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Research on the optimization and coordination mechanism of early warning indicators for financial crises under the trend of financial regulatory innovation

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Abstract. To effectively prevent the outbreak of financial crises, constructing a resilient early-warning mechanism now constitutes a core mandate in macroprudential supervision. This paper employs literature review methods, combined with case analysis and the macroprudential regulatory framework, to explore optimization methods for early warning indicators of financial crises under new trends in financial regulation, and proposes innovative approaches. The paper investigates how to identify and quantify the three key drivers of financial crises: macroeconomic imbalances, market over-speculation, and financial institution risks; innovative approaches leveraging high-frequency financial datasets with ensemble learning algorithms to enhance the real-time accuracy of early warning indicators; the synergistic effects of cross-level regulatory information sharing, multi-stakeholder collaborative processes, and two-way feedback mechanisms; and demonstrates that constructing a multi-dimensional indicator system covering macro, market, and institutional levels can comprehensively reflect the accumulation and propagation of systemic risks. The utilization of big data feature engineering and machine learning models has significantly improved the prompt detection of warning signals, resulting in a marked decrease in false alarm rates. Information sharing and multi-party collaborative warning processes, combined with two-way feedback between market participants and regulators, have achieved closed-loop management and synergistic efficiency gains in the warning system.

Keywords: financial crisis, risk warning, collaborative regulatory mechanism, big data, new trends in financial regulation

1. Introduction

The frequent occurrence of financial crises has sparked global concern over the stability of the financial system, especially in a globalised financial environment where the interdependence of financial markets means that a financial crisis in any one country can have global repercussions [1]. Consequently, identifying the early indicators of a financial crisis and implementing effective interventions has emerged as a critical concern for global financial regulation. As financial markets become increasingly complex, traditional financial crisis early warning models have gradually revealed their limitations, and the selection and application of early warning indicators urgently require optimisation. Against this backdrop, new regulatory trends require profound optimization of early-warning indicators to enhance financial system resilience, enabling timely crisis response and effectively preventing the outbreak of financial crises [2].

Early warning indicators have traditionally relied on macroeconomic data (such as GDP growth rates, unemployment rates, and price indices), but these indicators have inherent lagginess and struggle to promptly reflect financial market risks [3]. As a result, scholars have begun to explore the use of multi-dimensional data sources to construct more precise warning systems. Some scholars have proposed indicators based on market sentiment and investor behaviour; scholars contend that market sentiment predicts financial crisis emergence [4]. With technological advancements, an increasing number of studies have begun to explore the application of big data and artificial intelligence technologies in financial crisis early warning models. However, existing research still has shortcomings in the synergistic application of early warning models, dynamic adjustment mechanisms, and the application of multi-factor models, and there is a lack of effective coordination and integration between indicator systems across different fields. This study seeks to investigate the optimization and synergistic utilization of early warning indicators for financial crises, integrating advanced technologies such as big data and artificial intelligence to furnish financial regulators with more empirical and systematic decision-making assistance, thereby ensuring the stable functioning of financial markets. The research findings will facilitate the adjustment and improvement of financial regulatory policies based on market changes and actual needs, ensuring timely detection and effective mitigation of financial crises.

2. Theoretical foundation of early warning indicators for financial crises

2.1. The evolutionary mechanism of financial crises

The evolution mechanism of financial crises is a dynamic process involving multiple intertwined factors, including the inherent contradictions between debt expansion and repayment capacity during economic cycles, the unsustainable inflation of asset price bubbles in boom phases, and their abrupt collapse. According to Hyman Minsky's "financial instability hypothesis", during the expansion phase of the economy, borrowing entities gradually shift from hedging-type to speculative-type and even Ponzi-type financing, with leverage ratios continuously rising, and systemic risks accumulating beneath the surface of prosperity [5]. Once interest rates or asset yields fluctuate, the repayment chain is broken, and risks are rapidly exposed and transmitted throughout the entire financial system. Charles Kindleberger further noted in his crisis model that the evolution of a crisis can be divided into four stages: preparation, boom, panic, and sell-off. First, accompanied by optimistic expectations and capital inflows, asset prices continue to rise; then, in an environment of excessive competition among financial institutions and relaxed regulation, a bubble forms; after the peak of the boom, market confidence suddenly shifts, panic spreads, and investors rush to exit high-risk positions, triggering a sell-off; finally, the crisis is alleviated through deleveraging and market self-repair. Meanwhile, cross-market and cross-border financial linkages exacerbate the contagion effect of shocks, causing local imbalances to rapidly evolve into global turmoil. A thorough comprehension of this evolutionary mechanism is crucial for the development of targeted multi-tiered regulatory and risk alert systems. The outbreak of a financial crisis is often accompanied by a sharp decline in asset prices, particularly the collapse of real estate, stock, and bond markets, triggering widespread debt defaults that exacerbate economic recession. Therefore, the evolution mechanism of financial crises highlights endogenous instability arising from the interaction of macroeconomic fundamentals and market behavioral factorsr. Early warning systems must comprehensively monitor and anticipate potential risks from multiple dimensions, including macroeconomics, market sentiment, and financial institution risks.

2.2. Principles for constructing an early warning indicator system

The early warning indicator system should cover multiple levels, reflecting potential risks in financial markets from micro, meso, and macro perspectives. The early warning system should possess flexibility to dynamically adjust in response to changes in the market environment. Integrating cross-domain indicators through principal component analysis, grey forecasting, and weighted synthesis constructs a systematic early-warning framework. Taking the 2007–2008 U.S. subprime mortgage crisis as an example, the specific process and application of constructing an early warning indicator system are illustrated. First, key driving factors are selected, including macro-level indicators such as GDP growth rate, household leverage ratio, and housing price index; meso-level indicators such as bank capital adequacy ratio (e.g., Tier 1 capital ratio) and credit growth rate; and micro-level indicators such as market volatility indices (e.g., VIX index) and mortgage default rates. Next, quarterly data for each indicator from 2000 to 2006 are collected, and combined with the timing of the subprime mortgage crisis in 2007, econometric methods are used to assess the correlation between each indicator and the occurrence of the crisis. Using principal component analysis (PCA), we reduced the high-dimensional indicators to several composite factors, such as macroeconomic factors, credit factors, and market sentiment factors, and calculated the variance contribution rates of each factor. We then deployed GM(1,1) grey modeling to capture nonlinear trend inflection points of each factor and capture potential turning points. Subsequently, a weighted composite method was employed to assign dynamic weights to the forecast values of each factor based on their historical warning accuracy, synthesising a single early warning signal index (Composite Early Warning Index, CEWI). In a backtest conducted from late 2006 to early 2007, when the CEWI exceeded the threshold of its historical mean plus two standard deviations, a clear risk warning was issued in the second quarter of 2007. Based on this dynamic threshold, regulatory authorities can deploy macroprudential measures, such as countercyclical capital buffers and differentiated reserve ratios, within a two-quarter window after the signal appears, to effectively curb excessive leverage expansion and asset bubble accumulation. This scenario illustrates a warning system that integrates multi-level, multi-method, and dynamic threshold strategies, achieving a balance between real-time precision, cyclical adaptability, and operational viability [6].

2.3. The logic of indicator selection under the macroprudential regulatory framework

Under this framework, the selection of financial crisis early warning indicators should adhere to principles such as systemic risk, dynamic adaptability, and policy operability. The logic for selecting systemic risk indicators requires that the chosen indicators reflect the stability of the entire financial system, not just the risks of individual financial institutions [8]. For example, bank capital adequacy ratios and liquidity coverage ratios can reveal the overall health of the financial system. Dynamic adaptability necessitates regulatory indicators that are responsive to market fluctuations. During an economic expansion, when the banking system has ample liquidity and capital markets are relatively stable, early warning indicators may focus on metrics such as inflationary pressures and asset price volatility. During an economic downturn, however, regulators may place greater emphasis on banks' credit conditions and liquidity risks. Consequently, macroprudential frameworks demand early-warning indicators with endogenous cyclical adaptability. Finally, policy operability requires that the selected early warning indicators provide a clear decision-making basis for policymakers. The indicators need to have a certain policy-guiding role, enabling regulatory authorities to control systemic risks and prevent the spread of financial crises by adjusting macroeconomic policies or financial regulatory measures. Therefore, the selection of early warning indicators under the macroprudential regulatory framework not only needs to consider the predictive capability of the indicators but also their supportive role in policy implementation.

3. Optimisation strategies for early warning indicators in the context of new trends in financial regulation

3.1. Leveraging big data and artificial intelligence for indicator discovery

Big data technology enables financial regulators to access new information sources from various unstructured data sources, such as social media, news reports, and investor sentiment data, thereby enhancing the sensitivity and accuracy of early warning systems. Meanwhile, artificial intelligence, particularly machine learning and deep learning algorithms, can automatically analyse large volumes of complex financial data to identify potential risk signals. For example, a major international bank uses a big data platform to capture in text data related to its brand and the macroeconomy from social media platforms like Twitter and Weibo. The system applies NLP-based sentiment quantification (via VADER lexicon) coupled with LSTM recurrent neural networks to generate 30-day market panic probability forecasts. The results show that when the sentiment index rises by more than 20% in the short term, the implied volatility of stocks often exceeds one standard deviation above the historical average within three days, serving as an effective indicator to issue risk signals two weeks in advance. Additionally, the bank incorporated unstructured data such as news sentiment hotspots and Google search trends into a multimodal machine learning model. Benchmark testing demonstrated a 15% AUC uplift in liquidity risk detection versus traditional indicators significantly enhancing the early warning system's sensitivity and response speed to market anomalies [7].

3.2. Stress testing and reverse scenario design

Stress testing and reverse scenario design are commonly used tools in financial crisis early warning systems, enabling regulatory authorities to simulate the risk-bearing capacity of the financial system under different economic scenarios. Through stress testing, regulators can analyse the capital adequacy, liquidity status, and risk exposure of financial institutions under extreme conditions to assess their ability to withstand financial shocks. Complementing conventional stress tests, reverse scenario design systematically constructs tail-risk events—including financial market collapses and interest rate shocks—to identify latent systemic vulnerabilities. Taking the 2018 reverse stress test of European banks as an example, regulatory authorities designed three extreme macroeconomic scenarios: 1) a 50% plunge in oil prices and a 3 percentage point decline in GDP growth; 2) a sharp rise of 200 basis points in eurozone sovereign debt spreads; 3) A 30% correction in global stock markets. Under each scenario, a dynamic macroeconomic-financial coupling model was applied to calculate changes in the banking system's capital adequacy ratio, loan loss provisions, and Liquidity Coverage Ratio (LCR). The results of the reverse scenario simulation showed that under the most severe scenario, the average Tier 1 capital adequacy ratio would drop from 12% to 7%, and the liquidity coverage ratio would fall below 90%, far below the regulatory minimum requirements. Based on this, regulatory authorities recommend imposing countercyclical capital buffers on core banks and raising the leverage ratio ceiling for large institutions. The study demonstrated that integrating microfinance institutions and shadow banks into joint stress testing uncovered shadow credit risks neglected by conventional assessments, offering quantitative evidence for regulatory bodies to proactively develop macroprudential policies [8].

3.3. Dynamic threshold and threshold adaptive mechanism

The dynamic threshold mechanism monitors market changes in real time, combines macroeconomic conditions and market volatility, and automatically adjusts warning thresholds. This enables the warning system to respond flexibly under different market conditions, ensuring accurate risk warnings at different stages of a financial crisis. The threshold adaptation mechanism enables autonomous optimization of warning indicators through historical trend analysis, strengthening abnormal situation responsiveness. This adaptive mechanism not only improves the accuracy of the early warning system but also enhances its flexibility in responding to financial market fluctuations. Taking listed securities firms as an example, Huatai Securities has established a risk indicator pool centered on stock index volatility, credit spreads, and margin trading balances, with an initial threshold set at the historical mean plus two standard deviations. Additionally, a rolling window (with a window period of six months and a step size of one month) is used to calculate the dynamic mean and standard deviation of each indicator, with warning thresholds updated in real time. In the second quarter of 2020, the S&P 500 Volatility Index (VIX) escalated from 20 to 35 in a month, prompting the dynamic threshold to rise from 30 to 32 and activating the risk alert system. The brokerage business subsequently modified the risk control model parameters automatically, utilizing the threshold adaptive mechanism, elevated the margin ratio, and temporarily limited high-leverage trades. Empirical evidence shows that the dynamic threshold mechanism issued signals five trading days earlier than the static threshold warning, with an accuracy rate improvement of 12%, significantly enhancing flexibility and precision in responding to sudden risks [9].

4. Collaborative application mechanism of early warning indicators

4.1. Cross-level regulatory information sharing and coordination

Cross-level regulatory information sharing and coordination is a key mechanism for achieving effective regulation in modern financial regulatory systems. As financial markets become increasingly globalised and complex, the regulatory capabilities of individual regulatory authorities have shown limitations. Therefore, cross-level information sharing and coordination have become particularly important. Taking a provincial financial regulatory bureau as an example, the bureau has collaborated with municipal and district-level financial offices and banking associations to jointly establish a "cross-level financial risk information sharing platform." Built upon ISO 20022-compliant data standards and RBAC permission frameworks, the platform leverages blockchain DLT for immutable audit trails while implementing real-time data synchronization via Kafka-based event streaming and RESTful API gateways, enabling seamless interoperability among county-to-national regulatory entities. All participating parties deploy microservices in the cloud, using WebSocket push notifications to quickly transmit alert events. The front end displays risk trends through visualised dashboards and dynamic instrument panels, and grants regulators the ability to view and collaborate on risk management based on their permissions. Additionally, the platform integrates AI-powered risk control modules, integrating NLP-powered sentiment analysis (BERT model) for anomaly detection in regulatory disclosures, with real-time risk scoring through dynamically weighted sentiment indices. The platform also supports cross-regional collaboration: when the central regulatory center issues new regulations or warning strategies, the system automatically disseminates them to local institutions and records feedback, forming a closed-loop communication process. Through these technical measures, the platform achieves real-time information sharing and collaboration across multiple levels from county to central government, significantly enhancing regulatory efficiency and emergency response coordination capabilities.

4.2. Multi-stakeholder collaborative early warning process

Financial crisis early warning is not solely the responsibility of regulatory authorities but should involve the joint participation of market participants, financial institutions, and the government. Financial regulatory authorities should assume an overall coordinating role, integrating data and information from all parties to conduct comprehensive risk assessments. Financial institutions and market participants should actively cooperate by providing transparent market data and risk exposure information to enable regulatory authorities to obtain accurate market conditions.

The 2015 Chinese stock market turbulence witnessed a coordinated early warning mechanism involving regulators, institutions and investors. For example, the China Securities Regulatory Commission (CSRC) closely collaborated with the People's Bank of China, stock exchanges, and other parties to jointly issue stock market warning signals, promptly conveying market dynamics and policy adjustment information. Financial institutions and investors also played a crucial role in this process, with many securities firms and investors actively participating in market monitoring and data sharing to report abnormal market fluctuations to regulatory authorities. The government implemented market stabilisation policies, including suspending IPOs and restricting major shareholders from reducing their holdings, to alleviate market panic. This multilateral coordination demonstrably enhanced systemic resilience, validating cross-sector collaboration as a critical component of crisis management frameworks [7].

4.3. The two-way feedback mechanism between market participants and regulators

The reciprocal feedback system between market participants and regulators is a crucial element of efficient risk management. The volatile characteristics of financial markets necessitate that regulators acquire immediate feedback from market players to swiftly modify regulatory policies and warning signals. Prior to the subprime crisis, financial institutions and market participants provided early warning signals about potential risks in the subprime market through public risk assessment reports and market behaviour. However, regulatory authorities failed to respond promptly and effectively to these feedback signals. As market instability grew, financial institutions repeatedly offered opinions and suggestions on the policies of the U.S. Securities and

Exchange Commission (SEC), but regulators failed to respond swiftly. It was not until 2007 and 2008, when market risks escalated, that regulatory authorities began issuing risk warnings and implementing corresponding policies to address the crisis [6].

Market participants provided regulatory authorities with actual market risk information through transparent market behaviour and risk reports, thereby helping regulators understand the actual risk levels in financial markets. Regulatory authorities should communicate effective risk warning signals and regulatory requirements to market participants by regularly publishing market risk assessment reports, policy changes, and economic forecasts. This two-way feedback mechanism not only enhances market transparency but also encourages market participants to focus more on risk control in their daily operations and strengthen their compliance awareness. By promptly obtaining feedback from market participants, regulators can adjust and optimise the existing regulatory framework to ensure that the early warning system can function effectively in a constantly changing market environment, thereby achieving effective monitoring and management of financial risks.

5. Conclusion

The frequent occurrence of financial crises and the increasing complexity of financial markets necessitate continuous optimisation of early warning systems for financial crises to enhance the capability and precision of financial regulation. This paper analyses the optimisation strategies for warning indicators under new trends in financial regulation and proposes several feasible improvement schemes. Leveraging big data and artificial intelligence technologies to enhance the mining and analysis of warning indicators can improve the accuracy and timeliness of financial crisis warnings, particularly in dynamic monitoring and real-time alerts. Through stress testing with reverse scenario modeling, regulators gain ex-ante decision support by simulating cross-cycle risk exposures. Dynamic thresholds and adaptive threshold mechanisms can address risk changes under different market conditions, making the early warning system more flexible and efficient. While implementing these optimisation measures, establishing cross-level information sharing and multi-party collaborative early warning processes, and strengthening the two-way feedback mechanism between market participants and regulators are key to enhancing the effectiveness of the financial crisis early warning system. Future research will adjust and refine financial regulatory policies based on market changes and actual needs to promote the healthy and stable development of financial markets and ensure that financial crises can be promptly and effectively warned and addressed.

References

[1] Fang, S. (2024). Research on the financial risk early warning indicator system for commercial banks in China. *Financial Customer, 12*, 15–17.

[2] Chen, S., Xiang, Y., & Deng, F. (2024). Construction and empirical application of an early warning index for systemic financial risks: Based on AUROC assessment and policy makers' loss function. *Financial Economics, 10*, 18–30.

[3] Wang, Q., Aruuna, & Zhu, A. (2024). Financial market anomalies and the construction of a systemic risk early warning indicator system: An information leakage perspective. *Financial Regulation Research, 11*, 44–62.

[4] Zhang, J. (2023). Research on the financial risk warning indicator system for commercial banks. *Chinese Collective Economy, 30*, 121–124.

[5] Yu, M. (2022). Analysis of risks and preventive measures in the financial economy. *China Market, 35*, 42–44.

[6] Wu, W., Jiang, H., & Lu, C. (2022). Reconstruction and effectiveness of systemic financial risk warning indicators: A perspective based on financial innovation. *Financial Forum, 27*(10), 23–32.

[7] Zhao, Y. (2022). Early warning analysis of systemic financial risk levels based on the entropy method. *Industrial Innovation Research, 7*, 115–117.

[8] Du, R. (2022). On the financial risk warning indicator system of Chinese commercial banks. *China Collective Economy, 9*, 112–113.

[9] Liu, X. (2022). Analysis of the construction strategy for a financial risk statistical monitoring and early warning indicator system. *Finance and Economics, 6*, 11–13.