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Macroprudential Policies in the Light of the Development of Information Technologies: A Synthesis on the Effective Early Warning Signals[1]

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Abstract. In response to recent recurrent crises, innovative macroprudential policies (MaPs) have been framed and implemented to address the weaknesses of market-led microprudential mechanisms and enhance the stability of financial systems. However, the effectiveness of the tools used to implement MaPs remains a critical research question. Early warning signals (EWS) serve as indicators of potential future crises. This paper explores approaches for identifying EWS to optimize the impact of MaPs, particularly in light of advances in information technology. It provides a comprehensive review of academic studies that identify effective EWS by analyzing numerical data through econometric and machine learning (ML) methods or by extracting economic insights from text using deep learning (DL) techniques — innovative methods for financial supervision and regulation. The findings, considering current regulatory practices, highlight the benefits of ML-based approaches for processing large sets of numerical data and the growing potential of text-based methods for assessing economic expectations.

Keywords: cost of regulation, early warning signals, financial crisis, financial stability, macroprudential policy

ИССЛЕДОВАТЕЛЬСКАЯ СТАТЬЯ

Макропруденциальная политика в свете развития информационных технологий: изучение эффективных сигналов раннего предупреждения

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Аннотация. Инновационные меры макропруденциальной политики (MaPs) были разработаны и реализованы в ответ на недавние повторяющиеся кризисы для устранения рыночных микропруденциальных уязвимостей и укрепления стабильности финансовых систем. Однако эффективность различных инструментов макропруденциальной политики по-прежнему остается критически важным вопросом исследований. Сигналы раннего предупреждения (EWS) используются в качестве индикаторов вероятности будущего кризиса. Целью данной статьи является изучение подходов к определению EWS для максимизации эффективности MaPs в свете развития информационных технологий. В статье представлен всесторонний анализ академических работ, которые определяют эффективные EWS путем анализа числовой информации с использованием эконометрических методов и методов машинного обучения (ML) или путем извлечения экономической информации из текста на основе методов глубокого обучения (DL), которые можно рассматривать как инновационные подходы к финансовому надзору и регулированию. Полученные результаты с учетом текущей практики регулирования указывают на преимущества определения эффективных EWS с помощью подходов машинного обучения для анализа числовых данных, поскольку этот подход позволяет одновременно обрабатывать большое количество переменных; и потенциал развития применения методов извлечения экономической информации из текстовых данных для определения ожиданий.

Ключевые слова: издержки регулирования, сигналы раннего предупреждения, финансовый кризис, финансовая стабильность, макропруденциальная политика

1. Introduction

In the wake of the 2007–2008 global financial crisis (GFC), financial regulators developed more preventive, macro-level policies to stabilize markets. Macroprudential policies (MaPs) and related tools like Early Warning Signals (EWS) have become the main regulatory mechanisms over the past few decades, replacing the market-driven microprudential rules of the 1990s and 2000s. Numerous recent studies (Adrian et al., 2022; Laeven et al., 2022; Belkhir et al., 2022) highlight the effectiveness of MaPs. For instance, Adrian et al. (2022) emphasize the positive impact of MaP measures during the COVID-19 pandemic and the strong policy framework established after the GFC in mitigating the financial impact of the pandemic.

However, other studies point to the costs of MaPs such as reduced credit supply to businesses (Laeven et al., 2022a), increased financial stability at the expense of efficiency in the non-financial sector (Belkhir et al., 2022), greater risks in the non-banking sector (Adrian et al., 2022), and a potential decline in economic growth (Laeven et al., 2022a).

Research often attributes these effects to MaP measures. However, the impact of other factors, such as economic crises, declining demand and income, and financial shocks, should not be overlooked. Ultimately, if the goal of MaP is to reduce the likelihood of a financial crisis, the most effective approach would be the one that minimizes side effects.

The costs associated with activating MaPs have been underexplored despite their confirmed effectiveness (Laeven et al., 2022). Finding a balance between the benefits and costs of MaPs is a key challenge for authorities (Laeven et al., 2022; Borio et al., 2022) and can be achieved through careful calibration of policy instruments. Proper calibration can also reduce the need for intervention throughout the cycle (Laeven et al., 2022a, p. 4).

There are few tools that assist policymakers in selecting the right measures and timing for MaP implementation (Barbieri et al., 2022). Barbieri et al. (2022) propose a model that breaks down credit growth into three components: overall credit growth, idiosyncratic demand, and supply components. The model regresses bank and firm credit growth on a full set of time-fixed effects, defining the "common component" as the median of these effects. Schmitz et al. (2022) emphasize reducing regulatory overlap and using the capital buffer flexibly, while acknowledging the challenges posed by data lags and uncertainties. European Systemic Risk Board (ESRB, 2014) recommends six categories: private-sector credit developments and debt burden, overvaluation of property prices, external imbalances, mispricing of risk, and strength of bank balance sheets.

This paper aims to identify relevant EWS and approaches to help policymakers calibrate MaP instruments more efficiently. Through a detailed analysis and comparison of various EWS models, we highlight the most effective methods for improving MaP calibration and policy outcomes.

There is a widespread opinion that A. Smith was in favour of market self-regulation, while many economists of the later period, especially after the crisis of the 1930s, were in favour of state intervention and regulation of markets. This position is only partially true (Toporowski, 2005). And Smith supported the idea of free trade and non-interference in business. At the same time, both Smith and Quesnay favoured control over finance, particularly restrictions on interest rates, because both noted the tendency for money and credit markets to be captured by the interests of non-productive or speculative economic activity.

A new stage of development of views on the need to regulate finance was reached after the crisis of the 1930s. Keynes believed that the reason for the dependence on subjective estimates of market value is uncertainty, the speculator cannot know the future value of his investments. Expectations tend to become overly optimistic as a boom develops and overly pessimistic as a recession develops. In a recession, lender and borrower confidence must be restored in order to attract investment and hence profits. Keynes recognised that this could not be done through the banking system alone. There must be a combination of lowering short-term interest rates, open market operations and restoring the attractiveness of illiquid assets.

More recent research also supports the need for financial stability. Hyman Minsky advocated a policy of government economic stabilisation. He believed that uncontrolled credit expansion could lead to financial collapse.

The article is structured as follows. The second section analyzes approaches for identifying effective Early Warning Signals (EWS). The third section explores models that extract economic information from numerical data for EWS identification and proposes improvements. The fourth section examines the role of artificial intelligence (AI) and machine learning (ML) in identifying EWS as key innovations in financial supervision and regulation. The fifth section investigates AI as a tool for extracting economic information from text data. The sixth section focuses on practical aspects, evaluating indicators used by the European Central Bank (ECB) to assess financial stability and the dynamics of risk indicators alongside MaP measures post-2008. The final section concludes with an evaluation of EWS methods used by central banks and their effectiveness in measuring systemic risk and other MaP outcomes since 2008.

2. Analysis of Approaches to Identify Effective Early Warning Signals

There is no single approach to defining a good EWS. Signaling norms are usually not enshrined in MaP regulations and are still the subject of academic research. Since macroprudential policy is responsible for dealing with systemic crises, the definition of a good measure of systemic risk as a measure of EWS seems relevant. As Liu and Pun (2022) note, a good measure of systemic risk should provide an early signal reflecting the likelihood that the system will experience a crisis within a certain period of time.

The difficulty in identifying clear crisis signals stems from the constantly evolving financial environment, the emergence of financial innovations, and the fact that past crises may not reflect current conditions. As Vrontos et al. (2021) argue, recessions vary in nature and causes, making them hard to predict with the same triggers. Bluwstein et al. (2023) highlight other challenges, such as the limited number of observed crises, which complicates reliable modeling. Additionally, crisis indicators often appear too late, and "Knightian uncertainty" means that some events can't be predicted. Moreover, it is not easy to translate complex early warning models into simple and understandable indicators.

The literature review shows two main approaches to signal identification: numerical analysis of economic data and text analysis. The first, more common, uses econometric methods like probit, logit models, or ML approaches. The second, less studied, focuses on extracting information from text sources like news or social media using deep learning (DL). The key difference between AI technologies and conventional software lies in AI's ability to learn. Unlike traditional systems, which rely on predefined algorithms, AI systems learn from data, adjusting internal parameters to produce solutions (Di Patti et al., 2022).

Machine learning (ML) is an AI technology that uses mathematical models to help computers learn from data without direct human instruction. ML tools identify hidden, non-obvious relationships in data, enabling predictions and recommendations.

Deep learning is a type of ML based on Artificial Neural Networks — AI models that represent a multilayer system of connected and interacting logical computing units (artificial neurons). The goal of creating artificial neural networks was to imitate the process of human thinking.

Table 1

Classification of Approaches to EWS Identification

Type of analysis	Approach	Examples
Extracting economic information from numerical data	Econometric	Borio et al. (2019) Eberhardt and Presbitero (2018) Chen and Svirydzenka (2021)
	Machine learning (ML)	Bluwstein et al. (2023) Vrontos et al. (2021) Alessi and Detken, 2018)
Extracting economic information from text data	Deep learning (DL)	Li et al. (2019) Fulo and Kocsis (2023) Gu and Kurov (2020)

Source: Compiled by the author.

The following sections provide a detailed discussion of various approaches to defining EWS. The survey begins by comparing standard econometric methods with ML in identifying economic patterns from numerical data.

3. Extracting Economic Data from Numerical Data for EWS Identification and Improvement

Approaches for extracting economic information from quantitative data are the most common methods for identifying early warning signals (EWS). These methods can be broadly categorized into two classes: econometric approaches and machine learning (ML) approaches. According to Chen and Svirydzenka (2021) and Casabianca et al. (2019), quantitative approaches for EWS identification can be further divided into three groups:

1. Probit / logit models. Regression models with a restricted dependent variable in which the probability of a crisis is estimated as a function of a number of variables. The outcome variable is binary (crisis/non-crisis) and the probability that an event (crisis) will occur is estimated as a function of factors. Borio, Drehman and Xia (2019), and Eberhardt and Presbitero (2018) use this kind of models to show that the methodology has the advantage of estimating the relative importance of variables jointly, even though it is difficult to consider a large number of indicators simultaneously.

2. Signal approach. The non-parametric approach involves setting a threshold above which the likelihood of a crisis increases. However, the signal approach uses each indicator in isolation, and the model does not allow aggregation of individual warnings. The simplest solution is to count the number of leading indicators signaling a distress. A variant of this approach is presented by Chen and Svirydzenka (2021).

3. Machine learning. More recent non-parametric approaches such as artificial neural networks, which are complex non-linear multi-level and fully data-driven inference procedures that focus on predictive accuracy. It is a data mining tool capable of analyzing complex data sets. The two previous approaches — logit/probit models and the signal approach — are standard econometric techniques. In contrast, machine learning (ML) is a subset of artificial intelligence. Recent debates within the AI community have highlighted that ML approaches can be influenced by biased inputs, potentially reinforcing existing biases[1].

The analysis of the approaches to identify the best / relevant EWS have been done by Eberhardt and Presbitero (2018), Borio et al. (2019), Chen and Svirydzenka (2021), and Alessi and Detken (2018). These studies provide a comprehensive and empirical overview of the issue over the last few decades, covering large groups of countries, including both advanced economies (AEs) and emerging market economies (EMEs). The research, conducted by the International Monetary Fund and the Bank for International Settlements — organizations directly involved in developing MaP tools globally — offers broad geographical scope and practical insights. The results are presented in Table 2 below.

A distinctive feature of the study by Alessi and Detken (2018) is its use of a significantly larger set of explanatory variables compared to those in standard econometric studies. This underscores the capacity of ML techniques to process extensive data and identify patterns among multiple variables.

[1] In this article, we do not consider examples of using AI to identify the best EWS. In addition, the advantage of standard econometric techniques is the ability to estimate the statistical relationship between an indicator and the probability of a crisis event.

Table 2

Analysis of Approaches to Identifying Effective EWS

Source	Borio, Drehman, Xia (2019)	Eberhardt, Presbitero (2018)	Chen, Svirydzenka (2021)	Alessi, Detken (2018)
Methodology	Panel probit model	Logit model	Non-parametric signal extraction approach, Logit model (robustness check to EWS)	Binary classification tree, Random Forest (machine learning technique)
Time horizon and countries	16 AEs (1985–2017), 14 EMEs (1996–2000)	60 low-income countries (1981–2015)	34 AEs, 25 EMEs (1960–2014)	28 EU members from 1970Q1 till 2013Q4
Indicator prediction time	3 years	Up to 11 years	Up to 5 years	Not specified
How to identify a recession	Business cycle (output, employment, real GDP)	Systemic banking crisis	Financial cycle	Banking crisis episodes in EU countries from 1970 to 2010 were discussed by Babecky et al. (2014), who aggregated information on crisis occurrences from various studies and conducted an ad-hoc survey among country experts, primarily from national central banks.
Explanatory variables	Term spread (10 years and 3 months), Composite financial cycle indicator (CFCI)[1], Debt service ratio (DSR)[2]	44 primary commodity prices — aggregate commodity price (ACP)[3], control variables. Other macroeconomic variables	Multiple variables, including credit, equity and property prices, leverage	The analysis includes a range of credit-related indicators, such as broad credit aggregates compiled by the BIS, narrower bank credit aggregates, and the debt service ratio. It also examines macroeconomic indicators like real GDP growth, the current account as a percentage of GDP, M3 money aggregate, and the real effective exchange rate, along with the house price-to-income ratio and the house price-to-rent ratio. Additionally, market-based indicators are considered, including long-term (10 years) and short-term (3 months) interest rates, both adjusted for CPI changes. In total, more than 30 variables were analyzed.

Source: Compiled by the author.

[1] Medium-term cyclical fluctuations in real (inflation-adjusted) credit, the credit-to-GDP ratio and real property prices, which are then averaged to derive a composite measure of the financial cycle (Drehmann et al. (2012))

[2] Interest payment and amortisation of the private non-financial sector relative to income (Drehmann et al. (2015))

[3] Monthly data for 44 global primary commodity prices from the IMF Primary Commodity Price Database, in combination with annual information on country-specific net export/GDP and export/GDP for each primary commodity (Gruss, 2014; Bazzi & Blattman, 2014).

The methodology employed in these studies is notably similar, characterized by empirical analysis, with time horizons ranging from 30 to 54 years and samples encompassing 30 to 60 countries. However, there is a considerable variance in the prediction time for indicators, with different papers adopting time horizons of 3, 5, and 11 years. This raises the question of what time frame is adequate for macroprudential measures to respond effectively in preventing or mitigating a crisis, as well as which time horizons are most suitable for identifying indicators.

The studies also differ in their definitions of the onset of recession. Two papers (Borio et al., 2019; Chen & Svirydzenka, 2021) base their definitions on financial and business cycles, considering factors such as output, employment, and real GDP. In contrast, Eberhardt and Presbitero (2018) and Alessi and Detken (2018) focus specifically on the moments of a banking crisis. Given that not every banking crisis necessarily leads to an economic downturn or a decline in living standards, the first approach appears more appropriate. Therefore, we can suggest that incorporating social and person-centered indicators — such as well-being, life satisfaction, and happiness levels — could enhance the assessment of the crisis's impact.

None of the methods examined address the relationship between the depth of a recession and the levels of early warning signal indicators. Establishing such a relationship could be valuable for calibrating macroprudential measures, thereby enhancing their operational scope and effectiveness.

Each study evaluates multiple explanatory variables suggested by EWS, resulting in the identification of the best indicators for forecasting crises in the studied samples. However, the findings across different studies for the same group of countries often vary. For instance, Borio et al. (2019) identify credit, credit-to-GDP ratios, property prices, and partially debt service ratios as the best financial cycle indicators for advanced economies, while Chen and Svirydzenka (2021) focus on equity prices and the output gap.

Since the reviewed literature indicates no single indicator that can serve as an effective early warning signal even for a homogeneous group of countries, it seems reasonable to adopt a system of indicators for managing macroprudential measures.

Alessi and Detken (2018), employing ML methods, demonstrate the feasibility of a simultaneous analysis of large datasets. In the next section, we will explore the application of AI methods, including those based on ML, for identifying EWS.

4. Features of Artificial Intelligence and Machine Learning for EWS Identification

Recent scientific and technological advancements have led to a growing body of academic research on AI and its potential applications in financial studies. AI technologies are increasingly being developed in the financial sector, assisting risk managers, financial institutions, and regulatory authorities in enhancing their analyses and forecasting of market behavior and trends. For example, AI algorithms have proven valuable in areas such as corporate default forecasting (Fraisse & Laporte, 2022), credit risk modeling (Brezigar-Masten et al., 2021), assessing the credit quality of bank customers (Krivorotov, 2023), and estimating and predicting default losses (Kellner et al., 2022).

As noted by Danielsson et al. (2022), AI refers to computational algorithms that make decisions typically made by humans, often leveraging ML for information retrieval. Machine learning is a fundamental component of most AI applications (Danielsson et al., 2022) and involves acquiring knowledge about the environment the AI needs to control. The effectiveness of available methodological approaches and their accuracy depend on the quantity and quality of data. Learning can be categorized as supervised or unsupervised. Unsupervised learning focuses on discovering patterns in data without any prior knowledge of the underlying problem structure, with these patterns then being translated into mathematical logic.

Many authors agree on the positive predictive power of ML models compared to standard econometric approaches (Bluwstein et al., 2023; Baret et al., 2023; Vrontos et al., 2021; Liu & Pun, 2022). The high performance of ML models is attributed to several advantages. First, these models can easily and flexibly learn a variety of signals from data, including nonlinearities and interactions, unlike regression-based models (Bluwstein et al., 2023). Additionally, ML methods are generally not susceptible to reverse causality (Baret et al., 2023).

However, some disadvantages of this approach warrant consideration, even as research continues to find ways to overcome them. While ML models demonstrate high predictive power, issues related to data remain prominent. Machine learning methods rely on identifying patterns in existing data, but several difficulties in data collection and utilization can hinder the effectiveness of these models (Danielsson et al., 2022):

1. Measurement problems, fragmentation and hidden relationships limit the information that can be collected.

2. Measurement problems, fragmentation, and hidden relationships limit the information that can be gathered. Furthermore, the financial system is constantly undergoing structural changes; new types of market participants emerge, while others exit, and financial innovations create new opportunities, diminishing the value of historical data for modeling.

3. Algorithms may make decisions based on statistical patterns that are either misleading or change as the AI attempts to exploit them.

Although early ML algorithms required extensive datasets, many new ML architectures (support vector machines, random forests, and various boosting-based methods) have more accessible data requirements (Baret et al., 2023). Some other difficulties in the application of ML mechanism are described in the academic literature, while ways to address these shortcomings are proposed.

Bluwstein et al. (2023) highlight that predictions made by "black box" models are often difficult to interpret and explain. The authors propose solutions, such as separating ML predictions into contributions from individual variables using Shapley values and regression techniques, which can help identify the key economic drivers of the models. Baret et al. (2023) point out that ML methods are susceptible to overfitting, a common error where the model learns to describe the training data rather than the underlying phenomenon. They suggest that such errors can be avoided by employing a withholding check or more robust k-fold cross-validation. In holdout validation, the dataset is divided into a "training" set for model training and a "test" set for evaluating model performance on unseen data.

Research applying ML techniques (Bluwstein et al., 2023; Vrontos et al., 2021) to identify pre-crisis situations demonstrates the high predictive power of these models. For instance, Bluwstein et al. (2023) forecast financial crises one to two years in advance by analyzing macroeconomic and financial variables from 17 advanced economies over more than 140 years, resulting in a binary variable indicating financial crises. Their study compares the performance of logistic regression with several ML models, including decision trees, random forests, extremely randomized trees, support vector machines (SVMs), and artificial neural networks. The findings indicate that, except for individual decision trees, all ML models exhibit strong predictive power and outperform logistic regression.

Vrontos et al. (2021) apply ML techniques to predict recessions in the United States, estimating recession predictability from 1979 to 2019. They find that the introduction of various ML techniques significantly improves accuracy. Among these, binary logit models with penalized likelihood (LASSO and Elastic Net) and the k-nearest neighbors (k-nn) method consistently perform well across short-, medium-, and long-term forecasting horizons, followed by regularized discriminant analysis, Bayesian analysis, and random forests, particularly for short-term forecasts. The study also confirms the predictive power of the yield curve for a 12-month horizon.

Several recent studies have similarly employed ML techniques for analysis. Liu and Pun (2022) note that ML algorithms enhance the predictive power of systemic risk measures, using examples from U.S. and Hong Kong companies. Ari et al. (2021) present a new dataset detailing the dynamics of problem loans across 92 banking crises since 1990, revealing commonalities in the accumulation of problem loans but significant heterogeneity in their resolution rates. Kamruzzaman et al. (2022) estimate systemic risk in financial markets using an AI-based model that incorporates various inputs, including portfolio data, trading data, market data, financial reports, market conditions, and industry data.

Currently, the application of ML technologies for analyzing numerical financial and economic information to identify EWS of potential financial crises is widespread. Additionally, the vast amount of textual information generated by economic agents is increasingly recognized by academic researchers as a valuable source of economic data that can be transformed, for instance, into an index. In the next section, we explore examples of using AI to extract economic information from textual data.

5. Artificial Intelligence for Extracting Economic Information from Text Data

A specialized area of AI application in finance is the use of technology for extracting economic information from text data, particularly through deep learning technologies for text analysis. Research literature highlights several advantages of this approach, as summarized in Table 3 below:

One can point to many valuable works that apply DL techniques to analyze text to extract economic information such as Li et al. (2019), Fulo and Kocsis (2023), and Fulo and Kocsis (2023). Below, we provide a brief outline for each of these approaches.

Table 3

Advantages of Extracting Economic Information from Textual Data

Description	Source
Information on the Internet is published more often than official statistics, contains a lot of unused qualitative information that can be used to improve forecasting.	Li et al. (2019)
Textual data convey predictive expectations, including perceptions of various risk scenarios, whereas traditional micro and macroeconomic data reflect recent history.	Fulo and Kocsis (2023)
Information from social media is more timely than information from traditional media and is more likely to be relevant.	Gu and Kurov (2020)

Source: Compiled by the author.

Li et al. (2019) predict crude oil prices based on analyzing online media texts to identify more immediate market antecedents of price fluctuations through DL techniques, extracting hidden patterns in online media using a convolutional neural network (CNN). Sentiment features in news text extracted using CNN model show a significant relationship with price changes. A feature clustering method based on topic latent distribution model (LDA) is proposed. Text analysis techniques are used to classify text, sentiment analysis and topic models to convert unstructured text into a representative format that is structured and can be processed by a machine. It is shown that textual and financial features complement each other in making more accurate crude oil price forecasts.

Fulo and Kocsis (2023) propose a method for extracting textual information about macroeconomic fundamentals. The technique is applied to the Reuters news corpus for 2007–2022 from Factiva, containing about 1.8 million news articles (88 countries and 11 regions), to create news indices of country fundamentals. The approach to determining tone in economics and finance is to use large predefined dictionaries that categorize adjectives into positive/negative categories, then assign a tone score to the document. The word lists are either selected manually or through a supervised learning approach. Creation of time-series text indices on key macro topics at the country level that aggregate information: topic (what the text is about) and tone (whether the text reflects optimism/pessimism). Incorporating the derived news indices alongside traditional macro variables significantly increases the explanatory power attributed to fundamentals (for example, explain about half of the changes in sovereign spreads by changes in fundamentals).

Gu and Kurov (2020) study the information content of firm-specific sentiment extracted from Twitter. Tweets represent information not yet reflected in stock prices (analysts' recommendations, analysts' target prices, quarterly earnings). They study tweets about specific types of events, perform textual analysis using existing word classifications, and use the relative frequency of bullish or bearish terms to modify investor sentiment. On average, the returns of firms with the most positive sentiment over the next 24 hours are 0.27 % higher than the returns of firms with the most negative sentiment. This difference is significant if transaction and exchange trading volumes are high.

Table 4

Examples of Extracting Economic Information from Textual Data

Source	Li et al. (2019)	Fulo and Kocsis (2023)	Gu and Kurov (2020)
What is forecast	Crude oil prices	Macroeconomic variables	Stock prices
Source of information	Online media texts	Reuters news for 2007–2022 from Factiva, containing approximately 1.8 million news articles (88 countries and 11 regions)	Tweets devoted to specific types of events
What is done	Text analysis using convolutional neural network (CNN) for text classification, sentiment analysis and topic patterns.	Creation of news indices for the country's main indicators on key macro topics using a set of predefined regular expressions and a Bayesian feature selection model.	Analysis of changes in investor sentiment using word classifications based on the relative frequency of bullish and bearish terms.

Source: Compiled by the author.

Table 5

Difficulties in the Application of Text Analysis and Possible Solutions

Description	Solution	Source
Different topics within a single transaction day are likely to have different effects on the price of crude oil. Crude oil news can usually be categorized into several topics such as “oil stocks”, “stock market”, “foreign exchange market”, “political events”, etc.	It is necessary to group textual features (quantitative variables extracted from news texts, including sentiment characteristics) into different topics for each transactional day.	Li et al. (2019)
Document-level tonality becomes ambiguous if there are multiple themes in the text; expression dependency (for example, GDP growth or unemployment).	Features can be extracted from text using regular phrases or by identifying them when they appear with the maximum spacing between words.	Fulo and Kocsis (2023)
Social media contain more noise than information. It is difficult, if not impossible, to detect and analyze all tweets.	Many firms are using social media to communicate with investors and clients.	Gu and Kurov (2020)

Source: Compiled by the author.

The vast amount of information available today requires advanced methods for effective analysis. Although the predicted variables and sources of textual data may differ, the techniques for extracting economic insights remain similar. These methods rely on specialized dictionaries of words and phrases to gauge the sentiments of economic agents and predict potential shifts in key indicators. The findings from this analysis can be integrated with financial data to enhance accuracy. However, applying these methods comes with certain challenges that need to be resolved.

The application of technologies of text analysis to economic data is promising and complements quantitative data analysis methods, which can also be used to identify EWS of potential financial crises.

6. Practical Aspects of the Effectiveness of MaPs and Applied EWS

We examine the practice of financial stability assessment by regulatory authorities (ECB, 2023). The report outlines more than 100 indicators that describe the region’s financial stability, emphasizing the complexity of this phenomenon. It highlights the need for early warning signals to capture various aspects of financial stability. The report divides the indicators into four groups: the macro-financial and credit environment, financial markets, the banking sector, and the non-bank financial sector.

It seems appropriate to classify the indicators into two main categories: simulate and expected values[1] and achieved values (which include the stock market, real estate, corporate and government debt, banking profits, and lending). Regardless of the grouping, analysis of financial stability involves a large set of variables, making machine learning methods essential for processing vast amounts of data.

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[1] Estimated changes in nominal bond holdings after a 1 percentage point increase in yields; estimated changes in nominal bond holdings after a 1 % increase in financial market uncertainty; model prediction of sectoral absorption and yield changes after higher issuance announcement and financial market volatility shock; stylised simulation of hedging flows from a €1 million investment in EURO STOXX 50 options, by time to expiry; stylised simulation of hedging flows from a €1 million investment in EURO STOXX 50 options with one day to expiry, by moneyness; stylised simulation of hedging flows from a €1 million investment in EURO STOXX 50 options with one day to expiry, by put/call ratio.

We also aim to determine whether MaP is effective. To do this, we analyze the dynamics of risk assessment indicators available on the ECB data portal[1]. We focus on eight types of indicators, using France as an example, with data spanning from 2003 to 2024 (or 2023).

The first stage of our analysis focuses on studying the indicator values from 2003 to 2008. Following the GFC, macroprudential policy measures, particularly Basel III, were introduced to strengthen financial stability. Our aim is to assess whether these indicator values changed after 2008, and from this, we can draw two conclusions: (1) whether macroprudential measures effectively reduce financial risks, and (2) which indicators are the most reliable for evaluating the impact of these measures.

The lending margins of MFIs (Monetary Financial Institutions)[2] on loans for house purchases steadily declined from 2.0354 in 2003 to 0.8044 in 2008. However, immediately after the GFC in 2009, the margin jumped to 2.431, then consistently decreased to 0.9974 by 2022. In 2023 and 2024, the margins even turned negative, possibly reflecting changes in real estate prices.

The loans-to-deposits ratio (MFIs excluding ESCB) showed an upward trend from 2003 (117.8761) to 2008 (139.2491), indicating rising loan volumes and a lower propensity to save. This aligns with the view that rapid credit growth can lead to financial crises. The ratio remained high from 2009 to 2012 (140.259–131.18) but declined steadily until 2022 (100.6494), before showing an increase in 2023 (103.041). This trend provides insights into the effectiveness of MaP measures.

MFIs lending margins on loans to non-financial corporations (NFC) did not exhibit clear trends during from 2003 to 2008, nor in subsequent years through 2024.

Similarly, lending margins on new loans to households and non-financial corporations showed no distinct pattern before or after 2008. However, it is worth noting that the indicator fluctuated between 0.80 and 1.64 from 2003 to 2022, recently dropping to 0.6782 in 2023 and 0.5992 in 2024. In 2008, it stood at 0.9083.

The annual growth rate of new loans to households and non-financial corporations was high in 2005 and 2006 (20.4968 and 24.3556), but in 2008, it fell sharply to –7.7478. Negative growth continued until 2013–2015, with a peak rebound in 2016 (42.7897). However, by 2024, the value had dropped to –22.1949. Despite these substantial fluctuations, the relationship between indicator changes and the application of MaP measures after the GFC is not immediately apparent.

The share of variable-rate loans in total loans to households and non-financial corporations decreased significantly, from 69.93 % in 2003 and 70.58 % in 2006, to values between 40 % and 27 % starting in 2011. The share of variable-rate loans for house purchases also dropped sharply, from 26 % to 36 % in 2003–2006 to just 1.01 % in 2017 and 3.32 % in 2024. This indicates the impact of MaP measures on reducing the risk associated with variable-rate loans for borrowers.

MFIs lending margins on outstanding loans to households and non-financial corporations declined significantly after the GFC. In 2003, the margin was 2.1168, but

[1] https://data.ecb.europa.eu/data/datasets/RAI?dataset%5B0%5D=Risk%20Assessment%20Indicators%20%28RAI%29&filterSequence=dataset&advFilterDataset%5B0%5D=Risk%20Assessment%20Indicators%20%28RAI%29 (Date of access: 13.06.2024).

[2] Margin is a highly liquid collateral required in order to cover adverse market price movements. The initial margin is calculated on the basis of a formula set by the counterparties to a trade or by a central counterparty (CCP).

by 2013, it fell below 0.9711. In 2023 and 2024, the margins turned negative, reaching –0.0167 and –0.4048, respectively.

Key indicators such as MFIs lending margins on loans for house purchases, the loans-to-deposits ratio, the share of variable-rate loans to households and non-financial corporations, and MFIs lending margins on outstanding loans all show significant shifts in dynamics after the GFC, which can be interpreted as evidence of the effectiveness of MaP measures. Five of the eight risk assessment indicators examined showed persistent changes post-GFC. Given the stability of these indicators following the implementation of stronger MaP measures, they can be considered EWS for regulators. These indicators, combined with historical data and corresponding macroprudential policy interventions, can be used for policy calibration.

7. Conclusion

MaPs have proven to be an effective tool in mitigating the scope and impact of financial crises, particularly after the Global Financial Crisis (Adrian et al., 2022; Laeven et al., 2022; Belkhir et al., 2022). However, MaPs also come with certain costs, including a reduction in credit supply to the business sector (Laeven et al., 2022a), improved financial sector stability at the expense of reduced efficiency in the non-financial sector (Belkhir et al., 2022), increased risks in the non-banking sector (Adrian et al., 2022), and a decrease in economic growth potential (Laeven et al., 2022a).

MaP is not static and requires calibration or new tools based on the likelihood of a financial crisis, with EWS serving this purpose. However, as demonstrated in the various studies discussed in this article, no single or universal set of signals exists. Many indicators, including aggregate indices (Eberhardt and Presbitero, 2018; Borio et al., 2019; Chen & Svirydzenka, 2021), can be considered EWS. It is clear that any model aiming to predict the likelihood of a financial crisis should integrate a system of optimal indicators from multiple areas and likely focus on specific characteristics for different groups of countries.

Our literature review has led us to the following key conclusions regarding EWS:

1. There is no consensus on the time horizon for EWS. It may be more appropriate to base the time horizon on the action of MaP tools, considering how long it takes from calibration or the introduction of a tool to its effects;

2. The studies do not focus on calibrating MaP tools but rather on the relationship between EWS and the occurrence of a financial crisis.

The research papers examined in this article are methodologically similar, relying on empirical analysis. They assess crisis moments and test various indicators as explanatory variables. However, both the definitions of crisis moments and the specific sets of explanatory variables differ across studies.

Methods for identifying EWS can be broadly categorized into two groups: those using numerical data and those using textual data. Numerical data analysis is more common and typically involves two approaches: econometric analysis and machine learning. Machine learning enables the processing of larger datasets, which is especially valuable for assessing financial stability and detecting early warning signals. This is supported by the European Central Bank's 2023 Annual Financial Stability Report, which includes more than 100 parameters characterizing financial stability.

Deep learning techniques are well established for text analysis and can complement the assessment of potential crises. By evaluating sentiment in news and social media postings, we can gauge signals and expectations of a crisis. The relevance of such indicators is indirectly supported by the European Central Bank's Financial Stability Report, which categorizes several indicators as simulation/expectation.

Despite the abundance of methods for identifying EWS and the indicators themselves, questions remain about how to effectively calibrate macroprudential policies based on the received signals. We propose to address this issue by using signals that have demonstrated a correlation with MaP measures. Our study examines the evolution of risk assessment indicators presented on the ECB website, focusing on France from 2003 to the present. Five of the eight indicators analyzed showed a consistent change in trend after 2008, coinciding with the tightening of MaP measures. On the one hand, this confirms the effectiveness of MaP measures. On the other, it suggests that these specific indicators, which have already shown a correlation with changes in MaP, may serve as valuable benchmarks for calibrating MaP.

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