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# Analysis of Factors Influencing Credit Access of Vietnamese Informal Labors in the Time of COVID-19 Pandemic

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**Abstract:** Credit is considered as an essential tool to make informal labor's income better. In order to improve quality of their life, the state should have some supports them in credit access. This study analyzes factors causing credit access of informal labors to be changed in the time of COVID-19 pandemic. Using survey data collected from 2020 VHSSL (2019–2020), this approach has two models including a binary logit model and a multinomial logit model (MLM). The results revealed that the positive factors including education, material, collateral, credit size, credit source, credit debt which are likely to affect to credit access, however age, family size, ethnicity, interest, paid money are negative. Besides, it also concludes that quality of life of informal labor is considerably influenced by credit access, collateral, credit source, credit debt from the observed samples. Additionally, this paper recommends some policies to enhance informal labor's access to credit and their quality of life.

**Keywords:** urban; rural; informal labor; credit access; quality of life

## 1. Introduction

The global devastation caused by COVID-19 is only just beginning, with the severe threat to public health as well as having negative impacts on economies (Lee et al. 2021). Especially, the worst impacts are already being felt by informal labors, who face a dismal spectrum of probabilities of job losses, from diminishing sharply in earnings among the self-employed to job losses among paid labors (Rajneesh 2020). In Vietnam, the coronavirus (COVID-19) pandemic has significantly affected the economy and informal labors who are with little access to health and social security services. In general, average income of these labor decreased significantly, reaching to 25% in 2019 and 35.7% in 2020 (ILO 2020).

Credit access is an important component of the government's economic policy in almost nations. Many studies also show that credit access is one of the important factors affecting the informal sector in growth and development. The informal labors having accessibility of credit can invest and maximize their profit. Furthermore, credit improves productivity and raises living standards by breaking the vicious circle of poverty among informal labors (Li et al. 2011). Twumasi et al. (2020) confirmed that credit is an essential input for these labors because it enables them to enhance capital accumulation and can increase their income and savings as well as their ability to repay the loan. When informal labors can borrow loans, they will apply new technologies, improve productive activities, income and encourage them to intensity their participation (Nguyen et al. 2019). Therefore, credit is a powerful instrument for poverty reduction and improvement in the quality of life in informal labor sector.

In Vietnam, the government has given some support programs to help informal labors in both rural areas and urban areas to increase access ability and other financial services in order to overcome difficulties caused by the Covid 19 pandemic over the period of three years, starting form 2019. In general, the staged model applied for crisis management during the second and the third wave of COVID-19 in Vietnam has been successful (Da et al. 2021). In the 2000s, Vietnamese goverment has established some preferential credit funds for the

informal sector to improve informal workers on access to credit. However, many these labors are constrained and still excluded from access to credit. Many funds and formal banks are not willing to support them because they see these labors as a risky job (Pham 2020).

The main objective of this study is to analyze the factors influencing access to credit for informal labor sector in Viet Nam in the period of Covid 19 pendamic. More specifically, the paper determines the factors that affect their credit access including household characteristics (gender, age, education, ethnicity, family size, marital status, area, collateral, etc.) and credit characteristics (duration of credit, source of credit, political instability, size of credit, number of credits obtained, usage of the credit, savings, guarantees, interest . . . ). Furthermore, by comparing specific characteristics between the informal labors in rural and urban areas, the study analyzes and evaluates the impacts of credit access on improving quality of life for informal labors in the Time of COVID-19.

## 2. Literature Review

The most visible influence of the COVID-19 on world economy is to the unemployed, the self-employed, casual and gig-workers, small-scale entrepreneurs and businesses, which can be imperfectly described as those people and enterprises being in the informal sector. Informal includes individuals that might undertake piecework in their own premises, street vendors and most domestic workers. They lack of protection for non-payment of wages and retrenchment without notice, and often work under limited occupational safety conditions with no sick pay and health insurance (Sayed and Peng 2021).

In the developing countries, informal sector takes up a large proportion, with more than 2 billion people, representing 60% of workers and 80% of enterprises (ILO 2020). Overall, the COVID-19 crisis with the scale and rapid spread as well as large-scale lockdowns for a long time is a serious problem for the informal sector where poverty levels are high and already close the poverty line (Caiazza et al. 2021). Even if the pandemic subsides, we cannot expect things to return to their normal state in a medium run. In spite of having much talk about what policy actions less-developed countries can undertake to minimize the economic costs of the pandemic, in reality, few middle-income nations have the means to afford cautious and meaningful policy action (Rajneesh 2020). According to Hua and Shaw (2020), some countries are supplying tax relief measures and credit guarantees, but meaningful action needs constructive government organization to implement these measures.

Besides, many studies have discussed about factors that impede the farmer's access to agricultural credit. Most of these studies focus on agrarian credit borrowers. These researchers mostly draw their attention to household characteristics, asset ownership, regional characteristics (Kedir 2003; Ferede 2012) including factors as gender, age of the head of household, household size, membership in a financial solidarity group and socio-economic characteristics (Sekyi 2017).

Similarly, Twumasi et al. (2020) has shown that education, household size, association member, experience and region are variables affecting access to credit while Langat (2013) confirmed that access to credit depended on credit standards, assess return on credit, evaluate risk on loan to farm and transaction cost. In addition, size of credit, duration of credit, number of credits obtained, usage of the credit, savings, collateral security, interest rate also act as important components that influence access to credit (Bin 2021).

The following variables were tested based on the problem statement and relevant literature to know the statistical significance between farmers' access to credit and microfinance sources of capital (Agier and Szafarz 2013). Many factors inform the decision-making process by lenders of agricultural loans. These mechanisms are put in place by all microfinance institutions worldwide to tackle credit standards, assess return on credit, evaluate risk on loan to farm, and transaction cost (Langat 2013).

According to the conditions for credit access, the factors such as the type of financial organizations, policies are varieties used to determine access or not to credit (Sossou et al. 2017). The increase in individual credit may lead to customer selectivity basing on some main factors such as sufficient guarantees to obtain loans and a minimum collateral for loans.

In term of using models to examine the effect of credit access on producers, there are some types of models such as the linear regressive, binomial logit regression, probit model or logit models. Lassana and Thione (2020) used a binomial logit regression model to evaluate some main variables affecting cotton producers' access to credit. These variables are significant at the 5% level and impact on credit access are age, marital status and interest rate. Besides, other researchers have used the probit regressive model to examine factors influencing access to credit of a household. In particular, Pham et al. (2020) used this model to estimate factors having an influence to access formal credit of farmers in Soc Trang, Vietnam. They concluded that age, collateral for loans, and group membership can help improve their access to credit for rice farms.

Some studies have applied a multinomial logit model (MLM) was used to identify factors affecting the likelihood of a household being a non-borrower, a borrower with a preferential home loan or a borrower with commercial home loan (Nguyen et al. 2018). Moreover, a number of studies have used the MNL for estimating the likelihood of a housing borrowing loans from informal or formal credit sources (Doan and Tuyen 2015) or the probability of a small and middle-sized enterprise borrowing a formal or informal loan in Vietnam (Nguyen and Luu 2013). Besides, OLS model was specified to conclude that there were factors affecting to access to households and these factors were labors, the ratio of land value to total property value, the number of dependent members, the distance from home to place of loan (Diagne 1999)

Furthermore, some papers have used the logistic model to analyze the determinants of credit by farmers (Akudugu 2012; Garay 2007). Nouman et al. (2013) employed logistic regression to estimate the factors that influence the decision-making process by agricultural credit suppliers. They reviewed that the typical household characteristics that influence lenders' decision to grant household farmers' access to microfinance credit include social capital such as homogeneity, network connection, and socio-economic factors such as the farmers' income level, education, age, marital status, farming experience, farm size. When Diagne (1999) studied farm's access to credit in Malawi put the OLS model such as a tool to test factors having an influence on credit demand of farms. The factors affecting to credit demand included land, labors, farm size and location.

While He and Li (2005) have applied the probit model to show that education, age, income, savings and local policies are important factors affecting to access to credit of labors, Anane et al. (2021) notes that microfinance capital's source significantly influences farmers' access to credit through using logistic regression models. The analysis further revealed that land ownership, gender, and literacy strongly correlate with farmers' access to credit as well as establish that savings account, microfinance membership, and geographical location significantly influence the credit providers in decision-making process to grant a loan to the customer. His findings suggest that microfinance institutions have not been able to perform their business effectively because of capitalization. Similarly, Bin (2021) evaluates the major components of access to credit and their effects on the sustainability of SMEs in Cameroon by using the probit model and linear regression model with factors such as experience, interest rate, collateral security, corruption and size of loan.

Assogba et al. (2017) used the Logit model to conduct an analysis on the factors affecting farmers' access to credit. The model was specified to identify the relationships between access to credit and the socio-economic characteristics of the selected farmers including literacy (10.9%), years of schooling (3.9%), guarantor (18.9%), membership (31%), interest (11.7%) and collateral (12.4%). This study also recommended that governments should promote these factors to increase access to credit.

Besides these traditional models, some recent researches have used machine learning to utilize all data available and systematic models that are accurate, efficient, and objective. In term of credit scoring, Kumar et al. (2021) use systematic literature review methods to identify and compare the best fit AI-ML-based model adopted by various financial institutions worldwide. The main purpose of this study is to present the various ML algorithms highlighted by earlier researchers that could be fit for a credit assessment

of rural borrowers, particularly those who have no or inadequate loan history. Besides, in recent years, artificial intelligence (AI) techniques and machine learning have shown successful performance in credit scoring and credit access. This illustrates that machine learning derived model and artificial intelligence techniques can automatically adapt to changes in input data patterns—an infeasible task for a human analyst, especially when measured over long periods of time and big data which brings volumes and complexity of information (Adewumi and Akinyelu 2017; West 2000).

Overall, diverse determinants of credit access highlighted in the literature include household characteristics (gender, age, education, ethnicity, family size, marital status, area, collateral, etc.) and credit characteristics (duration of credit, source of credit, political instability, size of credit, number of credits obtained, usage of the credit, savings, guarantees, interest, etc.). Besides, many studies have used the linear regressive model to examine the impact of factors to access to credit in farmers, households and other labors (linear regressive, binomial logit regression, probit model, logit model, multinomial logit model . . . ). Although some of those studies did examine determinants of access to credit, not even one emphasized the credit access of informal labors especially in the Time of COVID-19.

## 3. Data and Methods

### 3.1. Data

In this study, household data were taken from the Vietnam Household Living Standard Survey (VHLSS) of 2020. The VHLSS was conducted by the General Statistics Office of Vietnam (GSO) with technical assistance from the World Bank. We used data from the sample of households, including 4500 households in two years from 2019 to 2020. This time is the Covid period in Viet Nam so government applied some policies to help informal labors to overcome difficulties caused by the Covid pandemic. The VHLSS sample was selected in a way to represent the entire country at the national, regional, urban, rural and provincial levels. The VHLSS contained rich information about demographic characteristics, employment and economic sources, education, health, housing, durable assets and land. In particular, the data included detailed information about credit characteristics and access to credit, including formal sector and informal sector. According to Vietnamese labor code 2021, informal labor is a person who does not have a labor contract. So, from 4500 households, we only choose households having members who are informal labors and access to credit from preferential funds in two years of COVID-19 pandemic (from December 2019 to 2020). As a result, 577 informal labors in rural areas and 387 informal labors in urban areas were chosen to collect information on characteristics of the households and credit characteristics of the households.

### 3.2. Methods

In this study, we also use binary logit model and multinomial logit model (MLM). First, we use binary logit model to show the factors that influence informal labor's access to credit. Next, we investigate the impact of credit access, among other factors related credit access on improving quality of life of informal labors in urban and rural areas in Vietnam. Second, we also apply the statistical analyses including descriptive statistics and multiple regression analysis. The factors were examined if they can asociate with the credit access of informal labors to improve quality of life. In this study, we also investigate factors affecting the level of improvement of quality of life. Improving quality of life scores of respondents, taken from a multiple-choice question: "When you receive this credit loan, how is your quality of life improved?". The four possible responses to the question are "much of an improvement", "slight improvement", "no improvement", and "decrease". Thus, for our analysis, improving the quality of life is constructed with a value from 1 to 4, corresponding to level of improving quality of life.

The response variable (quality of life) is a polychotomous variable having four categories including much of an improvement, a slight improvement, no improvement and decrease. So we use a multinomial logit model (MLM) to identify factors affecting access to

credit to improve quality of life for the informal labors. Some studies have used the MNL for estimating the access to credit from other sources and the probability of access to homebuyer credit in urban Vietnam (Doan and Tuyen 2015; Nguyen et al. 2018). To estimate the impacts of access to homebuyer credit and housing satisfaction among households buying affordable apartments in urban Vietnam, Nguyen et al. (Nguyen et al. 2018) has applied descriptive statistics and multiple regression analysis including using a multinomial logit model (MLM) with three group factors (objective attributes of households and objective characteristic of the environment).

Let $Pij$ ($j$ = 1, 2, 3, 4) expresses the probability of being in a given borrowing group of a household.

$i$ with: $j$ = 1 if the household has much of an improvement, $j$ = 2 if the household has a slight improvement, $j$ = 3 if the household has no improvement and $j$ = 4 if the household has a decrease. Then, the multinomial logit model is given by

$$Pij(j = kXi) = \frac{\exp(\beta k Xi)}{\sum_{j=1}^{4} \exp(\beta j Xi)} (j = 1, 2, 3, 4) \tag{1}$$

In order to make the model identified, $\beta j$ is set to zero for one of the categories, and coefficients are then interpreted with respect to that category, called the reference or base category (Cameron and Trivedi 2005). Thus, set $\beta j$ to zero for one of four groups, then the MNL model for each group can be rewritten as:

$$Pij(j = kXi) = \frac{\exp(\beta k Xi)}{\sum_{j=1}^{2} \exp(\beta j Xi)} (j = 1, 2, 4) \text{ and } Pij(j = 3Xi) = \frac{1}{\sum_{j=1}^{4} \exp(\beta j Xi)} (j = 1, 2, 3, 4) \tag{2}$$

which can be estimated using the method of maximum likelihood.

Table 1 describes the definition and measurements of variables included in the model of access to credit. The first group of variables is gender, age, education, family size, marital status, ethnicity, collateral. We use these variables in the analysis for the characteristics of informal labor, which is likely to enable them to meet requirements to credit access. The second group includes variables on credit source, credit size, paid money for using of credit, collateral. These factors might influence ability of access to credit of informal labors as well as quality of life improvement. Table 1 describes the definition and measurements of variables included in the model of access to credit.

**Table 1.** Definition of explanatory variables used in the regression model.

| Variables | Definition |
|---|---|
| Dependent variables | |
| Access to credit | Access to credit (1 = yes, 0 = no) |
| Quality of life | Improving quality of life, 1 = much of an improvement, 2 = slight Improvement, 3 = no improvement, 4 = decrease |
| Explanatory variables | |
| Household characteristics | |
| Gender | Respondent gender (1 = male; 0 = female) |
| Age | Informal labor's actual age (years) |
| Education | Actual schooling years |
| Ethnicity | Whether respondent is Kinh (1 = yes; 0 = no) |
| Family size | Number of household members (people) |
| Marital status | Get married (1 = married, 0 = otherwise) |
| Collateral | Have a collateral security (1 = yes, 0 = no) |
| Area | Live in urban and rural areas (1 = urban, 0 = rural) |

**Table 1.** *Cont.*

| Variables | Definition |
|---|---|
| Credit characteristics | |
| Source of credit | Organization supply (1 = banks, 2 = associations, 3 = local credit fun) |
| Size of credit | The amount of money borrowed |
| Credit debt | Unpaid credit loans (1 = if all loans have been paid, 0 = all loans have not been paid) |
| Paid money | A loan origination fee (million dong) |
| Interest | The interest rate charged to the borrower (%) |

## 4. Results and Discussion

### 4.1. Descriptive Statistics and Findings

Table 2 provides some background information on household characteristics (such as age, gender, education, ethnicity, family size, marital status, collateral, area) and credit characteristics of respondents (informal labors). It shows that the age, education level, gender, family size and marital status are quite similar between two groups of informal labors. However, ethnic type between two groups is difference. The proportion of Kinh people in urban areas is much higher (0.91%) among those being other ethnicities (0.76%).

**Table 2.** Descriptive statistics of variables.

| Variables | All | | Urban | | Rural | |
|---|---|---|---|---|---|---|
| | **Mean/Share** | **SD** | **Mean/Share** | **SD** | **Mean/Share** | **SD** |
| Dependent variables | | | | | | |
| Access to credit | 21.42% | | 23.57% | | 17.33% | |
| Quality of life | | | | | | |
| Much of an improvement | 36.83% | | 36.24% | | 36.22% | |
| Slight improvement | 43.17% | | 45.30% | | 49.22% | |
| No improvement | 10.37% | | 8.71% | | 7.97% | |
| Decrease | 8.23% | | 9.76% | | 6.95% | |
| Explanatory variables | | | | | | |
| Household characteristics | | | | | | |
| Gender | 51.92% | | 57.84% | | 55.29% | |
| Age | 33.77 | 19.81 | 31.89 | 19.73 | 32.08 | 19.91 |
| Ethnicity | 81.83% | | 82.56% | | 76.78% | |
| Education | 6.34 | 3.72 | 5.99 | 2.04 | 5.79 | 2.10 |
| Family size | 2.58 | 1.52 | 2.59 | 1.56 | 2.63 | 1.57 |
| Marital status | 69.40% | | 77.83% | | 74.34% | |
| Credit characteristics | | | | | | |
| Collateral | 29.82% | | 26.98% | | 33.56% | |
| Credit source | 2.64 | 0.82 | 2.65 | 0.81 | 2.64 | 0.83 |
| Banks | 19.00% | | 18.60% | | 13.00% | |
| Associations | 1.20% | | 0.70% | | 1.00% | |
| Local credit fun | 76.00% | | 77.20% | | 81.00% | |
| Credit size | 178,970.8 | 502,078.5 | 179,290.6 | 417,824.9 | 178,824.0 | 537,679.8 |
| Credit debt | 142,830.7 | 330,563.5 | 144,965.9 | 291,299.8 | 141,850.8 | 348,046.8 |
| Paid money | 84.74 | 559.21 | 149.25 | 843.93 | 55.13 | 360.86 |
| Interest | 2.95 | 4.15 | 2.44 | 3.53 | 3.19 | 4.41 |
| Number of observation | 963 | | 577 | | 387 | |

Source: authors' own calculation from the 2020 VHLSS.

As shown in Table 2, 33% of the rural informal labors borrowed loans with collateral and the figures are much higher (43%) for those in urban areas. On average, the mean value of credit size is 178,970.8 million VND for all areas, and slightly higher for those in urban areas (179,290.6 million VND) than those in rural areas (178,824.0 million VND). By

contrast, amount of paid money to having loans from urban informal labors is higher for those in rural areas (149.25 million VND and 55.13 million VND respectively). Regarding the characteristics of credit, the data in Table 2 also shows that credit source, interest is the same to 2 types of labors (2.65, 2.64 and 2.44, 3.19 respectively).

*4.2. Determinants of Access to Credit*

Table 3 presents the results from the Logit regression. The results show that some explanatory variables are statistically significant at the 10% level or lower, with their signs as expected. Furthermore, the Pseudo-$R^2$ equal to 0.26 and is highly significant, suggesting that this model is globally significant (Louviere et al. 2002).

**Table 3.** Determinants of access to credit for informal labor.

| Variables | All | | | Urban | | | Rural | | |
|---|---|---|---|---|---|---|---|---|---|
| | Coefficient | SE | *p*-Value | Coefficient | SE | *p*-Value | Coefficient | SE | *p*-Value |
| Gender | −0.14 | 0.68 | 0.03 | −0.07 | 0.06 | 0.02 | 0.04 | 0.78 | 0.00 |
| Age | −0.01 | 0.02 | 0.00 | −0.02 | 0.01 | 0.02 | −0.01 | 0.03 | 0.07 |
| Ethnicity | −1.63 | 0.69 | 0.01 | −0.11 | 0.11 | 0.03 | −1.20 | 0.76 | 0.03 |
| Education | 0.02 | 0.20 | 0.05 | 0.01 | 0.01 | 0.01 | 0.08 | 0.24 | 0.01 |
| Family size | −0.27 | 0.33 | 0.03 | −0.02 | 0.03 | 0.04 | −0.05 | 0.34 | 0.01 |
| Marital status | 0.93 | 1.01 | 0.09 | 0.04 | 0.08 | 0.06 | 1.05 | 1.13 | 0.08 |
| Collateral | 1.96 | 0.98 | 0.05 | 0.01 | 0.08 | 0.00 | 1.88 | 1.20 | 0.05 |
| Credit source | 0.01 | 0.29 | 0.01 | 0.01 | 0.03 | 0.01 | 0.07 | 0.33 | 0.02 |
| Credit size | 8.67 | 4.88 | 0.01 | 3.93 | 4.03 | 0.03 | 9.30 | 6.99 | 0.00 |
| Credit debt | 0.01 | 7.34 | 0.08 | 5.65 | 6.32 | 0.07 | 0.01 | 9.10 | 0.05 |
| Paid money | −0.01 | 0.01 | 0.00 | −0.01 | 0.01 | 0.04 | −0.01 | 0.01 | 0.02 |
| Interest | −0.03 | 0.09 | 0.02 | −0.01 | 0.01 | 0.01 | −0.02 | 0.08 | 0.03 |
| Constant | 0.07 | 2.10 | 0.03 | 0.29 | 0.19 | 0.03 | 0.16 | 0.22 | 0.03 |
| Number of observation | | 963 | | | 577 | | | 387 | |

Source: authors' own calculation from the 2020 VHLSS.

Firstly, education, marital status has a positive impact on receiving the preferential credit in two groups. Education has a statistic meaning ($p < 0.05$); an increase of one school year will raise ability to gain credit access 0.02 times and 0.08 times in urban and rural informal labors respectively and impact of education on access to credit for informal labors in urban areas is higher than these labors in rural areas because they depend completely on off—farm works which required more professional skill. These findings are similar to the studies of Anane et al. (2021) and Lassana and Thione (2020).

Besides, the results demonstrate that the Kinh are not more likely to have more loans than the other ethnic groups, who are hindered by barriers of language and cultural customs. The reason is that almost preferential loans are given for poor informal labors and minority ethnic so these labors can access more easily than other labors. The expansion of marital status, credit source, collateral will increase the ability for access to credit with 0.04, 0.01 and 0.01 respectively for urban informal labors and 1.05, 0.07 and 1.88 respectively for rural informal labors. There is a significant difference between collateral of informal labors in urban and in rural areas. The result evidences that collateral of informal labor in urban areas is more necessary than those in rural areas.

Paid money and interest have an impact on credit access. This might result from the fact that if informal labors have a good credit condition they will gain credit loans easily. Similarly, Pham et al. (2020) revealed that characteristic of credit influence positively to gain credit in inform labor group in Vietnam. Better these factors enable those to meet some required conditions of access to credit in both rural and urban areas. Besides, credit size, credit debt in urban and rural areas can have a positive impact on informal labors' credit access (see Table 3).

Regarding the access to credits, the results confirm that age, ethnicity, family size, paid money, interest are not related to the access to informal labor's credits. So the results might

recommend that there is no difference in access to credit among the surveyed labors in urban and rural areas. The finding is the same to Nguyen and Luu (2013).

### 4.3. Effects of Access to Credit on the Quality of Life Improvement

According to the Vietnam Household Living Standard Survey (VHLSS) of 2018 conducted by the General Statistics Office of Vietnam (GSO) with 4.500 households in two years (2017 and 2018), the number of informal labors received preferential credit was 545 labors including 181 urban informal labors and 364 rural informal labors. However, in the time of COVID-19 (2019–2020), these informal labors grew up to 946 informal labors including 577 informal labors in rural areas and 387 informal labors in urban areas in the Vietnam Household Living Standard Survey (VHLSS) of 2021.

According to credit structure of informal labors, the results show that the amount of loans is obtained mainly from local credit sources (77% in urban areas and 81% in rural areas). Meanwhile, these labors only receive credit support from policy banks with 19% in urban areas and 13% in rural areas (Figure 1). Only a few other loans are taken from associations and private individuals. The average amount of credit is 179.290 million VND and 178.824 million VND in urban and rural areas respectively.
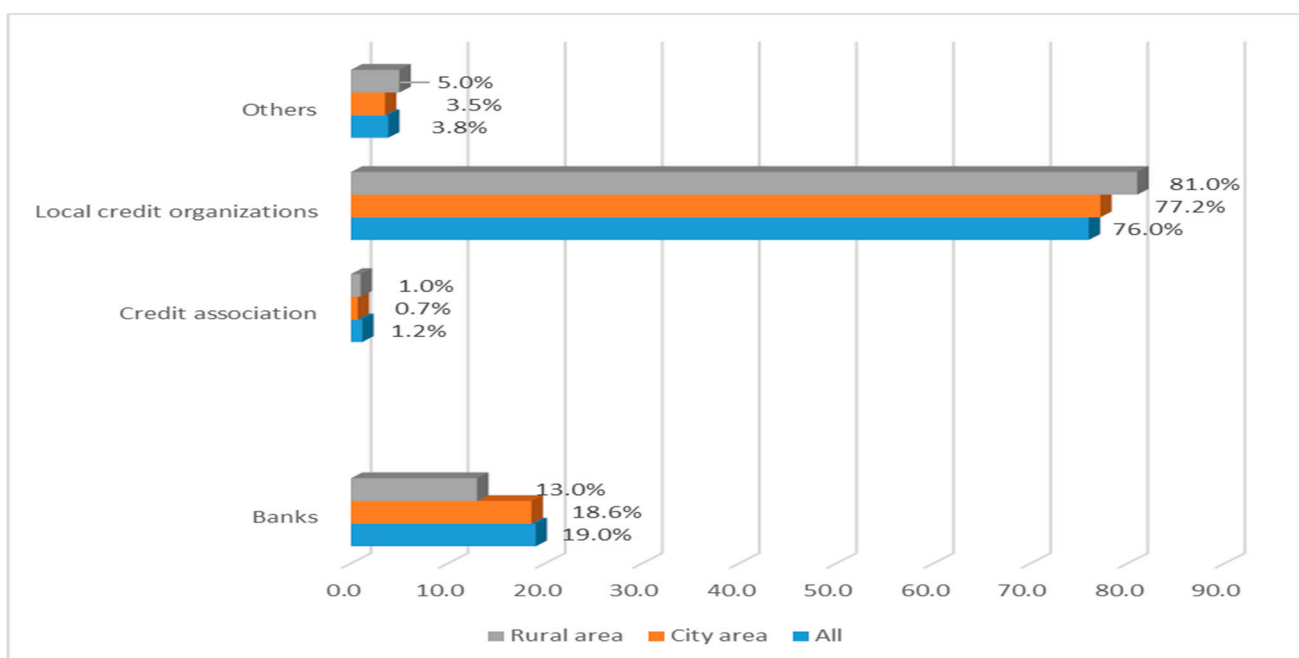


**Figure 1.** Structure of credit sources for informal labors in Vietnam. Source: authors' own calculation from the 2020 VHLSS.

Table 4 presents the results of the MNL (Multinomial Logit) model on improving quality of life for informal labors. The variables, which are credit access, education, collateral, credit source, credit debt, interest have meaning in explaining the impact of credit access to improving quality of life for informal. In Table 4, test F of regressive has a meaning ($p < 0.05$), which shows that there is no error in selection.

By access to credit, informal labors can increase the quality of life improvement; in particular, quality of life will raise by 0.21, 0.19 and 0.17 times in all areas, urban areas, rural areas respectively. Previous studies have echoed our conclusion on the role of credit access to informal labors. Le and Pham (2011) has proved access to credit and has increased income and quality of life for Vietnamese labors in informal sector. Pham (2020) has concluded that access to credit has positive impacts on reducing poverty and improving quality of life for rural labor in Vietnam.

**Table 4.** Effect of credit access on the quality of life improvement.

| Variables | All | | | Urban | | | Rural | | |
|---|---|---|---|---|---|---|---|---|---|
| | Coefficient | SE | *p*-Value | Coefficient | SE | *p*-Value | Coefficient | SE | *p*-Value |
| Credit access | 0.21 | 0.24 | 0.00 | 0.19 | 0.17 | 0.04 | 0.17 | 0.15 | 0.01 |
| Education | 0.26 | 0.21 | 0.00 | 0.16 | 0.08 | 0.02 | 0.31 | 0.31 | 0.00 |
| Collateral | 0.31 | 0.79 | 0.00 | 0.29 | 0.46 | 0.01 | 1.17 | 3.01 | 0.02 |
| Credit source | 0.09 | 0.25 | 0.00 | 0.34 | 0.16 | 0.02 | 0.11 | 0.30 | 0.01 |
| Credit size | 3.12 | 2.44 | 0.03 | 1.25 | 2.22 | 0.01 | 4.24 | 4.73 | 0.07 |
| Credit debt | 8.50 | 7.10 | 0.00 | −1.59 | 3.49 | 0/04 | 6.01 | 0.01 | 0.02 |
| Paid money | −0.01 | 0.06 | 0.00 | −0.01 | 0.01 | 0.04 | −0.04 | 0.02 | 0.03 |
| Interest | −0.25 | 0.14 | 0.00 | −0.11 | 0.06 | 0.01 | −0.20 | 0.24 | 0.05 |
| Number of observation | | | 963 | | | 577 | | | 387 |

Source: authors' own calculation from the 2020 VHLSS.

The other factors affected to quality of life improvement is education with the rate of 0.16 and 0.31 unit for urban and rural areas ($p < 0.05$) and there is a slightly difference between two groups. Besides, it is also noted that greater life quality can result from some factors including credit source, credit size, credit debt, collateral. The finding indicates that these factors have a statistic meaning and influence positively to improving quality of life. However, credit debt variable is a discrepancy among all areas, urban areas and rural area with 8.50, −1.59 and 6.01 respectively. These labors in urban areas are often the priority people in the credit support policies, so they may receive these special loans without history of credit (Le and Pham 2011).

However, some factors have negative impacts on improving quality of life such as collateral, paid money, interest. According to the results of model, the rise of paid money and interest to have credit loans will lead to a decrease 0.01 and 0.25 times in quality of life for Vietnamese informal labors. This can be explained informal labors need preferential credit policies to improve credit access ability and to increase quality of life . . . .

## 5. Conclusions

In summary, as can be seen from the model's results, credit access plays an essential role in improving quality of life for informal labors. Therefore, credit access can be considered as a necessary determinant in the effort of poverty reduction and overcoming difficulties caused by COVID-19 pandemic in Vietnam. Besides, the positive factors including education, material, collateral, credit size, credit source, credit debt which are likely to affect to credit access, however, age, family size, ethnicity, interest, paid money are negative. Moreover, it also concludes that quality of life of informal labor is considerably influenced by credit access, collateral, credit source, credit debt.

This paper has examined what factors affecting access to credit and improving quality of life for informal labors by using two methods of a binary logit model and a multinomial logit model (MLM). The research findings including:

First, the results show that access to credit has a statistic significance and positive impact on improving in quality of life in all areas, urban and rural (0.21, 0.19 and 0.17 respectively). This finding supports the argument of Pham (2020) who suggested that the role of credit in improving living standards for labors in urban and rural areas. As a result, improving quality of life of informal labors based on credit access is no longer considered as a main solution in development strategies of Vietnam in the time of COVID-19.

Second, education of informal labors influence positively their credit access that measured in all areas. Moreover, by using MNL model, the results indicate that education is likely to generate the better quality of life for those are in the urban group. This finding suggests that education expands the inequality in Vietnam. As explained earlier, more effect of education on credit access and the improvement of quality life can be resulted from the fact that informal labors who are in urbans are more likely to be taken part in training courses.

Third, creditworthiness (credit debt) creates the highest positive impact on credit access and improvement of life quality. Creditworthiness is how a lender determines that you will default on your debt obligations, or how worthy you are to receive new credit. Creditworthiness is what creditors look at before they approve any new credit to borrowers. Creditworthiness is determined by several factors including repayment history and credit score. Some lending institutions also consider available assets and the number of liabilities borrowers have when they determine the probability of default. In this time of COVID-19 with economic crisis, bankrupt and unemployment can be one of the reasons makes this credit debt becomes more and more important. Therefore, there is a need to plan some policies to enhance creditworthiness of informal labors, for instance, supports for pay bills on time, keeping credit card balances, verifying debt to income . . . .

Fourth, the study also claims that some of factors relating to the credit characteristics such as credit size, collateral of informal labor in rural areas have a higher impact. The policy implies here is that if increase these factors for rural informal labors might be an effective solution to enable rural informal labors to improve quality of life and overcome difficulties caused by the COVID-19 pandemic.

These findings have implications to improve access to credit where the government can formulate an preferential policy for informal labors by increase the number of credit organizations and offer microcredit facilities that can access to loans at low interest rates as well as give some solutions to enhance the environmental optimizing laws, facilitating technology exchange and innovation, promoting awareness of these labor about their access credit conditions (collateral, paid money, credit debt . . . ). Additionally, the government can also set up an insurance mechanism for informal labors to cover unpaid debts and stabilize household income (main guarantee for informal labors' credit). Besides, informal labors need to improve their occupational skills which are a set of knowledge and skills that they need for a specific job at the onset of the COVID-19 economic crisis.

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## References

Adewumi, Aderemi, and Ayo Akinyelu. 2017. A survey of machine-learning and nature-inspired based credit card fraud detection techniques. *International Journal of System Assurance Engineering and Management* 8: 937–53. [CrossRef]

Agier, Isabelle, and Ariane Szafarz. 2013. Subjectivity in credit allocation to microentrepreneurs: Evidence from Brazil. *Small Business Economics* 41: 263–75. [CrossRef]

Akudugu, Mamudu. 2012. Estimation of the Determinants of Credit Demand by Farmers and Supply by Rural Banks in Ghana's Upper East Region. *Asian Journal of Agriculture and Rural Development* 2: 189–200.

Anane, Isaac, Yue Zhang, and Fengying Nie. 2021. The Sources of Microfinance Capital and its Effects on Farmers access to Credit in Ghana. *SVU-International Journal of Agricultural Science* 3: 112–28. [CrossRef]

Assogba, Perceval Noel, Sènakpon E. Haroll Kokoye, Rosaine N. Yegbemey, Jonas André Djenontin, Zacharie Tassou, Joanna Pardoe, and Jacob A. Yabi. 2017. Determinants of Credit Access by Smallholder Farmers in North-East Benin. *Journal of Development and Agricultural* 9: 210–16.

Bin, Joachem Meh. 2021. Impact of Access to Credit on the Sustainability of Small and Medium Sized Enterprises in Cameroon. *American Journal of Industrial and Business Management* 11: 705–18. [CrossRef]

Caiazza, Rosa, Erik Lehmann, and Henry Etzkowitz. 2021. An absorptive capacity—Based system view of COVID-19 in the small business economy. *International Entrepreneurship and Manafement Journal* 17: 1419–39. [CrossRef]

Cameron, A. Colin, and Pravin K. Trivedi. 2005. *Microeconometrics: Methods and Applications*. New York: Cambridge University Press.

Da, Van Huynh, Thuy Thi Kim Truong, Long Hai Duong, Nhan Trong Nguyen, Giang Vu Huong Dao, and Canh Ngoc Dao. 2021. The COVID-19 Pandemic and Its Impacts on Tourism Business in a Developing City: Insight from Vietnam. *Economies* 9: 172. [CrossRef]

Diagne, Aliou. 1999. *Determinants of Household Access to and Participation in Formal and Informal Credit Markets in Malawi*. Discussion Paper 67. Washington, DC: International Food Policy Research Institute.

Doan, Tinh, and Tran Quang Tuyen. 2015. Credit participation and constraints of the poor in Peri-urban Areas, Vietnam: A micro-econometric analysis of a household survey. *Argumenta Oeconomica* 1: 175–200. [CrossRef]

Ferede, Kiros Habtu. 2012. *Determinants of Rural Households Demand for and Access to Credit in Microfinance Institutions: The Case of Atamata Woreda–Ethiopia' MA*. Wageningen: Wageningen University Research.

Garay, Annalyn Ramos. 2007. *Credit Accesibility of Smallscale Farmers and Fisherfolk in the Philippines. Review of Development and Cooperation*. Lincoln: University of Lincoln.

He, Guangwen, and Lili Li. 2005. *People's Republic of China: Financial Demand Study of Farm Households in Longren/Guizhou of PRC*. ADB Technical Assistance Consult's Report. Project Number: 35412. Guiyang: ADB.

Hua, Jinling, and Rajib Shaw. 2020. Corona Virus "infodemic" and emerging issues through a data lens: The case of china. *International Journal of Environmental Research and Public Health* 17: 2309. [CrossRef]

ILO. 2020. *COVID-19 and the World of Work*, 5th ed. Geneva: International Labour Organization. [CrossRef]

Kedir, Abi. 2003. *Determinants of Access to Credit and Loan Amount: Household—Level Evidence*. Urban Ethiopia' International Conference on Development Studies July 11–12, 2003, Addis Ababa, Ethiopia Paper 64. Kalamazoo: Western Michigan University.

Kumar, Anil, Suneel Sharma, and Mehregan Mahdavi. 2021. Machine Learning (ML) Technologies for Digital Credit Scoring in Rural Finance: A Literature Review. *Risks* 9: 192. [CrossRef]

Langat, Robert Cherutyot. 2013. *Determinants of Lending to Farmers by Commercial Banks in Kenya*. Nairobi: University of Nairobi.

Lassana, Touré, and Diop Ibrahima Thione. 2020. Analysis of Determinants of Access to Credit for Cotton Producers in Mali. *South Asian Journal of Social Studies and Economics* 6: 44–59. [CrossRef]

Le, Linh K., and Duong V. Pham. 2011. Analysis of factors determining the amount of formal credit loans of farm households in An Giang. *Banking Technology Magazine* 60: 8–15.

Lee, Han-Sol, Ekaterina A. Degtereva, and Alexander M. Zobov. 2021. The Impact of the COVID-19 Pandemic on Cross-Border Mergers and Acquisitions' Determinants: New Empirical Evidence from Quasi-Poisson and Negative Binomial Regression Models. *Economies* 9: 184. [CrossRef]

Li, Xia, Christopher Gan, and Baiding Hu. 2011. The welfare impact of microcredit on rural households in China. *Journal of Behavioral and Experimental Economics (formerly The Journal of Socio-Economics)* 40: 404–11. [CrossRef]

Louviere, Jordan J., David A. Hensher, and Joffre D. Swait. 2002. *Stated Choice Methods: Analysis and Application*. Cambridge: Cambridge University Press, ISBN 0-521-78830-7.

Nguyen, Anh Tuan, Tuyen Quang Tran, Huong Van Vu, and Dat Quoc Luu. 2018. Housing satisfaction and its correlates: A quantitative study among residents living in their own affordable apartments in urban Hanoi, Vietnam. *International Journal of Urban Sustainable Development* 10: 79–91. [CrossRef]

Nguyen, Nhung, and Nhung Luu. 2013. Determinants of financing pattern and access to formal-informal credit: The case of small and medium sized enterprises in Viet Nam. *Journal of Management Research* 5: 240–59. [CrossRef]

Nguyen, Ninh, Nguyen T. Phương, and Nguyen P. Quan. 2019. Analysis of factors affecting the accessibility of official credit for households in Thua Thien Hue province. *Journal of Science and Development* 8: 844–52.

Nouman, Muhammad, Muhammad Siddiqi, Syed Asim, and Zahid Hussain. 2013. Impact of Socio Economic Characteristics of Farmers on Access to Agricultural Credit. *Sarhad Journal of Agriculture* 29: 469–76.

Pham, Binh, Anh Huynh, and Tran C. Tho. 2020. Factors affecting formal credit access of rice farmers in Nga Nam town, Soc Trang province. *Journal of Scientific Research and Economic Development* 8: 2020.

Pham, Chuong Hong. 2020. *Evaluation of COVID-19 Response Policies and Recommendations*. Hanoi: National Economics University Publishing House.

Rajneesh, Narula. 2020. Policy opportunities and challenges from the COVID-19 pandemic for economies with large informal sectors. *Journal of International Business Policy* 3: 302–10.

Sayed, Adham, and Bing Peng. 2021. Pandemics and Income Inequality: A Historical Review. *SN Business & Economics* 1: 54.

Sekyi, Samuel. 2017. Rural households' credit access and loan amount in Wa Municipality, Ghana. *International Journal of Economics and Financial Issues* 7: 506–14.

Sossou, Comlan Hervé, Gildas Adjovi, Thomas Dogot, and Philippe Lebailly. 2017. *Analysis of the Determinants of Access to Credit for Agricultural Holdings in Benin*. Cotonou: National Institute of Agricultural Research of Benin (INRAB), p. 15.

Twumasi, Martinson Ankrah, Yuansheng Jiang, and Monica Owusu Acheampong. 2020. Determinants of agriculture participation among tertiary institution youths in Ghana. *Journal of Agricultural Extension and Rural Development* 11: 56–66.

Twumasi, Martinson Ankrah, Yuansheng Jiang, Evans B. Ntiamoah, Selorm Akaba, Kwabena N. Darfor, and Linda K. Boateng. 2020. *Access to Credit and Farmland Abandonment Nexus: The Case of Rural Ghana*. Hoboken: Wiley. [CrossRef]

West, David. 2000. Neural network credit scoring models. *Computers & Operations Research* 27: 1131–52.