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KAZAKH KBTU BRITISH
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Methods of Credit Portfolio Risk Analysis

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RELEVANCE OF THE TOPIC

The Growing Importance of Credit Risk Analysis

In today’s complex financial landscape, credit risk has emerged as one of the most critical challenges faced by banks, microfinance institutions, and regulators. The increasing volume of credit transactions, coupled with the volatility of borrower behavior, has made traditional assessment methods insufficient. Amid high delinquency levels and the limitations of static risk models, the demand for advanced, data-driven approaches is growing rapidly. The regulatory environment — shaped by Basel III, IFRS 9, and national supervisory standards — now requires institutions not only to estimate credit risk more accurately but also to provide transparent and interpretable justifications for their assessments.

The ability to detect early signs of borrower distress, monitor shifts in portfolio risk profiles, and make informed, real-time decisions is essential for maintaining financial stability. This need has driven the integration of mathematical modeling and machine learning into credit risk evaluation processes. The relevance of this topic is particularly strong in Kazakhstan’s financial sector, where risk oversight and digital transformation are strategic priorities. In this context, analyzing credit portfolio risk through quantitative and algorithmic methods is not only a research objective but a response to the evolving demands of modern finance.

PURPOSE AND RESEARCH OBJECTIVES

The primary aim of this diploma project is to explore and apply practical methods for credit portfolio risk analysis through the lens of mathematical and computer modeling.

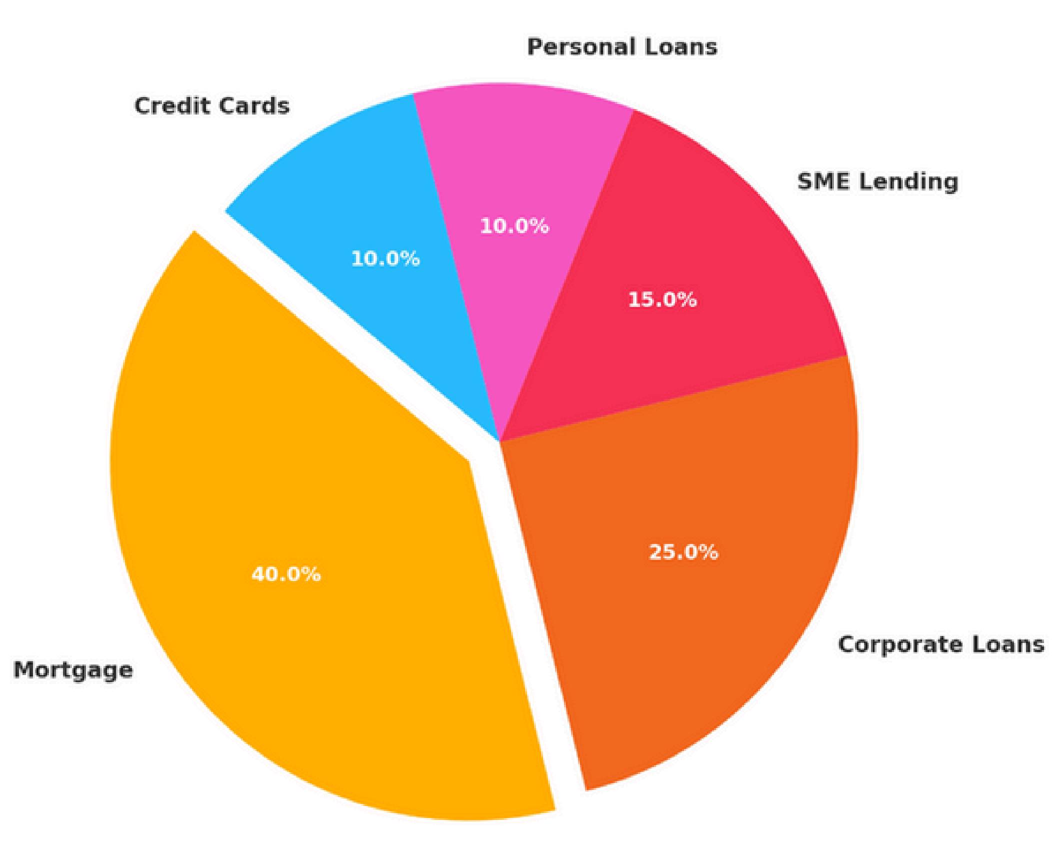
To achieve this objective, the following three main objectives were defined:

- 1.To study and describe the main concepts and models related to credit risk assessment, with a particular focus on how risk is measured and classified in portfolio analysis.
- 2.To develop and implement a mathematical model capable of assessing credit risk based on available data, including categorization of clients by risk level.
- 3.To interpret and visualize the results of the model, identifying patterns in credit behavior and drawing conclusions about the effectiveness of the proposed approach.

Theoretical Foundation

Macroeconomic Indicator	Expected Impact on Credit Risk	Level of Correlation (empirical)
Inflation Rate	Increases default likelihood	High
Unemployment Rate	Weakens repayment capacity	High
Exchange Rate Volatility	Affects foreign-currency borrowers	Medium
Interest Rate Shocks	Increases loan servicing burden	Very High
GDP Growth	Improves overall credit performance	Negative correlation

The Impact of Macroeconomic Factors on NPL Growth

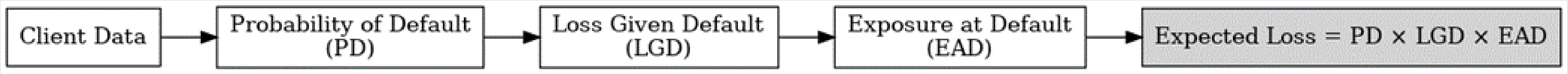


Structure of the loan portfolio by segments

Supervisory Tool	Purpose	Institution Responsible
Stress Testing	Assess resilience under shock	ARDFM / NBRK
Minimum Capital Adequacy Ratio	Ensure solvency	ARDFM
Credit Risk Classification	Prevent portfolio degradation	Commercial banks
Disclosure of ECL (IFRS 9)	Transparency in expected losses	Commercial banks
RegTech Monitoring	Early detection of systemic risk	ARDFM

Supervisory Tools Used in Kazakhstan's Credit Risk Regulation

METHODOLOGY AND MATHEMATICAL MODEL



Components of Expected Credit Loss Calculation

The total probability of transitions from any state must equal 1 (1):

$$\sum_{j=1}^{5} p_{ij} = 1$$

To formalize this behavior over time, we can apply discrete-time difference equations.

$$x_j(t+1) = \sum_{i=1}^{5} q_{ij} * x_i(t)$$

This equation models how clients redistribute themselves across different risk categories as time progresses, depending on the transition matrix

$$\frac{dx_j(t)}{dt} = \sum_{i=1}^{5} q_{ij} * x_i(t)$$

DATA ARCHITECTURE AND FEATURE ENGINEERING STRATEGY

Window	Covered Months	Overdue Count	Risk Category
risk_cat_m0	C0–C12	3	Doubtful 1
risk_cat_m1	C1–C13	4	Doubtful 2
risk_cat_m2	C2–C14	4	Doubtful 2
risk_cat_m3	C3–C15	3	Doubtful 1
risk_cat_m4	C4–C16	3	Doubtful 1
risk_cat_m5	C5–C17	3	Doubtful 1
risk_cat_m6	C6–C18	3	Doubtful 1
risk_cat_m7	C7–C19	4	Doubtful 2
risk_cat_m8	C8–C20	4	Doubtful 2
risk_cat_m9	C9–C21	4	Doubtful 2
risk_cat_m10	C10–C22	4	Doubtful 2
risk_cat_m11	C11–C23	3	Doubtful 1
risk_cat_m12	C12–C24	4	Doubtful 2

Example of Risk Label Assignment Across Rolling

SUPERVISED LEARNING FOR RISK GROUP PREDICTION

	precision	recall	f1-score	support
0	1.00	1.00	1.00	12
Дефолтные	1.00	1.00	1.00	3
Сомнительная 2	1.00	1.00	1.00	5
Сомнительная 3	1.00	1.00	1.00	11
accuracy			1.00	31
macro avg	1.00	1.00	1.00	31
weighted avg	1.00	1.00	1.00	31

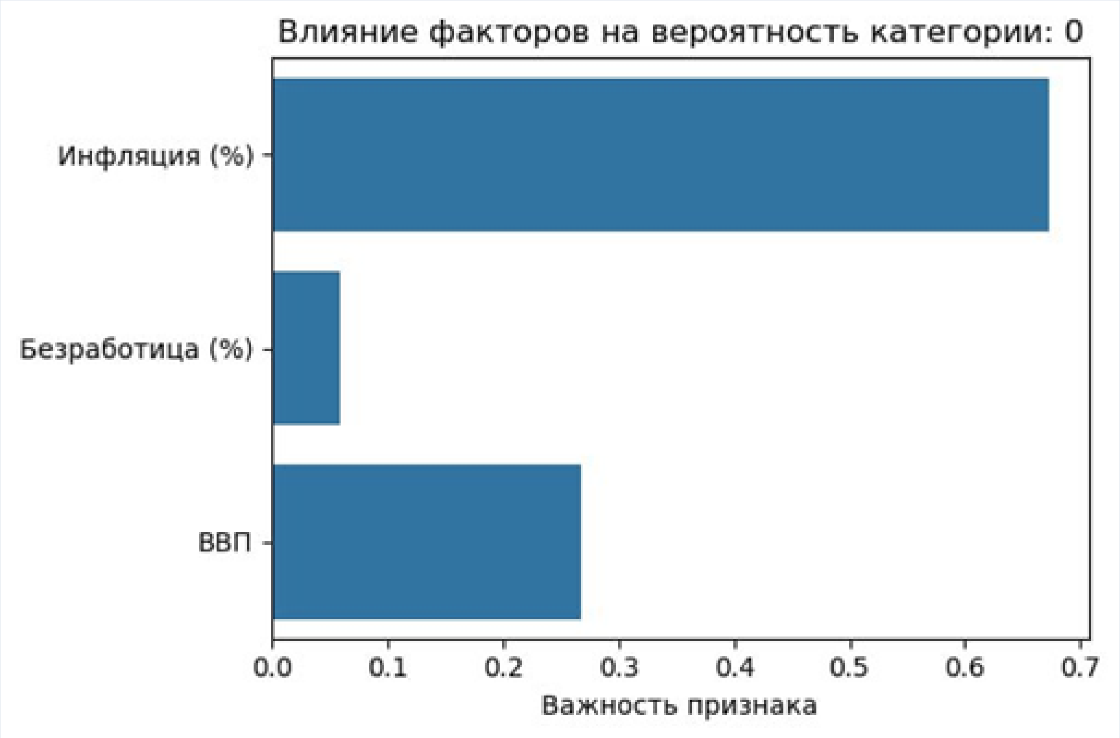
Классификационный отчёт:

Classification Report for Random Forest Model on Test Set

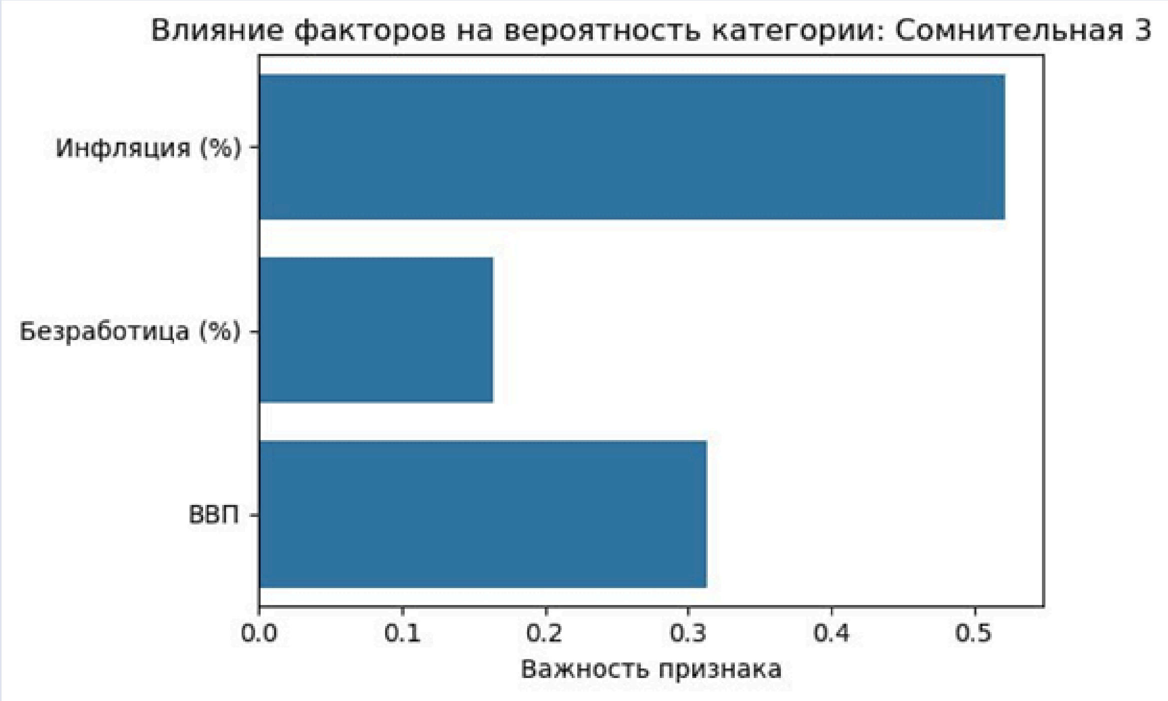
Feature	Relative Evaluation
risk_cat_m6	0.157
risk_cat_m7	0.143
overdueamount	0.132
DTI3M	0.121
risk_cat_m5	0.114
total_amount_kzt	0.098
term	0.091
AGE	0.078
AS3M	0.066

Ranked importance of features in the Random Forest model

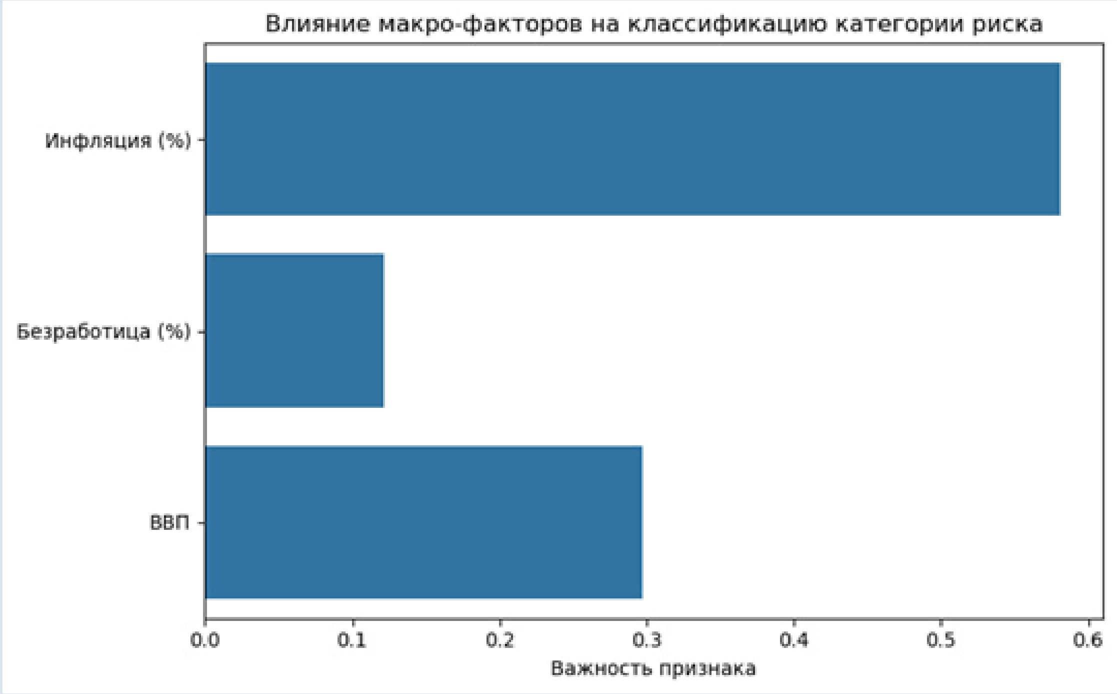
MODEL DEPLOYMENT AND INTERPRETABILITY ANALYSIS



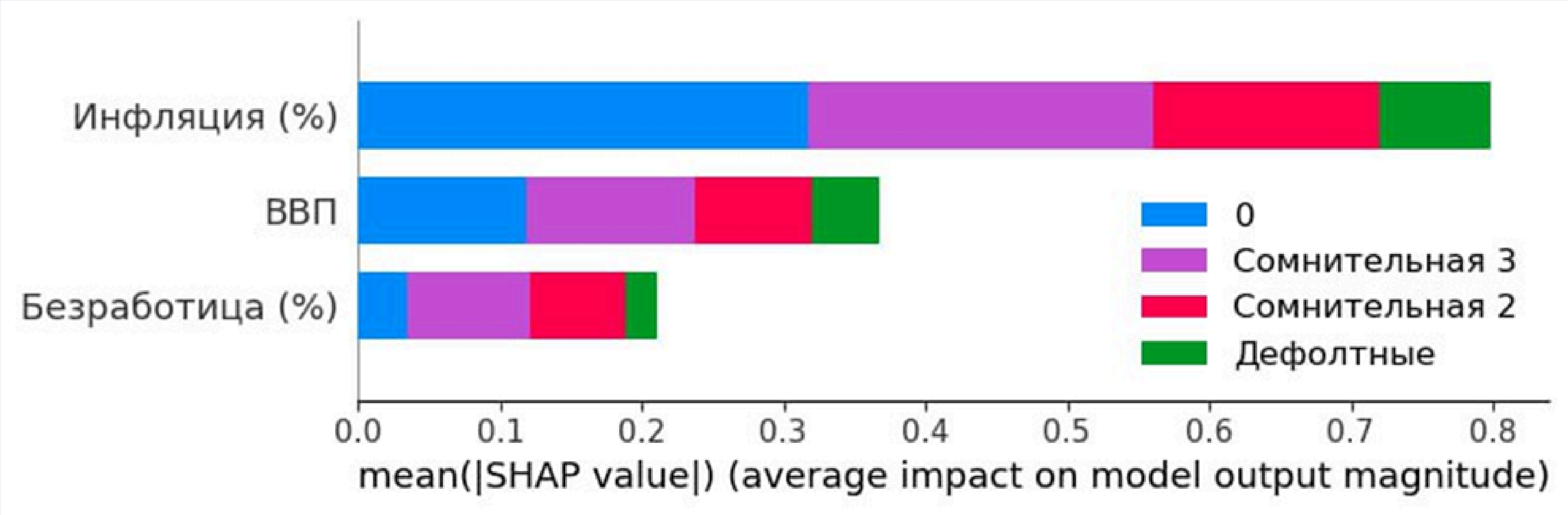
Influence of Macroeconomic Indicators on Probability of Classifying a Borrower as Category 0 (Standard)



Influence of Macroeconomic Indicators on Probability of Category “Doubtful 3”

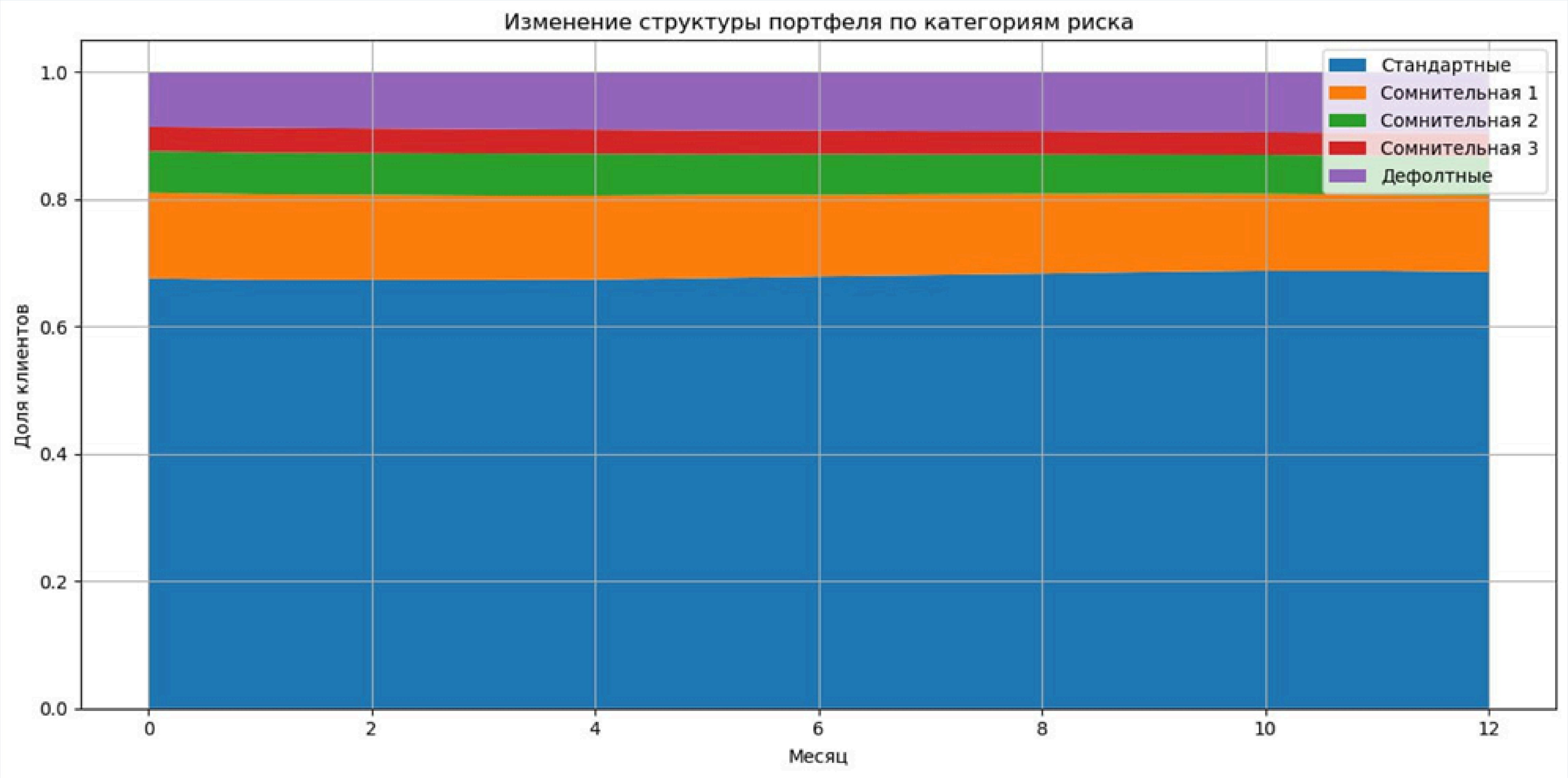


Aggregate Influence of Macroeconomic Factors Across All Risk Categories



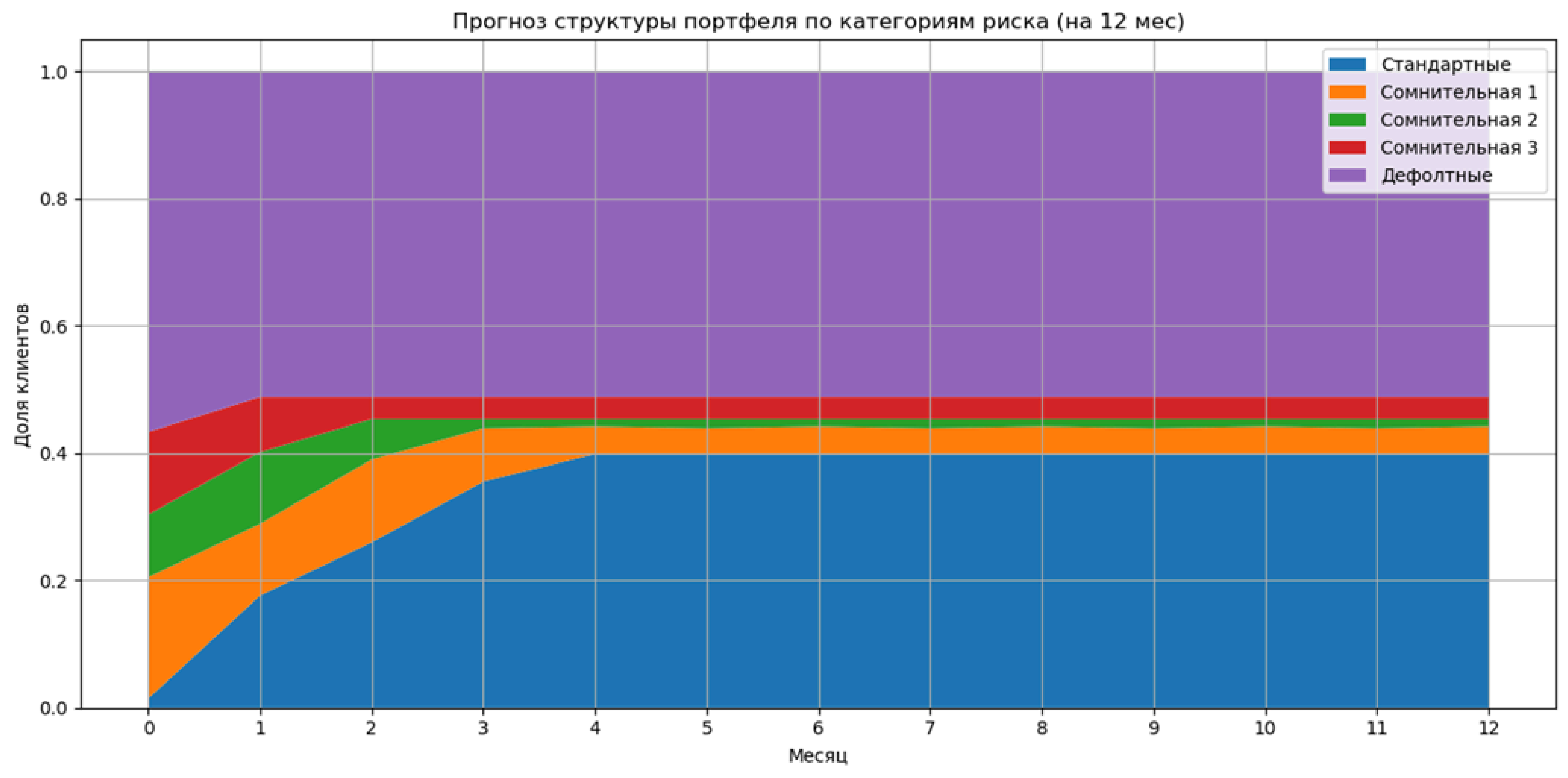
Average SHAP Impact by Risk Category and Feature

RISK CATEGORY DISTRIBUTION VISUALIZATION



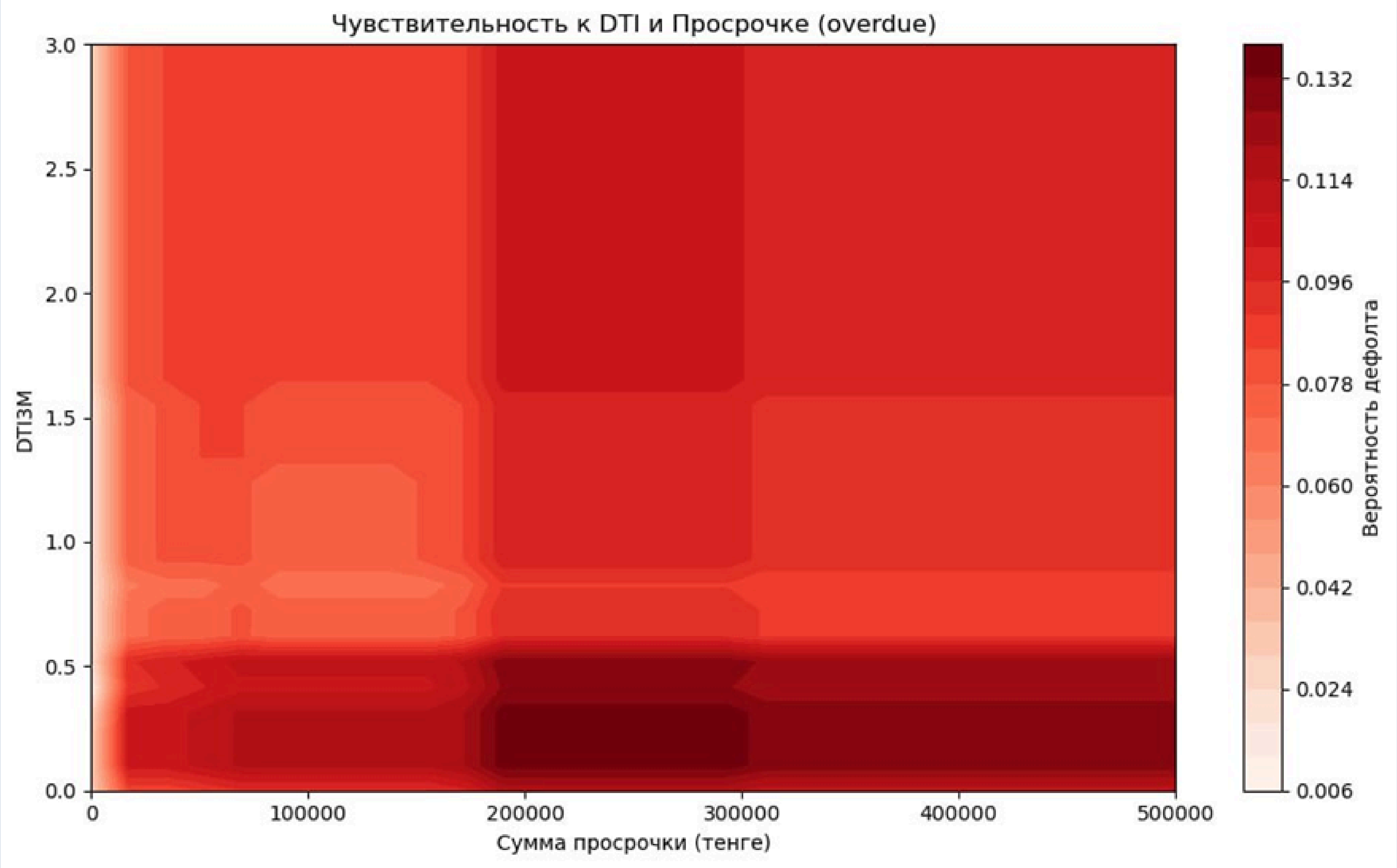
Portfolio structure evolution by risk categories over time

RISK CATEGORY DISTRIBUTION VISUALIZATION



Replication of portfolio structure trends

RISK CATEGORY DISTRIBUTION VISUALIZATION



Default Probability Surface Based on Debt-to-Income (DTI3M) and Overdue Amount

RISK CATEGORY DISTRIBUTION VISUALIZATION

To obtain a deeper understanding of the dynamics of credit risk, the work constructed sequential matrices of transitions between categories in different time intervals. Each of them reflects the possibility of moving clients between risk classes from month to month.

Risk Transition Matrix: Month 1 → Month 13

Conclusion

Throughout this thesis project, we moved from a theoretical exploration of credit risk to the development and implementation of a practical model capable of analyzing and forecasting portfolio-level risk. By incorporating both behavioral and financial client data, we applied a rolling window approach for dynamic analysis and employed machine learning techniques—specifically Random Forests—with interpretable outputs. This ensured the model was not only accurate but also transparent and actionable for analysts, risk managers, and regulatory stakeholders.

Special focus was placed on real-world applicability: threshold calibration, integration into business processes, API deployment, and interactive visual tools. We demonstrated that effective risk management requires a holistic approach that combines theory, data, and business context. The resulting system can serve as a foundation for ongoing credit risk monitoring and proactive decision-making in financial institutions.

Thank you for your attention!