Dynamic early warning systems for financial crashes using sentiment and market volatility

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<Date of submission placed here>

**Abstract**

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# Introduction <This is Heading 1>

## Motivation

Financial market crashes have historically affected to the economic and social disruptions, leading to the downturn, unemployment, and loss of investor confidence. Early detection and intervention are critical for minimizing the impact of such crises on those affected.

In recent years, sentiment analysis has emerged as a powerful tool in financial risk monitoring, offering insights into investor expectations, fears, and behaviours. When sudden shifts in investor sentiment are combined with traditional volatility indicators, they can provide early signals of impending market instability (Liu et al., 2023) [3]. However, most existing early warning systems rely on static models that struggle to adapt to the fast-changing dynamics of the modern financial markets (Kustina et al., 2023) [1]. By integrating both market and sentiment volatility within a dynamic framework, this research aims to develop more responsive and accurate tool for crash prediction.

## Aims and Objectives

The primary aim of this research is to develop a dynamic early warning system that involves market-based and sentiment-based volatility indicators to improve the early market crash detection models.

To achieve this aim, the study will pursue the following specific objectives:

1. To analyse the power of market and sentiment volatility, examining how their time-varying patterns relate to the occurrence of past financial crashes.
2. To utilize historical financial news data collected from Yahoo Finance (yfinance) API.
3. To develop a dynamic modelling framework that captures the relationship between market and sentiment volatility indicators.
4. To evaluate and compare the performance of the dynamic early warning system against traditional static models
5. To validate the model’s robustness across multiple market environments and past crisis period.

# Survey

## Background Survey

### Current Methods for Early Warning Systems (EWS)

Early warning systems (EWS) for financial crashes have evolved from simple statistical models to more advanced machine learning and nonlinear approaches. The traditional statistic models, such as logistic regression, have been widely used to detect early signals for financial crashes using predefined relationships between risk indicators and crash probabilities. Such models often suffer from rigid parameterization and lagging indicators, limiting their ability to capture regime shifts or sudden market changes (Kustina et. al., 2023) [1], in contrast with the more recent research that explored the nonlinear approach to overcome this limitation. Nonlinear algorithms, support vector machines (SVM), and neural networks have shown improved capacity for capturing the complex relationships in the real-world financial markets (Song et al., 2024) [2], allowing more flexibility when modelling market risks and crash probabilities as new data becomes available. Empirical evidence supports that dynamic nonlinear methods outperform static models, providing better crisis prediction under changing market environments (Song et al., 2024) [2].

Beside the market-based indicators, sentiment analysis has also gained attention in financial crash predictions. The rise of social media platforms such as Twitter (now known as X), along with financial news sources, has provided rich datasets for capturing investor mood and behaviours (Liu et al., 2023) [3]. However, extracting signals from this unstructured data often produces noisy which remains a challenge. Liu, Leu, and Holst (2023) proposed a method using FinBERT combined with an ensemble SVM to reduce noise and filter out irrelevant content from social media discussions (Liu et al., 2023) [3].

### Volatility as a Key Crash Indicator

Volatility remains one of the most important indicators in crash prediction research. To flag the potential financial instability, both realized volatility (observed historical price variability) and implied volatility (market expectations of future volatility derived from options pricing) have been used (Allaj & Sanfelici, 2023) [4]. Pattern of increased volatility generally precede market downturns, making it useful for EWS frameworks.

Mentioning the traditional risk measures, Value-at-Risk (VaR) and Expected Shortfall (ES) are widely used as quantitative measures to assess market risk and potential losses under various conditions. However, both VaR and ES forecasts often rely on models with specific distributional or structural assumptions (Allaj & Sanfelici, 2023) [4], which may not capture sudden market regime shifts, nonlinear behaviors, or sentiment-driven shocks. This is especially true in emerging markets, where volatility is typically higher and market dynamics are less predictable.

A recent study by Le (2024) [6] examined the effectiveness of combining multiple VaR and ES forecasting models in the context of the Vietnamese stock market. The research found that forecast combination techniques, such as weighted averaging of outputs from different models (e.g., GARCH, CAViaR, and ES-CAViaR), significantly improved the accuracy and reliability of risk forecasts, especially during periods of high market volatility. The combined models showed better back testing performance and greater compliance with regulatory risk thresholds, compared to any single model (Le, 2024) [6].

### Rationale for Focusing on Index-Level Predictions

Index-level models offer several advantages, including aggregation benefits that help reduce noise and unexpected shocks from individual stocks (Park et al., 2024) [5]. Research has shown that top-down index forecasts tend to be more accurate and informative than bottom-up aggregation of individual stock predictions, particularly for systemic risk assessment (Park et al., 2024) [5]. By concentrating on index-level sentiment and market volatility, the model can better capture macro-level signals that reflect broader market conditions.

Citation

[1] Lisa Kustina, Rachmat Sudarsono and Nury Effendi (2023). Market crash factors and developing an early warning system: Evidence from Asia, <https://doi.org/10.21511/imfi.20(3).2023.10>

[2] Song and Li (2024), Early warning signals for stock market crashes: empirical and analytical insights utilizing nonlinear methods, <https://doi.org/10.1140/epjds/s13688-024-00457-2>

[3] Liu, J., Leu, J., & Holst, S. (2023). Stock price movement prediction based on Stocktwits investor sentiment using FinBERT and ensemble SVM. PeerJ Computer Science, 9. <https://doi.org/10.7717/peerj-cs.1403>

[4] Erindi Allaj, Simona Sanfelici, Early Warning Systems for identifying financial instability, International Journal of Forecasting, Volume 39, Issue 4, 2023, Pages 1777-1803, ISSN 0169-2070, <https://doi.org/10.1016/j.ijforecast.2022.08.004>.

[5] Park, M., Peterson, M., & Weisbrod, E.H. (2024). Top-Down vs. Bottom-Up Index Forecasts: Are Market Strategists Strategically Pessimistic? SSRN Electronic Journal. Available at SSRN: https://ssrn.com/abstract=4695279 or <http://dx.doi.org/10.2139/ssrn.4695279>

[6] Le, T.H. (2024), "Forecasting value-at-risk and expected shortfall in emerging market: does forecast combination help?", Journal of Risk Finance, Vol. 25 No. 1, pp. 160-177. <https://doi.org/10.1108/JRF-06-2023-0137>

# Further Chapters

The content of these chapters depends on the project and should be agreed with your supervisor (e.g. description of the solution, evaluation results, etc).

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Figure 1: Some important shapes.

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*# This is a little bit of Python*

**for** i in range( 10 ):

**for** j in range( 10 ):

**print** i\*j,

**print**

Figure 2: A crucial algorithm for the project.

# Conclusion

Main conclusions of your project. Here you should also include suggestions for future work.

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# Bibliography

[1] C. Baier and J.-P. Katoen. *Principles of Model Checking*. MIT Press, 2008.