Hue University Journal of Science: Economics and Development
pISSN 2588-1205;eISSN 2615-9716
Vol. 133, No. 5C, 2024, pp. 43–65, DOI: 10.26459/hueunijed.v133i5C.7620

FORMAL CREDIT, RURAL HOUSEHOLD LIVING STANDARDS: A STUDY OF THE NORTH CENTRAL REGION OF VIETNAM

Le Viet Giap*, Nguyen Thi Khanh Trang, Pham Quoc Khang, Nguyen The Hung

University of Economics, Hue University, 99 Ho Dac Di St., Hue, Vietnam

* Correspondence to Le Viet Giap <lvgiap@hce.edu.vn>
(*Submitted: September 1, 2024; Accepted: September 27, 2024*)

Abstract. This study focuses on evaluating the impact of access to formal credit on the living standards of rural households in the North Central region of Vietnam. The propensity score matching (PSM) method was used on the Vietnam Household Living Standards Survey (VHLSS) 2020 database to examine this impact. The research results indicate that participation in formal credit has the potential to improve the living standards of households in the rural area of the North Central region. The improvement is approximately 2 percent of per capita income. In addition, this study also shows that formal credit can have a positive impact on poverty reduction. Specifically, participation in formal credit reduces poverty rates in rural areas of North Central Vietnam, although the reduction in these poverty rates is still modest.

Keywords: formal credit, rural credit, propensity score matching

1 Introduction

Access to credit, particularly microcredit, has long been recognized as an instrumental tool in alleviating hunger, reducing poverty, and enhancing household welfare in rural areas, especially within developing nations. For decades, it has been considered a pivotal factor in these countries' developmental processes [1].

In Vietnam, a dual credit system exists, comprising both formal and informal sectors. Formal credit institutions, including banks and regulated financial organizations, dominate the microcredit market, serving as the primary providers of small and medium-sized loans to rural households. While the informal credit sector, characterized by community funds and personal lending, continues to operate, it plays a relatively minor role in meeting households' small loan requirements, as evidenced by data from the Vietnam Household Living Standards Survey (VHLSS).

Formal credit in rural Vietnam plays a pivotal role in fostering agricultural development and enhancing the socioeconomic status of farming communities. Key financial institutions, including the Social Policy Bank and the Vietnam Bank for Agriculture and Rural Development, in conjunction with government initiatives, provide essential capital and financial support for agricultural production and related business activities. These institutions offer a diverse array of financial products and services, encompassing loans, agricultural credit, and specialized support packages tailored to the unique requirements of the farming sector. Such financial instruments enable farmers to acquire necessary equipment, seeds, and fertilizers, while also supporting ongoing agricultural operations.

The impact of formal credit extends beyond merely increasing agricultural productivity and efficiency; it serves as a crucial mechanism for poverty alleviation and income enhancement within rural communities. By providing stable capital sources, formal credit facilitates rural households' participation in development projects and expansion of business operations. However, it is imperative to acknowledge that access to and utilization of formal credit may present challenges, particularly regarding loan conditions and interest rates. Consequently, the development of flexible and judicious financial policies and mechanisms is essential to ensuring equitable credit access and benefits across all segments of the rural population.

The North Central region of Vietnam, including provinces such as Thanh Hoa, Nghe An, Ha Tinh, Quang Binh, Quang Tri, and Thua Thien Hue, is an area with rich and diverse land. However, this region faces many economic difficulties and poverty. Agriculture, although important, often encounters difficulties due to unfavorable land and weather conditions. Infrastructure, especially transportation and energy, is still lacking, reducing development opportunities. Poverty is frequently present, causing rural households to face difficulties in stable income. Additionally, natural disasters and climate change often affect production and daily life. The lack of education and healthcare is another challenge, making it difficult for the community to access basic services. Despite these challenges, the North Central region is striving to achieve sustainable development and improve the quality of life for the local community. According to the latest data published by the Ministry of Labor, Invalids, and Social Affairs, the multidimensional poverty rate of the North Central and Central Coastal regions is 8.03%, higher than the national average of 5.71%. This region is among the three regions with the highest poverty rates in the country, ranking third after the Northern Midlands and Mountainous region and the Central Highlands. The total number of poor and near-poor households in the North Central region, according to 2023 data, is 460,456 households [2].

Research on formal credit in rural areas of the North Central region of Vietnam is an important and necessary topic. This study contributes in several aspects. First, although there have been many previous studies on the topic of microcredit in general and some studies referring to the impact of formal credit in particular, this study is one of the few studies assessing that impact at the regional level. Specifically, the North Central region of Vietnam is an area with a high level of poverty but has not been paid attention to in the literature. The findings related to rural credit in other countries may not correspond to the characteristics of information in Vietnam in general and the study area in particular. Second, the research method is used appropriately with the VHLSS dataset, which is representative of Vietnam and the region, which will limit the selection bias often found in microcredit studies. Third, in this study, formal credit in Vietnam is studied for the first time in a comprehensive manner, taking into account most of the existing formal credit channels, while previous studies mainly focused on loans from social policy banks when referring to formal credit. Therefore, the research results provide a comprehensive and reliable assessment of formal credit in rural areas of North Central Vietnam, and the policy recommendations based on the research contribute to improving the living standards of rural households in Vietnam in general and for that poor region in particular.

2 Literature Review

The microcredit revolution has emerged as a significant tool in global socio-economic development efforts, particularly in poverty alleviation. In the context of global economic development, microcredit and rural credit models have demonstrated their crucial role in improving living standards and fostering economic growth in rural areas, especially in developing nations. These models are tailored to align with the unique economic, social, and cultural conditions of each country and region, resulting in a diverse and rich array of approaches and implementations.

The Grameen Bank model, pioneered by Muhammad Yunus in Bangladesh, stands out as one of the most prominent examples. This model specializes in providing small, uncollateralized loans to impoverished individuals, with a particular focus on women. The distinctive feature of Grameen Bank lies in its group lending methodology, where members collectively guarantee each other's loans, fostering trust and mitigating credit risk. The success of this model has led to its widespread adoption and adaptation globally. In Vietnam, the Vietnam Bank for Agriculture and Rural Development (Agribank) exemplifies the Rural Development Bank model. Agribank extends credit to farmers, agricultural cooperatives, and small to medium-sized enterprises in rural areas. Its diverse portfolio of credit products encompasses agricultural production loans, rural infrastructure development financing, and consumer credit, contributing significantly to rural economic development in Vietnam.

The People's Credit Fund system in Vietnam represents another microcredit model, where credit institutions are capitalized and managed by local residents. These funds provide microloans to support community members' production and business activities, thereby promoting local community cohesion and development. Credit Unions, popular in many countries, offer another noteworthy credit model. These member-owned and operated financial institutions provide services such as savings accounts, loans, and other financial products at preferential rates. This model not only facilitates members' access to financial services but also fosters a supportive economic community. Non-governmental organizations (NGOs) also play a pivotal role in microcredit provision. For instance, BRAC in Bangladesh and Fundación Capital in Latin America offer microloans in conjunction with training and technical support programs. This integrated approach enhances borrowers' production and business capabilities, thereby improving their income and quality of life [3]. Some contemporary rural credit models incorporate insurance components to protect farmers against weather-related risks, diseases, and price fluctuations. For example, credit programs combined with agricultural insurance in India not only provide loans but also ensure that farmers can safeguard their production against unforeseen risks. While these credit models vary in their implementation and target demographics, they share the common goal of improving living conditions and promoting economic development in rural areas. The efficacy of each model is contingent upon its adaptability to the specific conditions of each country and region, as well as the support provided by appropriate policies and management mechanisms.

In the literature, many studies have focused on examining the relationship or impact of various forms of microcredit in general and rural credit in particular. At the national level, previous studies have evaluated the impacts of this credit access on household living standards and welfare. In other words, microcredit has received considerable attention from the academic community, with an increasing number of empirical studies. The impact of microcredit on household welfare has been explored in many studies. Specifically, in China, Li, Gan, and Hu used survey data from Hubei Province. This study, applying the difference-in-differences method, showed that microcredit improved household welfare. Notably, the study also revealed that most participants were not the poor, contrary to the expected target group [4]. Recent research by Santana Félix and Belo used the generalized method of moments (GMM) on cross-sectional data from 11 Southeast Asian countries and indicated the positive impact of microcredit on poverty reduction [5]. In Bangladesh, Islam also provided evidence of the positive impact of microcredit. Islam further argued that this impact varied among household groups by income level, with the lowest income group benefiting the most [6]. Recently, Schroeder also demonstrated that loans from Grameen Bank and similar organizations in Bangladesh had a significant and positive impact on expenditure and per capita in the country [7]. Similarly, studies by McKernan also recorded the positive impact of microcredit on household self-employment profits [8]. You examined the role of microcredit on child nutrition in Gansu, China, using a quasi-experimental method and found that microcredit improved short-term nutritional levels [9]. Michel and Randriamanampisoa analyzed the role of microcredit in transforming household resources in the Madagascar highlands and found that microcredit participation was associated with higher capacity levels, contributing to improved household livelihoods [10]. Studies documenting positive effects often emphasize the productive use of credit, particularly when households invest in income-generating activities such as agriculture or small businesses. This enables them to increase income, improve consumption, and enhance access to essential services like education and healthcare, ultimately raising their living standards [11]. Affordable credit with favorable terms, such as low interest rates and flexible repayment schedules, has also been found to play a crucial role in positive outcomes, as it reduces the financial burden and allows households to invest in long-term economic activities [12]. Moreover, credit programs that incorporate financial education and support services tend to yield better results, as they enhance households' capacity to manage loans and avoid debt traps [13]. However, not all studies noted a positive impact of microcredit on welfare. Morduch showed that participation in microcredit programs did not have the expected statistical significance [14]. Eriksen and Lensink evaluated the impact of microcredit from a specific project in Ghana on expenditure and concluded that this impact did not persist over time [15]. There are several reasons why microcredit might fail to deliver sustained improvements in household welfare. First, many studies that report non-positive impacts highlight issues related to loan misallocation. When households use credit for consumption purposes rather than for productive investment, the expected economic gains do not materialize. This is especially the case in rural settings, where households may divert loans to meet immediate needs, such as healthcare or social obligations, rather than using the funds to generate income. For instance, research by Brett suggested that microcredit recipients sometimes use loans for non-productive consumption, which undermines the long-term sustainability of credit interventions. Another significant issue is over-indebtedness [16]. Some studies, such as those by Rahman, highlight the risks associated with multiple borrowing, where households take out loans from different lenders to repay existing debts. This can lead to a cycle of indebtedness, which erodes household welfare and can result in asset loss. When households are unable to repay loans, they may fall into deeper poverty rather than improving their living standards [17]. The mixed results in the literature on the effects of microcredit on household living standards and welfare reflect the complexity of rural economies and the multifaceted nature of credit interventions. Positive outcomes are more likely when credit is used for productive investments and provided with appropriate financial literacy and support systems. However, when credit is misallocated or when households face over-indebtedness and external shocks, the benefits of microcredit may fail to materialize or even lead to adverse outcomes. With mixed statistical results from current studies, more research is needed to further analyze the impact of microfinance.

In Vietnam, the role of microcredit, particularly formal credit, has garnered significant attention in recent years. Nguyen first documented the impact of microfinance, employing two-stage least squares (2SLS) and fixed effects models to demonstrate its poverty reduction effects. However, the study also revealed that a substantial proportion of microfinance clients were not from the intended target group of poor individuals, despite high credit demand among low-income populations [18]. More recently, Dang, Nanseki, and Chomei conducted a survey in Phu Tho Province, utilizing 2SLS methodology on 257 observations to assess microfinance's impact on income. Their findings indicated a modest welfare effect [19]. Nguyen et al. investigated factors influencing household access to preferential loans and their subsequent impact on income. Applying quantile regression to Vietnam Household Living Standards Survey (VHLSS) 2010 data, they found that preferential loans had a more pronounced effect on lower income quantiles [20]. cc, Saito, and Duong employed matched-difference-in-difference methods and input-output analysis on data from the Vietnam Household Resource Survey (VARHS) across 12 provinces. Their results corroborated the efficacy of microcredit as a development tool at both macro and micro levels [21].

However, at the regional level, there seems to be a lack of studies on the impact of access to formal credit on the living standards of rural households in specific geographical and economic regions. Most studies in Vietnam have been conducted at the national level or focused on the Northern mountainous region. There has not been any study evaluating formal credit activities in the North Central region of Vietnam. This is one of the geographical and economic regions with many notable points as presented in the introduction.

3 Data and Methodology

3.1 Data

This study uses the Vietnam Living Standard Survey 2020 dataset. The VHLSS 2020 is an integral part of the annual survey series conducted by the General Statistics Office of Vietnam, initiated in 2002. The main objective of this survey is to collect multidimensional information on household living standards, focusing on aspects such as income, consumption, education, health, and other factors affecting quality of life. The VHLSS 2020 data provides detailed information on household income and expenditure, helping to identify the extent and distribution of income within society. It also includes indicators on education, health, housing, utilities, and employment status, creating a comprehensive picture of the living conditions of the population. This data is not only a valuable resource for monitoring trends and evaluating policy impacts but also a useful tool for researchers, government agencies, and non-governmental organizations to make informed policy decisions and measures to improve community living standards. Notably, the VHLSS dataset ensures national, regional, and provincial representation. Therefore, the selected data from the VHLSS for the North Central region used in this study meets the representativeness requirement of the studied area.

3.2 Propensity Score Matching Method

There are various methods to evaluate the impact of credit access on the living standards of households. In the literature, studies published based on the Random Control Trial (RCT) method are considered one of the most highly regarded tools for evaluating the impact of different types of policies in general. RCT can yield reliable results because this method can eliminate biases from selection bias. Although highly regarded in terms of methodology and effectiveness, the biggest drawback and the major barrier to the widespread application of RCT in large-scale studies lie in the high cost of conducting research using RCT. Particularly in developing countries, there are not many impact evaluation projects/policies that can implement RCT on a large scale or within a country. When RCT cannot be conducted, researchers may choose several methods to evaluate this impact, aiming to address the selection bias issue, such as using instrumental variables or Propensity Score Matching (PSM). The PSM is one of the models of propensity score analysis created by Rosenbaum and Rubin [22]. This study chooses to approach the issue with PSM because the instrumental variable approach is generally quite sensitive to the variables selected. The PSM method is a robust statistical technique applied in the field of policy and social intervention impact evaluation. In this study, the Propensity Score (PS) is the probability of receiving the intervention, predicted based on a set of influencing factors, typically determined through a logistic regression model. The subsequent matching process creates a similarity between individuals in the treatment and control groups based on PS, forming a representative control group for reasonable comparison. The core concept of PSM involves computing the propensity score for each individual to generate a counterfactual group. In addition, the PSM method is more suitable than other non-experimental methods, such as Difference-in-Differences (DiD) in studying "Formal Credit and Rural Household Living Standards in the North Central Region of Vietnam," because PSM effectively addresses selection bias by matching households that received credit with those that did not, based on observable characteristics. This is crucial in contexts where credit allocation is non-random, as wealthier or more resourceful households are more likely to receive loans. PSM is also more appropriate when dealing with cross-sectional data, as it does not require the longitudinal structure that DiD depends on to account for pre- and post-treatment outcomes. Additionally, assessing time-varying effects of credit in rural Vietnam is complicated by external factors like changes in policies or regional development, which may violate DiD’s assumption of parallel trends over time. Therefore, PSM is better suited for studies where there are significant time-varying confounders and non-random treatment allocation.

The propensity score represents the probability of being assigned to the treatment group based on observable baseline characteristics, denoted as $Pr(D = 1 \mid X)$. This score is applicable not only in randomized experiments but also in non-experimental studies. In randomized experiments, $Pr(D = 1 \mid X)$ is known, as each individual is randomly assigned to either the treatment or control group, ensuring everyone has an equal chance of being in the treatment group, making $Pr(D = 1 \mid X)$ equal to 0.5. However, in non-experimental data, $Pr(D = 1 \mid X)$ is unknown and must be estimated. The propensity score matching method addresses this challenge, enabling researchers to replicate some of the key features of a randomized controlled trial within an observational study. Essentially, PSM aims to address selection bias and provide accurate estimates of the Average Treatment Effect on the Treated (ATT).

The main advantage of PSM lies in its ability to reduce bias in impact evaluation. By creating similarity in terms of PS, this method minimizes the discrepancies between groups and provides highly convincing evaluation results. This is crucial in situations where randomization cannot be conducted, making PSM a valuable tool for controlling extraneous variables. In addition, PSM is also particularly useful when only observational data is available and randomization is not feasible. This makes the method flexible and practical for real-world studies. The simplicity and ease of implementation of PSM make it a reasonable choice for studies that do not require extensive statistical expertise. However, to ensure the accuracy and generalizability of the results, PSM must be conducted with careful attention and thorough evaluation of the related assumptions.

3.3 Analytical strategy

The analytical strategy for assessing the impact of credit access on rural household income and poverty reduction in the North Central region of Vietnam by utilizing the propensity score matching method has four steps.

- Step one: Propensity score estimation

The initial step involves determining the likelihood of rural households accessing credit based on independent variables that are assumed to influence credit participation. Following the approach outlined by Caliendo and Kopeinig, two key decisions must be made when estimating propensity scores [23]. First, an appropriate econometric model must be selected, and second, the independent variables to be included in the chosen model must be identified. Given that this study examines two groups (those with access to credit and those without), a binary logistic regression model was selected. For the independent variables, those believed to simultaneously influence both the decision to access credit and the outcome variables were chosen, in line with Caliendo and Kopeinig's methodology. The model is described as follows.

$$Y_i = \alpha_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + \varepsilon_i \qquad (1)$$

In the equation (1), Y_i represents the dependent variable for household i, where Y is a dummy variable. Y is equal to 1 if a household has access to credit, and 0 if it does not. Meanwhile, X is a vector of explanatory variables that influence the likelihood of rural households accessing credit. This vector includes household characteristics, poverty status indicators, and community characteristics. The definitions of all independent variables are provided in Table A1. The final component ε_i represents the error term.

- Step two: Matching or resampling

In the second step, various matching methods are employed to balance the data based on the propensity scores estimated using the logit model and the probit model. These methods include one-to-one matching, one-to-one matching without replacement, k-nearest neighbors, radius matching with a caliper of 0.25 * σ_p (where σ_p is the standard deviation of the estimated propensity scores), as well as local linear regression, and Gaussian Kernel matching.

- Step three: Check the matching quality

The third crucial step in applying the PSM model is to evaluate the quality of the matching process. According to Caliendo and Kopeinig (2005), it is essential to assess the matching quality to ensure that the distribution of relevant variables is balanced across both groups. Various methods have been proposed in the literature to test matching quality, including analyzing the standard bias, counting the number of insignificant variables in the t-test, examining the balance of data after matching, and evaluating the pseudo-R^2.

- Step four: Postmacthing analysis

After selecting the optimal matching algorithm, the next step is to calculate the average treatment effects (ATTs). This is achieved by determining the average effect for the sampled households with specific values of the explanatory variables. Specifically, the ATT is estimated by taking the difference between the matched treatment and control group averages based on their propensity scores.

Moverover, one of the purposes of this study is to examine whether the accessing formal credit affects poverty reduction in North Central region. This study measures poverty by using three Foster-Greer-Thorbecke indexes. These indexes are the headcount index, the poverty gap index, and the squared poverty gap index. Three indexes can be calculated using a general formula [24] as follows.

$$P_\alpha = \frac{1}{N}\sum_{i=1}^{R}\left[\frac{z-I_i}{z}\right]^\alpha \quad (2)$$

where I_i is a welfare indicator (monthly income per capita) for household i, z is the poverty line in rural area, announced by the General Statistics Office of Vietnam for the period 2016-2020. N is the number of households in the sample. R is the number of households who are classified as poor. α is considered as an interpretation of poverty indexes and can take on the values 0 (P_0, headcount index) or 1 (P_1, poverty gap index) or 2 (P_2, squared poverty gap index).

The effect of accessing formal credit on poverty reduction is written as follows.

$$\Delta P_\alpha = P_\alpha(Y = 1, I_1) - P_\alpha(Y = 1, I_0) \quad (3)$$

As can be seen from the equation (3), the first term on the right side represents a poverty index that accounts for accessing formal credit. This term can be directly calculated from the sample. However, the second term cannot be observed, as it represents the counterfactual measure of poverty-essentially, the poverty level of households that accessed formal credit, had they not accessed formal credit. Since this term cannot be calculated directly from the sample, the propensity score matching method is applied to estimate the counterfactual outcome. These estimated outcomes are then used to compute the equation. The difference between the two indexes indicates the impact of accessing formal credit on poverty reduction.

4 Research results

The study applies the Propensity Score Matching method to the selected 2020 VHLSS dataset for the North Central region. This section presents notable results obtained when evaluating the impact of access to formal credit on the living standards of rural households in the North Central of Vietnam. In addition, to enhance understanding of the role of formal credit access, this study also examines the impact of formal credit on poverty.

4.1 Descriptive Statistic of the Sample

This study investigates the utilization of formal credit in rural areas of Vietnam's North Central region, focusing on four primary sources: the Vietnam Bank for Social Policies (VBSP), the Vietnam Bank for Agriculture and Rural Development (Agribank), commercial joint stock banks, and people's credit funds. The research emphasizes the impact of formal credit on household living standards, based on the assumption that these loans represent the most significant important and largest loans of households. Table 1 provides statistical data on access to these types of formal credit within the study sample. Notably, loans from VBSP and Agribank dominate household access in the North Central region, comprising nearly 43% and 42% of the total credit accessed, respectively. Credit accessed from joint stock commercial banks and people's credit funds accounts for a smaller proportion, about 9% and 6% respectively.

The key descriptive statistics of variables related to household characteristics are presented in Table 2 and Table 3. Specifically, Table 2 provides information on the mean, standard deviation, maximum, and minimum values of continuous characteristic variables. Similarly, the information on household characteristic dummy variables is detailed in Table 3.

Table 2 summarizes the descriptive statistics of continuous variables related to household characteristics, based on data from the Vietnam Household Living Standards Survey (VHLSS) 2020. The Table 2 provides an overview of the distribution of continuous variables in the study sample, offering insights into the characteristics of the surveyed households. The Table 2 includes 3,570 observations and presents the mean, standard deviation, minimum, and maximum values.

Table 1. Formal credit sources in North Central region

Formal credit	Frequency	Percentage
VBSP	392	42.98
Agribank	382	41.89
Commercial Joint Stock Bank	85	9.32
People's Credit Funds	53	5.81
Total	912	100

Source: Author's calculation based on VHLSS 2020

Table 2. Summary statistics of regression variables (Continuous variables)

Household characteristics (Continuous variables)	Observations	Mean	Std. Dev.	Min	Max
Age	3,570	3.932	0.280	2.773	4.615
Household size	3,570	1.178	0.492	0	2.485
Education	3,570	8.582	3.676	0	17
Share of dependents	3,570	0.362	0.302	0	1
Share of remittance	3,570	0.027	0.108	0	1

Source: Author's calculation based on VHLSS 2020

In addtion, Table 3 presents the summary statistics of regression variables that are categorical (dummy variables) based on data from the VHLSS 2020. The table provides the frequency and percentage distribution for various household characteristics. Among the 3,570 households surveyed, 676 (18.94%) are headed by females, while 2,894 (81.06%) are headed by males. 588 household heads (16.47%) are not married, whereas 2,982 (83.53%) are married. Especially, out of the total households, 212 households (5.94%) are classified as poor households in 2020.

Table 3. Summary statistics of regression variables (Dummy variables)

Household characteristics (Dummy variables)		Frequency	Percentage
Gender	Female	676	18.94
	Male	2,894	81.06
	Total	3,570	100
Marital status	Not married	588	16.47
	Married	2,982	83.53
	Total	3,570	100
Ethnicity	Other	357	10.00
	Kinh	3,213	90.00
	Total	3,570	100
Permanent resident document	No	17	0.48
	Yes	3553	99.52
	Total	3,570	100
Poor status	No	3,358	94.06
	Yes	212	5.94
	Total	3,570	100

Source: Author's calculation based on VHLSS 2020

4.2 Evaluating the impact of formal credit on the income of rural households and poverty reduction in the North Central of Vietnam

Estimating propensity scores

In this study, the propensity score of households participating in formal credit schemes are estimated based on two proposed models, namely the Logit and Probit models (Table 4).

Table 4. Empirical models of access to formal credit of rural households in the North Central of Vietnam

Variables	Logit Model	Probit Model
Age	-0.999***	-0.580***
	(0.163)	(0.096)
Household size	0.904***	0.523***
	(0.107)	(0.061)
Gender	-0.151	-0.094
	(0.143)	(0.085)
Education	0.011	0.007
	(0.012)	(0.007)
Marital status	-0.032	-0.014
	(0.168)	(0.099)
Permanent resident document	-1.360***	-0.818***
	(0.513)	(0.315)
Ethnicity	0.016	0.013
	(0.217)	(0.130)
Share of dependents	-0.947***	-0.536***
	(0.170)	(0.095)
Share of remittance	-0.176	-0.103
	(0.437)	(0.247)
Poor status	0.082	0.046
	(0.193)	(0.114)
Commune variables	Yes	Yes
Pseudo-R^2	0.070	0.072
Observations	3,570	3,570

Notes: The full set of results for all independent variables is shown in Table A2 of the Appendix. Standard errors are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: Author's calculation based on VHLSS 2020

Estimating propensity scores is the first step in policy impact evaluation using the Propensity Score Matching method. This study estimates the propensity scores of households accessing formal credit through two regression models: Probit and Logit. The results are consistent across both regression models. The regression results indicate that the household's access to credit in the North Central region is influenced by factors such as the age of the household head, family size, residence verification, and the dependency ratio. Specifically, the older the household head, the lower the likelihood of participating in formal credit schemes. An inverse relationship is also found for the factors of the dependency ratio and residence verification. Meanwhile, households with larger family sizes have a higher likelihood of accessing formal credit. All estimates of the above-mentioned factors are significant at the 1% level.

This section describes how to select an appropriate algorithm from a set of options including one-to-one, One-to-one (no replacement), k-nearest neighbors (k = 2), radius (0.25*σ), local linear regression, and Gaussian Kernel matching algorithms. The selection process considers two criteria proposed by Deheja and Wahba [25], which are balance checks and the falsification R^2 for each matching algorithm. The ideal matching algorithm should balance all explanatory variables and minimize the falsification R^2 value. Based on these criteria, the Radius matching algorithm (0.25*σ) was identified as the best choice. Therefore, the impact analysis process for the subsequent steps is based on the use of the Radius matching algorithm.

According to Table 6, the balance of household characteristic variables before and after matching scenarios is examined using the selected matching algorithms. The analysis results show that before matching, there were significant differences between the groups regarding household characteristics, including the age of the head, household size, gender, education, marital status, ethnicity, and asset value. However, the selected matching algorithms effectively balance these differences between groups, as shown in Table 6. Specifically, the Radius matching algorithm minimizes the bias that might arise from the explanatory variables, with bias reduction

Table 5. Performance criteria of matching algorisms

Matching algorism	Logit Model		Probit Model	
	(1)	(2)	(1)	(2)
One-to-one	24	0.007	25	0.009
One-to-one (no replacement)	25	0.003	25	0.004
k-Nearest neighbors (k = 2)	25	0.003	24	0.005
Radius (0.25*σ)	25	0.002	25	0.002
Local linear regression	24	0.007	25	0.009
Gaussian Kernel	21	0.005	21	0.005

(1) Number of insignificant variables (2) Pseudo-R^2

Source: Author's calculation based on VHLSS 2020

Table 6. Explanatory variables balance test

Variables	Logit Model			Probit Model		
	Mean		% bias reduction	Mean		% bias reduction
	Treated	Control		Treated	Control	
Age						
· Unmatched	3.845	3.962	99.8	3.845	3.961	99.8
· Matched	3.846	3.846		3.846	3.846	
Household size						
· Unmatched	1.327	1.128	98.4	1.327	1.127	97.7
· Matched	1.327	1.330		1.327	1.331	
Gender						
· Unmatched	0.837	0.802	97.4	0.837	0.802	96.4
· Matched	0.837	0.838		0.837	0.839	
Education						
· Unmatched	8.787	8.511	76.5	8.787	8.511	74.5
· Matched	8.787	8.851		8.787	8.857	
Marital status						
· Unmatched	0.883	0.819	97.1	0.883	0.819	94.9
· Matched	0.883	0.884		0.883	0.886	
Permanent resident document						
· Unmatched	0.989	0.997	69.3	0.989	0.997	54.5
· Matched	0.989	0.993		0.989	0.994	
Ethnicity						
· Unmatched	0.846	0.918	83.1	0.846	0.918	85.5
· Matched	0.846	0.859		0.846	0.857	
Share of dependents						
· Unmatched	0.325	0.337	75.7	0.325	0.337	77.0
· Matched	0.325	0.312		0.325	0.313	
Share of remittance						
· Unmatched	0.019	0.029	98.5	0.019	0.029	98.8
· Matched	0.019	0.019		0.019	0.019	

Source: Author's calculation based on VHLSS 2020

ranging from 69.3% to 98.8% for the Logit model. Similarly, this range for estimates from the Probit model corresponds to 54.4% to 99.8%.

Additionally, Table 7 shows that the Pseudo-R^2 value is very low after matching. This, along with the insignificance of the likelihood ratio test, indicates that households with access to credit and households without credit have similar distributions of random variables after matching. These results demonstrate that the matching process successfully balanced characteristics between the treated and comparison groups and confirm that the propensity score

Table 7. Insignificant likelihood ratio test

Sample	Pseudo-R^2	LR chi^2	p>chi^2
Logit model			
• Unmatched	0.071	2,89.2	0.000
• Matched	0.002	4.23	1.000
Probit model			
• Unmatched	0.071	289.2	0.000
• Matched	0.002	4.86	1.000

Source: Author's calculation based on VHLSS 2020

models were correctly specified. Simply put, the balance checks show that the control group is a good match for the treated group, as indicated in the study by Rehman et al. in 2021 [26]. All these tests together suggest that the Radius matching algorithm is the most effective for the data in this study and will therefore be used in the subsequent impact analysis steps.

Calculating Average Treatment Effect on Treated

According to Table 8, without applying PSM, the results of the unmatched data show a decrease in income or in other words, a negative impact of formal credit on rural household income. However, as explained in the research methodology section, after the data is balanced using PSM, the results of the matched data show more reliable results when overcoming the selection bias.

This matched result from Table 8 indicates that participation in formal credit schemes has had a positive impact on the per capita income of rural households in the North Central of Vietnam. Specifically, the income improvement is relatively small, with estimated improvements in income being 1.94% and 2.1% for the Logit and Probit models, respectively. This result is consistent with previous findings on the impact of rural credit or microcredit on household living

Table 8. ATT estimation result of household income per capita

Income per capita (Output variable)	Access (Treated Group)	No access (Control Group)	Difference	
	(,000 VND)	(,000 VND)	(,000 VND)	(%)
Logit Model				
• Unmatched	3,169.65	3,185.43	-15.78	-0.50
• Matched	3,170.32	3,110.13	60.19	1.94
Probit Model				
• Unmatched	3,169.65	3,185.43	-15.78	-0.50
• Matched	3,170.32	3,105.18	65.14	2.10

Source: Author's calculation based on VHLSS 2020

standards at the national level. In addition, the study shows a relatively small magnitude of this impact, with participation in formal credit improving household income by about 2% for the study area in rural North Central Vietnam.

The relatively small magnitude of income improvement, approximately 2%, observed in the study of formal credit in rural North Central Vietnam can be attributed to several key factors. One major reason could be the limited size of loans and how they are utilized by households. In many cases, small loans may not be invested in high-return activities, particularly in regions where infrastructure and market access are underdeveloped. Without sufficient access to markets, technology, or productive investments, the returns on these small loans are often limited. Additionally, external economic constraints, such as fluctuating agricultural prices or poor weather conditions, can further reduce the potential for households to generate significant income gains. Moreover, a portion of the credit may be used for consumption smoothing rather than productive investments, which diminishes its impact on income growth. When comparing these findings with similar studies in other regions, research shows varied results based on regional economic contexts. For example, a study in India by Swain and Varghese found that participation in microcredit programs increased household income by approximately 10%, a significantly larger impact than that observed in Vietnam [27]. This higher return is often due to more developed entrepreneurial ecosystems and better targeting of loan programs toward productive activities. Similarly, in Bangladesh, studies like those by Khandker show that microfinance has had substantial effects on poverty reduction, with income increases ranging from 5% to 15%, depending on the size and purpose of the loan [28].

In contrast, findings from Latin America show similarly modest effects as in Vietnam. For instance, research in Mexico by Angelucci et al. revealed that microfinance loans only led to an income increase of about 3% [29]. Similar findings in Peru indicated that credit programs resulted in a modest 4% income improvement, largely due to underdeveloped infrastructure, limited access to markets, and the tendency of borrowers to use loans for consumption rather than investment [30]. These comparisons suggest that the effectiveness of formal credit programs is highly context-dependent, and the magnitude of their impact on household income varies based on local economic conditions, loan targeting, and the ability to invest in productive activities.

The findings presented in Table 9 highlight the influence of formal credit access on poverty alleviation in rural areas of North Central Vietnam. In general, both logit and probit estimates reveal negative differences between the real and counterfactual values. It indicates that the ability to have formal credit access has a positive effect on poverty. Specifically, taking a look at the probit model estimates results, the actual headcount of poverty (P_0) for households that have formal credit access was 4.7 percent. If the household had not accessed formal credit, this number would have been 4.8 percent, 0.1 percent higher than the real value. Similarly, the formal credit access decreased the poverty gap index (P_1) by 0.005 points and the squared poverty gap index

Table 9. Impact of accessing formal credit on poverty in North Central region

	Logit model			Probit model		
	Actual	**Counter-factual**	**Diff.**	**Actual**	**Counter-factual**	**Diff.**
P_0	0.047***	0.049***	-0.002	0.047***	0.048***	-0.001
	(0.007)	(0.002)		(0.007)	(0.003)	
P_1	0.010***	0.013***	-0.003	0.010***	0.015***	-0.005
	(0.002)	(0.000)		(0.002)	(0.001)	
P_2	0.003***	0.006***	-0.003	0.003***	0.007***	-0.004
	(0.001)	(0.000)		(0.001)	(0.000)	

Notes: P_0: headcount ratio, P_1: poverty gap index, and P_2: squared poverty gap index. Standard errors are in parentheses. Standard errors are adjusted for sampling weights and estimated using non-parametric bootstrap with 500 replications. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: Author's calculation based on VHLSS 2020

(P_2) by 0.004 points. Therefore, the estimation results derived from the Probit model assumptions indicate that access to formal capital leads to a reduction in poverty rates, specifically P_0, P_1, and P_2. Similarly, when assessing this impact using the Logit model, the results consistently demonstrate that access to formal credit concurrently decreases the rates of P_0, P_1, and P_2.

In summary, the results indicate that the effect of formal credit access is consistent between the two models; it is evident that formal credit contributes to reducing poverty rates across all of the research estimates. Further commentary on these results acknowledges that the study's poverty rates were calculated based on income-based poverty standards, which might not fully capture the multidimensional aspects of household poverty. This study, therefore, suggests a future research direction that incorporates multidimensional poverty standards for a more comprehensive analysis of poverty reduction under the impact of formal credit in rural areas.

5 Conclusion

This study uses the Propensity Score Matching (PSM) method to evaluate the impact of access to formal credit on rural households in the North Central region of Vietnam. The results from the analysis indicate that access to formal credit improves the living standards of households in terms of income per capita in the study area. Specifically, rural household income could increase if they participate in formal credit schemes.

Evidence of the positive impact of formal credit on poverty rates is also found. The study's findings, derived from Probit and Logit model estimations, underscore the positive impact of formal credit access on poverty alleviation in rural areas of North Central Vietnam. Both models consistently demonstrate that access to formal capital leads to reductions in poverty measures, specifically the headcount ratio (P_0), poverty gap (P_1), and squared poverty gap (P_2), with differences between actual and counterfactual values. This consistency across models reinforces the reliability of the results, suggesting that enhancing access to financial resources is a viable strategy for poverty reduction.

Based on the research findings, several practical policy recommendations can be made to enhance the impact of formal credit on rural households in North Central Vietnam. First, expanding access to formal credit through simplified application processes and mobile banking could reach underserved populations. Offering favorable loan terms, such as lower interest rates and flexible repayment options, combined with larger loan sizes targeted at productive investments, would better support income growth. Financial literacy and capacity-building programs are crucial to ensuring that loans are used effectively for income-generating activities. To address the multidimensional nature of poverty, policies should integrate education, healthcare, and housing improvements alongside financial access. Monitoring and support systems are also needed to ensure proper loan utilization and repayment. Governments could incentivize private sector involvement in rural credit markets through tax breaks while integrating social protection programs with formal credit schemes to provide a safety net for the most vulnerable households. These measures, if implemented, could significantly improve household incomes and poverty reduction outcomes in the region.

However, the study also recognizes a limitation in its reliance on income-based poverty standards, which may not fully capture the multidimensional nature of poverty. Factors such as education, health, and living conditions are equally important in assessing overall household well-being. Consequently, the study proposes that future research should integrate multidimensional poverty standards to offer a more comprehensive analysis of the impact of formal credit access. This broader approach could provide more nuanced insights for policymakers, enabling the development of more effective poverty alleviation strategies that address the multifaceted nature of poverty in rural areas.

To sum up, the study’s findings underscore the crucial role of formal credit access in enhancing the economic conditions of rural households in North Central Vietnam. While the results highlight the need for policies that facilitate greater access to formal credit, especially in rural areas, they also reveal that the increase in household income as well as the impact on poverty alleviation resulting from such access is relatively modest. This suggests that while formal credit has a positive impact, its current implementation may not be sufficient to drive substantial improvements in household income. Therefore, more robust efforts are required to enhance the effectiveness of formal credit systems in these regions. This could involve not only increasing access but also ensuring that credit terms are favorable and that households are better equipped to utilize these loans effectively. Additionally, complementary support measures such as financial education, capacity building, and more flexible loan conditions might be necessary to maximize the benefits of formal credit and achieve more significant economic improvements for rural households.

References

1. Barslund, M., & Tarp, F. (2008), Formal and Informal Rural Credit in Four Provinces of Vietnam, *The Journal of Development Studies*, 44(4), 485–503. doi:10.1080/00220380801980.
2. Government Portal (2024), *Announcing national and regional multidimensional poverty rates in 2023*, extracted from https://xaydungchinhsach.chinhphu.vn/cong-bo-ty-le-ngheo-da-chieu-toan-quoc-va-theo-cac-vung-nam-2023 on 25th February 2024.
3. Morduch, Jonathan J., Cull, Robert J. (2017), *Microfinance and economic development (English),* Policy Research working paper, no. WPS 8252 Washington, D.C.: World BankGroup. http://documents.worldbank.org/curated/en/107171511360386561/Microfinance-and-economic-development.
4. Li, X., Gan, C., Hu, B. (2011), The welfare impact of microcredit on rural households in China, *The Journal of Socio-Economics*, 40(4), 404–411.
5. Santana Félix & Belo, T. F. (2019), The impact of microcredit on poverty reduction in eleven developing countries in south-east Asia, *Journal of Multinational Financial Management* Volumes, 52–53.
6. Islam, A. J. J. O. A. E. (2015), Heterogeneous effects of microcredit: Evidence from large-scale programs in Bangladesh, *Journal of Asian Economics* 37, 48–58.
7. Schroeder, E. (2020), The impact of microcredit borrowing on household consumption in Bangladesh, *Applied Economics,* 1–15. doi:10.1080/00036846.2020.
8. Mckernan, S. M. (2002), The impact of microcredit programs on Non-credit Program Aspects matter, *Review of Economics and Statistics*, 93–115.
9. You, J. (2012), The role of microcredit in older children's nutrition: Quasi-experimental evidence from rural China, *Food Policy*, 43, 167–179.
10. Michel, S. & Randriamanampisoa H. (2017), *The capability approach as a framework for assessing the role of microcredit in resource conversion: the case of rural households in the Madagascar highlands*, Oxford Development Studies.
11. Banerjee, A. V., & Duflo, E. (2011), *Poor Economics: A Radical Rethinking of the Way to Fight Global Poverty,* Public Affairs.
12. Khandker, S. R., & Samad, H. A. (2014), Dynamic effects of microcredit in Bangladesh, *World Bank Policy Research Working Paper (6821).*
13. Zeller, M., & Sharma, M. (1998), Rural Finance and Poverty Alleviation, *IFPRI Policy Briefs*.
14. Morduch, J. (1998), Does Microfinance Really Help the Poor? New Evidence from Flagship, Programs in Bangladesh, *Financial Access Initiative.*

15. Eriksen, S., & Lensink, R. (2015), Measuring the impact of an ongoing microcredit project: evidence from a study in Ghana, *Journal of Development Effectiveness*, 1–11. doi:10.1080/19439342.2015.1095.
16. Brett, J. A. (2006), We Sacrifice and Eat Less: The Structural Complexities of Microfinance Participation, *Human Organization*, 65(1), 8–19.
17. Rahman, A. (1999), *Women and Microcredit in Rural Bangladesh: An Anthropological Study of Grameen Bank Lending,* Westview Press.
18. Nguyen, V. C. (2008), Is a Governmental Microcredit Program for the Poor really Propoor? Evidence from Vietnam, *The Developing Economies*, 46(2), 151–187.
19. Dang T. H. Y., Nanseki T., & Chomei Y. (2017), The Impact of Microfinance on Household Welfare in Rural Vietnam: A Case Study in Phu Tho Province, *Journal of the Faculty of Agriculture Kyushu University*.
20. Nguyen, L. T., Hoai Nguyen, A. P., van Passel, S., Azadi, H., & Lebailly, P. (2018), Access to Preferential Loans for Poverty Reduction and Rural Development: Evidence from Vietnam, *Journal of Economic Issues*, 52(1), 246–269. https://doi.org/10.1080/00213624.2018.1430953.
21. Thanh, P. T., Saito, K., & Duong, P. B. (2019), Impact of microcredit on rural household welfare and economic growth in Vietnam, *Journal of Policy Modeling,* 41(1), 120–139. https://doi.org/10.1016/j.jpolmod.2019.02.007.
22. Rosenbaum, P. R., & Rubin, D. B. (1983), The central role of the propensity score in observational studies for causal effects, *Biometrika*, 70, 41–55.
23. Caliendo, M., & Kopeinig, S. (2005), Some Practical Guidance for the Implementation of Propensity Score Matching, *DIW Discussion Paper*, 485.
24. Foster, J., Greer, J., & Thorbecke, E. (1984), A Class of Decomposable Poverty Measures. *Econometrica,* 52(3), 761–766.
25. Deheja, R. H., & Wahba, S. (2002), Propensity score matching methods for non-experimental causal studies, *The Review of Economics and Statistics*, 84(1), 151–161.
26. Rehman, W. U., Degirmen, S., & Waseem, F. (2021), Propensity for and quality of intellectual capital divulgence across the BRICS banking sector: A knowledge-based perspective from emerging econ- omies, *Journal of the Knowledge Economy.*
27. Bali Swain, Ranjula & Varghese, Adel (2010), Microfinance 'Plus': The Impact of Business Training on Indian Self Help Groups, *Working Paper Series 2010:24, Uppsala University, Department of Economics*.
28. Khandker, S. R. (2005), Microfinance and Poverty: Evidence Using Panel Data from Bangladesh, *World Bank Economic Review*, 19(2), 263–286.

29. Angelucci, M., Karlan, D., & Zinman, J. (2015), Microcredit Impacts: Evidence from a Randomized Microcredit Program Placement Experiment by Compartamos Banco, *American Economic Journal: Applied Economics*, 7(1), 151–182.
30. Attanasio, O., Augsburg, B., Haas, R. D., Fitzsimons, E., & Harmgart, H. (2011), Group lending or individual lending? Evidence from a randomised field experiment in Mongolia, *European Bank for Reconstruction and Development*.

Appendix

Table A1. Definition of explanatory variables

Variable name	Definition
Household characteristics	
Age of head	Age of household head (take logarithm)
Household size	Number of family members (take logarithm)
Gender of head	Gender of household heads (0/1 dummy, 1 for male)
Education of head	Year of schooling of household head (take logarithm)
Marital status of head	Whether the head is married (0/1, 1 for married)
Resident document	Whether having permanent resident document (0/1, 1 for yes)
Ethnicity	Whether the head is from the majority group (0/1, 1 for Kinh)
Share of dependents	The proportion of members who are 15-65 years of age to total members (%)
Share of remittance	The share of remittance (domestic + foreign) to total income (%)
Poor status	Whether household classify the poor status in 2020 (0/1, 1 for poor status)
Community characteristics	
Size	The size of commune where the household lives (take logarithm)
No of households	The number of households in commune (take logarithm)
No of people	The number of people in commune (take logarithm)
Kinh	0/1 dummy, 1: Kinh is the main ethic groups found in commune
Buddist	0/1 dummy, 1: Buddist is the main religions in commune
Poor commune	Whether commune classify the poor in Program 135 (0/1, 1 for poor status)
Remote commune	Whether the commune is located in a remote area (0/1, 1 for remote area)
Income commune	The main income source of commune comes from agriculture (0/1, 1 for yes)
Poor households	The number of poor households in commune (take logarithm)
Benefits	The number of households receiving benefits in communes (take logarithm)
Post office	0/1 dummy, 1: having post office in commune
Community center	0/1 dummy, 1: having community center in commune
Radio station	0/1 dummy, 1: bank branch in commune
Irrigation system	0/1 dummy, 1: primary school in commune
Market	0/1 dummy, 1: market in commune

Source: Author’s explanation

Table A2: Empirical models of formal credit accessing of rural household (all variables)

Explanatory Variables	Logit model	Probit model
Age of head	-0.999***	-0.580***
	(0.163)	(0.096)
Household size	0.904***	0.523***
	(0.107)	(0.061)
Gender of head	-0.151	-0.094
	(0.143)	(0.085)
Education of head	0.011	0.007
	(0.012)	(0.007)
Marital status of head	-0.032	-0.014
	(0.168)	(0.099)
Resident document	-1.360***	-0.818***
	(0.513)	(0.315)
Ethnicity of head	0.016	0.013
	(0.217)	(0.130)
Share of dependents	-0.947***	-0.536***
	(0.170)	(0.095)
Share of remittance	-0.176	-0.103
	(0.437)	(0.247)
Poor 2020	0.082	0.046
	(0.193)	(0.114)
Size	0.133***	0.077**
	(0.051)	(0.030)
No. of households	0.379	0.191
	(0.342)	(0.201)
No. of people	-0.730	-0.399**
	(0.332)	(0.195)
Kinh	-0.423**	-0.247*
	(0.217)	(0.130)
Buddist	0.022	0.012
	(0.115)	(0.068)
Poor commune	-0.429**	-0.240**
	(0.203)	(0.119)

Explanatory Variables	Logit model	Probit model
Remote commune	0.252	0.160
	(0.185)	(0.108)
Income commune	0.002	0.010
	(0.117)	(0.069)
Poor households	-0.069	-0.039
	(0.050)	(0.029)
Benefits	0.033*	0.020*
	(0.020)	(0.012)
Post office	0.150	0.091
	(0.159)	(0.093)
Community center	-0.201	-0.120
	(0.142)	(0.084)
Radio station	-0.259*	-0.163*
	(0.145)	(0.087)
Irrigation system	-0.117	-0.068
	(0.104)	(0.062)
Market	0.093	0.059
	(0.096)	(0.057)
Constant	7.490***	4.331***
	(1.324)	(0.780)
Pseudo-R^2	0.070	0.071
Observations	3,570	3,570

Notes: Standard errors are in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: Author's calculation based on VHLSS 2020.