

DEVELOPING AN EARLY WARNING SYSTEM FOR LOAN CLASSIFICATION AND CREDIT RISK MANAGEMENT

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ABSTRACT

This thesis examines the development of an early warning system (EWS) for improving loan classification and credit risk management in commercial banks and other lending institutions. The proposed framework integrates borrower-level financial indicators, repayment behaviour, account activity, collateral quality, sectoral conditions, and macroeconomic signals into a unified risk-monitoring process. The study emphasizes the transition from periodic, backward-looking loan review to continuous and forward-looking risk detection. A multi-stage architecture is proposed in which data are collected, transformed into risk indicators, scored through rule-based and statistical models, and translated into traffic-light warning categories. The results of the framework design show that an effective EWS should not rely on a single probability-of-default estimate; it should combine quantitative thresholds, trend deterioration, behavioural triggers, and expert review. Such an approach can support earlier reclassification of vulnerable exposures, reduce delays in remedial actions, strengthen provisioning discipline, and improve portfolio-level risk visibility. The thesis also outlines governance requirements, model validation principles, and implementation priorities for banks seeking to align internal credit processes with IFRS 9 and modern supervisory expectations.

Keywords: early warning system, loan classification, credit risk, probability of default, non-performing loans, IFRS 9, credit monitoring, risk indicators.

ANNOTATSIYA

Ushbu tezis tijorat banklari va boshqa kredit tashkilotlarida kreditlarni tasniflash hamda kredit riskini boshqarishni takomillashtirish uchun erta ogohlantirish tizimini (EWS) ishlab chiqish masalalarini yoritadi. Taklif etilayotgan model qarz oluvchining moliyaviy ko'rsatkichlari, to'lov intizomi, hisobvaraqlar harakati, garov sifati, tarmoq holati va makroiqtisodiy signallarni yagona risk-monitoring jarayoniga birlashtiradi. Tadqiqot davriy va ortga qarab baholashga asoslangan kredit monitoringidan uzluksiz hamda istiqbolga yo'naltirilgan riskni

aniqlash tizimiga o'tish zarurligini asoslaydi. Ko'p bosqichli arxitektura doirasida ma'lumotlarni yig'ish, risk indikatorlarini shakllantirish, ularni qoidaviy va statistik modellar orqali baholash hamda "yashil-sariq-qizil" ogohlantirish zonalariga ajratish taklif etiladi. Natijalar shuni ko'rsatadiki, samarali EWS faqat bitta defolt ehtimoli ko'rsatkichiga tayanmasligi, balki miqdoriy chegaralar, salbiy trendlar, xulq-atvor triggerlari va ekspert tahlilini birlashtirishi lozim. Mazkur yondashuv muammoli kreditlarni erta aniqlash, tasniflashni o'z vaqtida yangilash, zaxiralash intizomini kuchaytirish va kredit portfeli riskini yaxshiroq boshqarishga xizmat qiladi.

Kalit so'zlar: erta ogohlantirish tizimi, kreditlarni tasniflash, kredit riski, defolt ehtimoli, muammoli kreditlar, IFRS 9, kredit monitoringi, risk indikatorlari.

АННОТАЦИЯ

В тезисе рассматривается разработка системы раннего предупреждения (Early Warning System, EWS), предназначенной для повышения качества классификации кредитов и управления кредитным риском в коммерческих банках и других кредитных организациях. Предлагаемая концепция объединяет финансовые показатели заемщика, платежную дисциплину, движение по счетам, качество обеспечения, отраслевые условия и макроэкономические сигналы в единую систему мониторинга риска. Обосновывается переход от периодического и ретроспективного анализа кредитов к непрерывному и перспективному выявлению признаков ухудшения качества активов. Предложена многоэтапная архитектура, включающая сбор данных, формирование индикаторов риска, оценку на основе правил и статистических моделей, а также распределение заемщиков по зонам «зеленый-желтый-красный». Результаты разработки показывают, что эффективная EWS не должна основываться исключительно на одном показателе вероятности дефолта: необходима интеграция количественных порогов, негативных трендов, поведенческих триггеров и экспертной оценки. Такая система способствует более раннему выявлению проблемных кредитов, своевременной реклассификации, повышению качества резервирования и прозрачности кредитного портфеля.

Ключевые слова: система раннего предупреждения, классификация кредитов, кредитный риск, вероятность дефолта, проблемные кредиты, IFRS 9, кредитный мониторинг, индикаторы риска.

INTRODUCTION

Credit risk remains one of the most material sources of potential loss for banks because the deterioration of a borrower's financial position is often gradual, while formal default recognition occurs only after the risk has already become severe. Traditional loan monitoring practices may therefore detect problems too late, particularly when they depend mainly on overdue status, annual financial statements, or manual portfolio reviews. An early warning system addresses this weakness by identifying deterioration signals before a contractual default or non-performing loan classification occurs.

The importance of early detection has increased under forward-looking accounting and supervisory frameworks. IFRS 9 requires banks to recognize expected credit losses and to identify significant increases in credit risk in a timely manner. At the same time, modern supervisory practice places greater emphasis on sound loan origination, continuous monitoring, borrower affordability, collateral quality, and timely management of distressed exposures. Consequently, loan classification can no longer be treated as a static accounting procedure; it must be linked to a dynamic process of risk identification, escalation, and corrective action.

The purpose of this thesis is to develop a practical EWS architecture for loan classification and credit risk management. The study focuses on four questions: which indicators should be monitored, how these indicators should be combined, how warning signals should affect loan classification and management actions, and what governance mechanisms are necessary to prevent false alarms or delayed intervention.

MAIN PART

An effective EWS begins with a clear data architecture. The core dataset should integrate information from the loan management system, current and settlement accounts, credit bureau records, financial statements, collateral registers, customer relationship management systems, and external macroeconomic databases. These data sources are complementary. Financial statements describe solvency and profitability, transactional data reveal current liquidity behaviour, credit bureau data capture indebtedness across lenders, collateral data affect loss severity, and macroeconomic variables provide a forward-looking view of sector and regional vulnerability.

At the borrower level, the most useful financial indicators include leverage, debt-service coverage ratio, interest coverage ratio, current ratio, operating cash-flow adequacy, profitability, revenue growth, receivables turnover, and capital erosion. Deterioration should be assessed not only against fixed thresholds but also against the borrower's own historical trend and peer group. For example, a debt-

service coverage ratio that remains above the formal minimum may still be an important warning signal if it has fallen sharply over several reporting periods.

Behavioural indicators provide earlier information for retail and small-business portfolios. Relevant triggers include increasing days past due, repeated use of grace periods, frequent overdrafts, declining account turnover, cash withdrawal spikes, missed salary inflows, repeated restructuring requests, utilization near credit limits, and rapid increases in external borrowing. These variables are particularly valuable because they can be updated daily or monthly, whereas audited financial statements may be available only annually.

The proposed EWS combines three analytical layers. The first layer is a rule-based trigger engine. It identifies hard events such as payments more than a predefined number of days past due, covenant breaches, adverse legal events, collateral impairment, or material credit bureau deterioration. The second layer uses a statistical risk score or probability-of-default model to estimate the borrower's changing default risk. The third layer applies trend analysis and expert judgement to capture information that is not fully represented in historical data, such as management instability, a sudden loss of a major customer, supply-chain disruption, or sector-specific regulatory change.

For operational purposes, the combined result can be translated into a traffic-light classification. A green exposure has no material warning signs and remains under standard monitoring. A yellow exposure shows early deterioration and should be subject to enhanced monitoring, updated borrower information, tighter limits, or a review of staging under IFRS 9. A red exposure shows severe deterioration and requires immediate remedial action, intensive credit review, restructuring assessment, collateral revaluation, or transfer to a workout unit. Importantly, the warning category should not automatically replace regulatory asset classification; it should serve as an input that prompts timely reassessment.

Table 1. Core EWS indicators and management responses

Indicator group	Examples	Warning logic	Typical action
Financial	DSCR, leverage, liquidity, profitability	Threshold breach or negative trend	Request updated financials; revise rating
Behavioural	DPD, overdrafts, account turnover, utilization	Repeated or accelerating deterioration	Enhanced monitoring; contact borrower
External	Credit bureau, litigation, sector stress	Material adverse event	Reassess PD, limits, and classification

Collateral	Coverage ratio, valuation age, marketability	Decline in coverage or enforceability	Revalue collateral; revise recovery assumptions
Macroeconomic	Rates, inflation, unemployment, sector output	Scenario deterioration	Portfolio overlays; sector limits; stress testing

RESULTS AND DISCUSSION

The design analysis yields five principal results. First, early warning performance improves conceptually when the system integrates both stock variables and flow variables. Stock variables such as leverage and collateral coverage describe the borrower's current position, while flow variables such as changes in account turnover, payment delays, and cash-flow volatility reveal the direction of risk. A system based only on static ratios can therefore miss rapid deterioration.

Second, signal prioritization is essential. If every minor deviation generates an alert, credit officers experience alert fatigue and may ignore important cases. The framework therefore recommends a hierarchy of triggers: critical events that require immediate escalation, material deterioration indicators that require review within a defined period, and soft signals that become relevant only when several occur together. This reduces noise while preserving sensitivity to genuine deterioration.

Third, loan classification should incorporate both current delinquency and forward-looking deterioration. A borrower may still be contractually current while its risk has increased substantially. Examples include a sharp fall in cash inflows, repeated covenant waivers, a significant increase in external debt, or the loss of a key market. In such cases, an EWS provides a structured basis for reviewing internal rating, IFRS 9 staging, pricing, exposure limits, and provisioning before arrears become severe.

Fourth, the system should be calibrated separately for major portfolio segments. Retail, mortgage, SME, corporate, and agricultural borrowers generate different data and exhibit different default patterns. A single universal threshold can therefore create systematic bias. Segment-specific models, combined with a consistent governance framework, provide a better balance between comparability and predictive relevance.

Fifth, governance is as important as model accuracy. Each alert should have an owner, escalation deadline, documented resolution, and audit trail. Model performance should be monitored through back-testing, stability analysis, discriminatory power, calibration, and override statistics. Management should also

review whether alerts lead to timely actions and whether repeated false positives are concentrated in particular segments. Without these controls, an EWS can become a reporting exercise rather than a genuine risk-management mechanism.

A practical implementation sequence can be organized into four stages. Stage 1 establishes a minimum viable EWS using high-quality internal behavioural and delinquency data. Stage 2 adds borrower financial ratios and credit bureau information. Stage 3 introduces statistical or machine-learning models and macroeconomic overlays. Stage 4 integrates the system with pricing, IFRS 9 staging, collections, restructuring, and portfolio stress testing. This phased approach limits implementation risk and allows institutions to improve data quality before introducing more complex models.

The main limitation of the proposed framework is that its predictive effectiveness depends on data completeness, local portfolio characteristics, and institutional calibration. Therefore, the indicator set and thresholds should not be copied mechanically from another bank. They must be validated against the institution's own default history and adjusted for product type, borrower segment, reporting frequency, and economic environment.

CONCLUSION

An early warning system is a critical bridge between loan monitoring, loan classification, expected credit loss measurement, and active credit risk management. Its primary value lies not in generating more data, but in transforming dispersed information into timely and prioritized management signals. The proposed framework combines financial ratios, behavioural indicators, external information, collateral quality, and macroeconomic factors within a three-layer analytical structure consisting of rule-based triggers, statistical risk scoring, and expert judgement.

The study concludes that an effective EWS should be forward-looking, segment-specific, explainable, and directly linked to management actions. Green, yellow, and red risk zones can simplify escalation, but the underlying thresholds must be calibrated and independently validated. Banks should also avoid excessive dependence on a single model or probability-of-default estimate. The strongest approach is a hybrid system in which quantitative analytics support, rather than replace, professional credit judgement. When embedded into governance, provisioning, limit management, and workout processes, such a system can improve the timeliness of loan reclassification, reduce credit losses, and strengthen the resilience of the loan portfolio.

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