EXPLORING THE RELATIONSHIP BETWEEN WILLINGNESS TO PARTICIPATE IN INSURANCE AND BANK LOAN APPROVAL FOR COFFEE FARMERS IN DAK LAK PROVINCE: A BAYESIAN MODEL AVERAGING APPROACH

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ABSTRACT

This study has employed Bayesian Model Averaging (BMA) to identify the most suitable model for assessing the eligibility of Vietnamese coffee farmers for bank loans, effectively avoiding overfitting and ensuring that only the most crucial variables were considered in the analysis. Findings from the study indicate that factors such as ethnicity, labor, yield, land ownership, and willingness to participate (WTP) in coffee insurance significantly influenced the farmers' eligibility for bank loans. Moreover, the study suggests that banks and insurance companies should also take into account additional factors, such as socio-economic context, household size and composition, land ownership, and risk-sharing programs, to enhance access to credit. With this valuable information, banks can forge partnerships with insurance companies to craft highly effective loan programs and insurance products tailored to Vietnamese farmers' unique needs. The simplicity, practicality, and strong predictive ability of the model chosen by BMA make it a valuable tool for guiding policy decisions.

Keywords: bank loan; willingness to participate; insurance; Bayesian Model Averaging; coffee farmers

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INTRODUCTION

The coffee industry is one of Vietnam's important agricultural sectors, significantly contributing to the country's economy. According to the 2021 coffee market report of the International Coffee Organization (ICO), Vietnam is the world's second-largest coffee producer and exporter after Brazil, accounting for about 16% of global coffee production. The report also indicates that the coffee industry is an important source of job creation in Vietnam, with around 2.6 million people engaged in coffee production and related activities. However, small-scale coffee farmers in Vietnam face many challenges, including volatile coffee prices, natural disasters, and limited access to credit and insurance (Seo, 2008; Vulturius et al., 2017). Similarly, a study by Ankrah et al. (2021) found that many farmers do not have access to insurance, which increases their vulnerability to various risks. Uninsured agricultural risks and limited access to credit are serious challenges in agricultural development and are recognized as major causes of poverty traps in Africa (Carter, 2019).

As can be seen today, access to credit and insurance is essential for farmers worldwide, as it helps farmers reduce risks and improve their economic well-being (Ray, 2013). Therefore, a study of the relationship between the WTP in insurance and the borrowing capacity of Vietnamese coffee farmers is needed for the following reasons. First, by participating in insurance programs, farmers can access financial assistance that can help them recover from damage and continue operating their businesses. In addition, insurance can provide farmers with peace of mind, encouraging them to invest in their farms and increase productivity (Yu et al., 2023). Second, small-scale farms often rely on loans to invest in their farms, purchase inputs, and cover other costs (Meyer et al., 2019; Balana and Oyeyemi, 2022). However, default rates are often high, especially among small-scale farmers who may lack collateral or credit history. Understanding the relationship between insurance willingness and loan performance can help identify factors contributing to defaults and inform policies that can improve access to credit use and reduce default rates.

Several studies have examined the relationship between the WTP in insurance and the borrowing capacity of smallholder farmers (Naranjo et al., 2019; Meyer et al., 2019; Ankrah et al., 2021; Ndegwa et al., 2020; Yu et al. , 2023; Wu and Li, 2023). Despite these findings, there still is limited research on the relationship between insurance willingness and loan performance, particularly among smallholder coffee farmers in Vietnam. This research gap is particularly relevant to the unique characteristics of the coffee industry, including its susceptibility to climate change, volatile prices, and limited access to credit and insurance. Therefore, this study aims to fill this gap by examining the relationship between WTP in insurance and loan performance of small-scale coffee farmers in Vietnam and examining questions such as: What factors affect loan results of Vietnamese coffee farmers?, and What challenges do Vietnamese coffee farmers face in accessing credit and insurance?

LITERATURE REVIEW

Studies on the Credit-Insurance

The purpose of this literature review is to examine the relationship between access to credit and WTP in insurance and its impact on Vietnamese coffee farmers based on international studies as well as specific studies conducted in Vietnam. Access to credit and insurance are two key components of farmers' portfolios, as they enable farmers to invest in productive assets, cope with losses, and stabilize their consumption over time (Marr et al., 2016). However, the use of credit and insurance depends on farmers' willingness to accept them, which is influenced by various factors such as socio-economic characteristics, risk perception, trust, and asymmetric information.

Several studies have examined the relationship between credit access, insurance participation, and their impact on agricultural outcomes in developing countries. Boucher et al. (2008) argued that the lack of formal insurance markets in rural areas of developing countries can lead to risk allocation problems, which can prevent potential borrowers from accessing credit due to the risk of collateral loss. To solve this problem, a combined credit and crop insurance approach can be used to improve credit markets and encourage agricultural investment. Sibiko et al. (2021) found that credit access and insurance participation have a contract complementarity effect on farmers' welfare, and the effect is greater for those using both instruments. Naranjo et al. (2019) conducted a study with coffee farmers in Costa Rica to analyze the impact of credit, insurance, and legal responsibility on their agricultural investments. The study showed that providing both credit and insurance increases investment, but the farmers' legal responsibility has no significant impact. The results of the study suggest that insurance alone may not be sufficient to stimulate investment in the absence of credit, and limited liability may not be an effective solution for farmers' financial risks. Overall, the research emphasized the interaction between credit and insurance and highlighted the need to design policies that consider both instruments to promote agricultural development in developing countries.

Some studies have investigated the impact of combining credit with mandatory insurance on risk allocation and farm investment. For example, Cheng (2014) found that providing insurance to risk-averse farmers in China led to more than half of them applying for credit, with two-thirds of the loans used for production investment. This suggests that combining credit with insurance could effectively increase access to credit and promote investment in agriculture. Similarly, Carter et al. (2017) showed that index-based crop insurance may be most effective when collateral requirements are low or when risks are insured by a well-designed index contract, which suggests that the design of insurance contracts can play an important role in promoting investment and reducing risk allocation. Karlan et al. (2014) conducted a randomized controlled trial in Ghana and found that uninsured risks constrain farmers' investments, while farmers subsidized with insurance are able to increase investment in their farms, suggesting that providing insurance to farmers can be an effective way to enhance investment in agriculture. However, they also noted that market-based agricultural credit policies alone are not sufficient to increase investment in this sector. Therefore, a combination of policies, including credit and crop insurance, is needed to support farmers in investing in their farms. On the other hand, Brick and Visser (2015) found that providing an insured loan did not increase investment in new technology in South Africa. They also found that risk-averse farmers are more likely to choose traditional seeds over high-yielding seeds, regardless of whether they had insurance or not. Their experimental design, however, did not account for other risk factors that could affect their results. Therefore, more research is needed to understand the role of risk aversion and other risk factors in farmers' decision-making processes and how this affects the effectiveness of combining credit with insurance to promote investment in agriculture. Experimental and theoretical evidence on the impact of crop insurance on farm investment is mixed.

On the one hand, studies by Hill and Viceisza (2012), Karlan et al. (2014), and Elabed and Carter (2014) suggest that providing crop insurance increases farm investment. However, on the other hand, studies by Karlan et al. (2014) and Brick and Visser (2015) indicate that combining credit and insurance is not necessarily associated with increased investment and may even lead to decreased investment (Giné and Yang, 2009). Studies conducted in Vietnam on specific crops have explored the correlation between farmers' access to credit, WTP for agricultural insurance, and their welfare (Luong TNH., 2015; Phan et al., 2022).

Studies on access to credit

Difficulties in accessing microfinance credit for farmers in Ghana have been identified as a major challenge, according to Anane (2021). To investigate the impact of microfinance capital sources on farmers' access to credit, a study was conducted with 2734 participants. The study found that microfinance capital significantly influenced farmers' access to credit, with additional factors such as land ownership, gender, and literacy rate also playing a role. Previous research has identified household characteristics, asset ownership, regional characteristics, and socio-economic characteristics as variables that influence credit access, according to Sekyi (2017), Ankrah et al. (2022), and Langat (2013). Furthermore, several models, including linear regression, binary logistic regression, probit model, or logit model, have been used to examine the impact of credit access on producers. For example, Lassana and Thione (2020) used a binary logistic regression model to evaluate the key variables affecting cotton producers' ability to access credit. Meanwhile, Linh et al. (2019) found that socio-economic factors such as age, household size, household income, education, gender, and land size influence farmers' credit access ability, and social capital also plays a role in Vietnam.

Despite the increasing number of studies on credit access and insurance in developing countries, gaps still need to be addressed. For instance, there is limited evidence on the general impact of credit and insurance on farmers' income, particularly in the context of coffee cultivation. Furthermore, the absence of prior research establishing a model for analyzing the factors that affect bank loan outcomes in coffee-growing households using this method highlights the imperative of utilizing the Bayesian Model Averaging (BMA) technique. This requirement is rooted in the need to create a robust and all-encompassing model proficient in precisely assessing the wide spectrum of factors that influence the results of bank loans in coffee-growing households. Institutional factors, such as government policies, financial regulations, and market structure, also need to be considered in shaping farmers' credit access and insurance readiness.

DATA AND METHODS

Data

Dak Lak province is located in Vietnam’s Central Highlands region, accounting for 3.9% of the country’s natural area. However, the province's coffee export turnover accounts for 21% of the whole country's total. As a result, Dak Lak coffee has been exported to 64 countries and territories around the world. In 2018 and 2019, the Dak Lak Statistical Office collected information from 480 coffee growers in Dak Lak who are considered the most important contributors to total household income (Ngoc Duc and Tin, 2022).

Methods

This study uses the work of Linh et al. (2019) from among previous work on the results of bank loans for coffee-growing farmers. Sixteen factors have been considered in constructing a research model suitable for the actual results of bank loans for coffee-growing farmers (Table 1). Among them, the WTP in coffee tree insurance is considered as a new factor that needs to be specifically examined for its impact on the results of bank loans and the ethnicity of the head of household.

The logistic regression model has the following form:

$$\ln\left(\frac{P(Y=1)}{1-P(Y=1)}\right) = \beta_0 + \sum_{j=1}^{16} \beta_j X_j + u \qquad (1)$$

where Y is the dependent variable; $X_1, X_2, \ldots, X_{16}$ are independent variables; β_0 is a constant; β_1, β_2,…, β_{30} are parameters; u is an error term with a logistic distribution; and e is an error term with a normal distribution. The implementation of BMA for logistic regression in this study is done by bic.glm command in software version R 4.2.2.

Table 1. Summary and symbols of variables

Number	Variable	Measurement (unit)
Y	LOAN	LOAN is a dummy variable that takes on the value of 1 if the householder has a bank loan and 0 if otherwise.
X_1	AGE	AGE is a continuous variable and is measured by the age of the household head (years).
X_2	GENDER	GENDER is a dummy variable that takes the value 1 if the head of the household is male, and the value 0 if the head of the household is female.
X_3	ETHNICITY	ETHNICITY is a dummy variable that takes the value 1 if the head of the household is from Kinh ethnicity and the value 0 if the head of the household is an ethnic minority.
X_4	EDUCATION	EDUCATION is a continuous variable and is measured by the number of years of schooling of the household head (years).
X_5	EXPERIENCE	EXPERIENCE is a continuous variable and is measured by the number of years of coffee production of the household head (years).
X_6	ASSOCIATIONS	ASSOCIATIONS is a dummy variable that takes the value 1 if the head of the household joins the farmer association and 0 if otherwise.
X_7	LABORS	LABORS is a continuous variable and is measured by the number of people in the household engaged in coffee production (person).
X_8	AREA	AREA is a continuous variable and is measured in hectares (ha).
X_9	TREE	TREE is a continuous variable and is measured by the age of the tree (years).
X_{10}	YIELD	YIELD is a continuous variable and is measured in quintals per hectare (quintals/ha).
X_{11}	INCOME	The variable INCOME is a continuous variable and is measured by the amount of money farmers earn per hectare of coffee (million VND/ha).
X_{12}	OWNERSHIP	OWNERSHIP is a dummy variable, which takes on the value 1 if the head of the household is the owner of productive land and the value 0 if otherwise.
X_{13}	PRICE	PRICE is a continuous variable representing 1 kg of coffee beans (VND/kg) selling price.

Table 1. Continued

X_{14}	STANDARDS	STANDARDS is a dummy variable that receives the value 1 if the householder produces coffee according to 4C and UTZ standards and 0 if otherwise.
X_{15}	MARKET	MARKET is a dummy variable that takes the value 1 if the householder sells coffee to the enterprise and 0 if otherwise.
X_{16}	INSURANCE	INSURANCE is a dummy variable that takes the value 1 if the household is willing to participate in coffee insurance according to the yield index and 0 if otherwise.

Source: Authors' finding

Model selection using Bayesian Model Averaging

To simplify, people usually tend to provide only one model (including all collected variables) to estimate and then infer if that model best fits the data. Therefore, this method may overlook other models constructed with a subset of collected variables, and one of these models may be more suitable. Hence, it is necessary to fully consider all models of a research problem and compare them to find the truly best model for the data (also known as the "best" model) (Raftery, 1995). Bayesian Model Averaging (BMA) uses the posterior probabilities of the models to selects a subset of 2^p models (ignoring interactions between independent variables). D is data, Δ is quantity of interest, and $\mathrm{M} = \{M_k, k = 1, 2, \dots, k\}$ is used to denote the set of all possible models to be considered. Then the posterior distribution of Δ is:

$$\Pr(\Delta|D) = \sum_{k=1}^{K} \Pr(\Delta|M_k, D). \Pr(M_k|D) \qquad (2)$$

$\Pr(\Delta|M_k, \mathrm{D})$ is an average of the posterior distributions under each model M_k, weighted by the corresponding posterior model probabilities $\left(\Pr(M_k|\mathrm{D})\right)(k = 1,2, \dots, K)$. In (2), the predictive distribution of Δ given a particular model M_k is

$$\Pr(\Delta|M_k, D) = \int \Pr(\Delta|\beta^k M_k, D)\Pr(\beta^k|M_k, D)\, d\beta^k$$

where $\beta^k = (\beta_0, \beta_1, \dots, \beta_p)'$ is vector of parameters in model M_k, and the posterior probability of model M_k is given by

$$\Pr(M_k|D) = \frac{\Pr(D|M_k)\Pr(M_k)}{\sum_{j=1}^{K} \Pr(D|M_j)\mathrm{P}(M_j)} \qquad (3)$$

Where

$$\Pr(D|M_k) = \int \Pr(D|\beta^k, M_k)\Pr(\beta^k|M_k)\, d\beta^k \qquad (4)$$

is the integrated likelihood of model M_k, $\Pr(\beta^k|M_k)$ is prior density of β^k under M_k, $\Pr(D|\beta^k, M_k)$ is likelihood of data, and $\Pr(M_k)$ is the prior probability that Mk is the true model

Let

$$\hat{\Delta}_k = E[D|\Delta, M_k]$$

Posterior mean and variance of Δ :

$$E[\Delta|D] = \int \Delta \sum_{k=1}^{K} \Pr(\Delta|M_k, D) \Pr(M_k|D)\, d\Delta$$

$$= \sum_{k=1}^{K} \hat{\Delta}_k \Pr(M_k|D)$$

$$Var[\Delta|D] = \sum_{k=1}^{K} \left(\mathrm{Var}[\Delta|D, M_k] + \hat{\Delta}_k^2\right) \Pr(M_k|D) - E[\Delta|D]^2$$

The implementation of BMA gives rise to two issues: the summation in equations (2) and the integral in equation (4). First, by managing the summation by *Occam's window* method models that have very small posterior probability will be omitted. Second, the Laplace method helps approximate $\Pr(D|M_k)$.

RESULTS

Descriptive statistics

Figure 1 presents descriptive statistics for two groups: those with a loan (415 households) and those without a loan (65 households). The two groups have similar mean values for GENDER, AGE, ETHNICITY, EXPERIENCE, and TREE. However, the group that received loans had a higher mean value of EDUCATION, LABOR, AREA, YIELD, INCOME, ASSOCIATIONS, OWNERSHIP, INSURANCE, STANDARDS, PRICE and MARKET than the group that did not get loans. In summary, the two groups have several similarities in terms of demographic variables such as gender, ethnicity, and association with an organization, however they differ in variables related to economic factors such as income, insurance, yield, and ownership. The variables related to work experience, number of labors, and number age of trees also show some differences between the two groups.

Model selection using BMA

In this study, we analyzed 16 independent factors (Table 1) and noted that the number of possible models does not include models with interactions between factors, which amounts to $2^{16} = 65{,}536$ models. After applying BMA, we identified the 5 best models out of 40 selected models with the highest posterior probability (Figure 2). Model 1, which includes 5 independent variables (ETHNICITY, LABORS, YIELD, OWNERSHIP, and INSURANCE), has the highest posterior probability (15.1%), Model 2 has 4 independent variables (ETHNICITY, LABORS, OWNERSHIP, and INSURANCE) and a posterior probability of 12.7%, Model 3 has 4 independent variables (ETHNICITY, LABORS, YIELD, and INSURANCE) and a posterior probability of 8.6%, Model 4 has 4 independent variables (ETHNICITY, LABORS, INCOME, and INSURANCE) and a posterior probability of 7.2%, and Model 5 has 5 independent variables (ETHNICITY, LABORS, INCOME, OWNERSHIP, and INSURANCE) and a posterior probability of 4.4%. Based on the analysis of the posterior probabilities, we determined the independent factors that significantly impact LOAN. The posterior probability (%) of independent factors affecting LOAN is as follows: LABOR (100%), INSURANCE (100%), ETHNICITY (89.2%), OWNERSHIP (59.8%), YIELD (40.2%), INCOME (22.5%), PRICE (11.7%), ASSOCIATIONS (5.8%), EXPERIENCE (5.6%), TREE (9.6%), STANDARDS (1.1%), EDUCATION (0.8%), AGE (5%), GENDER (0%), AREA (0%), and MARKET (0%) (see Figure 2). According to Wang (2004), researchers often use the model with the highest posterior probability, which is also the "optimal" model proposed by BMA. Therefore, in this study we chose Model 1, which has the highest posterior probability (15.1%), to analyze the factors affecting the dependent variable LOAN.

To evaluate the performance of Model 1 we first checked for multicollinearity using the correlation matrix. Figure 4 shows that all pairs of variables have correlation coefficients with absolute values less than or equal to 0.3, indicating that Model 1 does not have multicollinearity. Next, we tested the hypothesis that all coefficients in Model 1 are simultaneously zero using the likelihood ratio statistic (LR). According to Gujarati and Porter (2009), the LR statistical test for Model 1 has a probability value of Pr(> Chi2) < 0.0001, indicating that the factors included in Model 1 are significant. We then tested the Brier index and AUC of Model 1. The Brier index was found to be 0.091, which is close to 0, and the AUC was 0.841, which is greater than 0.8 (Wigton 1986). These results indicate that Model 1 is a great model. Based on the above results, we conclude that Model 1 has good predictive ability and satisfies the following criteria of model selection: simplicity, completeness, and practical significance. Specifically, Model 1 has 5 independent variables, all of which are statistically significant and have theoretical and economic significance. Additionally, these variables are easy to investigate.

Figure 1. Descriptive statistics

Descriptive statistics by group

LOAN: 0

	vars	n	mean	sd	min	max	range	se
LOAN	1	415	0.00	0.00	0.0	0.00	0.00	0.00
GENDER	2	415	0.97	0.17	0.0	1.00	1.00	0.01
AGE	3	415	43.33	7.96	25.0	68.00	43.00	0.39
ETHNICITY	4	415	0.61	0.49	0.0	1.00	1.00	0.02
EDUCATION	5	415	8.33	3.14	1.0	16.00	15.00	0.15
LABORS	6	415	2.65	1.04	1.0	7.00	6.00	0.05
EXPERIENCE	7	415	17.07	6.63	3.0	40.00	37.00	0.33
AREA	8	415	1.24	1.36	0.1	16.00	15.90	0.07
YIELD	9	415	27.89	6.78	15.0	46.00	31.00	0.33
INCOME	10	415	43.16	8.96	16.8	58.71	41.91	0.44
ASSOCIATIONS	11	415	0.97	0.17	0.0	1.00	1.00	0.01
OWNERSHIP	12	415	0.82	0.39	0.0	1.00	1.00	0.02
INSURANCE	13	415	0.48	0.50	0.0	1.00	1.00	0.02
TREE	14	415	13.40	1.87	11.0	18.00	7.00	0.09
STANDARDS	15	415	0.03	0.17	0.0	1.00	1.00	0.01
PRICE	16	415	36893.25	981.18	34800.0	40100.00	5300.00	48.16
MARKET	17	415	0.02	0.15	0.0	1.00	1.00	0.01

LOAN: 1

	vars	n	mean	sd	min	max	range	se
LOAN	1	65	1.00	0.00	1.00	1.00	0.00	0.00
GENDER	2	65	0.98	0.12	0.00	1.00	1.00	0.02
AGE	3	65	42.62	7.73	27.00	61.00	34.00	0.96
ETHNICITY	4	65	0.57	0.50	0.00	1.00	1.00	0.06
EDUCATION	5	65	8.85	3.69	1.00	16.00	15.00	0.46
LABORS	6	65	3.57	1.16	2.00	7.00	5.00	0.14
EXPERIENCE	7	65	15.74	5.83	8.00	35.00	27.00	0.72
AREA	8	65	1.56	0.90	0.40	5.05	4.65	0.11
YIELD	9	65	32.22	5.83	24.00	44.40	20.40	0.72
INCOME	10	65	47.83	3.93	36.02	53.98	17.96	0.49
ASSOCIATIONS	11	65	1.00	0.00	1.00	1.00	0.00	0.00
OWNERSHIP	12	65	0.98	0.12	0.00	1.00	1.00	0.02
INSURANCE	13	65	0.88	0.33	0.00	1.00	1.00	0.04
TREE	14	65	12.83	1.73	11.00	17.00	6.00	0.21
STANDARDS	15	65	0.06	0.24	0.00	1.00	1.00	0.03
PRICE	16	65	37504.62	998.66	36000.00	39700.00	3700.00	123.87

Source: Authors' finding

Figure 2. Five models with the highest posterior probability

```
Call:
bic.glm.data.frame(x = xvars, y = yvars, glm.family = binomial(link = "logit"),     strict = FALSE, OR = 20)


  40  models were selected
 Best  5  models (cumulative posterior probability =  0.4807 ):

              p!=0    EV          SD          model 1     model 2     model 3     model 4     model 5
Intercept     100    -8.820e+00  2.335e+02  -7.986e+00  -6.711e+00  -6.395e+00  -7.428e+00  -8.472e+00
GENDER          0.0   0.000e+00  0.000e+00       .           .           .           .           .
AGE             5.0  -1.393e-03  7.755e-03       .           .           .           .           .
ETHNICITY      89.2  -9.289e-01  4.605e-01  -1.179e+00  -9.634e-01  -1.092e+00  -9.667e-01  -1.003e+00
EDUCATION       0.8   1.875e-04  4.931e-03       .           .           .           .           .
LABORS        100.0   5.620e-01  1.408e-01   5.106e-01   5.764e-01   5.866e-01   5.606e-01   5.167e-01
EXPERIENCE      5.6  -1.917e-03  9.820e-03       .           .           .           .           .
AREA            0.0   0.000e+00  0.000e+00       .           .           .           .           .
YIELD          40.2   2.409e-02  3.325e-02   6.069e-02       .       6.475e-02       .           .
INCOME         22.5   1.264e-02  2.673e-02       .           .           .       6.313e-02   5.146e-02
ASSOCIATIONS    5.8   8.719e-01  2.335e+02       .           .           .           .           .
OWNERSHIP      59.8   1.253e+00  1.309e+00   2.099e+00   2.216e+00       .           .       1.844e+00
INSURANCE     100.0   2.140e+00  4.324e-01   2.116e+00   2.264e+00   2.077e+00   2.196e+00   2.202e+00
TREE            9.6  -1.499e-02  5.532e-02       .           .           .           .           .
STANDARDS       1.1  -7.494e-03  1.045e-01       .           .           .           .           .
PRICE          11.7   3.325e-05  1.062e-04       .           .           .           .           .
MARKET          0.0   0.000e+00  0.000e+00       .           .           .           .           .

nVar                                             5           4           4           4           5
BIC                                         -2.638e+03  -2.638e+03  -2.637e+03  -2.637e+03  -2.636e+03
post prob                                    0.151       0.127       0.086       0.072       0.044
```

Source: Authors' finding

Regression analysis

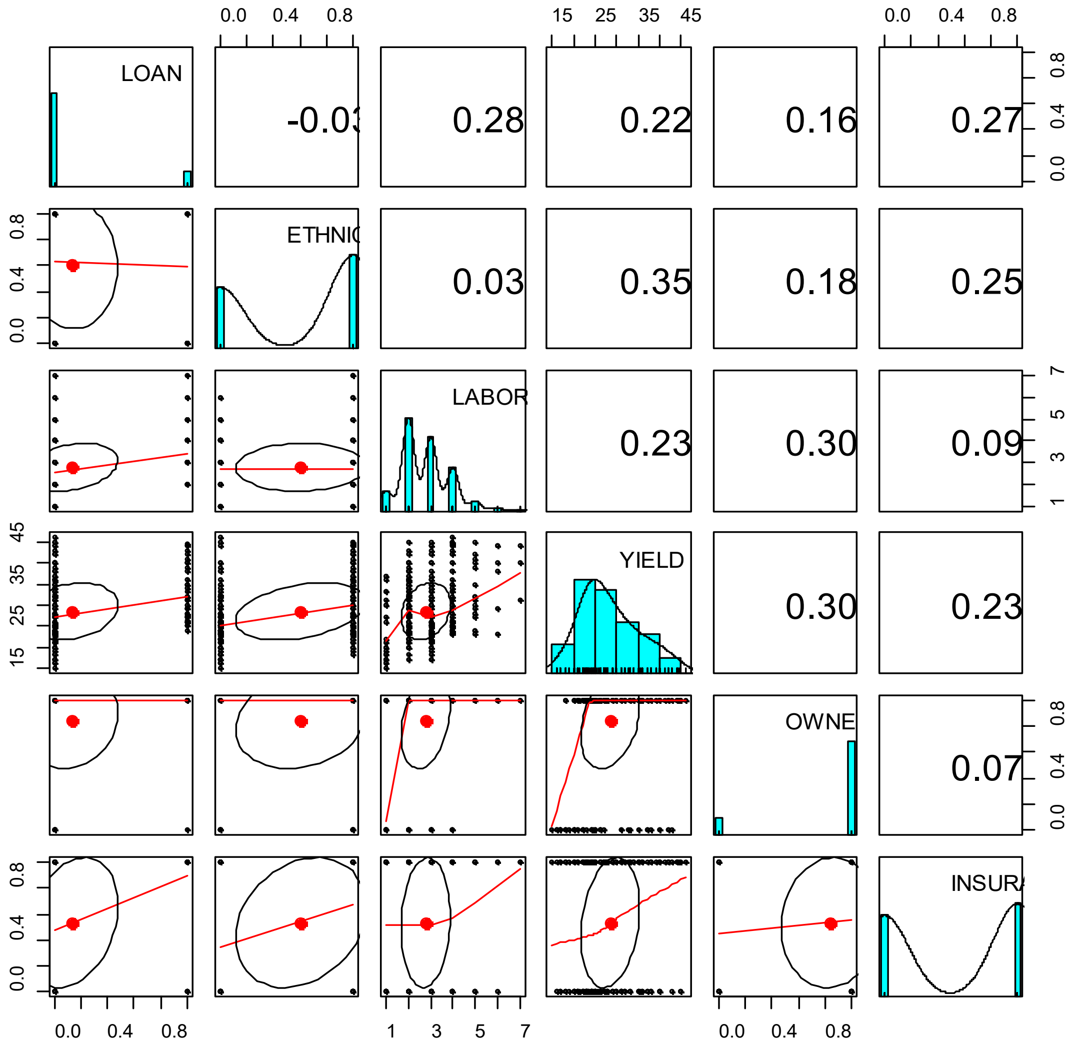
According to the results of Model 1 in Figure 3, household heads who are the Kinh are 0.306 times more likely than ethnic minorities to be eligible for bank loans (odds ratio = $e^{-1.1794} = 0.306$. When labor increases by 1 person, eligibility for bank loans increases by 1.665 times. When yield increases by 1 quintal/ha, eligibility for bank loans increases by 1.062 times. The head of the household who owns productive land is 8.155 times more likely to be eligible for bank loans than those who are not willing to participate in coffee insurance. The household willing to participate in coffee insurance is 8.296 times more likely to be eligible for bank loans than those not willing to participate in coffee insurance.

Figure 3. Logistic regression results of the selected model

```
Logistic Regression Model

lrm(formula = LOAN ~ ETHNICITY + LABORS + YIELD + OWNERSHIP +
    INSURANCE, data = vars)

                      Model Likelihood     Discrimination    Rank Discrim.
                         Ratio Test           Indexes           Indexes
Obs           480    LR chi2      92.66    R2       0.321    C       0.841
 0            415    d.f.             5    R2(5,480)0.167    Dxy     0.683
 1             65    Pr(> chi2) <0.0001   R2(5,168.6)0.405   gamma   0.684
max |deriv| 9e-06                          Brier    0.091    tau-a   0.160

          Coef    S.E.   Wald Z Pr(>|Z|)
Intercept -7.9857 1.2488 -6.39  <0.0001
ETHNICITY -1.1794 0.3402 -3.47  0.0005
LABORS     0.5106 0.1341  3.81  0.0001
YIELD      0.0607 0.0239  2.54  0.0112
OWNERSHIP  2.0986 1.0442  2.01  0.0445
INSURANCE  2.1158 0.4244  4.99  <0.0001
```

Source: Authors' finding

Figure 4. Correlation matrix of Model 1



Source: Authors' finding

CONCLUSION AND RECOMMENDATIONS

According to the study, Model 1 has good predictive ability and the results highlight the importance of selecting statistically significant, economically and theoretically significant variables. Using BMA in selecting the "best" model helps avoid overfitting and ensures that only the most important variables are included (Viallefont et al., 2001). Furthermore, the simplicity of Model 1 makes it easy to investigate and is practical to use in informing policy decisions. The identified variables, such as the ethnicity of the household head, labor, yield, land ownership, and WTP in coffee insurance, provide insights into the factors that affect the eligibility of Vietnamese farmers for bank loans.

The first variable identified in Model 1 is the ethnicity of the household head. This finding highlights the importance of considering the socio-economic context of ethnic minority groups in Vietnam. It may indicate that ethnic minority households have historically faced greater barriers to accessing formal financial services and that policies targeting addressing these barriers can positively impact them. The second variable identified is labor. This finding suggests that households with a larger workforce may be more attractive to lenders, as they are better able to generate income and repay loans. It also highlights the importance of household size and composition in determining the eligibility of farmers for bank loans. The third variable identified is yield. This finding suggests that farmers who are able to achieve higher yields may be seen as more creditworthy by lenders. It may also indicate that farmers who are able to achieve higher yields are more likely to have a stable and predictable income, making them better able to repay loans. The fourth variable identified is land ownership. This finding highlights the importance of land ownership in accessing credit and may indicate that land is used as collateral for loans or that farmers who own land are seen as more creditworthy by lenders. The fifth variable identified is the WTP in coffee insurance. This finding suggests that lenders may perceive farmers who are willing to participate in risk-sharing schemes as more reliable borrowers, and could also indicate that these farmers have a better understanding of the risks associated with coffee production and are better able to manage these risks. This is consistent with the study by Naranjo et al. (2019). However, the number of households willing to participate in insurance is very small; most of the households are not willing to participate. This can be explained by herding behavior or overconfidence when the farmer has specialized knowledge in his field (Quang et al., 2023). On that basis, it is recommended that policymakers should develop linked credit and insurance products to improve lending efficiency, production technology and increase productivity, as well as increase the ability to access credit. This will reduce the risk of falling into permanent poverty by enabling individuals to take insurance. Credit and linked insurance products are also an emerging agricultural insurance model in China (Yu et al., 2023).

In conclusion, the results of Model 1 can be valuable in informing policies aimed at increasing Vietnamese coffee farmers' access to credit. The study highlights the importance of considering the socio-economic context of ethnic minority groups, household size and composition, land ownership, and risk-sharing programs in accessing credit. Banks and insurance companies can use this information to target specific groups, such as ethnic minorities, and incentivize behaviors such as coffee insurance participation, increasing the likelihood of eligibility for bank loans. Additionally, by understanding the factors that affect eligibility, banks can work with insurance companies to design more effective loan programs and insurance products to meet the needs of Vietnamese coffee farmers.

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