**Chapter 1 Introduction**

**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). 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). By integrating both market and sentiment volatility within a dynamic framework, this research aims to develop more responsive and accurate tool for crash prediction.

**Purpose**

The primary purpose of this research is to develop a dynamic early warning system (EWS) that integrates both market-based and sentiment-based volatility indicators to enhance the early detection of financial market crashes. Given the increasing complexity and unpredictability of financial markets, especially during periods of heightened uncertainty, there is a growing need for more adaptive and timely forecasting models.

This study seeks to address by analysing how time-varying patterns in market-based and sentiment-based volatility relate to the occurrence of past financial crises. Specifically, the research will make use of historical financial news headlines to extract relevant sentiment signals. These sentiment indicators will then be combined with traditional market-based volatility measures, using the S&P500 closing prices, within a dynamic modelling framework designed to capture the evolving relationships between these variables over time..

**Chapter 2 Survey**

**2.1 Background Survey**

**2.1.1 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), 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), 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).

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). However, extracting signals from this unstructured data often produces noisy which remains a challenge. Liu, Leu, and Holst (2023) proposed a method using FinBERT[[1]](#footnote-1) combined with an ensemble SVM to reduce noise and filter out irrelevant content from social media discussions.

Huang et al. (2020) showed that FinBERT, which is specifically pre-trained on financial texts including earnings call transcripts, analyst reports, and financial news articles, significantly outperforms general-purpose language models like BERT and traditional approaches in various financial information extraction tasks, including the LM dictionary, NB, SVM, RF, CNN, and LSTM. The model's specialized training on domain-specific vocabulary and financial terminology enables it to better understand the context inherent in financial communications, resulting in improved accuracy for sentiment classification, named entity recognition, and relationship extraction from financial documents (Huang et al., 2020). However, it is important to note that FinBERT demonstrated superiority applies specifically to financial text analysis tasks, and not directly to modelling financial market volatility.

As noted by Parras-Gutiérrez et al. (2014), forecasting models usually designed for short-term or one-step-ahead predictions due to the increasing in difficulty and unreliability of medium- and long-term forecasts caused by error propagation over time. To complement this perspective, Allaj and Sanfelici (2023) introduced a time-varying window (e.g., T = 22, 66, 132 days) in the context of early warning systems for financial instability. This approach acknowledges the changing nature of financial markets and allows models to capture different temporal dynamics ranging within a unified structure. Together, these insights lead to a multi-horizon modelling method that balances predictive accuracy with a greater understanding of time.

**2.1.2 Key Crash Indicator**

Most studies operationalize a financial crash using a binary crash indicator equation, where a crash is identified based on a significant drop in asset prices or index returns over a specified time window. A common method involves calculating the log return of closing prices over a fixed period (e.g., 5-day or 10-day intervals) and labelling an observation as a "crash" if the return falls below a predefined threshold which often set at the 10th percentile of historical returns or a fixed percentage drop, such as −10% (Kaminsky et al., 1998). Nonetheless, early warning models also extend to other types of financial crises, such as currency and sovereign debt. Kaminsky and Reinhart (1999), for example, define currency crises based on a sharp depreciation of the exchange rate coupled with reserve losses, using an exchange market pressure index. Bussière and Fratzscher (2006) extend this framework to sovereign debt crises by incorporating a wide range of macroeconomic variables, flagging a crisis when key thresholds are breached.

In addition, volatility also 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 price-volatility feedback rate have been used (Allaj & Sanfelici, 2023). Pattern of increased volatility generally precede market downturns, making it useful for early warning system 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), which may not capture sudden market regime shifts, nonlinear behaviours. This is especially true in emerging markets, where volatility is typically higher and market dynamics are less predictable.

A recent study by Le (2024) 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).

**2.1.3 Lags Selection**

In time series analysis, lags involve using past data points to predict the future values. Specifically, a lagged variable is a prior value of the same variable, shifted backward in time by a specific number of time steps. The purpose of including lags is to capture the temporal dependencies, persistence, or self-correlation which commonly found in sequential data such as stock returns, volatility, or macroeconomic indicators (Box, Jenkins, & Reinsel, 2008).

The choice of how many lags to include directly impacts a model’s ability to capture relevant temporal dependencies. Parras-Gutiérrez et al. (2014) addressed this issue in the context of short-, medium-, and long-term time series forecasting using the L-Co-R algorithm, which incorporates a cooperative-competitive evolutionary strategy to automatically select appropriate lags. Their approach revealed that lag structures reflect a broader challenge in time series modelling: too few lags may underfit, missing important dependencies, while too many lags may lead to overfitting or increased computational complexity. The study emphasizes that adaptive or data-driven lag selection methods, such as genetic algorithms or information-theoretic criteria (e.g., AIC, BIC), can enhance model generalizability.

**2.1.4 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. According to Park et al. (2024), the 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. By concentrating on index-level sentiment and market volatility, the model can better capture macro-level signals that reflect wide-range market conditions (Park et al., 2024).

**2.2 Research Objectives**

The goal of this project is to assess the following objectives:

1. To investigate the contribution of both market-based and sentiment-based volatility indicators to financial crash prediction by evaluating their feature importance.
2. To develop a dynamic modelling framework to capture the evolving relationship between sentiment-driven and market-based volatility indicators.
3. To evaluate and compare the predictive performance of the proposed dynamic early warning system against traditional static statistical models, with a particular focus on assessing the added value of sentiment-based inputs.
4. To validate the robustness and generalizability of the developed model across different market environments and historical crisis periods.

**2.3 Research Questions**

Based on the stated objectives, this study seeks to answer the following key research questions:

1. How do market-based and sentiment-based volatility indicators individually and jointly relate to the timing and occurrence of past financial crashes at the index level?
2. Can a dynamic early warning system outperform traditional static models in predicting financial market crashes?
3. To what extent does sentiment volatility enhance the performance of early warning models compared to using market-based indicators alone?
4. Is the proposed dynamic early warning system model robust and generalizable across different market conditions and historical crisis periods?

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1. https://huggingface.co/ProsusAI/finbert [↑](#footnote-ref-1)