https://doi.org/10.31489/2025Ec4/1211

JEL: D14
ORIGINAL RESEARCH
Received: 09.06.2025 | Accepted: 07.10.2025

Analysis of the impact of socio-economic factors on household credit behavior

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Abstract

Purpose of the research is to identify the socio-economic determinants of loan delinquencies among households in Kazakhstan, considering the specifics of the regional context and the spread of digital lending.

Methodology is based on the analysis of cross-sectional survey data from 256 households conducted in 2023 in the Kapshagay region. To test two hypotheses, logit and probit regressions were applied: H1 — the number of loans is positively associated with the risk of default; H2 — low per capita household income increases the probability of delinquency.

Originality / value of the study lies in the use of microdata that reflect actual borrowing practices in an emerging financial market, as well as in the inclusion of demographic characteristics that are rarely considered in borrower assessments. Unlike traditional models employed by banks for automated credit decision-making, this study additionally analyzes variables such as per capita household income. This makes it possible to more accurately capture social vulnerability and potential insolvency risks among different population groups.

Findings show that the number of active loans significantly increases the probability of default, whereas per capita household income does not have a substantial effect. Social status and credit accessibility also proved to be significant factors.

The study contributes to the literature on financial vulnerability and may be useful for regulators and microfinance organizations in developing sustainable lending policies.

Keywords: Default risk, household debt, credit behavior, Kazakhstan, logit-probit models, socioeconomic determinants, digital lending.

Introduction

The relevance of studying household over-indebtedness is of particular importance in the context of implementing the United Nations Sustainable Development Goals (SDGs). In particular, this concerns the objectives of reducing poverty and improving well-being through inclusive economic growth [1]. Excessive debt burden may undermine these goals, as it leads to an increase in the number of socially vulnerable population groups.

According to the World Bank report (December 2024), nearly 19 % of Kazakhstani households are already in a state of financial vulnerability, experiencing difficulties in meeting basic living needs [2]. Moreover, consumer loans—issued without adequate income growth—are increasingly becoming the primary source of financing for these groups. This situation indicates the emergence of systemic risk: under conditions of high inflation and stagnant real incomes, combined with costly borrowing, the probability of widespread defaults increases, threatening both the sustainability of household budgets and the stability of the financial sector as a whole. An additional factor is the technological accessibility of credit, in particular online loans and mobile banking applications, which lowers the entry threshold for borrowing and contributes to rising indebtedness without proper assessment of repayment capacity. While the digitalization of financial services promotes borrowing, it simultaneously amplifies the risk of default, especially among financially vulnerable population groups [3].

At the same time, commercial banks are oriented toward the retail market, since loans to individuals generate higher returns than corporate lending. This institutionally reinforces the banks' motivation to stimulate consumer lending, including among vulnerable groups. Financial vulnerability is most pronounced among households with low incomes and limited financial literacy [4].

The purpose of this article is to conduct a comprehensive study of the factors underlying household over-indebtedness, combining a systematic review of academic literature with empirical analysis using logistic modeling. Particular attention is paid to identifying the socio-economic determinants influencing the

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probability of loan delinquencies, as well as to developing recommendations aimed at strengthening the financial resilience of the population.

Literature Review and Research Positioning

The analysis of recent scientific publications makes it possible to identify key socio-demographic and economic characteristics that influence household credit behavior. Most researchers agree that variables such as age, gender, education, income, family size, and employment are significant predictors of loan delinquencies. However, approaches to their study vary considerably in both methodological and empirical aspects.

1. Comparison of Methodologies and Variables

The studies of Xiao and Yao, Dempere, and Malik use aggregated household survey data to examine the relationship between family structure and the ownership of different types of debt [5,6,7]. These works apply logit modeling with a focus on mortgage and student loans. In contrast, the present study relies on microdata that include specific cases of delinquencies, which makes it possible to model not only the probability of holding debt but also the actual risk of default.

The studies by Fernández-López S. [8, 9] and Chen F. [10] focus on the role of financial literacy, emphasizing that it can amplify or mitigate the impact of income and employment on borrower behavior. These works employ survey-based financial literacy indices and their interaction with behavioral variables, whereas our model applies an objective indicator—per capita income—which increases sensitivity to social vulnerability without relying on respondents' self-assessment.

Białowolski R. [4] applies a comparative approach between subjective and objective over-indebtedness, revealing that the type of loan and the level of education influence the perception of debt burden. In contrast, our study focuses not on perception but on the actual presence of delinquencies, confirmed by specific payment status.

The study by Xidonas P. [11] uses EU microdata and examines access to credit, including the probability of rejection. It applies binary choice models with an emphasis on employment and housing status. Although the structure of this model is close to that employed in the present study, the key distinction lies in the context: our model is based on data from an emerging financial market—Kazakhstan—where access to digital loans is not accompanied by a centralized borrower assessment system.

2. Financial Literacy and Behavior

The studies by Mutsonziwa and Fant [12], as well as De Oliveira Santini [13], highlight the impact of cross-borrowing and low financial literacy on the propensity for delinquency. However, their focus is on African and Latin American countries, and they rely on survey-based methods. In contrast, our study incorporates variables that reflect the structure of current indebtedness and models the actual behavior of borrowers at the household level.

Diba, Abrantes-Braga, and Veludo-de-Oliveira [14] emphasize "reborrowing" because of distorted perceptions of credit conditions. While we do not directly examine cognitive biases, our findings show that multiple loans (Numlo) significantly increase the risk of default, thereby empirically confirming the consequences described in these behavioral models.

3. Debt Burden, Assets, and Digitalization

Madeira [15] and Białowolski [4] examine the structure of debt and the sensitivity of households to interest rates. These studies rely on macroeconomic panels or aggregated data, whereas our analysis employs individual-level observations, which allows for a more precise assessment of the relationship between the number of loans and delinquency at the microdata level.

Agarwal and Chua [3] raise the important issue of digital lending and its dual impact—on the one hand, expanding access, and on the other, increasing the risk of excessive borrowing. Our study addresses the indirect effects of digitalization, pointing to the lack of systematic information sharing among lenders, which enables borrowers to obtain loans from multiple institutions within a single day.

4. The Kazakhstani Context

In the Kazakhstani context, the study by Mukan M. et al. [16] raises questions about the influence of financial literacy on the choice of microcredit products but does not analyze socio-demographic factors such as age, income, or family structure. Ishuova Zh., Daribayeva M., and Boluspayev Sh. [17,18] focus on macro-level aspects—consumption smoothing and market regulation—whereas the present study concentrates on the individual level, modeling the probability of delinquency as a function of borrowers' socio-economic characteristics.

Thus, the main distinction of this study from the existing literature lies in:

- the use of micro-level data on actual delinquencies, rather than relying solely on self-reported or aggregated indicators;
- the integration of demographic variables into risk assessment models, including rarely used variables such as per capita income;
- the focus on the regional Kazakhstani context, where the specifics of the financial infrastructure (absence of centralized credit scoring, weak digital transparency, active microcredit expansion) require adapted approaches to risk analysis.

This makes it possible to refine existing findings and provide an empirical basis for developing effective scoring tools tailored to the realities of emerging markets.

The empirical base of the study was formed from a cross-sectional sample of 256 households surveyed in 2023 in the Kapshagay region of Almaty oblast. Data collection was carried out through a targeted questionnaire survey, considering the socio-demographic diversity of respondents (age, gender, education, employment, family composition). The resulting data make it possible to quantitatively assess the impact of socio-economic characteristics on credit behavior and the level of default risk.

The current socio-economic situation in Kazakhstan is characterized by the growth of consumer lending and an increasing debt burden, particularly in vulnerable regions. Against this backdrop, a key question arises: which household characteristics increase the risk of loan delinquencies? To address this, the study formulates the main research question: which socio-economic factors have a significant impact on the probability of delinquency?

For empirical verification, two hypotheses are formulated: H1: An increase in the number of active loans is associated with a higher probability of default; H2: Low per capita household income increases the risk of delinquency. Testing these hypotheses will not only confirm the findings presented in the literature but also adapt them to the regional context. Thus, the study aims to refine the factors of financial vulnerability and to provide an evidence base for corrective policies in the field of consumer lending.

Main part of the study

Macroeconomic Context: Inflation and Rising Indebtedness

A comparison of household lending dynamics with persistently high interest rates and inflationary spikes indicates a deterioration in household debt sustainability. Despite rising living costs, borrowing volumes continue to grow, reflecting the escalating problem of over-indebtedness. The situation appears particularly concerning in 2023, when an inflationary surge did not curb credit expansion but, rather, coincided with its acceleration.

Figure 1 presents the dynamics of consumer lending, inflation, and household income in Kazakhstan for the years 2023–2025.

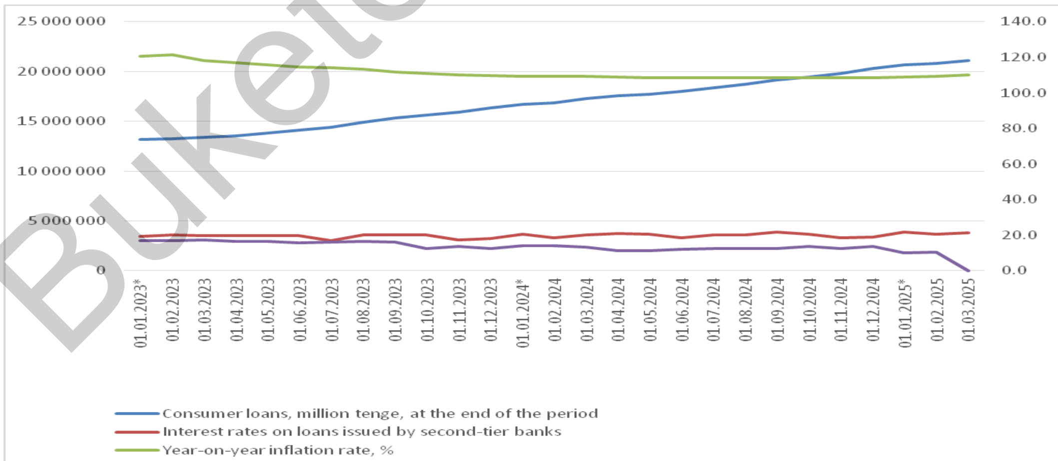

Figure 1 presents the dynamics of consumer lending, inflation, and household income in Kazakhstan for the years 2023–2025.

Note — compiled by the author based on data from the National Bank of the Republic of Kazakhstan [19,20].

As can be seen, the growth of household debt burden significantly outpaces income growth, which exacerbates the problem of over-indebtedness and reduces households' financial resilience. This illustrates how the macroeconomic situation helps explain the micro-level factors identified. An analysis of macroeconomic data for 2023–2025 reveals a pronounced imbalance between the growth of indebtedness and the dynamics of household income. The total volume of loans issued to individuals increased by approximately 70 %—from 13 to 22 trillion tenge—whereas the nominal annual growth of per capita monetary income fluctuated within the range of 10–14 %, with some months even showing a slowdown. Taking into account high inflation, real household income remained almost stagnant or grew only marginally, which reinforced dependence on borrowed funds [19,20].

Of particular concern is that, against the backdrop of inflationary pressure and limited income growth, average interest rates on consumer loans remained at the level of 20–25 % per annum, while in certain segments (e.g., unsecured microfinance) they could exceed 40 %. This makes the debt burden especially heavy for vulnerable household groups. Households are forced to increase borrowing in order to offset the effects of inflation and maintain consumption, while the share of income allocated to debt servicing continues to rise. As a result, their ability to cope with additional expenses or economic shocks deteriorates.

Research Methodology and Statistical Data

To analyze the factors influencing the probability of loan delinquencies among Kazakhstani households, the logistic regression method was applied. This approach is a standard tool for modeling events with binary outcomes, such as the presence or absence of a loan delinquency [21,22]. Logit and probit models make it possible to capture the nonlinear relationship between predictors and the probability of an event, as well as to interpret the results through odds ratios and marginal effects.

The study is based on a cross-sectional sample of 256 households surveyed in 2023 in several localities of Almaty oblast (Kapshagay, Zarechnoye, Kerbulak, and others) [23]. Data collection was carried out within the framework of the *"Society Without Debt"* project of the Uly Dala Association for Rural Business Development, using a stratified questionnaire survey that covered the main socio-demographic characteristics: age, gender, education, employment, family composition, income, and parameters of debt burden (Table 1).

Dependent Variable:

days — a binary variable that takes the value 1 if a loan delinquency of more than 90 days is present, and 0 otherwise;

Key Explanatory Variables:

Numlo — the number of active loans, reflecting the degree of debt burden;

IncPer — per capita household income, calculated as total income (Inc) divided by the number of household members (Perhouse), measured in tenge;

City — type of settlement (urban/rural);

Age — age of the respondent;

Gen — gender of the respondent (male/female);

Edu — level of education (primary, secondary, higher);

Sst — social status (employed, retired, student, etc.);

Monpay — total monthly payment on all loans (in tenge).

Table 1 — Description of Variables Used in the Study

№	Variable	Symbol	Description and Measurement
1	Place of residence of the respondent	City	urban / rural
2	Age	Age	Age of the respondent, years
3	Gender	Gen	Gender of the respondent: male/female
4	Education	Edu	Level of education of the respondent (primary, secondary, higher, etc.)
5	Social Status	Sst	Social status of the respondent (e.g., employed, retired, student, etc.)
6	Large Family	Lfam	Large family (yes/no)
7	How many people live in the household, including the respondent?	Perhouse	Number of people living together in one household
8	Do you have any loans or debts?	Avlo	Does your household currently have any loans or debts? (yes/no)
9	Number of loans	Numlo	Number of active loans in the household
10	Monthly loan payment	Monpay	Amount of total monthly payment on all loans, tenge
11	Are there any loans delinquent for more than 90 days?	days	Presence of overdue loan payments of more than 90 days (yes = 1, no = 0)
12	Total monthly household income	Inc	Total monthly household income, tenge
Note — compiled by the authors based on [23]			

The logit model has the following form:

$$\Pr(\text{days}_i = 1) = \frac{e^{\beta_0+\beta_1\cdot\text{Numlo}_i+\beta_2\cdot\text{IncPer}_i+\beta_3\cdot\text{Age}_i+\beta_4\cdot\text{X}_i}}{1+e^{\beta_0+\beta_1\cdot\text{Numlo}_i+\beta_2\cdot\text{IncPer}_i+\beta_3\cdot\text{Age}_i+\beta_4\cdot\text{X}_i}} \quad (1)$$

where:
$\Pr(\text{days}_i = 1)$ — probability that household i has a loan delinquency,
Numlo_i — number of active loans,
IncPer_i — per capita household income,
X_i — vector of socio-demographic variables (gender, education, status, place of residence),
β — estimated model coefficients.

$$\Pr(\text{days}_i = 1) = \Phi(\beta_0 + \beta_1 \cdot \text{Numlo}_i + \beta_2 \cdot \text{IncPer}_i + \beta_3 \cdot \text{Age}_i + \beta_4 \cdot \text{X}_i) \quad (2)$$

where Φ denotes the standard normal distribution function.

H1: An increase in the number of active loans is associated with a higher probability of delinquency ($\beta_1 > 0$).
H2: Low per capita household income increases the risk of default ($\beta_2 < 0$).

The application of logit and probit models is determined by the binary nature of the dependent variable and is supported by academic practice in credit risk assessment [24]. Both models allow for capturing the probabilistic nature of financial behavior, in contrast to linear regression, which is inadequate for modeling binary outcomes [22].

The proposed empirical model differs from those previously discussed in the literature both in methodological approach and in the context of application. The main distinctions and novelty can be summarized as follows:

1. Regional context and specifics of digital lending.

In contrast to most foreign studies focused on stable financial systems [10,11], the present research relies on data from Kazakhstan—a country with a rapidly developing microcredit market and a relatively high share of vulnerable households. A distinctive feature of the Kazakhstani context is the widespread practice of simultaneously obtaining multiple loans through online applications, often without proper assessment of the borrower's solvency. This circumstance necessitates a specific model that takes into account both the number of loans and demographic characteristics.

2. Per capita income (IncPer)

Unlike most studies that use total household income as an explanatory variable [21], the present research employs the derived variable IncPer—per capita household income. It was constructed from survey data by dividing the total monthly household income (Inc) by the number of household members (Perhouse). Such normalization provides a more accurate measure of financial vulnerability, reflecting the resources available per individual within the household. This is particularly relevant for large families and extended households, which are common in rural areas of Kazakhstan. This approach offers a more sensitive assessment of repayment capacity than using gross household income.

3. Extended use of socio-demographic characteristics.

In contrast to models focused on behavioral indicators of financial vulnerability and their relationship with credit availability and debt burden [14,16], the present study analyzes structural socio-demographic variables: age, gender, education, social status, and household composition. Examining variables such as age, gender, level of education, and family structure makes it possible to better understand hidden factors of social vulnerability that are not directly observable but significantly affect the risk of delinquency. This enhances the accuracy of models under conditions of diverse borrower socio-economic backgrounds.

4. Methodological robustness: logit and probit modeling.

To enhance the reliability of the results, both logit and probit estimations were applied. This dual approach makes it possible to test the robustness of the findings with respect to the specification of the error distribution [22,25]. Both types of models produced consistent results, which strengthens the credibility of the empirical conclusions.

1. Kazakhstani context: original survey microdata are used, reflecting local practices of digital lending, including multiple borrowing and microfinance.

2. Per capita income (IncPer): unlike the traditional approach of using total household income, a more accurate indicator of repayment capacity is proposed, one that is adapted to large families.

3. Integration of socio-demographic variables: the model incorporates factors not typically included in most banking data—age, gender, education, and status—allowing for a more comprehensive assessment of default determinants.

Results and conclusions

The results of the logit and probit regressions are presented in Table 2 and Table 3. The main objective of the analysis is the empirical testing of hypotheses H1 and H2 regarding the impact of the number of active loans and per capita income on the probability of loan delinquencies. The estimations were carried out using robust standard errors.

H1: An increase in the number of loans raises the risk of default ($\beta_1 > 0$);

H2: Low per capita income increases the risk of default ($\beta_2 < 0$).

Table 2 — Results of logit and probit regressions for estimating the probability of delinquency

	Characteristic	Logit	Probit
1	2	3	4
2	Number of observations	252	252
3	Wald chi2(9)	42.21	46.25
4	Prob > chi2	0.0000 (model statistically significant)	0.0000 (model statistically significant)
5	Pseudo R2	0.1964	0.1977
6	Numlo (coefficient)	0.541216 (statistically significant, p = 0.005)	0.3071444 (statistically significant, p = 0.002)
7	Other variables	Age, IncPer, City, Gen, Edu, Sst: not statistically significant (p > 0.05)	Age, IncPer, City, Gen, Edu, Sst: not statistically significant (p > 0.05)
8	Constant	-2.604637 (statistically significant, p = 0.010)	-1.56204 (statistically significant, p = 0.001)
Note — compiled by the authors based on [23]			

In both models, the variable Numlo is a significant predictor with a positive effect on the probability of default, fully confirming hypothesis H1.

Table 3 — Results of Logit and Probit Regressions for Hypothesis Testing

	Variable	Logit: Coef. (p-value)	Probit: Coef. (p-value)	Hypothesis outcome
1	2	3	4	5
2	Numlo (number of loans)	0.541 (0.005)	0.307 (0.002)	H1 confirmed
3	IncPer (per capita income)	–0.521 (0.455)	–0.305 (0.342)	H2 not confirmed
4	Age	0.181 (0.563)	0.116 (0.469)	Not significant
5	City	–0.688 (0.482)	–0.301 (0.505)	Not significant
6	Gen	–1.252 (0.300)	–0.476 (0.319)	Not significant
Note — compiled by the authors based on [23]				

In both models, the variable Numlo is a significant predictor with a positive effect on the probability of default, fully confirming hypothesis H1.

The variable IncPer shows a negative sign in both models, which is consistent with hypothesis H2; however, in both cases the coefficients are statistically insignificant.

The results of the logistic and probit regressions showed that the number of open credit lines (Numlo) has a statistically significant positive effect on the probability of loan delinquency. This confirms the hypothesis that borrowers with a larger number of open credit lines are more prone to delinquencies. However, other socio-demographic variables, such as age, per capita income, place of residence, gender, education, and social status, did not show a statistically significant impact on the probability of delinquency. Both models (logistic and probit) demonstrated overall statistical significance ($p < 0.0001$), but relatively low pseudo R^2

values (around 0.19), indicating that other important factors influencing the probability of delinquency are not captured in the model.

Table 4 — Marginal Effects (margins, dy/dx)

	Variable	Logit: dy/dx (p)	Probit: dy/dx (p)
1	2	3	4
2	Numlo	0.0192 (0.036)	0.0256 (0.014)
3	IncPer	–0.0185 (0.476)	–0.0255 (0.387)
Note — compiled by the authors based on [23]			

The effect of the variable Numlo on the probability of default is significant in both the logit and probit models: an additional loan increases the risk of delinquency by approximately 2–2.5 %.

The effect of income (IncPer) is negative but statistically insignificant.

The analysis of marginal effects for the logit model showed that the number of open credit lines (Numlo) has a statistically significant positive impact on the probability of loan delinquency. An increase of one active loan raises the probability of delinquency by an average of 1.92 percentage points ($p = 0.036$), all else being equal.

A similar result was obtained in the probit model: the variable Numlo also demonstrated a positive and statistically significant effect. An additional credit line increases the probability of default by an average of 2.56 percentage points ($p = 0.014$) (Table 4).

Other socio-demographic characteristics—age, per capita income, type of settlement, gender, level of education, and social status—did not show a statistically significant effect on the probability of delinquency in either model ($p > 0.1$).

To estimate the marginal effects, mean values of the predictors were used, along with robust standard errors, which account for potential heteroskedasticity and enhance the reliability of interpretation.

Table 5 — Classification Quality

	Metric	Logit Model	Probit Model
1	2	3	4
2	Classification accuracy	93.65 %	93.65 %
3	Sensitivity	11.76 %	11.76 %
4	Specificity	99.57 %	99.57 %
5	PPV (precision)	66.67 %	66.67 %
6	NPV	93.98 %	93.98 %
Note — compiled by the authors based on [23]			

Both models—the logistic and probit regressions—demonstrated high overall classification accuracy (93.65 %), indicating their ability to correctly identify the majority of borrowers. However, a more detailed analysis of performance metrics revealed a substantial imbalance between sensitivity and specificity.

In particular, the sensitivity of both models was only 11.76 %, indicating an extremely low ability to detect borrowers with an actual risk of default. In other words, the models correctly classify only about one out of nine borrowers who became delinquent. This critically limits their practical value for credit institutions, as a significant number of high-risk clients remain unidentified.

At the same time, the specificity of the models turned out to be very high—99.57 %, indicating a high accuracy in recognizing reliable payers. Such asymmetry in model performance points to a bias toward the majority class (clients without delinquencies), which may be a consequence of strong class imbalance in the sample.

Low sensitivity is a key limitation: it increases the likelihood of granting loans to borrowers with a high risk of delinquency, which, in turn, may lead to substantial financial losses.

The estat classification command showed:

Overall classification accuracy: 93.65 %

Sensitivity (true positive rate): 11.76 %

Specificity (true negative rate): 99.57 %

This means that the model predicts the absence of default well, but performs poorly in predicting its occurrence, which is typical for imbalanced samples with a low share of defaults (Table 5).

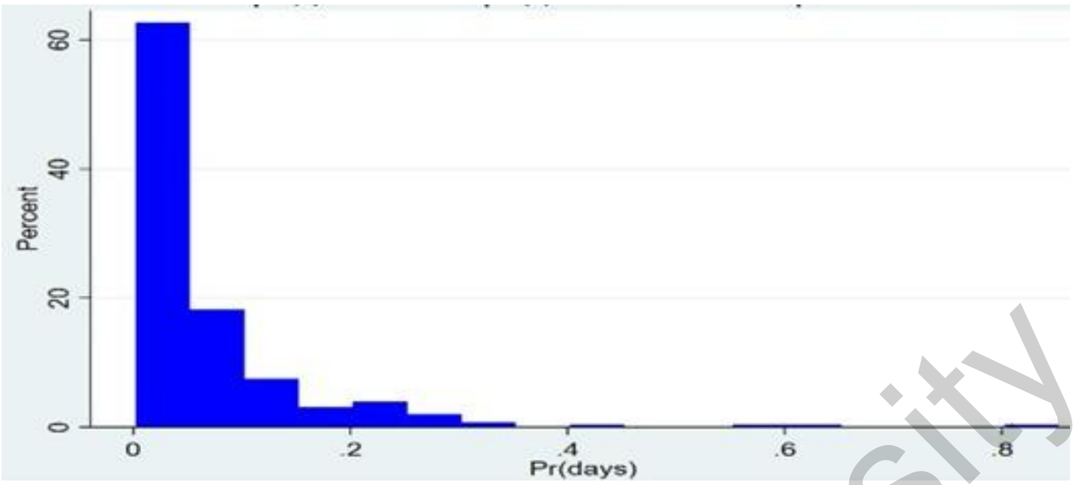

Figure 2 — Distribution of Predicted Probabilities of Default

Note — visualization and analytical processing of data were carried out using artificial intelligence tools based on [23].

The distribution of predicted default probabilities in Figure 2 shows that most households are concentrated in the low-probability zone (<10 %). However, there is a clearly defined "risk group" with probabilities above 30 %. This indicates the existence of vulnerable households characterized by a high debt burden and weak financial resilience.

5. Goodness-of-Fit (Pearson Test)
Model χ^2 (df = 152), Logit: 241.08
Model χ^2 (df = 152), Probit: 214.37
p-value Logit = 0.0000
p-value Probit = 0.0006

The probit model shows a better fit to the data (smaller deviation), although both models formally fail the goodness-of-fit test—an indication of possible model misspecification.

6. Multicollinearity (VIF)
Logit model: Mean VIF = 5.31
Probit model: Mean VIF = 2.87

Both models show no signs of serious multicollinearity (VIF < 10). The probit model demonstrates a more stable predictor structure.

The results of the analysis confirmed the significance of the variable "number of active loans" in predicting the risk of delinquency, thereby supporting hypothesis H1. An increase in the number of active loans statistically significantly raises the probability of default in both the logit and probit models, with similar coefficients and marginal effects.

At the same time, hypothesis H2, which assumed a negative effect of income level on the risk of delinquency, did not receive statistical support. Although the coefficients had the expected sign, they did not reach statistical significance, which may indicate the influence of unobserved factors—such as income instability, type of credit product, or borrowers' behavioral characteristics.

Despite high overall classification accuracy (93.65 %), both models demonstrated extremely low sensitivity (11.76 %), which substantially limits their practical applicability. The probit model showed slightly better robustness according to the goodness-of-fit criterion (χ^2), as well as lower multicollinearity (VIF) and a somewhat stronger marginal effect for the key variable Numlo.

In addition, the Pearson test revealed a statistically significant deviation of both models from the observed data, which may be associated with omitted predictors, unaccounted nonlinear relationships, or specification errors.

Recommendations for model improvement:

Use class balancing methods (SMOTE, weighted loss functions);

Include additional behavioral and macroeconomic variables;

Lower the classification threshold;

Apply modern machine learning algorithms (XGBoost, Random Forest).

Conclusions

The conducted study made it possible to empirically confirm a significant relationship between the level of household indebtedness and the risk of delinquency, which is consistent with the findings of a number of foreign studies [26]. It was established that each additional loan obligation increases the probability of default, making this indicator a key factor in the construction of scoring models.

At the same time, per capita household income did not demonstrate statistical significance, despite the negative direction of its effect. This may be explained by the fact that formal income does not reflect the actual repayment capacity of borrowers, particularly under conditions of digital and parallel borrowing. These findings are consistent with Madeira [15], who emphasizes that income instability and unpredictability are more important than its nominal level.

The analysis also revealed the influence of social status and credit accessibility, highlighting the need to account for behavioral and institutional factors in credit risk assessment models. The obtained results demonstrate the potential of logistic models when relevant variables are included; however, they also indicate the limited predictive power of such models without addressing class imbalance and behavioral aspects.

Practical Recommendations

- Development of scoring tools that are sensitive to the number of active loans, taking into account the structure of current debt rather than relying solely on formal repayment capacity.
- Digitalization of credit data through a unified platform that allows for tracking parallel loan applications submitted by borrowers across different MFIs and banks.
- Creation of early warning systems for borrowers with multiple loans, including referral to debt management programs.
- Expansion of financial literacy programs, with a focus on socially vulnerable groups (pensioners, students, the unemployed).
- Introduction of restrictions on multiple borrowing for clients with a high debt burden, in order to reduce systemic risk.

Directions for Further Research

Expansion of the sample and use of panel data to analyze the dynamics of credit behavior.

Application of machine learning techniques (Random Forest, XGBoost) to identify non-trivial patterns of default behavior.

Inclusion of psychological and behavioral factors, including analysis of borrowers' digital activity (frequency of online loans, behavior on lenders' websites).

Evaluation of the effectiveness of implemented recommendations based on experimental or quasi-experimental data.

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