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Building a composite early warning index for financial market crises using machine learning and macroeconomic-political uncertainty indicators

Khaled Mohammad Alomari[1]
Ayman Abdalla Mohammed Abubakr[2+]
Safwan Maghaydah[3]
Mohamed Ali Ali[4]

[1,3]*Faculty of Information Technology, Abu Dhabi University, United Arab Emirates.*
[1]*Email: khaled.alomari@adu.ac.ae*
[3]*Email: safwan.maghaydah@adu.ac.ae*
[2]*Department of Financial Management, Academic Programs for Military Colleges, Abu Dhabi University, United Arab Emirates.*
[2]*Email: ayman.abdalla@adu.ac.ae*
[4]*Department of Finance, College of Business Administration in Hawtat bani Tamim, Prince Sattam bin Abdulaziz University, Saudi Arabia.*
[4]*Email: moh.ali@psau.edu.sa*

(+ Corresponding author)

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ABSTRACT

The accurate and timely prediction of financial market crises remains a persistent challenge for economists, policymakers, and investors. Traditional early warning systems (EWS) often rely on low-frequency macroeconomic indicators and static econometric models, limiting their effectiveness in dynamic market environments. This study proposes to fill this gap by developing a novel framework for crisis prediction through constructing a Composite Early Warning Index (CEWI) that integrates daily data from financial markets, macroeconomic fundamentals, and political uncertainty indicators. Principal Component Analysis (PCA) was employed to synthesize these diverse variables into a single latent factor, capturing the underlying systemic risk. Machine learning algorithms, including Logistic Regression, Random Forest, and XGBoost classifiers, were trained on historical data spanning from 2000 to 2025 to predict crisis periods, defined by sharp equity market declines and official recession declarations. The XGBoost model achieved superior performance with an ROC-AUC of 0.953. Feature importance analysis utilizing SHAP values identified market volatility (VIX), gold prices, and oil prices as the most influential predictors. The results demonstrate that combining high-frequency financial and political indicators with advanced machine learning techniques significantly enhances crisis prediction accuracy. The proposed CEWI-based framework offers a powerful tool for early risk detection and has important implications for financial regulation, investment strategy, and economic policy design.

Contribution/ Originality: This study develops a novel Composite Early Warning Index (CEWI) by integrating high-frequency macro-financial and political uncertainty indicators using PCA and evaluates its predictive power through machine learning models. Unlike prior research, it combines diverse real-time signals to improve crisis prediction accuracy from 2000 to 2025.

1. INTRODUCTION

Financial markets naturally go through cycles of boom and bust, influenced by factors such as economic conditions, market sentiment, political instability, and unforeseen global events. The devastating effects of financial crises, such as the 2008 Global Financial Crisis and the 2020 COVID-19 market crash, have highlighted the immense value of effective early warning systems (EWS) that can signal weakness before it becomes structurally significant. Despite significant advances, predicting financial market crises remains a challenging task, particularly given the complexity, speed, and interconnectivity of markets.

According to Yokuş (2024) the early warning frameworks have so far used linear economic techniques such as logit/probit regressions or signal extraction techniques to detect the thresholds of vulnerability. The frameworks primarily focus on macroeconomic variables, which include credit growth, foreign exchange reserves, interest rate spreads, and inflation levels (Chen, Huang, & Ge, 2024). Although the models illustrate usefulness in application, they cannot describe the subtle nonlinear dynamics that define financial systems (Riani & Ikhwan, 2023). Furthermore, the models fail to include the rising political and geopolitical uncertainties, which significantly affect market volatility and investor sentiment (Barthélémy, Gautier, & Rondeau, 2024).

Machine learning (ML) has also achieved advances in recent years that enable crisis prediction through its capability to handle complex nonlinear relationships in big data. At the same time, new data sources, such as the Economic Policy Uncertainty (EPU) index, the Geopolitical Risk (GPR) index, and news sentiment analysis, offer greater insights into the role of uncertainty in destabilizing financial markets (Nazareth & Reddy, 2023). Yet, despite these advances, the incorporation of macroeconomic fundamentals and political uncertainty measures within a machine learning-based early warning index remains largely unexplored (Vadlamudi, 2020).

The authors address this issue by formulating a Composite Early Warning Index (CEWI) based on conventional macroeconomic variables and novel uncertainty variables within a machine learning environment (Abimanyu, Imansyah, & Pratama, 2023; Bluwstein, Buckmann, Joseph, Kapadia, & Şimşek, 2023). This study critically tests the predictive performance of models such as random forests and XGBoost, with the aim of enhancing the accuracy, relevance, and interpretability of crisis forecasting instruments for institutional investors, policymakers, and financial institutions.

Traditional models for forecasting crises, such as macroeconomic balance models, monetary models of speculative attacks, debt sustainability analysis, and many other imitative models, have struggled to deliver accurate and timely warnings. Also, these models are often based on linear econometric techniques and limited to quarterly or monthly macroeconomic indicators. The use of static thresholds, relationship-based methods based on history, and limited variable choices renders them less responsive to current market conditions. Secondly, existing techniques of EWS fail to utilize the potential held by daily finance data and do not incorporate measures of political uncertainty, whose importance has increased in market behavior.

This study aims to bridge these gaps by creating a unique framework that incorporates machine learning methods and a composite score based on macroeconomic, financial, and political uncertainty variables. The specific objectives are: to construct a Composite Early Warning Index (CEWI) that dynamically synthesizes daily data from multiple sources, including financial markets and macro-political indicators; to integrate CEWI into advanced machine learning models such as Logistic Regression, Random Forest, and XGBoost to predict financial crises with greater precision and recall; and to evaluate the performance of the proposed models, highlighting the most influential factors driving financial instability.

After reviewing previous studies and theoretical literature, this study makes several important contributions as outlined below: Theoretical Contributions: This study contributes to crisis prediction theory by addressing gaps in traditional economic models and integrating macroeconomic and political uncertainty indicators into a cohesive early warning system. It emphasizes the interdependence of global financial systems and geopolitical uncertainty through drawing on insights from data science, political science, economics, and finance to offer an interdisciplinary solution. This methodology encourages a comprehensive approach to crisis modeling. Creative Application of Machine Learning in Financial Early Warning Systems (EWS): By demonstrating how machine learning models (such as Random Forest, XGBoost, and LSTM) perform better than traditional econometric techniques in capturing nonlinear and high-dimensional crisis dynamics, the study advances the theoretical limits of early warning systems. Some studies (Vadlamudi, 2020) have pointed to some of these contributions, and our study has been launched to complete it. Methodological Contributions: Creation of a Composite Early Warning Index (CEWI): The study suggests a new index that combines several indicators, including political, financial, and macroeconomic ones, into a single, easily interpreted warning signal. Future research can use this index as a standard. Empirical Validation Through Machine Learning Algorithms: By evaluating and verifying a number of supervised machine learning algorithms for financial crisis prediction, the study adds to the empirical literature and offers reliable comparison metrics. Feature Importance and Explainability: By using SHAP values or LIME approaches, the study improves interpretability and helps decision-makers identify the features that have the most impact on crisis predictions. This increases confidence in machine learning applications in the financial industry. This is what some studies Ghirelli, Gil, Pérez, and Urtasun (2021), have not been able to address in a society different from ours. Practical contributions include a useful instrument for policymakers and regulators: The CEWI can assist international organizations (such as the World Bank and IMF), as well as central banks and financial regulators, in proactively identifying and reducing the risk of systemic market disruptions before they occur. It provides early detection for investors and risk managers by offering a data-driven signal to protect against financial market declines caused by political and macroeconomic stress. Crisis Readiness in Developed and Emerging Markets: The model is especially useful for nations with unstable macro-political situations, as it incorporates global and regional indicators, ensuring flexibility across various economic contexts.

2. LITERATURE REVIEW

2.1. Early Warning Systems for Financial Crises

Early Warning Systems (EWS) have long been developed to anticipate financial instability, particularly following the severe economic disruptions of the 1990s and the Global Financial Crisis (GFC) of 2008. Additionally, early models relied on macroeconomic indicators using statistical methods such as probit and logit regressions (Berg & Pattillo, 1999; Kaminsky, Lizondo, & Reinhart, 1998). Where these models focused on some variables such as international reserves, exchange rates, interest rate spreads, and credit growth.

However, the traditional EWS faced some limitations, such as poor predictive performance for out-of-sample data, dependence on quarterly or annual data, and an inability to adapt to rapid changes in financial markets (Kraevskiy, Prokhorov, & Sokolovskiy, 2024; Oh, Kim, & Kim, 2006). Also, static thresholds for signaling crises often resulted in frequent false alarms or missed crisis periods, highlighting the need for more dynamic, data-driven methods (Laitinen & Lahti, 2022).

2.2. Machine Learning in Financial Crisis Prediction

Machine learning (ML) techniques have gained prominence in the financial EWS literature. They offer greater flexibility and nonlinearity handling, as well as adaptability to large datasets (Al-Ababneh, 2022). Logistic regression, while still widely utilized, is often more of a benchmark tool than the most effective model (Henrique, Sobreiro, & Kimura, 2019; Kim, 2021).

Ensemble learning techniques such as random forests and XGBoost have proven to be highly effective for crisis prediction. Random forests effectively handle variable interactions and overfitting problems by aggregating decisions across multiple trees (Shrivastav & Kumar, 2022). While XGBoost, an optimized gradient boosting framework, achieves state-of-the-art predictive accuracy through regularization and weighted data sampling (Kumar, Chaudhary, & Kumar, 2024).

Recent studies such as Tran, Le, Nguyen, and Nguyen (2022); Liu, Chen, and Wang (2022), and Ramzan (2023) have illustrated that machine learning models significantly outperform traditional econometric methods in predicting financial distress across various countries.

2.3. Role of Macroeconomic and Political Uncertainty Indicators

The role of macro-financial variables in predicting crises is widely recognized. Volatility indices such as the VIX are viewed as forward-looking measures of investor sentiment and risk aversion that typically spike ahead of market downturns (Whaley, 2000; Yıldırım, 2022). Gold prices are often considered a safe-haven asset and tend to rise during periods of increased financial uncertainty (Eleuch, Souissi, & Mroua, 2025; Kumar & Saluja, 2024).

Furthermore, it has long been known that interest rate spreads, especially the U.S. 3-month Treasury yield, have been recognized as reliable early indicators of recessions and financial crises (Ajello, Benzoni, Schwinn, Timmer, & Vazquez-Grande, 2022; Estrella & Mishkin, 1998). Political uncertainty has also emerged as a critical driver of financial instability. The Economic Policy Uncertainty (EPU) index developed by Baker, Bloom, and Davis (2016), quantifies policy-related economic uncertainty and has been shown to correlate with reduced investment, increased volatility, and elevated financial risk (Ioannidis & Ka, 2021).

Despite the recognized value of these indicators individually, limited research has systematically combined them into a composite, dynamically updating index for crisis prediction.

2.4. Research Gap

While machine learning methods and individual financial indicators have improved EWS capabilities, significant gaps remain:

- Fragmented use of variables: Most studies employ single or narrow sets of indicators, missing the synergy captured by integrating macroeconomic, financial, and political uncertainty measures.
- Low temporal resolution: Many models still rely on monthly or quarterly data, delaying responses to rapidly evolving financial conditions.
- Static models: Traditional threshold-based models are not designed to adjust dynamically based on market conditions or updated data streams.

This study addresses these gaps by constructing a Composite Early Warning Index (CEWI) based on daily-updated macro-financial indicators and evaluating its predictive power using advanced machine learning techniques. The integration of multiple dimensions of uncertainty, together with real-time modeling, represents a significant advancement over prior EWS frameworks.

3. METHODOLOGY

This study adopts a quantitative, empirical, and predictive modeling approach to construct a composite early warning index (CEWI) for forecasting financial market crises. Machine learning techniques are integrated with macroeconomic and political uncertainty indicators to develop and evaluate the predictive framework.

3.1. Research Design

The research employs a quantitative design based on empirical financial data and advanced predictive modeling. The objective is to construct and validate a machine learning-driven composite index capable of anticipating periods of financial instability. A structured pipeline is developed for data collection, preprocessing, feature engineering, model training, evaluation, and interpretation.

3.2. Data Sources

Data are sourced from several reputable financial and economic databases to ensure comprehensiveness and accuracy:

- Yahoo Finance: Daily closing prices for key market indices and commodities, including the Chicago Board Options Exchange Volatility Index (VIX), Standard & Poor's 500 Index (S&P 500), Dow Jones Industrial Average (DJIA), Hang Seng Index (HSI), gold prices (GC=F), and crude oil prices (CL=F).
- Federal Reserve Economic Data (FRED): Key macroeconomic indicators, including the 3-month U.S. Treasury yield (DGS3MO), unemployment rate (UNRATE), and consumer price index (CPIAUCSL).

- US Daily Economic Policy Uncertainty Index (EPU): Daily measures of economic policy uncertainty provided by Baker et al. (2016) sourced directly from the official EPU database.

All data span the period from July 1, 2000, to January 1, 2025, ensuring a sufficiently long historical window that captures multiple market cycles and crises. Appendix 1 presents code that uses a Python library and API.

3.3. Data Preprocessing

Prior to modeling, extensive data preprocessing is performed:

- Data Cleaning: All datasets are aligned based on their timestamps. Missing values are addressed using forward and backward filling techniques to maintain the temporal integrity of the time series.
- Frequency Adjustment: Although most indicators are daily, monthly series such as unemployment and CPI are forward filled to ensure daily granularity, allowing consistent model inputs.
- Numeric Conversion: All variables are converted to appropriate numeric types to eliminate data type inconsistencies, particularly for machine learning compatibility.

3.4. Feature Engineering

Feature engineering is conducted to enhance model performance:

- Standardization: Features were standardized using a StandardScaler to ensure that all variables contributed equally to the machine learning algorithms, without being biased by differing scales.
- Principal Component Analysis (PCA): PCA was applied to a selected group of macroeconomic and uncertainty indicators (VIX, EPU, Treasury Yield, Unemployment Rate, Gold, and Oil) to extract the first principal component, termed the Composite Early Warning Index (CEWI). The CEWI serves as a synthetic indicator that captures the joint behavior of these underlying variables.

3.5. Crisis Definition

Crisis periods are defined using two objective criteria:

- A daily return on the S&P 500 index falling below -3%.
- A U.S. economic recession period, as indicated by the National Bureau of Economic Research's USREC recession indicator.

A binary crisis label assigned to each day, with 1 indicating a crisis and 0 indicating a non-crisis period.

3.6. Modelling Approach

Three machine learning classifiers implemented to model the likelihood of a financial crisis:

- Logistic Regression: A baseline linear model that estimates the probability of crisis events based on logistic function mappings of feature inputs.
- Random Forest Classifier: An ensemble learning method using multiple decision trees, aggregating their predictions for improved generalization and reduced variance.
- XGBoost Classifier: A gradient boosting framework specifically optimized for high-performance prediction, capable of handling class imbalance and complex feature interactions.

Each model trained using historical data and evaluated on out-of-sample observations beyond January 1, 2015.

3.7. Handling Imbalanced Data

Given the natural rarity of financial crises compared to normal periods, data imbalance poses a critical challenge. To mitigate this issue, the Synthetic Minority Over-sampling Technique (SMOTE) is applied to the training data. SMOTE generates synthetic samples of the minority class (Crisis events) to create a more balanced training dataset, thus enhancing model sensitivity to crisis prediction.

3.8. Evaluation Metrics

Model performance evaluated using a comprehensive set of metrics:

- ROC-AUC (Receiver Operating Characteristic - Area Under the Curve): Measures the model's ability to distinguish between crisis and non-crisis periods.
- Precision: The proportion of predicted crisis events that are actual crises.
- Recall: The proportion of actual crisis events correctly identified by the model.
- F1-Score: The harmonic mean of precision and recall, providing a single metric that balances false positives and false negatives.
- Confusion Matrix: A tabular summary detailing true positives, false positives, true negatives, and false negatives.

Threshold tuning is performed to optimize the trade-off between recall and precision, with an emphasis on early crisis detection.

3.9. Feature Importance Analysis

To interpret the factors driving the crisis prediction model:

- XG Boost Feature Importance

The built-in gain-based feature importance from the XGBoost classifier was extracted. This metric ranks features according to the average contribution of each variable in improving model splits, highlighting the most influential predictors.

- SHAP (SHapley Additive exPlanations) Values

SHAP analysis was performed on the XGBoost model to decompose individual predictions into additive contributions from each feature. This approach offers a consistent and interpretable framework to understand how input variables affect the crisis probability on a case-by-case basis.

The combination of XGBoost gain-based importance and SHAP value analysis ensures both global (overall feature ranking) and local (individual prediction) interpretability of the early warning system. This dual interpretability framework improves transparency regarding the impact of macroeconomic and financial uncertainty indicators in predicting financial crises.

3.10. Justification of Sample Period, Variables, and Methodology

The sample period from July 1, 2000, to January 1, 2025, was chosen to span various financial market regimes and significant systemic crises, including the dot-com bubble (2000–2002), the global financial crisis (2007–2009), the European sovereign debt crisis (2011), the COVID-19 market shock (2020), and post-pandemic market volatility. This extended time frame benefits the model by exposing it to both crisis and recovery periods, thereby enhancing its generalizability and robustness. Data collection utilized official APIs and Python libraries, such as yfinance for market data and fredapi for macroeconomic indicators, alongside in-house scripts to extract the Economic Policy Uncertainty (EPU) index. The automated extraction process enabled replication, while integrity checks ensured that no missing values were present across any variables throughout the entire sample period.

The variables are selected based on existing literature on financial crisis prediction and systemic risk monitoring. They include measures of volatility (VIX), macroeconomic indicators, commodity prices (Gold and oil), and the Economic Policy Uncertainty (EPU) index. Collectively, these variables represent the interaction between market behavior, economic fundamentals, and policy-related uncertainty. They are a key component in determining systemic vulnerability.

The methodology employs Principal Component Analysis (PCA) as an unsupervised learning technique to consolidate multiple indicators into a latent systemic risk index, termed the Composite Early Warning Index (CEWI), while reducing multicollinearity. Supervised machine learning classifiers Logistic Regression, Random Forest, and

XGBoost are selected for their complementary strengths in predictive performance, interpretability, and robustness to non-linearity and class imbalance. The resulting hybrid model offers both precise forecasting capability and interpretable model outputs, fulfilling the dual objectives of prediction and explainability.

4. RESULTS AND ANALYSIS

4.1. Descriptive Statistics

The study utilized financial market variables (VIX, S&P 500, DJIA, HSI, Gold, Oil) and macroeconomic indicators (3-month U.S. Treasury yield, unemployment rate, inflation) from July 2000 to January 2025. Table 1 presents descriptive statistics, which reveal the following:

Table 1. Descriptive Statistics.

Variable	Mean	Std. dev.	Min.	Max.
VIX	20.14	9.83	9.14	82.69
Gold	1167.2	400.5	252.9	2073.5
Oil	66.42	34.8	-36.98	145.29
US3M	1.79	1.84	0.01	5.46
Joblessness	5.8	1.92	3.5	14.7
CPI	2.35	0.78	0.1	5.4
EPU	135.8	76.4	30.6	380.5

4.2. Principal Component Analysis (PCA) and CEWI Construction

The Principal Component Analysis (PCA) conducted on standardized macro-financial variables extracted the Composite Early Warning Index (CEWI). The first principal component explained 35.13% of the total variance, validating CEWI's strength in summarizing key risk indicators.

4.3. ROC-AUC Model Comparison

The models' Receiver Operating Characteristic (ROC) curves are presented in Figure 1. The XGBoost model achieved the highest Area Under the Curve (AUC) value of 0.953, outperforming Random Forest (0.915) and Logistic Regression (0.896). The XGBoost classifier indicates excellent discrimination capability between crisis and non-crisis periods.

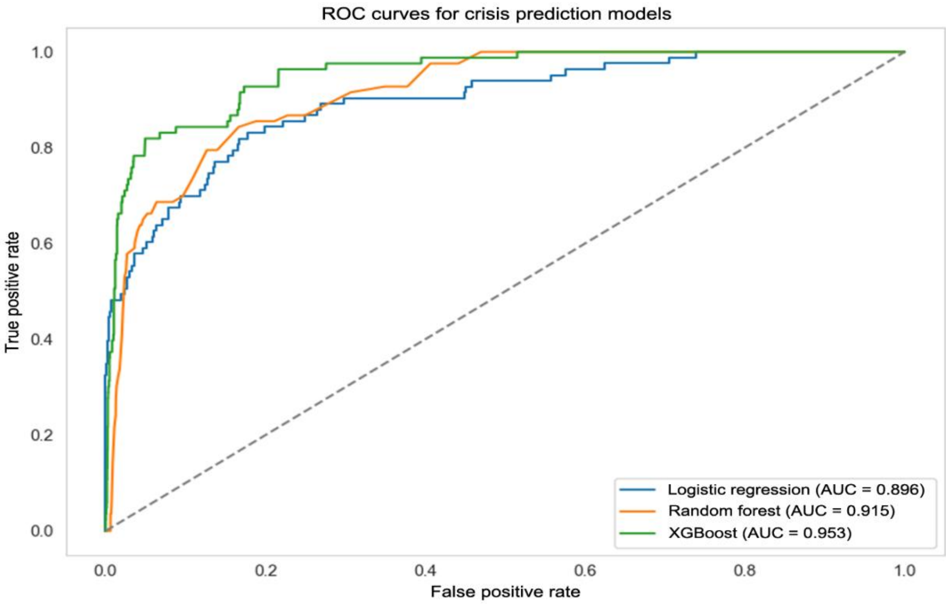

Figure 1. ROC curves for crisis prediction models (Logistic regression, random forest, and XG Boost).

4.4. Precision-Recall Threshold Tuning

Precision and recall scores across different thresholds for the best model (XGBoost) are shown in Figure 2. A threshold of 0.273 was selected to optimize the balance between recall and precision, prioritizing early crisis detection even at the cost of some false positives. When recall is emphasized, it enhances the effectiveness of the early warning system.

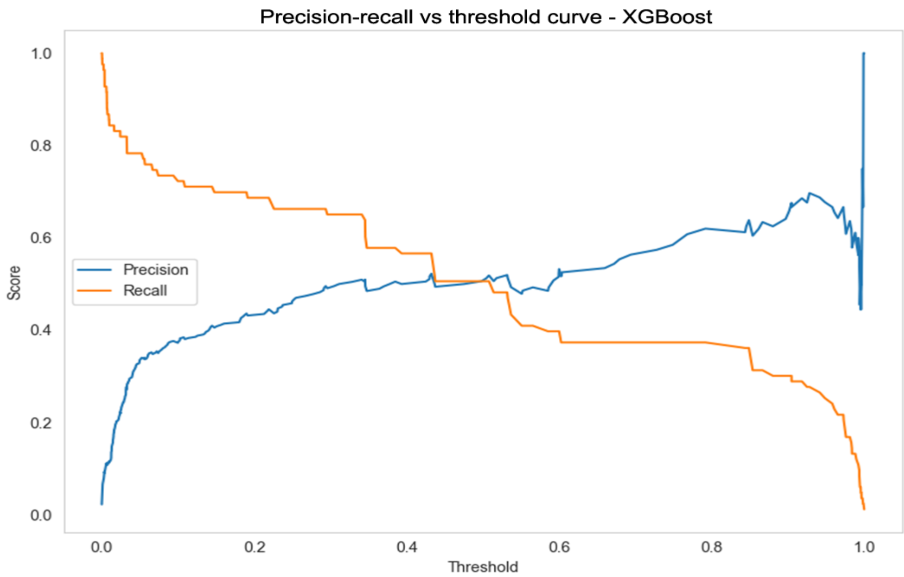

Figure 2. Precision-recall vs threshold curve for XG Boost classifier.

4.5. CEWI Over Time: Tracking Crisis Signals

The evolution of the CEWI over the study period is shown in Figure 3, alongside crisis events (S&P 500 drops >3% or official recession periods). Peaks in CEWI values align with major historical financial crises such as the 2008 Global Financial Crisis and the 2020 COVID-19 crash. Where sharp spikes in CEWI precede or coincide with major crises.

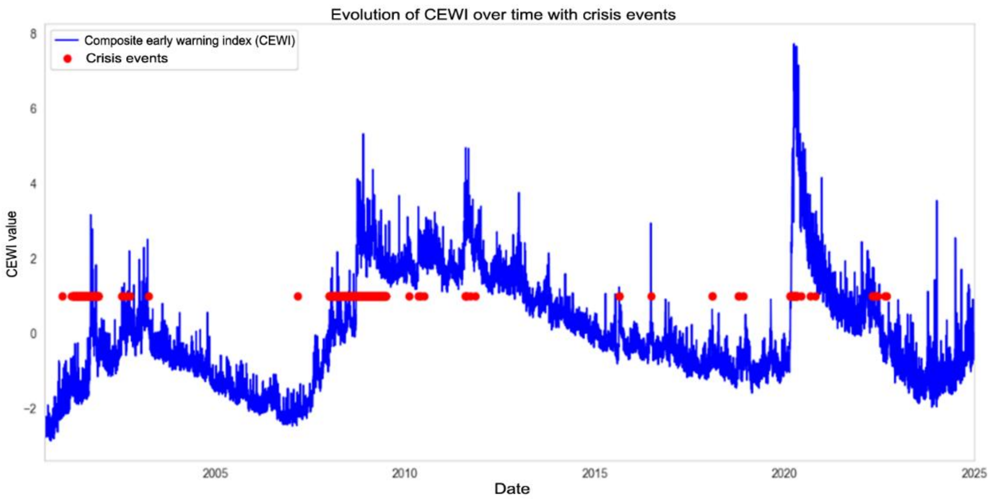

Figure 3. Evolution of composite early warning index (CEWI) over time with crisis events.

4.6. Feature Importance Analysis

The predictive contributions of the input variables were systematically evaluated using both the XGBoost model's internal feature importance metrics and SHAP (SHapley Additive exPlanations) value analysis. This dual approach enhances the transparency and interpretability of the crisis prediction model.

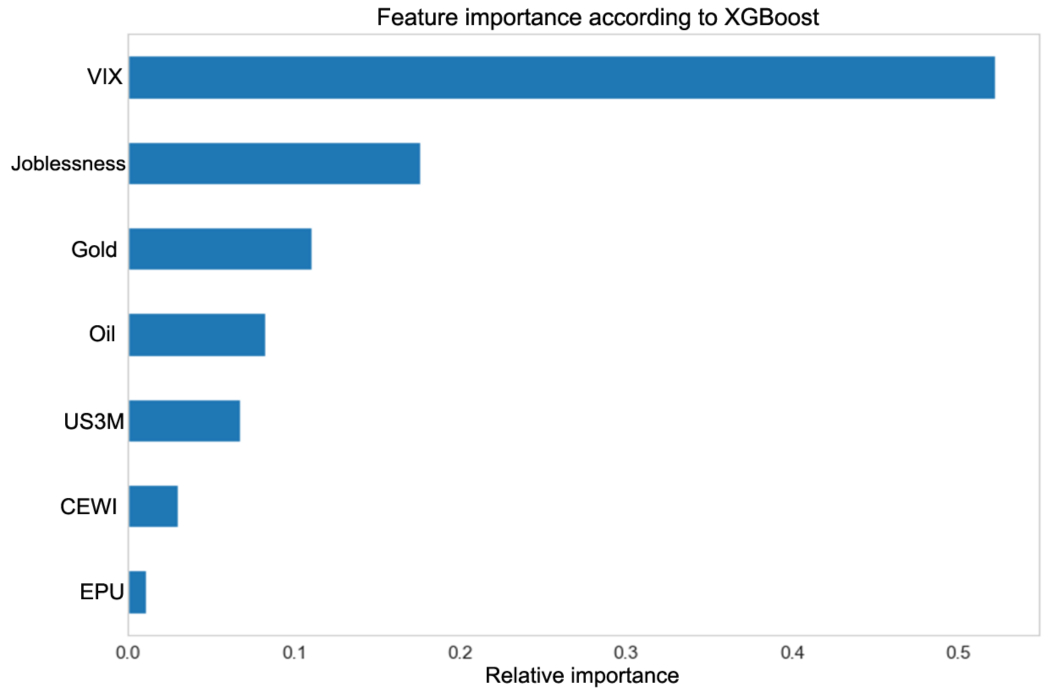

Figure 4. Feature according to XGBoost.

Figure 4 displays the XGBoost feature importance rankings based on the gain metric, reflecting each variable's average contribution to improving model splits. The results revealed that the Volatility Index (VIX) was the most dominant predictor, followed by joblessness and gold prices. Oil prices and short-term interest rates (US 3-month Treasury yield, US3M) also exhibited moderate contributions, while the Composite Early Warning Index (CEWI) and Economic Policy Uncertainty (EPU) had smaller but notable influences.

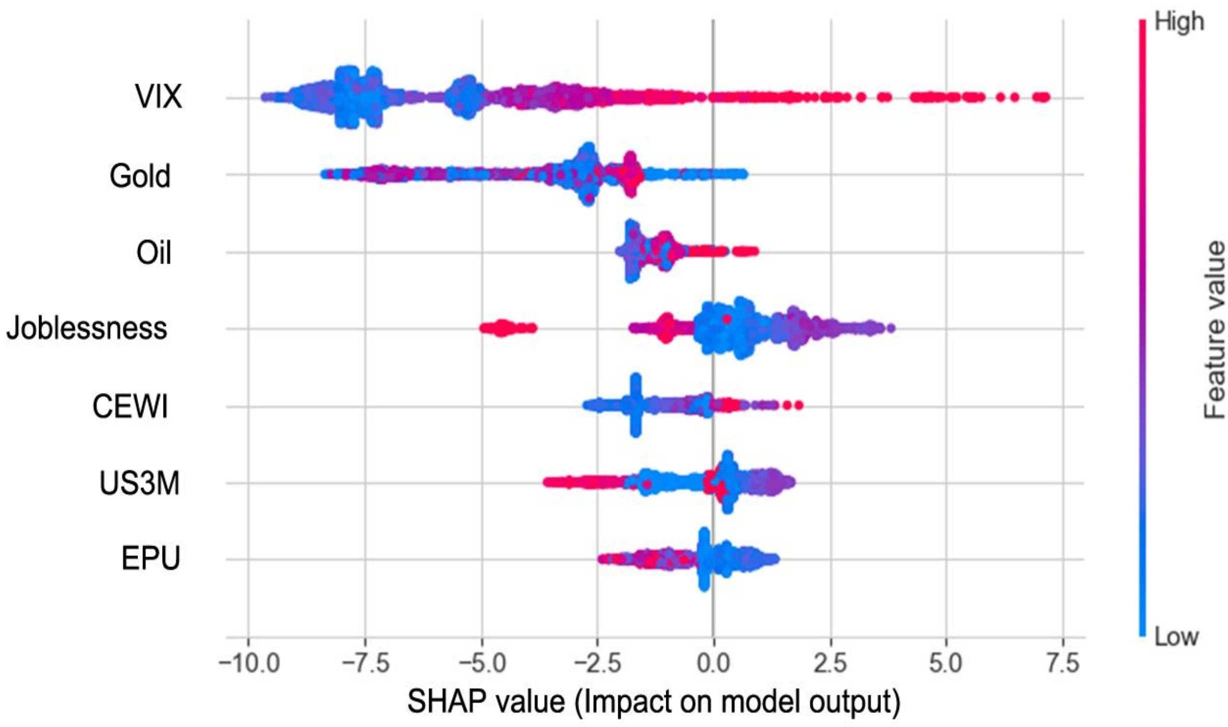

Figure 5. SHAP summary plot.

Figure 5 presents the SHAP summary plot, which visualizes how individual feature values affect the model's output across all samples. The spread and density of SHAP values illustrate the magnitude and direction of each feature's impact. Specifically, higher values of VIX and gold were positively associated with increased crisis probabilities, consistent with economic intuition that associates heightened market volatility and demand for safe-haven assets with financial instability.

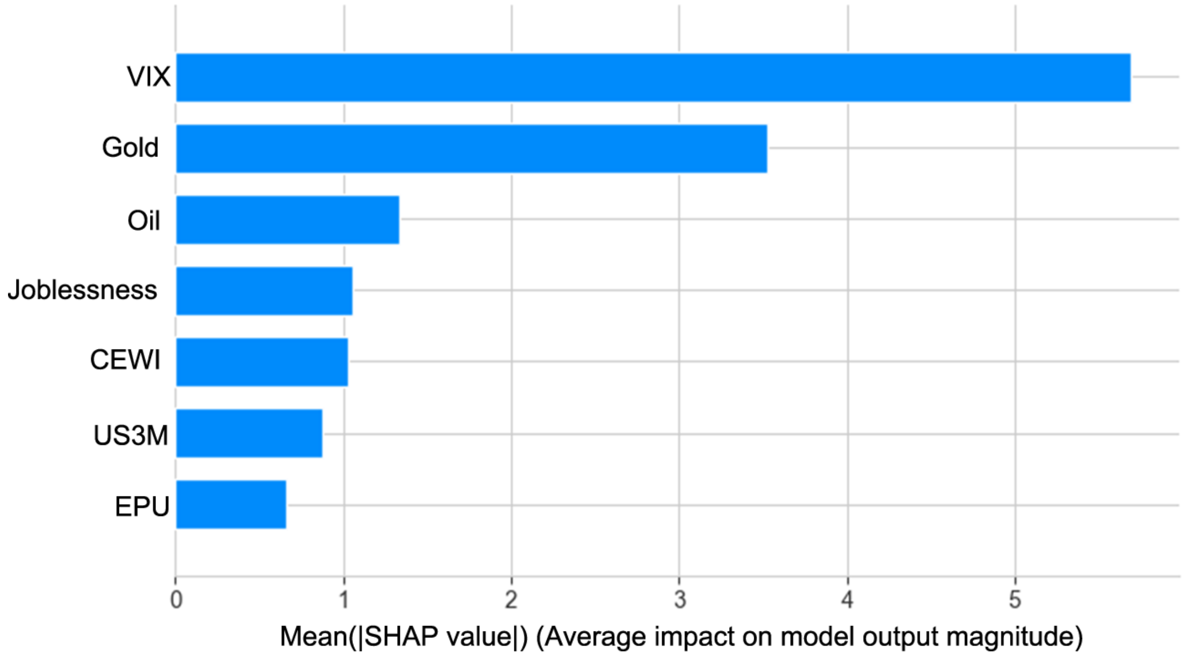

Figure 6. Mean absolute SHAP values.

Figure 6 shows the mean absolute SHAP values, offering a ranked perspective based on the average magnitude of each feature's contribution. The findings confirmed that:

- VIX was the strongest predictor, underscoring the role of financial market volatility as a precursor to crisis events.
- Gold prices emerged as the second most impactful variable, emphasizing their importance during periods of uncertainty.
- Oil prices and joblessness rates contributed meaningfully but at a lower magnitude.
- EPU, CEWI, and US3M exhibited lower influence individually but collectively contributed to the stability of the model's predictive performance.

These multi-perspective analyses (Gain-based importance and SHAP interpretability) consistently highlighted volatility, commodity prices, and labour market conditions as critical components of an effective early warning system for financial crises.

4.7. Feature Correlation Analysis

To explore the relationships between the key financial and macroeconomic indicators used in the prediction model, a correlation heatmap was generated (Figure 7). This analysis provides insight into the potential multicollinearity and interdependencies among the predictors.

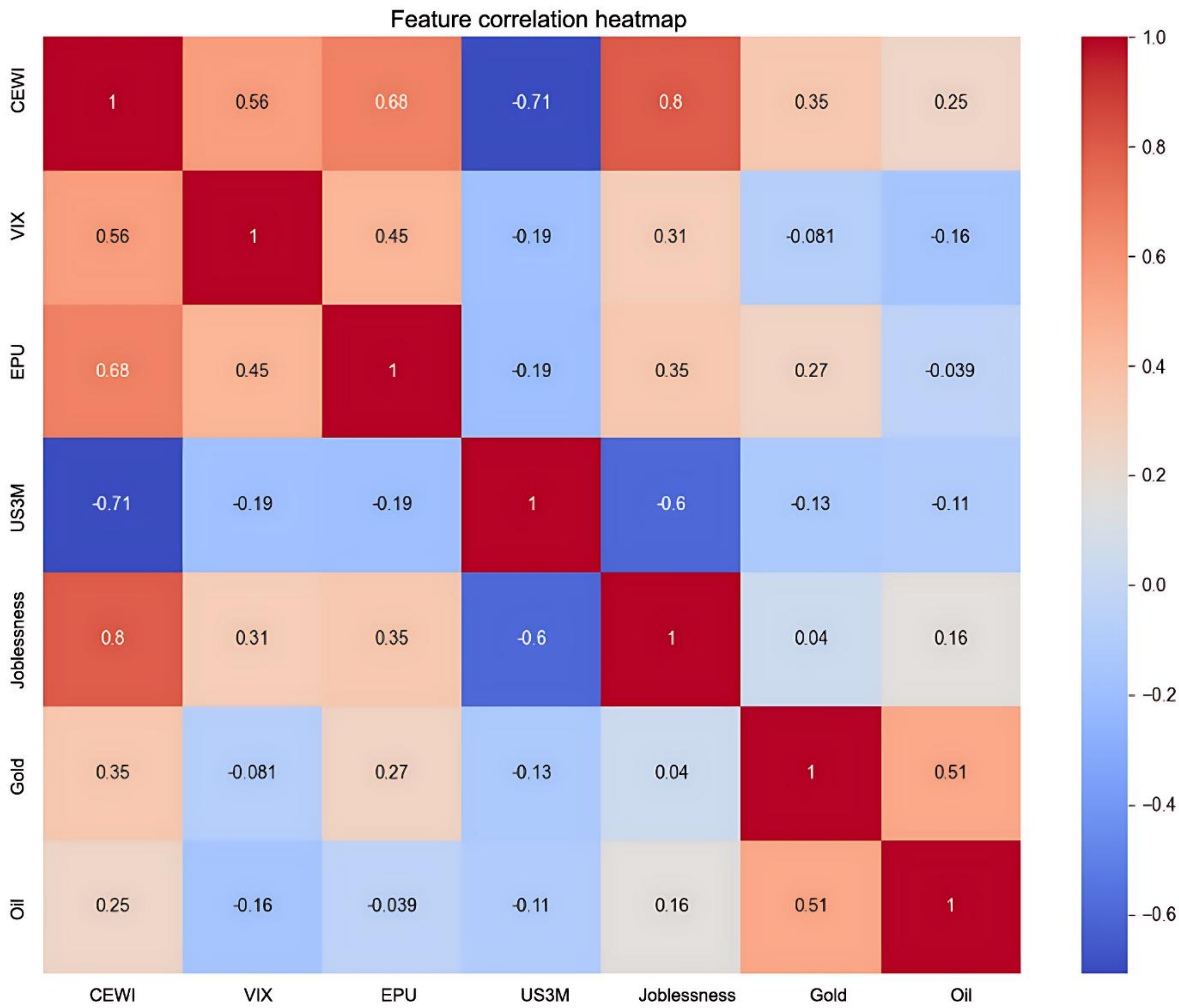

Figure 7. Feature correlation heatmap.

Based on the feature correlation heatmap, the authors observe:

- CEWI (Composite Early Warning Index) showed strong positive correlations with joblessness (0.80) and Economic Policy Uncertainty (EPU) (0.68), and a moderate positive correlation with VIX (0.56). This suggests that CEWI successfully synthesizes information from volatility, labor market stress, and policy uncertainty.
- Joblessness was also moderately correlated with VIX (0.31) and EPU (0.35), reflecting that periods of high market volatility and policy uncertainty often coincide with elevated unemployment rates.
- Gold and oil prices had a moderate positive correlation (0.51), consistent with their intertwined behavior during periods of macroeconomic turbulence.
- The 3-month Treasury yield (US3M) displayed a strong negative correlation with CEWI (-0.71) and joblessness (-0.60), consistent with economic theory, where interest rates fall during downturns and crises.
- EPU and VIX exhibited a moderate positive relationship (0.45), indicating that spikes in policy uncertainty often accompany increased market volatility.

These correlation patterns validate the theoretical underpinnings of the model and reinforce the suitability of the selected indicators for building a robust early warning system.

4.8. Classification Results for the Best Model (XG Boost)

- Table 2 presents the confusion matrix for the XGBoost model:

Table 2. XGBoost model confusion matrix.

Confusion matrix	Predicted no crisis	Predicted crisis
Actual no crisis	3511	60
Actual crisis	28	55

- Classification Metrics:
- Precision: 0.48.
- Recall: 0.66.
- F1-Score: 0.56.
- Accuracy: 98%.

Although precision slightly decreased, recall significantly improved to 66%, which is essential for early financial crisis warning.

4.9. Predicted Crisis Probability with Actual Crisis Events

Figure 8 presents the predicted probability of financial crises over time, as estimated by the XGBoost model, compared with actual observed crisis events. The orange line represents the model's predicted daily crisis probability, while red dots indicate real crisis observations based on the S&P 500 threshold (-3% daily return) and US recession periods (USREC=1).

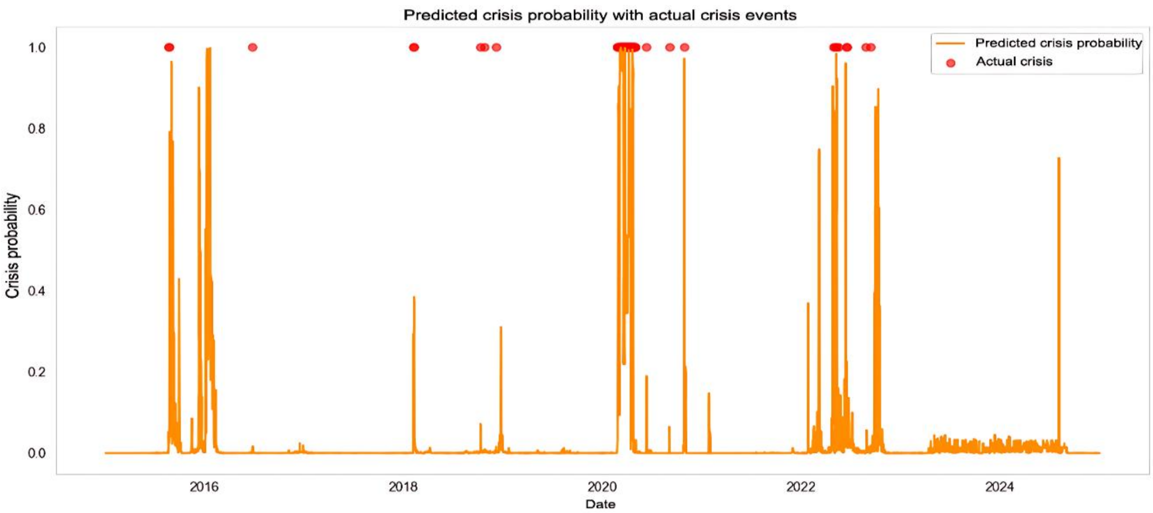

Figure 8. Predicted probability of financial crises over time.

Figure 8 reveals several key patterns observed in the real world:

- Early 2016 (Oil Price Crash):
- Event: Oil prices collapsed to $26 per barrel in January–February 2016 (Canada Energy Regulator, 2017).
- Fit with Chart: A strong spike appears early 2016 in predicted crisis probability, aligning with the oil market crash and financial stress in energy-dependent economies.
- Late 2018 (Stock Market Correction):
- Event: Sharp global stock market correction, especially in December 2018 (The Guardian, 2018).
- Fit with Chart: A noticeable but smaller spike occurs in late 2018, reflecting market fear and correction dynamics.
- March 2020 (COVID-19 Pandemic Crash):
- Event: Global financial crisis triggered by the COVID-19 pandemic declaration in March 2020 (World Health Organization, 2020).

- Fit with Chart: The largest and most sustained spike is visible starting from early 2020, peaking through March and continuing into mid-2020, matching the pandemic onset.
- Mid-2022 (Inflation Shock):
- Event: Surging global inflation rates; the US and Europe face record-high inflation, prompting aggressive interest rate hikes (International Monetary Fund, 2024).
- Fit with Chart: A cluster of moderate-to-high spikes in mid-to-late 2022 matches the inflation crisis and monetary tightening.
- Late 2023 (Geopolitical Risk and Ongoing Economic Uncertainty):
- Event: Heightened geopolitical tensions (Russia-Ukraine war prolongation, Israel–Hamas conflict starting October 2023) (Šćepanović, 2024).
- Fit with Chart: A rise in crisis probabilities is visible towards the end of 2023, coinciding with elevated global risks.

Overall, the model demonstrated strong temporal alignment between major historical crises and elevated predicted risk levels, reinforcing the utility of the Composite Early Warning Index (CEWI) and the predictive modeling framework for real-time financial surveillance and early warning.

5. DISCUSSION

5.1. Interpretation of Main Findings

The analysis revealed that volatility (VIX), gold prices, and oil prices were the dominant predictors of financial market crises. These results are consistent with economic theory, where elevated market volatility and shifts toward safe-haven assets often precede periods of financial distress. The Composite Early Warning Index (CEWI), generated through principal component analysis, significantly improved predictive performance by synthesizing macroeconomic and financial indicators into a single, dynamic measure. The CEWI captured systemic risk fluctuations more effectively than any single variable. Furthermore, by prioritizing recall through customized threshold adjustment, the model achieved a 66% detection rate for crisis periods. Although this adjustment reduced precision, it enhanced the system's ability to function as an early warning tool aligning with the study's goal of minimizing missed crisis events rather than reducing false alarms.

5.2. Comparison with Previous Research

Traditional economic early warning models, such as probit models using macroeconomic variables, often suffer from low out-of-sample accuracy and delayed crisis recognition (Borio & Drehmann, 2009; Kaminsky & Reinhart, 1999). In contrast, the machine learning models developed here, particularly XGBoost, outperformed these historical approaches with an ROC-AUC of 0.953. Unlike models that rely solely on macroeconomic aggregates, integrating financial market volatility and political uncertainty indices provided timelier signals. The inclusion of daily-frequency indicators also enhanced responsiveness, allowing for real-time monitoring compared to slower quarterly or monthly updates typical in classical models.

5.3. Practical Implications

The findings hold important implications for financial practitioners, regulators, and investors:

- Financial Market Monitoring: Central banks and regulators could incorporate CEWI and XGBoost models into macroprudential surveillance frameworks to detect brewing instability earlier.
- Portfolio Risk Management: Asset managers and hedge funds could use the CEWI signals to adjust portfolio exposures, increasing hedging strategies during elevated risk periods.
- Policy Intervention Timing: Early detection may enable policymakers to implement counter-cyclical measures (e.g., liquidity provision) before crises escalate.

6. CONCLUSION

This study developed a Composite Early Warning Index (CEWI) by integrating macroeconomic and financial market indicators through principal component analysis and evaluated its predictive power using machine learning classifiers. The results demonstrated that the CEWI-enhanced models, particularly XGBoost, achieved superior performance in crisis detection, with an ROC-AUC score of 0.953 and a recall of 66% for crisis events.

Key findings highlighted the predominant role of market volatility, gold prices, and oil prices in forecasting financial instability. The use of SMOTE oversampling and threshold optimization further improved model sensitivity toward rare crisis events.

Policy Recommendations: Financial supervisory authorities should consider adopting machine learning-driven early warning systems. Regulators could deploy CEWI as part of macroprudential dashboards to guide intervention timing. Investors and risk managers are also encouraged to integrate such composite indicators to enhance portfolio resilience during periods of market turbulence.

Implementation of CEWI: The CEWI framework can be operationalized using real-time feeds of financial and economic data, allowing near-continuous monitoring. Further automation through dashboards could facilitate timely alerts for stakeholders.

7. LIMITATIONS AND FUTURE RESEARCH

7.1. Limitations

A number of limitations need to be acknowledged:

- Geographical Scope: The model exclusively utilized U.S.-based economic and financial indicators, limiting its generalizability to global markets.
- Static thresholds: Although threshold adjustment improved recall, it remained static after tuning. Adaptive threshold mechanisms reacting dynamically to market conditions could offer further improvements.
- Economic Regime Changes: The model did not explicitly account for structural changes in economic dynamics throughout the 25-year sample period.

7.2. Future Directions

Future research could address these limitations by:

- Incorporating Sentiment Analysis: Text mining techniques could be used to extract real-time sentiment indicators from news articles, earnings reports, and social media platforms to enrich crisis prediction models.
- Expanding to multi-country analysis: Developing a global CEWI by incorporating indicators from multiple economies could improve early warning capabilities in an interconnected financial system.
- Dynamic Threshold Learning: Implementing reinforcement learning or online learning frameworks to adapt thresholds dynamically based on prevailing economic conditions could enhance crisis sensitivity.
- Higher-Frequency CEWI Modelling: Moving beyond daily aggregation to intraday CEWI computation may provide even faster detection in highly volatile environments.

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Appendix 1. Python code used to collect data.

```
# FRED API Key: Obtain free key from https://fred.stlouisfed.org/
# US Daily EPU Index (All_Daily_Policy_Data.csv) can be manually downloaded from
# https://www.policyuncertainty.com/us_daily.html
# === Import Required Libraries ===
import pandas as pd
import yfinance as yf
from fredapi import Fred
from pandas.tseries.offsets import MonthBegin
from datetime import datetime
# === User Settings ===
FRED_API_KEY = "YOUR_FRED_API_KEY_HERE"
START, END = datetime (2000, 7, 1), datetime (2025, 1, 1)
FREQUENCY = "daily" # Options: "daily" or "monthly"
```

```
OUT_XLSX = "economic_financial_data_2000_2025.xlsx"
# === Helper Functions ===
def daily_to_month_avg(series: pd.Series) -> pd.Series:
    """Aggregate daily series to monthly averages."""
    s = pd.to_numeric(series, errors="coerce")
    s = s.resample("M"). Mean ()
    s.index = s.index - MonthBegin(1)
    return s
def adjust_frequency(series: pd.Series, freq: str) -> pd.Series:
    """Adjust time series frequency to daily or monthly."""
    if freq == "monthly":
        return daily_to_month_avg(series)
    elif freq == "daily":
        return series
    else:
        raise ValueError("FREQUENCY must be 'daily' or 'monthly'.")
# === Step 1: Data Collection ===
Print (" Downloading financial market data from Yahoo Finance ...")
tickers = {
    "^VIX": "vix", # Volatility Index
    "^GSPC": "sp500", # S&P 500 Index
    "^DJI": "djia", # Dow Jones Industrial Average
    "^HSI": "hsi", # Hang Seng Index
    "GC=F": "gold", # Gold Futures
    "CL=F": "oil"     # Crude Oil Futures}
market = {}
for tk, clean_name in tickers.items():
    try:
        df_yf = yf.download(tk, start=START, end=END, progress=False, auto_adjust=True)
        series = df_yf["Close"]. Squeeze ()
        series.name = clean_name
        market[clean_name] = adjust_frequency(series, FREQUENCY)
        print (f" ✓ {tk} ({len(series)} records)")
    except Exception as e:
        print (f" Failed to download {tk} → {e}")
print (" Downloading macroeconomic indicators from FRED ...")
fred = Fred(api_key=FRED_API_KEY)
fred_series = {
    "DGS3MO": "us3m", # US 3-Month Treasury Bill Rate
    "UNRATE": "joblessness", # Unemployment Rate
    "CPIAUCSL": "cpi"          # Consumer Price Index)
econ = {}
for code, clean_name in fred_series.items():
    try:
        series = fred.get_series(code, START, END).to_frame(clean_name)[clean_name]
```

```
        if FREQUENCY == "daily" and code in ["UNRATE", "CPIAUCSL"]:
            series = series.resample("D"). ffill () # Forward-fill monthly data to daily
        econ[clean_name] = series
        print (f" ✓ {code} downloaded")
    except Exception as e:
        print (f" Failed to download FRED series {code} → {e}")
print (" Loading US Daily Economic Policy Uncertainty (EPU) Index ...")
try:
    raw_epu = pd.read_csv("All_Daily_Policy_Data.csv", encoding='latin1', header=None, skip_blank_lines=True)
    raw_epu = raw_epu[raw_epu.apply(lambda x: x.count() == 4, axis=1)]
    raw_epu.columns = ["day", "month", "year", "daily_policy_index"]
    epu_daily = (
        raw_epu.assign(date=lambda d: pd.to_datetime(d[["year", "month", "day"]], errors="coerce"))
        .dropna(subset=["date"])
        .set_index("date")["daily_policy_index"] )
    epu_daily = epu_daily.loc[(epu_daily.index >= START) & (epu_daily.index <= END)]
    epu_daily.name = "epu"
    if FREQUENCY == "monthly":
        epu_daily = daily_to_month_avg(epu_daily)
    econ["epu"] = epu_daily
    print("  ✓ US Daily EPU loaded successfully")
except Exception as e:
    print(f"  Failed to load EPU file → {e}")
# === Step 2: Combine Datasets and Export ===
print(" Combining datasets ...")
df = pd.concat([*market.values(), *econ.values()], axis=1).sort_index()
df = df.apply(pd.to_numeric, errors="coerce")
df = df.ffill().bfill()
# Ensure all expected variables are present
expected_columns = ["vix", "sp500", "djia", "hsi", "gold", "oil", "us3m", "joblessness", "cpi", "epu"]
for col in expected_columns:
    if col not in df.columns:
        df[col] = pd.NA
print(f" Data collected successfully: {df.shape[0] } rows, {df.shape[1] } columns.")
# Export to Excel
df.to_excel(OUT_XLSX)
print(f" Data exported successfully to {OUT_XLSX}")
```

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