer's own tastes, the number of buyers, the information about the use of the commodity, government rules and policies, expectations, age, whether conditions, and the reference group (Browning & Zupan, 2020; Nelson & Consoli, 2010). Specifically, for households, demand is influenced by several factors such as income, education, age, sex (of the household head and other household members), weather conditions, location, tastes, and preferences as well as the household size (among other factors). In this line, Sheth et al. (1991) add that the decision to consume or to use goods depends on the five values, namely, functional value, emotional value, conditional value, social value, and epistemic value, which define the consumer's behavior. To them, any of the five values or all of them may affect the decision to have or use the goods or services. In the Life-Cycle Hypothesis, households tend to save during working times, that being, individuals intend to even out their consumption in the best possible manner over their entire lifetimes by accumulating when they earn and dis-saving when they are retired (Tran, 2022). It is hereby assumed that all individuals choose to maintain stable lifestyles (Wijaya et al., 2020). Another theory known as Intertemporal Consumption Theory was developed by Fisher in 1930 (Thimme, 2017). This is a specific form of a life cycle model and can be referred to as a two-period life-cycle model. The theory states that the choices are influenced by the relative value people assign to two or more payoffs at different points in time. As for a Relative

Income Hypothesis that was developed by Brown et al. (2015), it states that an individual's attitude to consumption and saving is not only explained by present levels of absolute and relative income, but also by levels of consumption attained in a previous period. However, the random-walk hypothesis that combines the permanent-income hypothesis and consumers' rational expectations shows that changes in consumption over time seem to be unpredictable. In addition, households' decisions about consumption largely depend on the occupation status of its members. In this line, Tran (2022) asserts that earning risks vary with the types of occupation. Those with stable jobs like civil servants are likely to save less compared to those facing occupation uncertainty. This precautionary saving hypothesis, which posits that individuals save more when facing income uncertainty, is supported by empirical evidence. For instance, studies by Fuchs-Schündeln and Schündeln (2005) and Skinner (1988), as cited by Tran (2022) and Carroll (2001), demonstrate that individuals with less stable employment, such as service workers and laborers, tend to have lower financial wealth compared to those with more stable incomes, such as civil servants. Economists have been analyzing household decisions using a unitary approach (or traditional approach) and non-unitary approach. Following the unitary approach, a household behaves as a unique individual where all household members commit to maximize a single utility function given the constraints (Fiala & He, 2017) while the non-unitary approach of household behavior recognizes that all the household members cannot maximize their utility via a unique utility function (Soriya, 2019).

Access to credit, consumption, and household's welfare

In recent decades, there has been a significant increase in empirical studies examining the influence of microcredit on poverty alleviation. As interest in this topic has grown, so have debates regarding the extent to which microcredit affects the well-being of its recipients (Akotey & Adjasi, 2016). The literature identifies three perspectives: those that view the impact as positive, negative, or neutral. Blanchard (2017) argue that low-income consumers with poor access to credit are likely to consume only the totality of their current low income, which implies that they have no means to smooth their consumption. According to Tonch and Sohn (2022), credit availability affects household expenditures, more specifically housing and the acquisition of business fixed assets. As for Moradi and Mokhatab (2019) and Gabeshi (2022), credit is a vital input for all economies since it enables the purchase of home supplies and all other kinds of consumer expenditures, as well as all forms of business investment items. It is also necessary for financing exports, imports, and all types of government expenditure, which ultimately contributes to avoiding economic recession. This implies that the decline of access to credit is a good engine for a fall in expenditures, low utilization of resources, and low level of production of goods and services (Mankiw, 2016). Viewed from consumers' perspective, credit access from any source (formal or informal) results in more purchase of goods and services (mostly consumer durables) than the purchase would be without the loan availability (Dwivedi, 2016) and thus, this leads to improving the living conditions (Browning & Zupan, 2020). For rural households, rural microfinance is an influential engine of poverty alleviation (Kumari, 2020) and has been hailed to be an essential tool to economic empowerment of poor households (Amendola et al., 2016). It correlates with increase of household income and consumption levels, less severe income inequality and enhanced welfare

(Mahjabeen, 2008). Furthermore, Islam and Maitra (2012) reveal that the access to credit enables the rural households to diversify their livelihood sources and serves as a tool to smooth the household consumption. With a focus on the use of received loans in rural areas, Bocher et al. (2017) emphasized that household total consumption increases with an increase in access to credit. Amendola et al. (2016) add that increasing access to credit results in the decline of dependence on household production and amplified flow of investment funds in human capital. While there is well-documented evidence of the positive impact of rural loans, it is important to note that related statements are not entirely conclusive. Empirical studies conducted in the developing world have put forth conclusions suggesting a negative or negligible impact of credit on the well-being of beneficiaries. The study by Markgraf and Rosas (2023) advances a conclusion that the social effects of credit access are not unique across different income and risk groups, implying that it may be influential in some cases but not so in some others. In the same line, Bateman (2010) quoted by Akotey and Adjasi (2016, p. 381) contend that the "*so-called welfare impact vehicles – income and employment generation, consumption smoothing, gender empowerment and a helper of the helpless (poorest) – through which microfinance is acclaimed to impact positively on the poor are all myths and largely built on hype and on egregious half-truths*". These viewpoints are further supported by the review conducted in sub-Saharan Africa by Van Rooyen et al. (2012, p. 2249) who claim that *"microfinance does harm, as well as good, to the livelihoods of the poor."* Likewise, Bocher et al. (2017) allude that microcredit does not help the neediest people to improve their living conditions and further deteriorates the situation of the most impoverished. Brief, these points of view can be expressed in the sentence by Adams and von Pischke (1992), quoted by Coleman (2002, p. 108), who conclude that *"debt is not an effective tool for helping most poor people enhance their economic condition, be they operators of small farms or micro entrepreneurs, or poor women"*. To them, *"access to credit is not a significant problem faced by small agricultural households and that factor and product prices, land tenure, technology, and risk are the factors limiting small farmer development"* (Coleman, 2002, p.108). Considering the reviews of empirical literature mentioned above, it is evident that a refined and contextualized understanding is required to assess the extent to which credit affects rural well-being. This is of the utmost importance, especially in the context of the increased attention that microcredit has received as a strategic tool to alleviate poverty. The persistent question revolves around whether rural residents, regardless of their economic status — be it non-poor, poor, or extremely poor genuinely experience unidirectional benefits from credit provisions.

Access to credit and its effect: A conceptual framework

Access to credit has had an important place in the literature of the developing world in recent years. This renewed interest in this theme is justified by the growing recognition of its importance in promoting economic growth, alleviating poverty, and enhancing the overall quality of life in these areas. Empirical studies have shown that access to credit is affected by individual, household, and community and institutional variables. In his study conducted in Uganda, Mpunga (2008) identified that factors such as location, age, level of education, occupation, the value of household assets, and gender strongly influenced the demand for credit in rural areas in Uganda. Similarly, in his studies conducted in Ghana, Sekyi (2017) found that gender, age, occupation in farming and trading, credit history, and household income played a substantial role in influencing access to formal credit. In addition, the

farming experience, hired labour, group membership and source of credit, literacy levels and acreage of land under cultivation have been found to have a positive effect while the distance to financial institutions was revealed to negatively affect the access to credit (Bakhshoodeh & Karami, 2008; Shadrack, 2017, Hananu et al., 2015). As for the impact of access to credit, authors have demonstrated that it has a direct and indirect link with household welfare (Bocher et al., 2017; Hossain & Knight, 2008; Petrick, 2004). According to Lin et al. (2019), constrained households from accessing credit experience limitations in participation in income generating activities and using improved seeds and other agricultural inputs. The increase in capital at household level may not have direct effect on household living standards but it could have a positive and significant indirect effect through its positive influence on access to agricultural inputs (fertilizers, improved seeds, and external labour), post-harvest technologies, and service delivery in off-farm activities, which improve the household off-farm and farm productivity. To Quach (2017, p. 129), *"access to credit has a positive and significant long-term impact on household welfare in terms of per capita expenditure, per capita food expenditure and per capita non-food expenditure."* This assertation is confirmed by Quach and Mullineux (2007) who argued that access to credit is a strategic instrument to reduce poverty in rural areas. The below diagram shows that credit empowers household members, enhances social relationships, and improves household savings, access to housing, needs stabilization (education, health, clothes, etc.) and food and nutrition security, which contribute to reducing poverty in rural areas.

Following all what is discussed in the above theoretical literature review, the conceptual framework of this study as depicted in Figure1 gives a synthesized form showing the categories of factors affecting rural household's access to credit, the transmission of credit use and mechanisms of the effect of credit on household welfare, and the direction of the effect of some variables on the others.

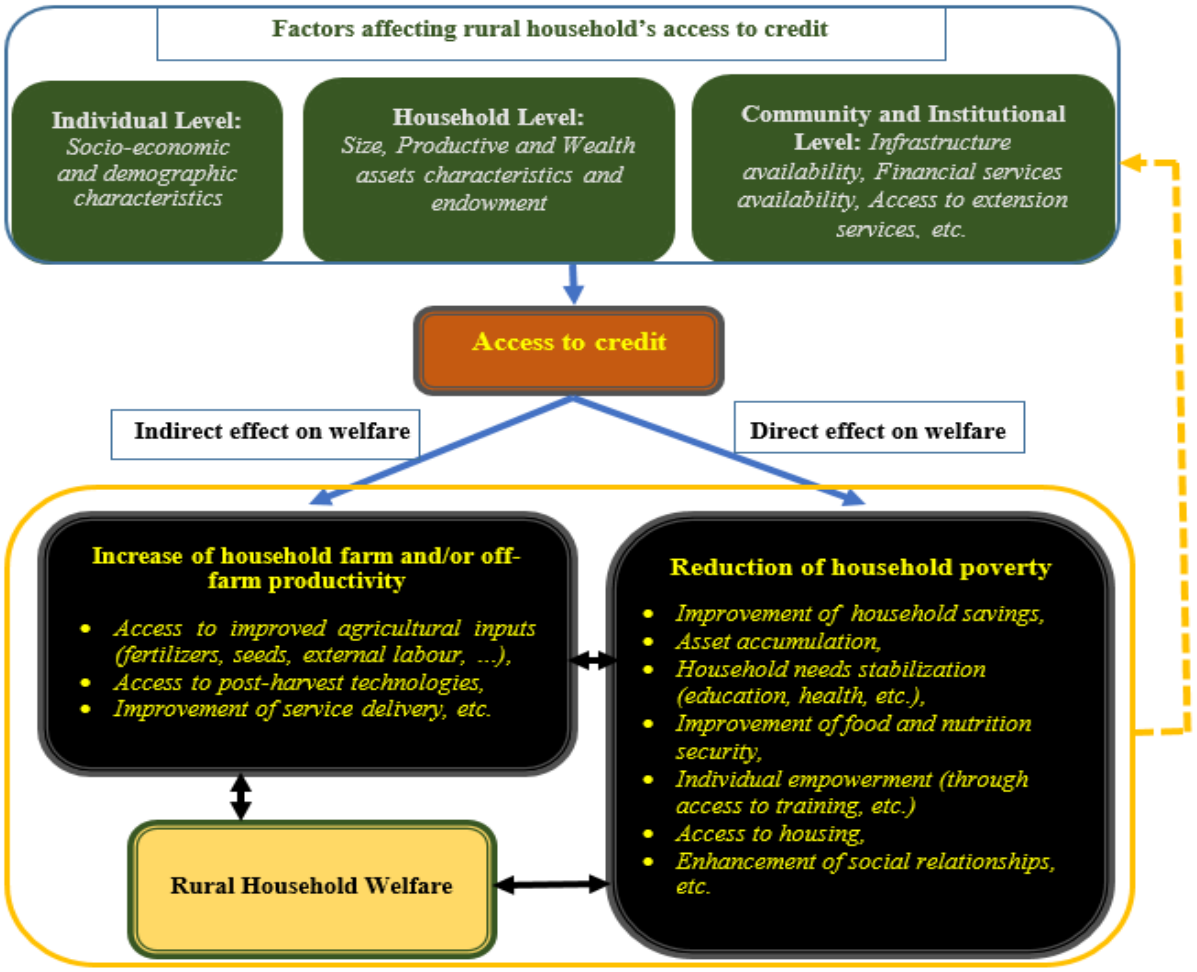

Figure 1. Conceptual framework of effect of access to credit on rural household welfare

Source: Author, based on Bocher et al. (2017) and Awotide et al. (2015)

4. Methodological approach

Data and variables

The empirical assessment of the effect of access to credit on consumption in Rwandan rural households was based on recent data from a nation-wide household-level Comprehensive Food Security and Vulnerability Analysis (CFSVA) survey conducted in 2015 by the National Institute of Statistics of Rwanda and the Ministry of Agriculture and Animal Resources. This study targeted only rural areas with a sample of 6,183 rural households representing 82.4% of the total targeted sample. The CFSVA survey targeted all 30 districts and captured information on demographics (education, age, and gender), household's size, assets endowments, agricultural and off-farm activities, income, credit, and remittances. In addition, the collected data contain information on household food and non-food expenditures, remittances and other sources of income, and access to credit, which is the key feature for the purpose of this study and allow to get the complete picture of credit and consumption in surveyed households.

Justification of the choice of outcome and independent variables

The literature has extensively documented the linkage between household consumption expenditure, dietary diversity and the household socio-economic status and food security (see for instance FAO, 2013; Hoddinot & Yohannes, 2002; Hatloy et al., 2000). In this line, Swindale and Bilinsky (2006, p.2) highlight that *"a more diversified diet is highly correlated with such factors as caloric and protein adequacy, percentage of protein from animal sources (high quality protein), and household income. Even in very poor households, increased food expenditure resulting from additional income is associated with increased quantity and quality of the diet".* Therefore, as proxies of welfare, this study used the household monthly consumption expenditure (MCE) which is the value of consumption goods and services used or paid for by a household to directly meet its needs, and the household food consumption score (FCS) considering both the quality and quantity of food group access (FAO, 2013; Swindale & Bilinsky, 2006).

The selection of the independent economic variables such as land ownership, house ownership, livestock holding, poverty status, monthly income, number of livelihood activities, and remittances in this study was motivated by their expected effect on the treatment and outcome variables and the need for control economic structure of the rural household. The land, house and livestock are seen as indicators of wealth (Sheuya & Burra, 2016) and the source of trust for the borrower when applying for a small loan in financial institutions. The number of livelihood activities, off-farm employment, the number of grown crops and the land size at household level constitute indicators of a rural household wealth as a better-off rural household tends to have larger lands and increase the number of grown crops. Livelihood activities and off-farm employment are often seen as ways of diversifying household income and improving welfare in rural areas. In the same line, remittances are considered as key in household welfare and have a positive effect on consumption expenditure and poverty status (Selim et al., 2009). The current study considers socio-demographic variables as well. Such variables include the location of the settlement, the legal marriage, gender, education level of the household head, and the household size. The location of the settlement is related to expenditure as dwellers in urban areas may have higher spendings than those in rural areas and included to control for the location effect on the welfare status. The gender of the household head is selected following the literature that demonstrates its linkage with household poverty level (Appleton, 1996). Education is a key variable that can affect positively household welfare and the access to credit as a literate and/or a wealthier farmer is likely to have a better understanding and then be open to financial products and services. The household size is linked to the household standard of living (Meenakshi & Ray, 2002) while the household head age is considered as being important to household economic status. The latter has a significant influence on access to credit and welfare since older people are less likely to get a loan than their young counterparts.

Table 3: Description, type, expected signs and justification of the choice of the variables

Variables	Type	Description	Expected sign
Monthly Consumption Expenditure (MCE)	Outcome/ Continuous	The monthly expenditure of the household on goods and services in Rwf	Endogenous Variable
Food Consumption Score (FCS)	Outcome/ Continuous	The household food consumption score	Endogenous Variable
Dietary Diversity Score (DDS)	Outcome/ Count	The household dietary diversity score measure with count data	Endogenous Variable
Household size	Independent/ Continuous	The number of household members	+/-
Age of the head of household (in years)	Independent/ Continuous	The age of the household head in years	-
Livestock holding in TLU	Independent/ Continuous	The number of livestock holding at household level in TLU	+
Number of grown crops by the household	Independent/ Continuous	The number of grown crops by the household	+
Number of livelihood activities of the household	Independent/ Continuous	Number of livelihood activities of the household	+
Location (1-Kigali City, 0-Elsewhere)	Independent/ Dummy	The residence area of the household	+
Poverty status (1-Poor, 0-Otherwise)	Independent/ Dummy	The poverty status of the household	-
Gender of household head (1-Male, 0-Female)	Independent/ Dummy	The gender of the household head	+
Household head with the primary education (1-Yes, 0-Otherwise)	Independent/ Dummy	The household head at least finished the primary level of education	+
Land size (1-More than 0.5 ha, 0-Otherwise)	Independent/ Dummy	The size of the land	+
Off-farm employment (1-Yes, 0-Otherwise)	Independent/ Dummy	Household involved in off-farm employment	+
Household received remittances (1-Yes, 0-Otherwise)	Independent/ Dummy	Household received remittances from friends and relatives	+
House ownership (1-Yes, 0-Otherwise)	Independent/ Dummy	Ownership of the house occupied by the household	+
Legal marriage (1-Yes, 0-Otherwise)	Independent/ Dummy	The household head and spouse are legally married	+

Analytical framework

The assessment of the impact of credit on consumption expenditure, food consumption score and household dietary diversity score cannot be done using causal inference especially on cross-sectional data with unknown counterfactual situation (Bidzakin et al., 2019) as it is the case in this study. To overcome this challenge, it is recommended to investigate the impact by analyzing the differences in outcomes among rural households that got loans from financial institutions and those that did not using econometric models (Dehejia et al., 2002). It is in this framework that this research employed an endogenous switching regression approach to analyze the impact of credit access on household welfare. This approach partitioned rural households into borrowers and non-borrowers to capture the differential outcomes between these groups. Additionally, matching techniques were used to compare the observed outcomes of borrowers with those of non-borrowers, serving as a robustness check. Following Stuart (2010), this study combined simultaneous modeling with matching methods to account for both observed and unobserved factors that may influence the outcomes.

Endogenous Switching Regression Model

The assessment of the effect of access to credit on outcome variables may be performed using a single classical mathematical model with an outcome variable and a list of explanatory variables. However, following Awotide et al. (2015), the estimation of this model yields inconsistent estimators resulting from the fact that access to credit is optional. The associated econometric problem has been described as the self-selectivity bias. In this case, it is probable that some households (with members who have a high level of education, an increased income, etc.) have better access to credit than others (for instance, poor households), or that households with access to credit may have different characteristics from those without access. This subgroup heterogeneity becomes problematic as unobserved characteristics are distributed differently across households with access and those without access. In addition, these unobserved variables may be correlated with exogenous factors, thus resulting in the presence of endogeneity. This violates the Gauss-Markov theorem and leads to biased estimators (Greene, 2012). The way of addressing this issue is to use the Endogenous Switching Regression Model (ESRM), one of the usual simultaneous equations models (Freeman et al., 1998) where the access to credit equation and outcome equations are estimated separately for those who had access to credit (borrowers) and those who did not have access to credit (non-borrowers).

According to the utility maximization theory, rural households choose to choose whether or not to borrow from a financial institution based on the utility they receive (Awotide et al., 2015). Let us consider a household *i* with an intention to borrow from a financial institution. The household decides to borrow when the expected utility of borrowing from the financial institutions is greater than that of not borrowing. Note that not only does the household head decide to borrow because of the magnitude of the expected utility but also access to credit is affected by other socio-demographic and economic aspects of the household. Then, the borrowing decision for the household *i* can be formalized using the Probit specification model as follow:

$$U_i^* = \phi X_i + \xi_i;\ with\ U_i = 1\ if U_i^* > 0\ and\ \ U_i = 0\ if U_i^* < 0 \qquad (B1)$$

Where, U_i^* is the latent variable is not observable, X_{it} is the vector of household characteristics affecting the access to credit, ϕ the vector parameters to be estimated, and ξ_i the error tem. U is a dummy variable with $U_i = 1$ for borrowing households, and $U_i = 0$ otherwise.

In terms of household consumption, the literature has shown that in practice, households with access to credit have a different behavior in terms of household food and non-food expenditure compared to those without access to credit. Access to credit may affect the outcome variables whose specifications, for borrowers (Equation B2) and non-borrowers (Equation B3), are presented as follow:

$$Y_{1i} = \psi_1 H_i + \varepsilon_{1i} \text{ if } U_i = 1 \quad \text{(B2)}$$

$$Y_{0i} = \psi_0 H_i + \varepsilon_{0i} \text{ if } U_i = 0 \quad \text{(B3)}$$

Here, Y_{1i} and Y_{0i} are the outcome variables (monthly consumption expenditure, food consumption score and household dietary diversity score) for borrowers and non-borrowers respectively, H_i is the vector of household characteristics, ψ the vector of parameters to be estimated, i stands for households, and ε_{1i} and ε_{0i} the error terms.

The identification of covariates of equations (B2) and (B3) requires that at least one variable in *X* does not appear in *H*. The error terms of the equations (B1), (B2), and (B3) are hypothesized to have a trivariate normal distribution with mean vector zero and non-singular covariance matrix of the form:

$$Cov(\xi, \varepsilon_1, \varepsilon_0) = \begin{bmatrix} \sigma_1^2 & \sigma_{10} & \sigma_{1\xi} \\ \sigma_{10} & \sigma_0^2 & \sigma_{0\xi} \\ \sigma_{1\xi} & \sigma_{0\xi} & \sigma_\xi^2 \end{bmatrix} \quad \text{(B4)}$$

where $Var\ (\varepsilon_1\ ) = \sigma_1^2;\ Var\ (\varepsilon_0\ ) = \sigma_0^2; Cov\ (\varepsilon_1, \varepsilon_0) = \sigma_{10}; Cov\ (\varepsilon_1, \xi) = \sigma_{1\xi};\ \ Cov(\varepsilon_0, \xi) = \sigma_{0\xi}.$

According to Bidzakin et al. (2019), due to unobserved household characteristics associated to the selection bias, ξ is correlated with the error terms $(\varepsilon_1, \varepsilon_0)$ and the expected values of ε_{1i} and ε_{0i} , conditional on the sample selection are non-zero:

$$E(\varepsilon_{1i}|\ U_i = 1) = E(\varepsilon_{1i}|\xi_i > -X_i\phi) = \sigma_{1\xi}\left[\frac{\theta(\frac{X_i\phi}{\sigma})}{\varphi(\frac{X_i\phi}{\sigma})}\right] \equiv \emptyset_{1\xi}\lambda_1 \quad \text{(B5)}$$

$$E(\varepsilon_{0i}|\ U_i = 0) = E(\varepsilon_{0i}|\xi_i > -X_i\phi) = \sigma_{0\xi}\left[\frac{-\theta(\frac{X_i\phi}{\sigma})}{1-\varphi(\frac{X_i\phi}{\sigma})}\right] \equiv \emptyset_{0\xi}\lambda_0 \quad \text{(B6)}$$

Where θ and φ; are the probability density and cumulative distribution function of the standard normal distribution respectively. The ratio of θ and φ evaluated at $X_i\phi$ is referred to as the Inverse Mills Ratio λ_1, λ_0 which are the selectivity terms and provide the correlation between access to credit and the outcome variable. The selection bias is then counted for by incorporating into (B5) and (B6) the terms λ_1 and λ_0. σ is the covariance of the error terms.

The estimation of the Endogenous Switching Regression Model is performed in two stages. In the first stage, the probit model of the equation (B1) is estimated, and then, in second stage, the estimates are used to determine λ_1 and λ_0 in equations (B5) and (B6). As this two-stage procedure is criticized for generating heteroscedastic residuals unless complex adjustments are made to obtain consistent standard errors (Bidzakin et al. (2019), quoting Lokshin and Sajaia, 2004), the Full Information Maximum Likelihood (FIML) technique proposed by Lokshin and Sajaia (2004) is used and helps estimating the borrowing equation and outcome equations simultaneously with consistent standard errors (Bidzakin et al., 2019). By jointly estimating all equations in the system and considering the correlations between their error terms, FIML addresses the endogeneity problem, leading to more consistent and unbiased parameter estimates (Bidzakin et al. (2019). In this research, the FIML technique was applied to estimate the ESRM using the *movestay* command in STATA (Lokshin & Sajaia, 2004). The dietary diversity score is a count data variable, and its model was estimated using *teescount* command using the Poisson regression (Hasebe, 2020).

Matching Methods: Propensity Score Matching and Coarsened Exact Matching

There is a list of matching methods that have been developed to assist in the construction of a valid control group. Matching refers to the selection of individuals in the control group based on how well they match the overall characteristics of the treatment group. One of the popular matching techniques that has been used in quasi-experimental design, especially in the case of a large list of observable characteristics is the Propensity Score Matching (PSM) (Rosenbaum & Rubin, 1983). This technique is widely used and enables the formation of matched groups involving many covariates and matches groups' subjects with the predicted scores using regression techniques. However, its use has been discouraged by researchers following the critics that it approximates an experimental design with lower standards than necessary and increases imbalance, inefficiency, model dependency, and bias (King & Nielsen, 2019).

The Coarsened Exact Matching (CEM) is another matching technique that has become popular since a couple of years as an alternative but powerful technique which *"dominates commonly used existing matching methods in its ability to reduce imbalance, model dependence, estimation error, bias, variance, mean square error, and other criteria"* (Iakus et al., 2011, p. 2). CEM yields in causal effect estimates with lowest variance and bias for any sample size and offers four main benefits: (i) it is computationally very efficient, even for large datasets, (ii) bounds the imbalance between the treatment and control groups, (iii) meets the congruence principle, and (iv) automatically restricts the matched data to areas of common empirical support (Blackwell et al., 2009).

Following Iakus et al. (2011), the principle of this technique is based on recording of data values of a list of selected covariates. Original covariates are transformed or coarsened into meaningful categories preserving the genuine information, using a coarsening or binning strategy. CEM then assigns each unit or individual into defined and distinct sub-groups whose members are matched with individuals on the coarsened variables. Specifically, CEM is applied following this 6-step algorithm (Blackwell et al., 2009):

1. Start with the covariates Z and make a copy, here denoted as Z*.

2. Recode or coarsen Z* into bins based on automatic binning algorithm or bin sizes set by the researcher or data analyst.
3. Create one stratum per unique observation of Z* and place each observation in a stratum.
4. Assign these strata to the original data, Z, and discard any unit whose stratum does not contain at least one treated and one control unit.
5. Weight the matched units based on the size of their strata in case of unequal number of units in treated and control groups.

Each weight is a product of two ratios, namely, the ratio equal to the matched households in control group and the matched households in treated group, and the ratio between the matched households in in a stratum s of treated group and the matched households in stratum s of the treated group.

6. Compute the treatment effect using the original uncoarsened covariates.

In this study, the CEM algorithm is applied to calculate treatment effect using the *cem* command in STATA (Blackwell et al., 2009).

5. Empirical results and discussion

In this section, the empirical results of the study are presented. The data analysis proceeded through the econometric analysis of the impact of borrowing from a financial institution on the total household monthly expenditure, the food consumption score, and the dietary diversity score. The econometric analysis was performed using the propensity score matching, the coarsened exact matching methods, and the endogenous switching regression technique on a sample of 6,183 rural households, among which 19.8% corresponding to 1,227 rural households borrowed from financial institutions.

Exploratory analysis of variables

Outcome variables and access to credit

Descriptive analysis was performed on important variables grouped in five categories namely location variables, socio-demographic variables, household wealth and livelihood variables, community facility variables, and land and agriculture related variables. The results are presented for continuous variables and categorical variables separately. The t-test was used to compare the means of borrowers with that of non-borrowers while the chi-square test was used to assess the relationships between concerned categorical variables and credit access.

Table 4 reveals that regarding household monthly consumption expenditure, households headed by those who have had access to credit committed monthly more than double compared to their counterparts who have not borrowed from financial institutions with 76,172.1 Rwf and 35,663.1 Rwf respectively. Credit borrowers have high household consumption score, and household dietary diversity score (50.0 and 4.8 respectively) compared to those of households of non-borrowers who have on average of 43.1 and 4.4 respectively. The statistical inference showed that the mean differences between borrowers and non-borrowers are highly significantly different for household monthly consumption expenditure, household food consumption score and household dietary diversity score.

Table 4: Welfare proxies and categories of rural households

	Borrowers	Non-borrowers	Total sample	t-value
	N=1227	N=4956	N=6183	
	Mean	Mean	Mean	
Monthly Consumption Expenditure	76,172.1 (115402.6)	35,663.1 (80763.7)	43,702.0 (90168.5)	11.6***
Food Consumption Score	50.0 (19.3)	43.1 (18.3)	44.4 (18.7)	11.2***
Dietary Diversity Score	4.8 (1.2)	4.4 (1.2)	4.5 (1.2)	11.0***

Note: Values in (.) are standard deviations of corresponding mean values and *** denotes the significance level at 1%. All the significant differences have corresponding p-values of 0.000.

Households' characteristics and access to credit: A descriptive analysis

As reported in Table 5, the household size, the age of the household head, Tropical Livestock Unit (TLU), the number of grown crops as well as the number of livelihood activities are important quantitative variables that are common in analyzing the aspect of access to credit. The results in the table reveal that the average household size is higher than in the group of borrowers. Borrowers are younger than non-borrowers with 44 years and 48 years respectively. The TLU, the number of grown crops and the number livelihood activities of borrowers are larger than those of non-borrowers from financial institutions. These results portray the fact that the above-mentioned variables are among the contributing factors that affect the credit access by rural households.

Table 5: Descriptive statistics of continuous variables

	Borrowers	Non-borrowers	Total sample	t-value
	N=1227	N=4956	N=6183	
	Mean	Mean	Mean	
Number of livelihood activities	1.9 (0.6)	1.7 (0.6)	1.7 (0.6)	8.3***
Number of grown crops	3.3 (1.5)	3.1 (7.9)	3.1 (7.1)	2.1***
Age of household head in years	44.0 (12.8)	48.0 (16.0)	47.2 (15.5)	-9.3***
Household size	5.3 (2.9)	4.6 (2.0)	4.7 (2.0)	11.3***

Livestock holding in TLU	0.6 (1.0)	0.4 (0.8)	0.5 (0.8)	6.5***

Note: Values in (.) are standard deviations of corresponding mean values and *** denotes the significance level of the difference between the means at 5%.

Table 6 reports descriptive statistics on the categorical variables and the relation between them and access to credit. The results highlight that the residence area is not statistically linked to access to credit. The same findings reveal that the gender, the legal marriage status, and the level of the household head's education level are the important socio-demographic variables that are statistically associated to the access of credit. The same applies to the household wealth related variables, namely, the poverty level, land size, land ownership, and house ownership, off-farm employment, and remittances that are statistically related to the access of credit in rural Rwanda.

Table 6: Descriptive statistics of selected categorical variables

	Borrowers		**Non-borrowers**		**Total sample**		**Chi-square value**
	N=1227		N=4956		N=6183		
	Frequency	%	Frequency	%	Frequency	%	
Location *1-Kigali City* *2-Otherwise*	33 1194	2.7 97.3	164 4792	3.3 96.7	197 5986	3.2 96.8	1.2
Poverty status *1-Poor* *2-Non-poor*	463 590	44.0 56.0	2780 1900	59.44 0.6	3243 2490	56.64 3.4	83.3***
Household head legally married *1-Yes* *2-Otherwise*	822 405	67.0 33.0	2661 2295	53.7 46.3	3483 2700	56.3 56.3	70.7***
Household head with at least primary education *1-Yes* *2-Otherwise*	568 659	46.3 53.7	1333 3623	26.97 3.1	1901 4282	30.7 69.3	173.7***
Gender *1-Male* *2-Female*	1008 219	82.2 17.8	3528 1428	71.22 8.8	4536 1647	73.42 6.6	60.5***
House ownership *1-Yes* *2-Otherwise*	1168 59	95.2 4.8	4592 364	92.77 .3	5760 423	93.26 .8	9.9***
Land size *1-More the 0.5 ha* *2-Otherwise*	527 505	51.1 48.9	1528 2465	38.36 1.7	2055 2970	40.95 9.1	55.5***

Off-farm employment					567					
1-Yes	*0-*	226	1001	18.4	4389	11.48	793	5390	12.88	42.8***
Otherwise				81.6		8.6			7.2	
Remittances	*1-*		42		62	1.3				
Yes		1185		3.4	4894	98.7	104	6079	1.7	28.0***
2-Otherwise				96.6					98.3	

Note: *** denotes the significance level at 5%. All the significant differences have corresponding p-values of 0.000.

Households' characteristics and access to credit: A linear discriminant analysis

There are a variety of techniques used for multidimensional data analysis. Authors from a range of research disciplines have shown interest in these techniques due to their paramount role in dimensionality reduction and hence mitigating model overfitting. These techniques are classified in two categories: supervised and non-supervised. The supervised approaches require the labeling of classes while the un-supervised techniques do not take class labels into account (Tharwat et al., 2017). Among the most used algorithms include the Principal Component Analysis (PCA), the Multivariate analysis of Variance (MANOVA) and the Linear Discriminant Analysis (LDA) which are among the commonly used techniques for data reduction. The PCA is an unsupervised technique used to reduce the data dimensionality by creating new variables, named principal components, as linear combinations of the original variables and maximize the overall variance captured by these principal components. MANOVA is used to examine the treatments effects on multi-responses (Abapihi et al., 2020) whereas LDA as a supervised algorithm serves to reduce the data dimensionality by projecting the dataset onto a lower-dimensional space while maximizing the separability between groups (Anello, 2022). Although these techniques gained popularity, the MANOVA is not preferred to PCA or LDA due to its underlying assumption of multivariate normality which is difficult to fulfil (Abapihi et al., 2020). PCA and LDA share fundamental characteristics, such as the principle of dimension reduction. However, they diverge in that LDA maximizes the ratio of variances between groups and within groups whereas PCA create components which maximize the variance in a dataset (Anello, 2022). As the LDA is classified as the most famous and well-used supervised technique (Tharwat et al., 2017) that outperforms the PCA especially for group discrimination (Martinez & Kak, 2001; Anello, 2022), this study used the LDA approach for exploratory data analysis to complement the above descriptive analysis. The results are detailed in the paragraphs below.

The analysis resulted in the formation of one canonical discriminant function due to the presence of two groups of the grouping variable. This discriminant function is associated to an eigenvalue of 0.062 and an estimated canonical correction of 0.241. As a test of the canonical function, the findings show an estimated Wilk's Lambda of 0.942 associated to the test statistic $\chi^2 = 267.627$ with a level of significance of 0.000. These findings highlight the statistical significance of discriminating the data into two classes and confirm that the formed canonical discriminant function performs better than chance in separating the two groups of households (borrowing households and non-borrowing households).

Table 7: Summary of the canonical discriminant function

	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
First canonical discriminant function	.062[a]	100.0	100.0	0.241
	Wilks' Lambda	**Chi-square**	**df**	**Sig.**
	0.942	267.627	14	0.000

The results related to the classification of households are detailed in the table below. The information in the table reveals that out of the households used to create the model, 3,122 of the 4,956 non-borrowing households are classified correctly while 772 of the 1,227 borrowing households are classified correctly. Overall, 63% of households were classified correctly.

Table 8: Households classification results

Group Membership		Predicted		Total
		Not borrowed	Borrowed	
Original	Not borrowed	3122	1834	4956
	Borrowed	455	772	1227
	Not borrowed	63.0	37.0	100.0
	Borrowed	37.1	62.9	100.0

The analysis also reported (Table 9) the standardized coefficients of the canonical discriminant function. Following Rencher (1992) and Rencher and Scott (1990) who suggests to use the absolute values of the coefficients to rank the variables based on their contribution to the discriminant function, a deep examination of these standardized coefficients reveals that the number of livelihood activities, the number of grown crops, the age of the household head, the household size, the poverty status, the level of education of the head of the household, and the involvement of the household head in off-farm employment are the most important household characteristics that contributed to discriminating the households into classes. These results corroborate those from the results of the descriptive analysis (Table 5 and Table 6) using the test of the means on the quantitative and the chi-square test of independence on qualitative variables.

Table 9: Test of equality of group means and standardized coefficients of the canonical discriminant function

	Wilks' Lambda	F	df1	df2	Sign.	Standardized coefficients
How many livelihood activities does your household have?	0.993	33.235	1	4483	0.000	0.205
How many crops did your household cultivate in the last agriculture year?	0.995	24.035	1	4483	0.000	0.212
How old is the head of household	0.988	53.884	1	4483	0.000	-0.307

How many members does your household have?	0.985	68.470	1	4483	0.000	0.314
Tropical Livestock Unit (TLU)	0.996	17.651	1	4483	0.000	0.038
Household location	1.000	1.436	1	4483	0.231	-0.084
Household poverty status	0.985	68.279	1	4483	0.000	-0.309
Household head legally married	0.993	32.984	1	4483	0.000	-0.004
Household head finished at least the primary level	0.979	93.858	1	4483	0.000	0.387
What is the gender of the head of household	0.993	33.765	1	4483	0.000	0.014
Ownership of the house	0.999	3.874	1	4483	0.049	0.109
The size of the land owned by the household	0.994	25.740	1	4483	0.000	0.160
Off farm employment	0.993	32.325	1	4483	0.000	0.296
Household received remittance from relatives and friends	0.999	2.898	1	4483	0.089	0.127

Impact of access to credit: ESRM estimation results

Tables 10, 11 and 12 portray significant differences for the welfare outcome variables and other variables between borrowers and non-borrowers due to a series of observable and unobservable factors. In the following sections, the results of the Endogenous Switching Regression analysis using the full information maximum likelihood estimation are reported. Continuous variables in the three models have been transformed into their logarithms due to the difference in their measurement scales. The analysis considered three welfare outcome variables, namely, the household dietary diversity score, the household food consumption score, and the household total consumption expenditure as the dependent variables. One model for each of the three welfare variables has been formulated and estimated. The significance of r0 and the value of the log-likelihood ratio at the 1% level highlights the presence of selection bias and the joint dependence between the outcome and selection models, respectively. Moreover, following Bidzakin et al. (2019) and given the significant Wald test statistic at the 1% level, which provides strong evidence of endogeneity in the three formulated models, the use of the endogenous switching regression model with Full Information Maximum Likelihood (FIML) estimation is justified. The analysis revealed various factors affecting the access to credit and the welfare variables. The results on ATT for the dietary diversity score, the food consumption score, and monthly consumption expenditure are presented.

For the dietary diversity score variable, the estimation used the MLE of the endogenous-switching Poisson regression with count data. The MLE of the Switching Poisson Regression for the household dietary diversity score yielded in the significant coefficient r0 for non-borrowers attesting the presence of selection bias. The estimation of the variables against the household dietary diversity score (Table

10) reveals that the livestock holding in TLU, having a land size of more than 0.5 ha, having finished a primary education level, being in rural areas of the City of Kigali, and the number of livelihood activities were found to be significant and positively affecting the household dietary diversity score for both borrowers and non-borrowers. Being categorized as poor is a factor negatively affecting the household dietary score for both borrowers and non-borrowers. The size of the household is a factor negatively affecting the household dietary score for both borrowers and non-borrowers while the age of the household head was found to exert a negative influence on the dietary score of non-borrowers. This is because in general, large rural households are with meager resources and struggle to correctly feed the entire family even when they have had access to a small credit as the latter is generally used for purposes such as education, health, purchase of agricultural inputs, etc. that are not directly related to household food security.

Regarding household demographic characteristics, a particular case is noted for the age of the household head which is negatively affecting the access to credit and the outcome variable for non-borrowers. Non-borrowers from rural settings are generally characterized as resource constrained people and the more their age increases, the lower their level of access to high standards of living becomes. The findings also reveal that remittances constitute a driver of access to credit and affect positively the household food security level as far as the dietary diversity score is concerned. Furthermore, an increase in the number of cultivated crops and livelihood activities and attainment of at least the primary education and off-farm employment in the household play an important role in increasing the likelihood of accessing the credit and the level of the quality of food intake in non-borrowing households. This appears very intuitive and obvious as a literate and a wealthier farmer is likely to have a better understanding and then be more open to financial products and services than an illiterate and/or poor farmer who is less likely to manage his business with success. An increased number of people in the households seems to be a sign of labor endowment for rural household economic strives. The involvement of a household in off-farm employment builds confidence in farmer household and increases the likelihood of loan repayment. Other studies have found similar results on the drivers of access to credit and food security in household level (Armendariz and Morduch, 2005; Temesgen et al., 2017).

Table 10: Maximum Likelihood Estimates for the DDS Model

Variables	Model estimates					
	Access to credit		Borrowers		Non-borrowers	
	Coeff.	Robust St. Err.	Coeff.	Robust St. Err.	Coeff.	Robust St. Err.
Livelihood activities	0.128***	0.063	0.058**	0.026	0.033***	0.016
Number of cultivated crops	0.319**	0.063	0.031	0.029	0.123**	0.016

Age of HH head	-0.322***	0.087	-0.031	0.040	-0.134***	0.022
Household size	0.196***	0.060	-0.042	0.028	0.044***	0.015
Livestock holding in TLU	0.021	0.016	0.030***	0.007	0.021***	0.004
Location	0.104	0.167	0.167**	0.070	0.145***	0.044
Poverty status	-0.239***	0.050	-0.122***	0.024	-0.133***	0.013
Legal marriage status	0.019	0.050				
Education	0.215***	0.052	0.053**	0.022	0.076***	0.014
Gender	-0.013	0.077	-0.018	0.028	0.000	0.017
House ownership	-0.212*	0.126				
Land size	0.120**	0.051	0.048**	0.021	0.047***	0.013
Off-farm employment	0.302***	0.095	0.017	0.035	0.088***	0.028
Remittances	0.354*	0.200	0.152**	0.072	0.173***	0.057
Constant	-0.122	0.382	1.692***	0.164	1.941***	0.095
athrho0/athrho1			2.146***	0.119	-0.003	0.310
Wald χ^2(12)	Log	514.67***				
pseudolikelihood	LR	-1359.24				
test- χ^2(2)		208.74***				

***, ** and * denote statistical significance at 1%, 5% and 10% respectively.

The model estimation results reported in Table 11 for the household food consumption score resulted in negative coefficient rho1 and rho0 for both borrowers and non-borrowers. Since rho1 is negative and significant, the results indicate a positive self-selection issue and that households who decide to borrow from financial institutions have higher food consumption scores than a random household from the sample would have had. The joint dependence between the outcome equation and the selection equation between borrowers and non-borrowers is also confirmed by the statistically significant value of the log-likelihood ratio of the estimated model. The estimated significant coefficients of the model with the household food consumption score as the dependent variable are similar in direction to significant estimates of the previous model with the household dietary diversity score except the off-farm employment. This variable is negatively affecting the food consumption score of borrowers and some variations in terms of the magnitude of the estimates and the level of significance for some independent variables for both borrowers and non-borrowers. Regarding the factors affecting the access to credit, the results also show that most of estimated significant coefficients are similar in direction to the estimates of the previous model with differences in terms of magnitude and significance of some of the explanatory variables.

Table 11: Full Information Maximum Likelihood Estimates for the FCS Model

Variables	Model estimates					
	Access to credit		Borrowers		Non-borrowers	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Livelihood activities	0.148***	0.071	-0.081*	0.045	0.013	0.022
Number of cultivated crops	0.237**	0.068	0.003	0.044	0.104***	0.021
Age of HH head	-0.305***	0.098	0.064	0.063	-0.069**	0.021
Household size	0.347***	0.071	-0.204***	0.047	-0.016	0.021
Livestock holding in TLU	0.015	0.019	0.057***	0.012	0.053***	0.005
Location	-0.104	0.197	0.340***	0.124	0.268***	0.057
Poverty status	-0.139**	0.057	-0.058	0.037	-0.151***	0.017
Legal marriage Status	-0.027	0.063				
Education	0.230***	0.058	-0.064*	0.037	0.047**	0.020
Gender	-0.027	0.090	0.008	0.048	-0.001	0.022
House ownership	0.085	0.155				
Land size	0.052	0.058	0.040	0.037	0.089***	0.018
Off-farm employment	0.436***	0.103	-0.149**	0.061	0.004	0.041

Remittances		0.217	0.228	0.184	0.134	0.268***	0.078
Constant		-0.624	0.435	4.686***	0.268	3.956***	0.127
athrho0/athrho1				-0.131	0.151	-1.578***	0.140
Wald $\chi^2(12)$	Log pseudolikelihood		339.67*** -2638.35				
	LR test- $\chi^2(2)$		26.65***				

***, ** and * denote statistical significance at 1%, 5% and 10% respectively.

Table 12 reports the ESRM estimation results for the household monthly consumption expenditure. The general model diagnosis reveals the presence of self-selection. As the coefficients rh0 is significant and positive, this indicates that there is negative selectivity bias in the data highlighting that rural households with a monthly consumption expenditure below the average tend to self-select out from the rural loans scheme. This empirical finding seems to highlight the reality of rural areas as better-off households, say, with high level of expenditure, do not tend to request rural loans which are mostly provided by registered informal lenders. The model estimation yielded a statistically significant value of the log-likelihood revealing the joint dependence between the outcome and the selection models.

The estimation of the specified model of the access to credit gives similar results as those of the previous models except some little variations in terms of the magnitude and significance of the estimated coefficients. The household characteristics that are positively affecting the household monthly consumption expenditure for both borrowers and non-borrowers include the household size, the location, the level of education finished by the household head, being a male household head, the size of land, the remittances received by the households from friends and relatives, and the livestock holding in Tropical Livestock Unit considered in the model as the explanatory variables for both borrowers and non-borrowers. For a poor household, the results reveal a decrease in the likelihood of accessing the credit and a significant negative effect on the household total monthly expenditure for both borrowers and non-borrowers. Moreover, the findings show that an increase in the age of household head is a factor decreasing the probability of accessing rural loans. This sign of the estimates indicates that poor and older household heads are less likely to decide to borrow from financial institutions. The plausible explanation could be that lenders will be reluctant to offer loans to poor or old farmer for the fear that they will not be able to repay the contracted loans or that older people are no longer economically productive, hence, not able to pay back the money. These results corroborate those from other authors who found similar results regarding the statistically significant relationships between access to credit and both socio-demographic and economic household characteristics in Rwanda and elsewhere in rural areas of developing countries (Armendariz & Morduch, 2005; Calderon et al., 2008; Quoc et al., 2012; Muyombano & Mbabazize, 2016; Quach, 2016; Ntuite, 2020).

Table 12: Full Information Maximum Likelihood Estimates for the MCE Model

Variables	Model estimates					
	Access to credit		Borrowers		Non-borrowers	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Livelihood activities	0.162**	0.070	0.111	0.095	0.181***	0.054
Number of cultivated crops	0.327***	0.069	0.023	0.118	0.084	0.052
Age of HH head	-0.332***	0.098	0.082	0.152	-0.224***	0.073
Household size	0.335***	0.070	0.328***	0.125	0.475***	0.050
Livestock holding in TLU	0.002	0.019	0.039*	0.023	0.069***	0.014
Location	0.000	0.193	0.714***	0.238	0.829***	0.144
Poverty status	-0.141**	0.057	-0.570***	0.080	-0.534***	0.044
Legal marriage Status	-0.016	0.078				
Education	0.231***	0.058	0.196**	0.089	0.257***	0.049
Gender	-0.008	0.096	0.180*	0.094	0.123**	0.055
House ownership	0.068	0.198				
Land size	0.067	0.058	0. 270***	0.072	0.222***	0. 045
Off-farm employment	0.327***	0.105	0.108	0.135	0.196**	0. 096
Remittances	0.273	0.227	0.428*	0.248	0.553***	0. 192
Constant	-0.616	0.449	9.452***	0.645	10.188***	0.311
athrho0/athrho1			0.848***	0.087	0.026	0. 450
Wald $\chi^2(12)$ Log pseudolikelihood LR test- $\chi^2(2)$		640.26*** -5019.00 22.58***				

***, ** and * denote statistical significance at 1%, 5% and 10% respectively.

The estimation results of the effect of the access to credit on the welfare outcome variables are presented in Table 13 below. The household monthly consumption expenditure is the sole outcome variable significantly affected by access to credit. On average, household monthly expenditure on goods and services has increased by 69.9% for rural households who managed to borrow from financial institutions. This finding also corroborates those of other studies conducted in rural households of

developing countries that confirmed the positive effect of access to credit on household welfare, more particularly on household wealth and non-food items related expenditure (Quach, 2016; Bocher et al., 2017; Hossain & Knight, 2008; Petrick, 2004). This sounds intuitive in the current study context. In fact, as asserted by Kumar et al. (2020), household heads who happen to contract a small loan from microfinance institutions and/or community associations or tontines, have a burning need of addressing housing expenses, purchasing improved agricultural inputs and paying tuition fees, medical treatment and health insurances premiums, or meeting other noon-food related household needs.

Estimates of the effect of credit access on the household food consumption score and household dietary score are very small and not significant. This result concurs with Diagne and Zeller (2011) that rural household food security and nutritional status are not significantly affected by access to credit in Malawi. Similarly, Baborska et al. (2018) found that borrowing from a financial institution increases the likelihood of experiencing food insecurity in low-and middle-income countries. The plausible explanation of these results seems to be related to the nature of the credit offered to rural borrowers and the prioritization of rural households' needs. The demand for credit in rural areas is mainly driven by the need for on-farm and off-farm investments and offered credits are mainly oriented to that end (Diagne & Zeller, 2011). They need to improve the land productivity and increase the capital that could be invested in small income-generating activities. Rural households cannot borrow money for improving the quality and quantity of food except in marginal cases of famines and disasters. They are used to vulnerability and precarious life and, in the short term, most of them are concerned about what can guarantee them a (somewhat) better future. The effect of credit can be indirect and felt only when returns on investments are registered.

Table 13: Average treatment effect on the treated (ATT) using the ESRM

Outcome variable	Mean outcome		ATT		P>|t|
			Effect	% increase	
Monthly Consumption Expenditure	35897.3	21116.8	14780.5	69.9%	0.000***
Food Consumption Score	47.07	45.89	1.18	2.5%	0.998
Dietary Diversity Score	4.358	4.299	0.059	1.3%	0.122

*** denotes statistical significance at 1%.

Impact of access to credit: Robustness check using PSM and CEM results

PSM application: Estimation of propensity scores

The propensity scores were estimated through the estimation of the logistic regression model for credit access (for borrowers and non-borrowers). This estimated credit access model yielded in the following model diagnosis statistics: a Pseudo-R^2 of 0.0618, LRχ^2 (13) of 274.29 associated with a p-value of 0.0000, a Log-likelihood of -2081.9781 on 4485 households. The estimation of propensity scores enabled

to identify a region of common support of [0.041, 0.720], formed 6 blocks ensuring that the mean propensity score is not different for treated and control households in each block, and satisfied the balancing property. On total, two groups: one of 3593 households in control group and another one of 879 households in the treated group were formed. With the need to search for counterfactuals that match borrowers' households, households were matched using the Nearest Neighbor Matching (NNM) technique on the estimated propensity scores. The use of the NNM technique is justified by the fact that, as asserted by Bidzakin et al. (2019), the propensity scores form a continuous variable and matching treated households and counterfactuals with the same scores seems to be difficult. In addition, it is the simplest method to implement and the most straightforward matching estimator. The NNM method applied in this analysis used the widely used Mahalanobis distance and then, borrowers' households were matched with the closest non-borrowers' households.

CEM application: Coarsening procedure and diagnostic results of estimation models

Following Becker and Ichino (2002), who advise to consider together at least two matching methods to check for the robustness of the estimated treatment effect, in addition to the PSM, the Coarsened Exact Matching was estimated after recoding quantitative variables into bins as per the procedure developed by Blackwell et al. (2009). Before matching, the overall imbalance was of $\mathcal{L}_1$ = 0.8469 revealing a high global imbalance (or a separation) between the treated and control groups before matching (with $\mathcal{L}_1 = 0$ and $\mathcal{L}_1 = 1$ indicating perfect balance and full imbalance respectively). This value served as a benchmark for the balance assessment achieved through matching. It indicates that only 16% of the density of the multivariate empirical distributions of the pre-treatment characteristics for the treated and untreated groups overlap. This led to the stage of coarsening quantitative and categorical variables to increase the balance between the two groups. First, the recording into bins concerned quantitative covariates using 0, 2.5 and 7.5 as cut points for the variable "number of livelihood activities", and 0, 1.5, 6.5, 10.5 as cut points for the variable "number crops cultivated". The new imbalance level was estimated at $\mathcal{L}_1$=0.7837 translating a gain in overall balance of only 6%. Second, categorical variables were recorded into new variables. The location variable was recorded into two categories: Rural area of Kigali City and Rural area of other provinces; the wealth variable was recoded into 3 categories: poor, medium and wealth; the Land size variable was recoded into three classes: low size, medium size and large size, and the variable Education was recoded in four categories: No education, primary level, secondary level and tertiary level. For other categorical variables, their categories remained in their original forms as it was deemed not necessary to coarsen them.

The estimation of the new imbalance measure after coarsening both qualitative and quantitative covariates resulted in $\mathcal{L}_1$ = 0.3627 indicating a balance gain of 48% from the original unmatched data. Moreover, the in-depth analysis of the univariate imbalance results revealed a (almost) perfect balance in means as well as in the marginal distributions of covariates. Thus, with an overall balance level of 64% ($(1 - \mathcal{L}_1) * 100\%$), the following step was devoted to the application of the cem command to find households matching to the treated ones based on the performed coarsening. The cem command matched 235 strata, resulting in two groups of households: 4,037 in the control group and 1,108 in the treated group, with the findings indicating that CEM pruned fewer units compared to PSM. It also

generated weights used in the computation of the imbalance measures and the estimates of credit access causal effect. The estimation of the causal effect used original household characteristics and yielded the following overall model fit diagnosis statistics: F(14, 3820) of 45.35 with a p-value of 0.0000, F(14, 3820) of 86.09 with a p-value of 0.0000, and F(14, 3820) of 63.93 with a p-value of 0.0000, respectively for the following outcome variables: household monthly consumption expenditure, food consumption score, and dietary diversity score.

Effect of access to credit on rural household welfare using PSM and CEM

The results of the Average Treatment Effect on the Treated (ATT) calculated using PSM with the nearest neighbor matching and CEM are presented in the appendix. Based on the calculated standard errors, the results show that the ATT estimates by CEM are more robust for the three models compared to those produced by PSM. It is worth noting that values of the estimated effect are consistent for the two matching methods (16,688.32 Rwf for PSM and 16,643.53 Rwf for CEM).

An in-depth analysis of the findings reveals that the overall gain of credit access on the welfare outcome variables estimated by PSM and CEM is highly significant for only the Household consumption variable. On average, having accessed the credit increased the household expenditure on goods and services of about 16,600 Rwf. These results are consistent with those obtained using the ESRM technique, which are robust, with only slight differences likely attributable to the self-selection bias identified in the ESRM model estimation (Tables 10, 11, and 12). This is also shown by the decrease in the effect of access to credit estimated by the ESRM compared to estimates obtained by matching techniques. As an illustration, the new estimate of the effect on DDS household dietary diversity score was computed by fixing the values of rho0 and rho1 to 0 (or by ignoring the self-selection issue in the data). The new estimation reveals an increase in the estimate of the effect of credit access from 0.059 to 0.063 (corresponding to an increase of 6.7%). Therefore, ignoring the self-selection issue in the analysis of access to credit using empirical data may lead to biased results and potentially undermine the robustness of the findings.

6. Conclusion and policy implications

This research analyzed the effect of access to credit by rural households on the welfare status. The assessment considered the monthly consumption expenditure, the household food consumption score, and the household dietary diversity score as the welfare outcome variables using the Endogenous Switching regression model. This technique was adopted as a way of addressing the self-selection bias. The results show that the household size, having at least finished the primary level of education, the number of livelihood activities, the number of crops cultivated, the land size, off-farm employment, and remittances increase the likelihood of accessing the credit. The age of the household head and being poor proved to have a significant negative impact on the decision to borrow in rural households of Rwanda. In addition, the use of PSM and CEM estimation yielded results consistent with those obtained using ESRM and revealed that access to credit positively affects the welfare of rural

households by increasing the monthly consumption expenditure of borrowing households. The estimation also highlighted the robustness of the ESRM results compared to those from PSM and CEM, which were characterized by the existence of selection bias. A significant linkage between access to credit and the household food consumption score and dietary diversity score was not proven by the empirical analysis using both matching methods and endogenous switching regression technique. Although this study revealed insightful results with a substantial contribution to the literature, its main limitation rises from using old, cross-sectional, and limited data in terms of meaningful variables such as quantified uses of credit and categorized household expenditures that could allow to effectively estimate the effect of credit on welfare in rural areas.

The key recommendations are as follow:

- The results showed that the credit contributed to an increase in household expenditure on goods and services allowing them to increase their farm productivity and investment in off-farm activities. Therefore, policymakers and rural development partners should consider:
  (i) Strengthening the technical and financial capacities of local tontine associations to increase the amount of credit granted to rural householders.
  (ii) Establishing a public guarantee fund for rural dwellers presenting promising income generating projects. This will serve as a motivation for rural poor people who are reluctant to apply for loans due to the lack of collaterals.
- As the findings revealed a positive effect of increased number of livelihood activities on access to credit and outcome variables, the government of Rwanda should strengthen the on-going initiatives aiming at diversifying opportunities for job creation and income generation in rural areas.
- The credit may have significant short-and long-term effects on future rural households' welfare especially in terms of the dietary diversity via investment in livestock, farming, and other basic needs such as health and education. Therefore, future surveys could collect panel data which offer several advantages over cross-sectional data and allow researchers to estimate these effects effectively.
- Future studies should examine the effect of credit on food expenditure, an aspect that was not captured in this study, in order to provide insights into the linkage between access to loan and food security in rural areas.

References

Abapihi, B., Wibawa, G. N. A., Baharuddin, et *al*. (2020). ANOVA on principal component as an alternative to MANOVA. *J. Phys. : Conf. Ser.* 1899. DOI : 10.1088/1742-6596/1899/1/012103.

Adams, D. W. and von Pischke, J. D. (1992). Microentreprise Credit Programmes: Déjà Vu. *World Development* 20:1463-70.

AFR (2024). Rwanda FinsScope 2024 Report. Kigali: Access to Finance Rwanda.

Akotey, J. O. and Adjasi, C. K. (2016). Does microcredit increase household welfare in the absence of microinsurance?. *World development*, 77, 380-394.

Amendola, A., Boccia, M., Mele, G., Sensini, L. (2016). Financial Access and Household Welfare: Evidence from Mauritania. *Policy Research Working Paper Series*, 7533. Macroeconomics and Fiscal Management Global Practice Group, World Bank Group.

Anello, E. (2022). What Is the Difference Between PCA and LDA. *365 Data Science*. https://365datascience.com/tutorials/python-tutorials/lda-vs-pca/. Accessed on November 10, 2023.

Appleton, S. (1996). Women-headed households and household welfare: An empirical deconstruction for Uganda. *World Development, 24(12), 1811–1827.* doi:10.1016/s0305-750x(96)00089-7

Aredo, D. (1993). The informal and semi-formal financial sectors in Ethiopia: a study of the iqqub, iddr, and savings and credit cooperatives. *AERC Research paper 21*, Nairobi, Kenya.

Armendariz, B.A. and Morduch, J. (2005). The economics of microfinance. London: MIT Press.

Awotide, B. A., Abdoulaye, T., Alene, A., and Manyong, V. M. (2015). Impact of Access to Credit on Agricultural Productivity: Evidence from Smallholder Cassava Farmers in Nigeria. A Contributed paper Prepared for Oral Presentation at the *International Conference of Agricultural Economists (ICAE)*. Milan, Italy August 9-14, 2015.

Baborska, R., Hernandez-Hernandez, E., Magrinin, E. and Morales-Opazo (2018). The impact of financial inclusion on rural food security experience: a perspective from low-and middle-income countries. *MPRA* Paper No. 89249. https://mpra.ub.uni-muenchen.de/89249/

Bakhshoodeh, M., and Karami, A. (2008). Determinants of poor accessibility to microcredits in rural Iran. In *International Conference on Applied Economics* (67-71).

Beck, T. and Cull, R. (2015). Banking in Africa. In: Berger, A. N., Molyneux, P., Wilson, J. O. S. (Eds.), *The Oxford Handbook of Banking* (913–937). Oxford University Press.

Becker, O. S. and Ichno, A. (2002). Estimation of average treatment effects based on propensity scores. *The Stata Journal*, 2 (4), 358–377.

Bidzakin, J.K., Fialor, S.C., Awunyo-Vitor, D. and Yahaya, I. (2019). Impact of contract farming on rice farm performance: Endogenous switching regression, *Cogent Economics & Finance*, 7 (1), 1618229, DOI: 10.1080/23322039.2019.1618229

Blackwell, M., Iacus, S., King, G., and Porro, G. (2009). cem: Coarsened exact matching in Stata. *The Stata Journal*, Vol. 9 (4), 524–546.

Blanchard, O. (2017). *Macroeconomics* (7th edition). New Jersey, Upper Saddle River: Pearson Education, Inc.

Bocher, T. F., Alemu, B. A., & Kelbore, Z. G. (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.

Brown, S., Gray, D., & Roberts, J. (2015). The relative income hypothesis: A comparison of methods. *Economics Letters*, *130*, 47-50.

Browning, E. K. and Zupan, M. A. (2020). *Microeconomics: Theory and applications*. John Wiley & Sons.

Calderon, L. M., Garrido, S. and Navarro, J. D. (2008). Estudio piloto de evaluacion de impacto del programa de microcreditos de Cruz Roja Espanola en Ruanda. *Revista de Economia Mundial*, 19, 83–104.

Carroll, C. D. (2001). A theory of the consumption function, with and without liquidity constraints. *Journal of Economic perspectives*, 15(3), 23-45.

Coleman, B. E. (1999). The impact of group lending in Northeast Thailand. *Journal of Development Economics, 60(1), 105–141.* doi:10.1016/s0304-3878(99)00038-3

Dehejia, R. H., and Wahba, S. (2002). Propensity score-matching methods for nonexperimental causal studies. *The Review of Economics and Statistics* (2002) 84 (1), 151–161.

Demirgüç-Kunt, A., Klapper, L., Singer, D. (2017). Financial Inclusion and Inclusive Growth: A Review of Recent Empirical Evidence. *Policy Research Working Paper Series,* 8040. Development Research Group, Finance and Private Sector Development Team. World Bank Group. https://documents1.worldbank.org/curated/pt/403611493134249446/pdf/WPS8040.pdf

Demirgüç-Kunt, A., Klapper, L., Singer, D., Ansar, S., et al. (2018). The Global Findex Database 2017: Measuring Financial Inclusion and the Fintech Revolution. *Overview booklet*. Washington, DC: World Bank. License: Creative Commons Attribution CC BY 3.0 IGO

Diagne, A. and Zeller, M. (2001). Access to Credit and Its Impact on Welfare in Malawi. International Food Policy Research Institute, Washington, D.C, Research Report 116.

Diop, T., Ibrahim, F., Lo Hog Tian, M. J., Dona, Y., et al. (2023). Increasing Meaningful Financial Inclusion in Rwanda: Community-Based Savings and Credit Co-operative Societies. *Reach Alliance*. https://reachalliance.org/wp-content/uploads/2023/10/RwandaSACCOs-final67.pdf

Dwivedi, D. N. (2016). *Microeconomics: theory and applications* (3rd edition). Vikas Publishing House.

FAO (2013). *Guidelines for Measuring Household and Individual Dietary Diversity*. Rome: Food and Agriculture Organization of the United Nations.

Fiala, N. and He, X. (2017). Unitary or noncooperative intrahousehold model? Evidence from couples in Uganda. *The World Bank Economic Review*, *30*, S77-S85.

Fisher, I. (1930). The theory of interest. New York: MacMillan.

Freeman, H.A., Simeon, K.E., and Jabar M.A. (1998). Credit constraints and smallholder dairy production in the East African highlands: application of a switching regression model. *Agricultural Economics*, 19, 33-44.

Frohberg, K. and Müller, K.H. (2007). *The Impact of Microfinance on Rural Poor Households' Income and Vulnerability to Poverty: Case Study of Makueni District, Kenya* (Inaugural – Dissertation). Rheinischen Friedrich-Wilhelms-Universität zu Bonn.

Gabeshi, K. (2022). Overview of Credit Activities of Banks in the Developed Economies. *Management Strategies Journal*, *55*(1), 92-99.

Greene, W. H. (2012). Econometric Analysis (7th Edition). Prentice Hall.

Hananu, B., Abdul-Hanan, A., and Zakaria, H. (2015). Factors influencing agricultural credit demand in Northern Ghana. *African Journal of Agricultural Research*, *10*(7), 645-652.

Hasebe, T. (2020). Endogenous switching regression model and treatment effects of count-data outcome. *The Stata Journal*, 20 (3), 627–646. doi:10.1177/1536867x20953573

Hatloy, A., Hallund, J., Diarra, M.M., and Oshaug, A. (2000). Food variety, socioeconomic status and nutritional status in urban and rural areas in Koutiala (Mali). *Public Health Nutrition,* 3, 57-65.

Hoddinott, J. and Yohannes, Y. (2002). *Dietary diversity as a food security indicator*. FANTA 2002, Washington DC. Retrieved from http://www.aed.org/Health/upload/ dietarydiversity.pdf on August 25, 2022.

Hossain, F. and Knight, T. (2008*). Financing the poor: can microcredit make a difference? Empirical observations from Bangladesh*, Brooks World Poverty Institute, University of Manchester, Manchester.

Iacus, S. M., King, G. and Porro, G. (2012). Causal Inference Without Balance Checking: Coarsened Exact Matching. *Political Analysis?* 20(1), 1–24. https://doi.org/10.1093/pan/mpr013.

Islam. A. and Maitra, P. (2012). Health shocks and consumption smoothing in in rural households: Does microcredit have a role to play? *Journal of development economics*, 97(2), 232-243.

King, G., and Nielsen, R. (2019). Why Propensity Scores Should Not Be Used for Matching. *Political Analysis*, 27 (4): 435-454. https://doi.org/10.1017/pan.2019.11.

Kumari, P. (2020). Theoretical analysis of microfinance on poverty alleviation. *Journal of Economic Info*, *7*(3), 221-236.

Lin, L., Wang, W., Gan, C. and Nguyen, Q. T. (2019). Credit constraints on farm household welfare in rural China: Evidence from Fujian Province. *Sustainability*, 11(11), 3221.

Lokshin, M. and Sajaia, Z. (2004). Maximum likelihood estimation of endogenous switching regression models. *Stata Journal*, 4, 282–289. doi:10.1177/1536867X0400400306

Mahendra, D. S. (2006). Financial Inclusion: Issues and Challenges. *Economic and Political Weekly*, *41*(41), 4310–4313. http://www.jstor.org/stable/4418799

Mahjabeen, R. (2008). Microfinancing in Bangladesh: impact on households, consumption and welfare. *Journal of policy modeling*, 30(6), 1083-1092.

Mankiw, N. G. (2016). Macroeconomics (9th Ed.). New York: Worth Publishers.

Markgraf, J., and Rosas, G. (2023). *Borrowing welfare: Credit access and support for redistribution*.

Martìnez, A. M. and Kak, A. C. (2001). PCA versus LDA. *IEEE Transactions on Pattern Analysis and Machine Intelligence*. 23 (2), 228-233. DOI: 10.1109/34.908974.

Meenakshi, J., and Ray, R. (2002). Impact of household size and family composition on poverty in rural India. *Journal of Policy Modeling*, 24(6), 539–559. DOI:10.1016/s0161-8938(02)00129-1

MINECOFIN (2018). *Financial Sector Development Strategic Plan 2018-2024*. Kigali: Ministry of Finance and Economic Planning.

Mohamed, E. F., and Fauziyyah, N. E. (2020). Islamic microfinance for poverty alleviation: a systematic literature review. *International Journal of Economics, Management and Accounting*, *28*(1), 141-163.

Moradi, S., and Mokhatab R. F. (2019). A dynamic credit risk assessment model with data mining techniques: evidence from Iranian banks. *Financial Innovation*, *5*(1), 1-27.

Mpuga P. (2008). Constraints in Access to and Demand for Rural Credit: Evidence from Uganda. *A paper for presentation during the African Economic Conference (AEC)*, 12-14 November 2008 Tunis, Tunisia.

Muellbauer, J. (2016). *Macroeconomics and consumption*. University of Oxford.

Muyombano A., and Mbabazize, M. (2016). The contribution of Umwalimu SACCO on Socio-economic development of teachers; Case study of Gasabo District branch. *International Journal of Scientific and Research Publications*, 6 (12).

Nelson, R. R. and Consoli, D. (2010). An evolutionary theory of household consumption behavior. *Journal of Evolutionary Economics*, 20, 665-687.

NISR (2022a). *Comprehensive food security and vulnerability analysis*. 2022 Report. Kigali: National Institute of Statistics of Rwanda.

NISR (2022b). *Rwanda 2022 Statistical Yearbook*. Kigali: National Institute of Statistics of Rwanda.

NISR (2023). *Fifth Rwanda Population and Housing Census Report*. Kigali: National Institute of Statistics of Rwanda.

Ntuite, S. R. (2020). *The contribution of saving and credit cooperatives (SACCOS) on the improvement of members' socio-economic development in Rwanda: Opportunities and challenges. Evidence from Umwalimu SACCO- Huye District*. PhD Thesis, School of Economics, Department of Social sciences, University of Koblenz- Landau, Germany.

Okoyo, E.N., Wordofa, M.G., Hassen, J.Y. and Bezabih, M. (2021), "Welfare impacts of rural credit and saving program in Kurfa Chele district, eastern Ethiopia: a propensity score matching estimation", *Agricultural Finance Review*, Vol. 81 No. 4, pp. 596-613. https://doi.org/10.1108/AFR-06-2020-0087

Persaud, A. and Thaffe, W. (2023). The state of financial inclusion research on developing countries. *Transnational Corporations Review*, Vol. 15 (4): 22-34. https://doi.org/10.1016/j.tncr.2023.08.002

Petrick, M. (2004) Farm investment, credit rationing, and governmentally promoted credit access in Poland: a cross-sectional analysis. Food Policy, 29(3), pp. 275-294.

Quach, H. and Mullineux, A. (2007). The impact of access to credit on household welfare in rural Vietnam. *Research In Accounting In Emerging Economies*, 7, 279-307.

Quach, H. M. (2016). Does access to finance improve household welfare? Investment Management and Financial Innovations, 13(2), 76-86. doi:10.21511/imfi.13(2).2016.08

Quach, H. M. (2017). Does access to credit improve household welfare in the long-run? *The Journal of Developing Areas*, 51(1), 129-142.

Quoc, D, V., D'Haese, M., Lemba, J., and D'Haese, L. (2012). Determinants of household access to formal credit in the rural areas of the Mekong Delta, Vietnam. *African and Asian studies*, 11(3), 261-287.

Rencher, A. (1992). Interpretation of Canonical Discriminant Functions, Canonical Variates, and Principal Components. *The American Statistician*, Vol. 46, No. 3, pp. 217-225.

Rencher, A. C., and Scott, D. T. (1990). Assessing the Contribution of Individual Variables Following Rejection of a Multivariate Hypothesis. *Communications in Statistics, Part B-Simulation and Computation*, 19, 535-553.

Rosenbaum, P. R., and Rubin, D. B. (1983b). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70: 41–55.

Sekyi, S. (2017). Rural Households' Credit Access and Loan Amount in Wa Municipality, Ghana. *International Journal of Economics and Financial Issues*, 7(1), 506-514.

Selim, R., Bazlul, H.K., Guntur, S., Shikha, J. (2009). Remittances and Household Welfare: A Case Study of Bangladesh, *ADB Economics Working Paper Series*, No. 189. https://hdl.handle.net/11540/1840

Shadrack, O. (2017). Factors Affecting Farm Households' Access to Credit in the Afigya- Kwabre District of Ghana. *International Journal of Scientific Research in Social Sciences & Management Studies,* 2(1), 98-113.

Sheth, J. N., Newman, B. I., and Gross, B. L. (1991). Why we buy what we buy: A theory of consumption values. *Journal of business research*, 22(2), 159-170.

Sheuya, S. A., & Burra, M. M. (2016). Tenure Security, Land Titles and Access to Formal Finance in Upgraded Informal Settlements: The Case of Dar es Salaam, Tanzania. *Current Urban Studies*, 4, 440-460. http://dx.doi.org/10.4236/cus.2016.44029.

Soriya, T. H. E. A. N. G. (2019). *Money talks: in women's bargaining power in the Cambodian household* (Doctoral dissertation, American University).

Stijns, J-P. (2017). *Banking in sub-Saharan Africa: Interim Report on Digital Financial Inclusion*. Africa Day 2017, Berlin. European Investment Bank.

Stuart, A. E. and Rubin, B. D. (2008). Best Practices in Quasi-Experimental Designs. In Osborne, J. (Ed.) *Best practices in Quantitative Methods*, Sage Publications, California.

Stuart, E. A. (2010). Matching Methods for Causal Inference: A Review and a Look Forward. Statistical Science 25 (1): 1–21. https://doi.org/10.1214/09-STS313.

Swindale, A. and Bilinsky, P. (2006). *Household Dietary Diversity Score (HDDS) for Measurement of Household Food Access: Indicator Guide (v.2)*. Washington, D.C.: FHI 360/FANTA.

Temesgen F. B., Balaka A. A. and Zerihun, G. K. (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), 1-16. DOI 10.1108/AJEMS-03-2017-145.

Tharwat, A., Gaber, T., Ibrahim, A. et al. (2017). Linear discriminant analysis: A detailed tutorial. *AI Communications*. 30, 169-190.

Thimme, J. (2017). Intertemporal substitution in consumption: A literature review. *Journal of Economic Surveys*, *31*(1), 226-257.

Thomas, J. J. (1992). Informal financial sector: how does it operate and who are the customers? *London, GB: Overseas Development Initiative (ODI)*.

Tonch, H. A. and Sohn, W. (2022). The impact of informal credit on household welfare: evidence from rural Ethiopia. *Applied Economics Letters*, *29*(1), 12-16.

Tran, N. V. (2022). Understanding Household Consumption Behaviour: What do we Learn from a Developing Country? *The BE Journal of Economic Analysis & Policy*, 22(4), 801-858.

Triki, T. and Faye, I. (Eds.) (2013). *Financial Inclusion in Africa*. Tunis: African Development Bank.

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. http://dx.doi.org/10.1016/j.worlddev.2012.03.012.

Wijaya, A., Zainurossalamia, S., and Darma, D. C. (2020). Life-cycle hypothesis for consumption pattern: Example from Indonesia. *International Journal of Advanced Science and Technology*, *29*(4), 4712-4720.

Appendix

Effects of access to credit on welfare outcome variables using PSM and CEM

	Access to credit (1-Yes vs 0-No)	***Estimated ATT***	***Stand. Error***	***t-statistic***
Propensity score matching with Nearest Neighbor Matching method (random draw version)	Monthly Consumption Expenditure	16688.32	3560.99	4.68***
	Food Consumption Score	1.57	0.90	1.75
	Dietary Diversity Score	0.06	0.06	1.02
Coarsened Exact matching	Monthly Consumption Expenditure	16643.53	2499.53	6.66***
	Food Consumption Score	0.904	0.62	1.46
	Dietary Diversity Score	0.045	0. 04	1.06

Note: *** denotes the significance level at 5% with p-values of 0.000.

Mission

To strengthen local capacity for conducting independent, rigorous inquiry into the problems facing the management of economies in sub-Saharan Africa.

The mission rests on two basic premises: that development is more likely to occur where there is sustained sound management of the economy, and that such management is more likely to happen where there is an active, well-informed group of locally based professional economists to conduct policy-relevant research.

Bringing Rigour and Evidence to Economic Policy Making in Africa

- Improve quality.
- Ensure Sustainability.
- Expand influence.

www.aercafrica.org

Learn More

www.facebook.com/aercafrica

www.instagram.com/aercafrica_official/

twitter.com/aercafrica

www.linkedin.com/school/aercafrica/

Contact Us
African Economic Research Consortium
Consortium pour la Recherche Economique en Afrique
Middle East Bank Towers,
3rd Floor, Jakaya Kikwete Road
Nairobi 00200, Kenya
Tel: +254 (0) 20 273 4150
communications@aercafrica.org