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Proactive Crisis Management: Can New Tech Predict Financial Crashes?

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Problem of practice

If you work in finance—whether as an economist, policymaker, risk manager, portfolio manager, or analyst—you are always trying to stay prepared for the next financial crisis, knowing that the interconnectedness of global economies means a crisis anywhere could quickly ripple across markets and impact you. Predicting financial crises, however, has always been a challenge. Traditional models struggle to capture the complexity of global markets and how quickly shocks spread across regions and asset classes. To tackle this, research by Samitasa, Kampouris, and Kenourgios has found a powerful new approach: integrating network analysis and machine learning to create a robust Early Warning System (EWS) for financial crises.[1] By mapping the financial system as a network of interconnected assets, their model identifies key nodes—countries or assets—that act as primary transmission points for financial contagion. Further reinforcing the importance of machine learning methods, recent research by Bluwstein and team demonstrates that non-linear machine learning models consistently outperform traditional regression-based approaches in crisis prediction.[2] Their findings highlight critical indicators—credit growth and the yield curve slope—as essential inputs for identifying financial vulnerabilities.

Both studies underscore the need for data-driven, adaptive systems, powered by machine learning and informed by network dynamics, to improve crisis preparedness.

[1,2] The two articles - 'Machine learning as an early warning system to predict financial crisis' by Aristeidis Samitas, Elias Kampouris, and Dimitris Kenourgios featured in Volume 71 of *International Review of Financial Analysis*, and 'Credit growth, the yield curve and financial crisis prediction: Evidence from a machine learning approach' by Kristina Bluwstein, Marcus Buckmanna, Andreas Joseph, Sujit Kapadia and Özgür Şimşek, featured in Volume 145 of Journal of International Economics, show that machine learning significantly enhances early warning systems for financial crises by identifying key risk indicators.

Growing need to upgrade

Financial crises have long been a major concern for industry professionals and institutions. The primary goal has always been to predict a crisis before it unfolds. The global nature of modern finance means that financial distress in one market or institution can quickly spread across borders, amplifying the urgency for effective crisis prediction to ensure the resilience of global financial systems.

Historically, traditional econometric models were used for the prediction of financial crises. While these models have provided valuable insights, they have repeatedly fallen short in foreseeing the onset of crises. The 2008 Global Financial Crisis serves as a reminder of this shortcoming. The crisis resulted in global financial losses of approximately $2 trillion, wiped out over 8 million jobs in the U.S., and caused significant economic hardship globally.[3,4] In India, the government reported approximately 500,000 job losses, particularly in export-driven sectors, while GDP growth plummeted from an average of 9% in 2007-08 to 6.7% in 2008-09.[5,6] Traditional models couldn't account for modern financial systems' complex, interconnected nature, resulting in massive economic fallout.

The challenge is that financial crises rarely stem from a single cause. They emerge from the complex interplay of economic, financial, and behavioural factors. Market sentiment shifts, panic selling, and herd behaviour can trigger a domino effect, further complicating prediction efforts. This complexity underscores the need for advanced predictive tools—enter machine learning and network analysis. Unlike traditional methods, these technologies can model complex networks and forecast crises with greater precision and speed.

EWS leverages these advancements to monitor, identify, and signal impending financial distress by analysing critical economic and financial indicators. Such a system empowers stakeholders to take pre-emptive action, reducing systemic risks. By combining the structural depth of network analysis with the predictive power of machine learning (ML), the EWS offers a robust mechanism for detecting vulnerabilities and strengthening the resilience of financial markets. The strength of ML-based EWS is its ability to identify hidden risks and vulnerabilities and predict crises with higher accuracy.

Building a smarter EWS

An advanced EWS can process vast datasets—from stock prices and economic indicators to news sentiment—detecting early signs of financial distress that might otherwise go unnoticed. By mapping the financial system as a network of interconnected assets, institutions, and economies, such a system can pinpoint vulnerabilities where crises may originate, enabling a more proactive approach to risk management.

One of the frameworks in this space is the International Monetary Fund - Financial Stability Board (IMF-FSB)'s Early Warning Exercise (EWE), designed to identify low-probability, high-impact risks that could trigger systemic financial crises. Established in 2008 at the request of the G20, the EWE is a semi-annual assessment conducted by the IMF-FSB.[7] It was developed in response to the global financial crisis to help policymakers detect tail risk[a] and vulnerabilities that could lead to systemic shocks.

Traditional economic indicators and financial stress tests often fail to capture these tail risks, making EWE a critical tool for global risk assessment. The framework combines quantitative modelling with qualitative assessments, incorporating financial contagion models, stress testing[b], and macro-financial risk analysis. However, a key limitation lies in its reliance on expert judgment, while it enhances interpretability and introduces subjectivity.

A robust EWS must also be built on high-quality, continuously updated data that reflects evolving market conditions. The system's effectiveness depends on its ability to synthesise insights from multiple ML models, delivering real-time, actionable alerts.

Early Warning System leverages machine learning advancements to monitor, identify, and signal impending financial distress by analysing critical economic and financial indicators. Thereby empowering stakeholders to take pre-emptive action, reducing systemic risks.

Besides essential data, prolonged credit growth significantly increases crisis risk, particularly when paired with a flat or inverted yield curve. By incorporating these insights, ML-driven EWS can move beyond static risk assessments, identifying vulnerabilities before they escalate. Furthermore, frameworks from cooperative game theory, like Shapley values[c], enhance transparency by breaking down model predictions and explaining each feature's contribution. In the context of financial crisis prediction, they help interpret complex ML models by showing which economic indicators (e.g., credit growth, interest rates, and inflation) had the most influence in signalling an impending crisis.

When EWS didn't work

While ML holds great promise for crisis prediction, its effectiveness is not always as reliable as expected. One of the key challenges in assessing its limitations is the scarcity of well-documented cautionary tales. At a micro level, ML-driven early EWS has been increasingly used to

signal early warnings. This has likely contributed to financial stability, as evidenced by the relatively lower frequency of major financial crises since the 2008 global financial meltdown and the Eurozone crisis (2010–2012).[8] By this logic, emerging financial crises may serve as critical lessons on the potential limitations of ML-based EWS.

A notable example is the 2015 Chinese stock market crash. Machine Learning models used at the micro level by the financial institutions failed to detect market trends that signalled the impending downturn. More critically, existing EWS failed to anticipate the contagion effect across global markets. In hindsight, the ability to forecast such spillover effects could have been crucial, particularly for economies like India, which felt the shockwave of the crash. The impact was severe: the Shanghai Composite Index plunged by 30% in just three weeks, wiping out US$2.8 trillion in market value and triggering ripple effects worldwide.[9,10] In India, markets experienced a 6% drop in response.[11] This underscored the vulnerability of Indian financial markets to external shocks and highlighted the gaps in global crisis prediction models.

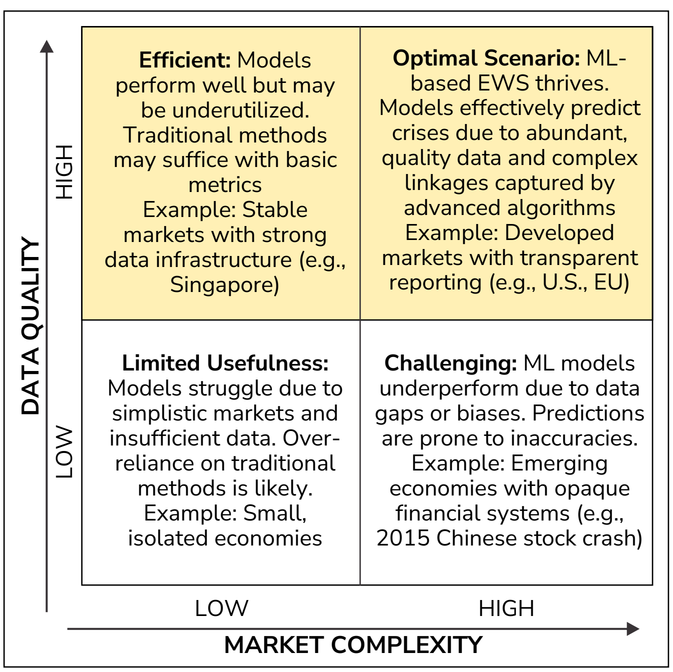
However, dismissing ML-based EWS as ineffective would be an oversimplification. The accuracy of any predictive model is only as strong as the quality and transparency of the data it is trained on. In the case of the Chinese market crash, it is possible that limited access to high-quality financial data, particularly in a market with significant regulatory opacity, contributed to biased and incomplete forecasts.

Ultimately, while ML is a powerful tool for crisis prediction, it must be continuously refined and complemented by human expertise to mitigate blind spots. Recognising when the ML models may fail is crucial to improving their predictive accuracy. A fundamental step in this process is understanding the conditions under which these models are most vulnerable.

When EWS will work

Integrating ML and network analysis into crisis prediction is not just a technological enhancement—it is an economic necessity to safeguard the financial system from crises that originate at micro, meso, or macro levels and evolve into systemic contagions. At the same time, potential users must recognise the boundary conditions for effectively leveraging ML-based EWS. These conditions can be categorised using the two-by-two matrix presented in *Figure 1*, which classifies EWS effectiveness based on data quality (Data) and market complexity[d] (Complexity).

Figure 1: Conditions for the Effectiveness of Machine Learning Based EWS



Source: Authors' analysis

As shown in Figure 1, High Data + High Complexity is the ideal condition for adopting machine learning in EWS. High-quality data enables precise modelling of interconnected risks. Low Data + High Complexity is the most challenging scenario—ML cannot accurately map contagion risks without adequate data.

Factors that can hinder the effectiveness of ML-based EWS:

- Data quality issues
- Interpretability challenges
- False alarm vs. Missed warnings

Beyond data availability and system complexity, several factors can hinder the effectiveness of ML-based EWS:

1. Data quality issues: Financial data is often noisy, incomplete, or biased, which can distort predictions. Recent research highlights that crisis prediction models are particularly sensitive to shifts in macro financial conditions, requiring continuous recalibration to remain reliable□

2. Interpretability challenges: ML models often function as black boxes, making it difficult to explain how predictions are generated. To address this, new approaches like Shapley values could be used to identify the contribution of each predictor.

3. False alarms vs. Missed warnings: As with any predictive model, machine learning based EWS must balance the risk of failing to warn about an impending crisis with the equally damaging consequence of raising false alarms, which may prompt unnecessary and disruptive mitigation actions.

The study by Samitasa et al. highlights some key limitations of ML-based EWS. The researchers developed a ML model to predict financial contagion within a network of stocks, bonds, and credit default swaps (CDS). The model relied on historical correlations between these assets, yet its primary limitation was that past correlations do not necessarily hold in the future. If market conditions shift unpredictably, such models—like many traditional EWS—may fail to provide meaningful early warnings. This study underscores three fundamental challenges in applying machine learning to financial crisis prediction:

Historical patterns vs. Unique events: Many EWS models assume that past market behaviours will repeat, using historical data as their primary learning base. However, financial crises often do not follow past trends. When entirely new permutations emerge, models trained on historical patterns can become obsolete. This raises a fundamental dilemma: if we assume 'this time is different', there is little foundation for predictive modelling; yet, if we presume history always repeats itself, we risk missing unprecedented shifts.

Economic vs. Non-economic crisis triggers: Most ML-based EWS models focus on economic indicators such as stocks, bonds, and CDS. However, financial crises are not always driven by economic factors alone. Geopolitical conflicts, pandemics, cyberattacks, and sudden regulatory shifts can also serve as triggers. If a ML model is trained solely on traditional financial variables, it risks overlooking critical non-economic disruptions. This highlights the need for multidimensional data integration, incorporating alternative risk factors beyond conventional financial metrics. For example, the COVID-19 crisis was not triggered by financial imbalances, yet it caused severe economic instability. This highlights the importance of integrating alternative risk factors, such as sentiment analysis and real-time macro indicators, into EWS models.

Selection of antecedents and correlation shifts: Even when relevant economic indicators are selected, their correlations can evolve over time. For instance, historical trends suggest that falling interest rates generally drive gold prices higher. Still, recent market behaviour has shown that geopolitical uncertainties exert a stronger influence on gold price movements.[12] This phenomenon underscores how the evolving correlations can limit the effectiveness of machine learning models, emphasising the need for continuous recalibration and broader contextual analysis. Financial systems are particularly vulnerable when multiple risk indicators—such as rapid credit expansion and an inverted yield curve — co-occur, rather than in isolation. This underscores the importance of capturing interactions between variables in EWS models.

Using EWS beyond crisis prediction

Despite the concerns surrounding ML-based EWS, their value is indisputable. These models hold significant potential for application in other high-risk domains, particularly supply chains and energy markets, where resilience and risk mitigation are critical.

In supply chain management, ML-based EWS can strengthen resilience by identifying risks, predicting disruptions, and enabling real-time monitoring. Companies like IBM have successfully leveraged ML to monitor supply chain risks and optimise operations, showcasing the scalability and efficiency of these models.[13] Similarly, machine learning can play a crucial role in maintaining economic stability in energy markets by forecasting price volatility, grid disruptions, and climate-related risks. Companies like Siemens utilise machine learning for predictive maintenance of energy infrastructure, preventing failures that could escalate into systemic crises.[14]

By integrating these advanced predictive capabilities, ML-based EWS can enhance stability, efficiency, and proactive risk management across diverse industries.

Glossary of technical terms used

[a] **Tail risk** refers to the probability of rare but extreme events occurring in financial markets, typically found at the far ends (or 'tails') of a probability distribution. These events have a low probability but high impact, often leading to severe market disruptions, financial crises, or systemic failures.

[b] **Stress testing** is a risk management technique that financial institutions, central banks, and regulators use to assess how financial systems, portfolios, or institutions perform under extreme but plausible adverse conditions.

[c] **Shapley value** in game theory is a solution concept of fairly distributing both gains and costs to several actors working in a coalition.

[d] **Market complexity** refers to the intricate and dynamic nature of financial markets, driven by multiple interacting factors such as investors' behaviour, regulations, technology, macroeconomic conditions, and financial instruments.

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