EMPOWERING FINANCIAL SUPERVISION: A SUPTECH EXPERIMENT USING MACHINE LEARNING IN AN EARLY WARNING SYSTEM

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Abstract

New technologies have made available a vast amount of new data in the form of text, recording an exponentially increasing share of human and corporate behavior. For financial supervisors, the information encoded in text is a valuable complement to the more traditional balance sheet data typically used to track the soundness of financial institutions. In this study, we exploit several natural language processing (NLP) techniques as well as network analysis to detect anomalies in the Spanish corporate system, identifying both idiosyncratic and systemic risks. We use sentiment analysis at the corporate level to detect sentiment anomalies for specific corporations (idiosyncratic risks), while employing a wide range of network metrics to monitor systemic risks. In the realm of supervisory technology (SupTech), anomaly detection in sentiment analysis serves as a proactive tool for financial authorities. By continuously monitoring sentiment trends, SupTech applications can provide early warnings of potential financial distress or systemic risks.

Keywords: suptech, natural language processing, machine learning, network analysis, sentiment.

JEL classification: C63, D81, G21.

Resumen

Las nuevas tecnologías han facilitado el acceso y el registro de una gran cantidad de nuevos datos, en forma de texto, compartidos (con un crecimiento exponencial) sobre el comportamiento humano y corporativo. Para los supervisores financieros, la información codificada en texto es un complemento valioso de los tradicionales datos de balances que se utilizan de forma habitual para evaluar la solidez de las instituciones financieras. En este estudio, empleamos varias técnicas de procesamiento de lenguaje natural (NLP, por sus siglas en inglés), así como análisis de redes, para detectar anomalías en el sistema corporativo español, lo que nos lleva a identificar los riesgos tanto idiosincrásicos como sistémicos. Utilizamos el análisis de sentimiento en el contexto empresarial para detectar anomalías en el comportamiento de empresas específicas (riesgos idiosincrásicos), mientras que aplicamos una amplia gama de métricas de redes para monitorear los riesgos del sistema. En el ámbito de la tecnología aplicada a la supervisión *(suptech)*, los sistemas de detección de anomalías actúan como una herramienta proactiva para las autoridades financieras. Al monitorear continuamente las tendencias de sentimiento, las aplicaciones de *suptech* pueden proporcionar alertas tempranas sobre posibles situaciones de estrés financiero o riesgos sistémicos.

Palabras clave: *suptech,* NLP, aprendizaje automático, supervisión de redes, sentimiento.

Códigos JEL: C63, D81, G21.

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1. Introduction

In recent years, advancements in supervisory technology, commonly known as SupTech, have transformed the landscape of financial supervision and regulation. As financial markets become increasingly complex and dynamic, SupTech tools are allowing supervisors to monitor, analyze, and respond to potential risks with unprecedented speed and accuracy (di Castri et al. 2023; Broeders and Prenio 2018; McCarthy 2023). Central banks and regulatory bodies are now investing in data-driven technologies that automate processes, enhance decision-making, and provide early warning signals for potential disruptions (Zeranski and Sancak 2020; Kristanto and Arman 2022). Notably, this innovation process significantly relies on the integration of technologies, specifically like machine learning (ML), or more generally artificial intelligence (AI), into these systems, facilitating real-time monitoring and predictive capabilities across various financial domains (Di Castri et al. 2019; Yıldız et al. 2022; Azuikpe et al. 2024).

One area of promising innovation within finance and economics is the use of text as a data source (Gentzkow et al. 2019), particularly unstructured data from news and other media. Indeed, this type of data has long been an underutilized resource in financial supervision. The use of text analysis offers a complementary layer of insight beyond traditional financial metrics, capturing market sentiment and providing context around significant corporate events (Di Castri et al. 2018). In this work, we particularly explore natural language processing (NLP) as a method to analyze vast quantities of textual data and identify trends that may indicate early signs of distress in non-financial corporations. By integrating NLP with ML techniques, we aim to create an early warning system that harness text-based data to enhance existing supervisory frameworks.

Our goal is the development of an experimental early warning system within a Central Bank leveraging machine learning tools, contributing notably to explore new use cases of text mining in central banking (see Hertig (2021), Bholat et al. (2015) or Araujo et al. (2024) for further references). The outcome of this work could flag potential risks based on corporate sentiment as extracted from financial news. To that extent, the aim will be to identify outliers in the sentiment of corporations, as extracted from financial real, which are deemed to be important for financial institutions. Mainly, the system follows a multi-step workflow.

We begin by sourcing a large corpus of news from Factiva, focusing on information that could impact corporations in Spain and might be significant for financial institutions. To evaluate the overall systemic risk, we use network analysis. For example, we evaluate centrality measurements and a wide range of other network metrics against volatility indicators, such as the implied volatility index for Spanish banks given by Gonzalez-Perez (2021), finding a strong resemblance. Additionally, we perform sentiment analysis on the news corpus, identifying anomalies in sentiment as outliers that could serve as early warning indicators on specific corporations. These anomalies are detected through anomaly detection analysis. We integrate these findings by matching a "traffic light" system with our previous network analysis insights to produce a prioritized set of alerts for human supervisors to follow up.

Finally, we showcase our results through three case studies of corporations that, ex-post, were known to have experienced periods of distress. This distress was evidenced by their decorrelation from the main stock exchange index in Spain (IBEX 35) at some point within our sample period, making them adequate fit-for-purpose candidates to evaluate our system. Our analysis demonstrates that distress periods for these corporations showed early warning red flags (with some limitations), supporting the efficacy of our approach as a complementary tool.

The remainder of this paper is structured as follows: In Section 2, we begin with a detailed literature review on SupTech and NLP applications in financial supervision. Next, in Section 3, we present the methodology, including data collection, network analysis techniques, and sentiment analysis. Finally, we discuss the empirical results, showcasing the efficacy of our early warning system through real-world examples. The paper concludes in Section 4 with a summary of findings, limitations, and potential applications for broader supervisory frameworks.

2. Literature review

Early warning systems (EWS) have become an essential tool in financial supervision, aimed at identifying vulnerabilities before they escalate into systemic risks (Davis and Karim 2008; Oet et al. 2013; Bholat et al. 2015; Barrell et al. 2010). These systems use various data-driven methods to detect signals of financial distress, allowing regulators and institutions to intervene proactively (Gramlich et al. 2010). Key studies, such as Kaminsky et al. (1998), developed an EWS framework using economic indicators to predict currency crises. Borio and Drehmann (2009) expanded on this by applying EWS to credit cycles, providing insights into financial stability through credit growth and asset price booms. More recently, Frankel and Saravelos (2012) have reviewed multiple EWS models, underscoring the importance of data variety and model complexity in achieving robust predictions. The advancement of machine learning (ML) techniques has enhanced different business areas an processes in banking (Gao et al. 2024), including EWS capabilities, as evidenced by works like those of Aikman et al. (2015), who used ML to improve crisis prediction accuracy by integrating economic, financial, and political indicators.

In recent years, sentiment analysis has emerged as a valuable approach for early warning systems, particularly with the increased availability of unstructured text data (Namaki et al. 2023). Textual data from financial news, social media, and other media sources provide a real-time gauge of market sentiment, often preceding movements in traditional financial metrics. Studies like Da et al. (2015) demonstrated how sentiment derived from Google search trends could serve as a predictor of asset prices and investor behavior, while Tetlock (2015) illustrated the predictive power of media sentiment in stock returns and earnings announcements. Several researchers have further incorporated sentiment analysis into financial EWS models. For example, Smales (2014) analyzed sentiment in news articles, finding that shifts in sentiment could provide early warning signals of volatility in equity markets. Song et al. (2018) built on this by applying sentiment analysis to corporate disclosures, demonstrating that sentiment changes could predict corporate financial distress. These studies highlight the role of sentiment in identifying warning signs, often capturing market participants' reactions to emerging events before traditional financial indicators respond.

Within this field of research, anomalies detection is a critical component of sentiment-based early warning systems, particularly in identifying sentiment outliers that may signal distress. Wang et al. (2014) show how Social media platforms, such as X, provide a vast source of information, which includes user feedback, opinion and information that enables to identify abnormal events in a timely manner. Similarly, Deng et al. (2018) utilized anomaly detection on financial news sentiment to pinpoint irregular patterns associated with heightened risk levels. More recent work by Kim et al. (2020) focused on social media data, developing an anomaly detection framework that identified sentiment spikes related to financial distress events.

All these studies emphasize the importance of identifying sentiment outliers, which often align with significant market events or impending financial instability. Integrating anomaly detection with sentiment analysis has proven effective in refining early warning systems, as it captures rare but impactful patterns within vast amounts of text data.

3. Data and Workflow

3.1. *Dataset*

The work detailed in this document was carried out using a database of 10 million news articles published by Spanish newspapers between 2018 and 2023. These news articles were obtained from Dow Jones - Factiva.

body	company_codes_occur	snippet	publication_date	title
string Natural lang.	string Text	string Natural lang.	bigint Integer	string Natural lang.
En el caso de este nuevo 'challenge', que es especia...	,onlnfr,	Un aviso a través de Facebook trata de concienciar ...	1643625960000	Alertan de una peligrosa moda en TikTok: pinchar ...
El jurado lo han formado Ana Criado, Alberto Omar...	,urioja,	Santa Cruz de Tenerife, 11 oct (EFE).- El narrador gr...	1665499980000	Pedro M. Costa, ganador del premio de relato corto...
El incendio de Laza, el más grave de estos días, tras...		Ourense, 11 ago (EFE).- Los incendios forestales reg...	1660242480000	Estables los fuegos en Galicia tras las tormentas y s...
Las precipitaciones comenzarán al mediodía por el...		Valladolid, 11 feb (EFE).- Sin apenas sol, con precip...	1644571560000	Día "desapacible" para ir a votar este domingo en C...
Y es que, a día de hoy, nuestra especie es una amal...		Elena Camacho¶¶Madrid, 30 may (EFE).- El miedo, ...	1653910800000	Experta: La evolución del cerebro ha favorecido alg...
La ministra no ha ofrecido detalles del impuesto qu...	,tjuanu,euruno,	Sevilla, 23 sep (EFE).- La ministra de Hacienda, Mar...	1663933200000	Montero pide a Feijoó que defina su posición sobre...
Presentar como un gran triunfo haber sumado casi ...		El Partido Popular ha ganado las elecciones en Cas...	1644786593000	Mal negocio
María Jesús, de vender al 'chino' a hacer perfumes ...	,lsack,	El tenista con 22 Grand Slam utiliza los relojes de Ri...	1654619721000	Este es el reloj de la suerte de Rafael Nadal en Rola...
En este sentido, indicó que han ganado a tres equi...		Málaga, 1 abr (EFE).- El técnico del Unicaja, Ibon Na...	1648827300000	Ibon Navarro: "El Valencia ha demostrado mayor c...
Ha calificado de "patético" que Alfonso Fernández ...		Toro (Zamora), 17 ene (EFE).- El candidato de Cs a l...	1642444920000	Igea: "Seremos absueltos y otros estarán en los Juz...
El Nikkei 225 japonés ganó un 1%, mientras que el ...		Redactada por Noemí Jansana ¶¶Las acciones de l...	1665042741989	Asia acaba con signo mixto, entre el frenazo de Wal...
La hija de Trump, Ivanka, y su hijo Donald Jr. tambi...		Por Karen Freifeld¶¶NUEVA YORK, 13 jul (Reuters) - ...	1657736245000	Trump y sus hijos mayores de edad declararán en i...
		Galicia vivió este mes de octubre el más lluvioso en...	1667433600000	METEOROLOGÍA; Galicia registra el octubre con má...

Figure 1.: Example of the News information found in Factiva

Figure 1 shows the information we can find in Factiva per article. For each article, the data used includes the title, snippet, body, newspaper or news agency, date of publication, and most importantly, the companies mentioned in the article.

3.2. *Workflow*

We propose a multi-step workflow (see Figure 2):

(1) We begin by scrutinizing a large corpus of news, focusing on Spanish news articles that mention highly relevant corporations in Spain. Those are the listed companies and other relevant firms listed in the BME exchange.[1]

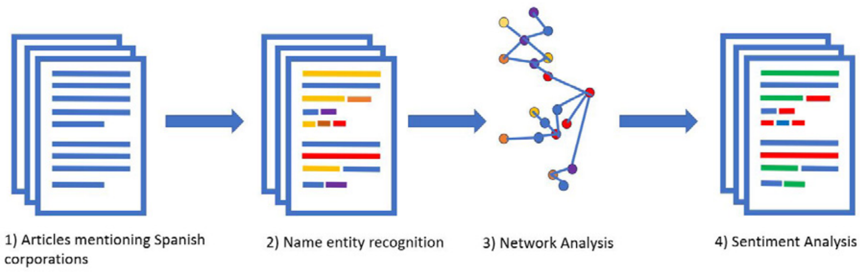


Figure 2.: Multi-step worflow

[1]For for information see https://www.bolsasymercados.es/bme-exchange/es/Mercados-y-Cotizaciones/Acciones/Mercado-Continuo/Precios/mercado-continuo

(2) A critical initial challenge is the accurate identification of corporate entities within the text. Named Entity Recognition (NER) serves as a foundational tool in this process, aiming to detect and classify entities such as company names, organizations, and other relevant entities from unstructured text. We further explore this challenge in 3.2.1.
(3) Then, to evaluate the importance of a single corporation in our setup, we use network analysis. We will evaluate several metrics of centrality and connectivity of corporations within the financial ecosystem in Section 3.2.2. We then show how these measures correlate to system risks measures such as a the Implied Volatility Index of Spanish corporations (VIBEX).
(4) Then, we perform sentiment analysis on the news corpus in Section 3.2.3. Then, we identify anomalies in sentiment as outliers that could serve as early warning indicators in Section 3.2.4. Finally, we show as outcome a "traffic light" system by corporation, to produce a prioritized set of alerts for human supervisors to follow up.

3.2.1. Named Entity Recognition

The financial domain presents unique challenges for NER due to the diverse and often ambiguous nature of corporate nomenclature. Companies frequently undergo rebranding, mergers, or acquisitions, leading to multiple names or abbreviations referring to the same entity. Additionally, financial texts often contain jargon, acronyms, and context-specific terms that can complicate entity recognition. Such variations necessitate the development of domain-specific NER models that can adapt to the evolving landscape of corporate identities in financial texts (Alvarado et al. 2015; Xu et al. 2016; Zhang and Zhang 2023). In our case we experienced issues with some of the company codes at Factiva, as some names might refer to corporations or other entities. Take as example the name "Santander", which can refer to the major bank in Spain (by total assets) or a city in the north of Spain. Similarly, for banks like BBVA, it is common for them to be reported under different names such as BBV or Banco Bilbao. For this reason, we apply Named Entity Recognition (NER). NER allows us to characterize each word as a specific type of entity, such as a person, organization, or location.

To this purpose, we developed an internal procedure for a proper NER. We use the open-source Python library SpaCy, which provides a robust implementation. SpaCy's pre-trained models can identify and categorize entities in text with high accuracy. By leveraging SpaCy, we can disambiguate names and ensure that our data accurately reflects the entities mentioned in the articles. This process involves training the model on a labeled dataset to recognize the context in which different names appear, thereby improving the precision of our analysis. In order to match the entities labeled by Spacy as "ORG" (Companies, agencies, institutions, etc.) to the list of relevant corporations in Spain, we add known name variations to the list, such as BBVA, BBV, Banco Bilbao, and we apply a Levenshtein ratio with a 0.9 threshold for comparison between the article text and our list.

3.2.2. Network Analysis

The financial sector is characterized by intricate interdependencies among corporations. Traditional risk models often overlook these complexities, potentially leading to an underestimation of systemic risks. This section describes how financial risks can be analyzed using networks, which we will use to spot corporations whose distress could derive in widespread contagion and potential systemic risk implications (see Acemoglu et al. (2015)). In particular, we will investigate networks formed from pairwise mentions of corporations within news articles, that is, which corporations appear in the same article. This method provides a dynamic view of corporate relationships and their evolution over time, offering valuable insights into potential risk contagion paths and systemic risks.

Usually, financial contagion exhibits a form of phase transition as interbank connections increase, as shown by Diebold and Yılmaz (2014), which provide a quantitative measure of connectedness aimed at identifying systemic risks and monitoring the health of the financial system. Their network topology offers insights into the transmission of shocks across financial firms, aiding in the development of more robust risk management strategies. In this same vein, Azqueta-Gavaldon et al. (2020) evaluate the dynamic network structure of stock returns in the United States, concluding that the topology of the network can help to detect changes in economic regimes in real-time.

Leveraging this rationale, we explore the network of corporations' mentions in our corpus of news. Nodes in the network represent corporations, and edges represent pairwise mentions in the news articles. Edges were weighted based on the frequency of mentions. Figure 3 depicts the pairwise graph computed over the entire year of 2022. The graph reveals a significant degree of connectivity, particularly evident in the dense cluster at the center.

Networks were constructed for different time periods to observe their evolution. The following network metrics were calculated for monthly period:

- **Degree Centrality:** Measures the number of edges connected to a node, indicating how many other corporations a particular corporation is mentioned with.
- **Eigenvector Centrality:** Eigenvector centrality measures the influence of a node in a network by considering not just the number of its connections, but also the importance of the nodes it is connected to. In other words, high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes.
- **PageRank:** Measures the importance of a node based on the number and quality of links to it, indicating a corporation's significance in the network. While Eigenvector measures only the quantity (how many connections to a node), PageRank assesses also the quality by checking if those connections are also high-scoring.

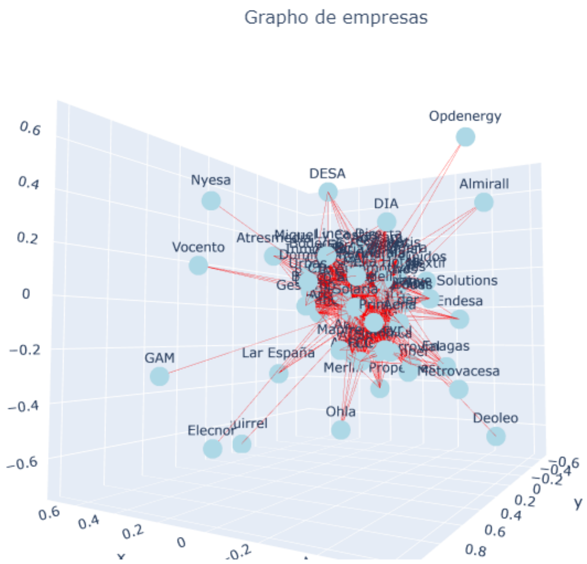
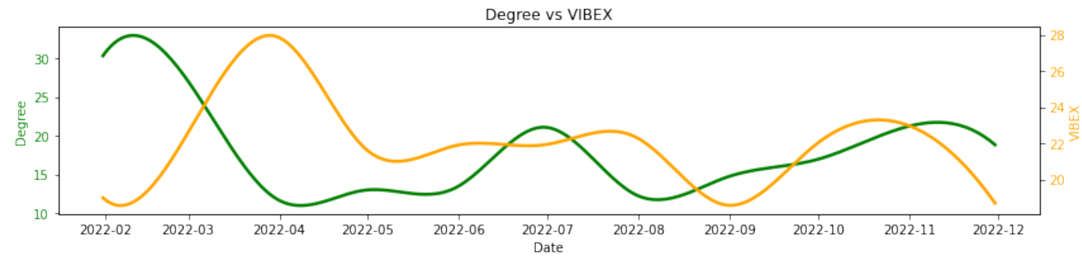


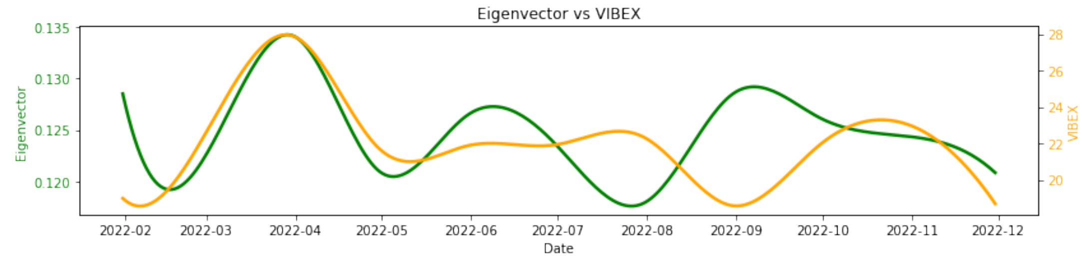
Figure 3.: Example of a Network Graph

Figures 4(a), 4(b), 4(c) display the evolution of a network over time. These networks are constructed by taking the mean of each corporation's score per month. Hence, in those months where corporations, on average, have a higher score, the network will peak. This is the case for the eigenvector centrality and PageRank in March 2022 during the invasion of Ukraine.

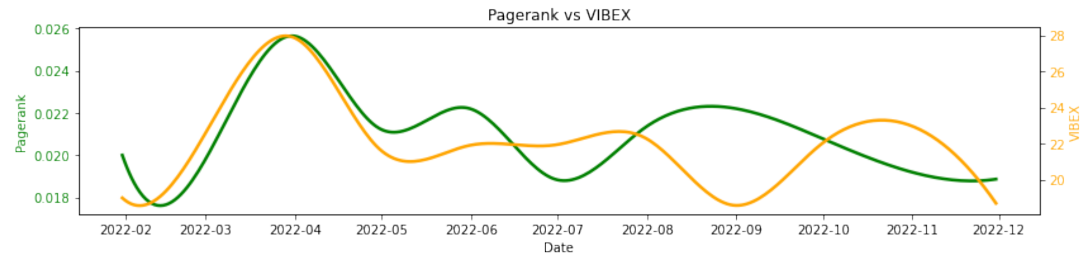
To further assess the behavior of the resulting networks, we borrow from Gonzalez-Perez (2021) the VIBEX, an idiosyncratic implied volatility for the Spanish banking industry. As can be seen, the PageRank measurement displays a higher correlation with the VIBEX (0.60), followed by the eigenvector centrality (0.35) and the degree centrality (-0.35). This finding underscores the significance of measures the importance of a node based on the number and quality of links to it in understanding market dynamics.



((a)) Panel A



((b)) Panel B



((c)) Panel C

Figure 4.: Network metrics and the VIBEX

A case study in the Spanish banking system

The exercise examines the nature of corporate relationships within a pre-selected group of entities, focusing specifically on the Degree centrality between banking corporations and non-banking corporations. The latter category includes financial corporations, excluding credit institutions, as well as non-financial corporations. Corporations with fewer than 50 financial news mentions during the sample period have been excluded from the analysis to ensure robust results.

Table 1 displays the percentages of pair wise matches. As can be seen, largest percentage (in 50% of the news in which one of the corporations is mentioned and paired with a banking corporation, the other one is also mentioned) corresponds to the relationship between Linea Directa[2] and Bankinter[3]. This can be atributed to the former legal ownership (significant control) of Linea Directa by Bankinter. Besides, the heightened connectedness between Innovative Solutions[4] and Banc Sabadell or Caixabank can be attributed to the geography, as all three corporations are based in Catalonia.

	B.Sabadell	**B.Santander**	**Bankinter**	**BBVA**	**Caixa**
Total	14%	16%	20%	27%	23%
Línea Directa	9%	10%	50%	15%	16%
Innovative Solutions	45%	4%	0%	5%	46%
Repsol	0%	31%	8%	15%	46%
Aena	4%	41%	4%	7%	44%
Atrys	33%	5%	8%	13%	41%
Oryzon	37%	5%	6%	11%	41%
Telefónica	4%	33%	6%	17%	40%
Grenergy	8%	9%	17%	30%	36%
Iberdrola	9%	17%	18%	35%	21%
Renta Corporación	31%	8%	14%	13%	34%
Inditex	10%	17%	19%	32%	22%
Applus	21%	14%	17%	15%	33%
Viscofan	13%	12%	24%	19%	32%
NH Hotel	14%	13%	15%	26%	32%
Azkoyen	18%	14%	19%	18%	31%

Table 1.: Percentage distribution across different entities.

The corpus of news that increases the number of links between Aena and Banco Santander is driven by the scale and relevance of both corporations, resulting in their inclusion in international news coverage.

In addition, the high connectedness between Iberdrola and BBVA is primarily due to statements made by Mexican President López Obrador against Spanish companies, including Iberdrola and BBVA.

In summary, connectivity among corporations can be categorized into four main areas: legal ownership or significant control, shared regional or political identity, scale and media relevance, and significant corporate events. These factors facilitate a deeper understanding of the relationships and interactions between corporations in the real world.

[2] Linea Directa Aseguradora (LDA) is a direct insurance company in Spain. Founded in 1995, it operates in the Motor, Home and Health insurances. In December 2019, Bankinter, the sole shareholder of LDA, announced its intention to turn Linea Directa into a listed company in 2020. Their shares have been admitted to official listing on the Madrid and Barcelona Stock Exchanges and are traded on the secondary market.

[3] Bankinter is a financial institution whose corporate purpose is the performance of banking activity. Founded in June 1965, it is listed on the Madrid stock exchange since 1972.

[4] Innovative Solutions Ecosystem (former Service Point Solutions) is a company listed on the Spanish stock market. ISE invests in innovative technology companies. Paragon Financial Investments Limited is the majority shareholder of Innovative Solutions Ecosystem, S.A.

3.2.3. Sentiment Analysis

Understanding there is a subset of potential candidates which distress could have systemic risk implications, we are interested in investigating potential warnings as well in corporations which could encounter financial distress at idiosyncratic level only. To this purpose, we use two techniques to measure sentiment in our corpus of text. One is dictionary-based, which can be considered as a benchmark, as it is a traditional NLP technique Loughran and McDonald (2011). The other one is a domain-specific version of the BERT model (Bi-directional Encoder Representations from Transformers), initially released by Google experts Devlin et al. (2019), which has the advantage of including context, using bi-directional attention.

Our final metric of sentiment will be the average of both approaches. Our aim is to capture the strengths and limitations of both methods, benefiting from the improvement that deep learning-based techniques might represent with respect to dictionary-based methods when it comes to understanding context in the news, but also leveraging the interpretable bag-of-words in our predefined dictionary, in order to assess the presence of anomalies through time.

Dictionary-based Method The dictionary-based sentiment analysis model leverages a proprietary lexicon designed to capture sentiment specifically within the financial domain. It is one of the most traditional and popular techniques to compute the sentiment of a text. It relies on a dictionary or predefined bag-of-words with positive and negative tone. Each custom dictionary is fine-tuned to include terms, phrases, and expressions relevant to the unique language of financial texts. This approach evaluates each term in a given text and assigns scores based on sentiment metrics such as polarity (positive or negative orientation) and intensity. Polarity captures the direction of sentiment, indicating whether terms are associated with favorable or unfavorable contexts. Meanwhile, negativity metrics help quantify the degree of pessimism by aggregating the weighted occurrence of terms identified as negative.

There are different dictionaries or collections, depending on the nature of the texts at hand. In finance, one of the most used dictionaries is Loughran and McDonald (2011). It contains 354 positive words and 2,337 negative words. While it is easy to use it straightforward, this approach makes strong assumptions about the meaning of specific words that were selected, so miss-specification can cause severe noise in dictionary-based sentiment indices.[5] This concern is presented by Hayo and Zahner (2023), who perform an analysis of variance (ANOVA) to show that about 80% of the variation in sentiment in Fed and ECB speeches is due to noise, which raises questions about the index's reliability as an indicator.

In any case, due to its popularity, we find it a suitable benchmark for our exercise. Since we can count the number of positive and negative words in the corpus of text that match our dictionary (Loughran and McDonald (2011)). Then, an easy way to calculate the sentiment of a text is computing the polarity. This index is a measure between -1 and 1 that is computed as follows:

$$Polarity = \frac{Positives - Negatives}{Positives + Negatives}$$

Additionally, this model's reliance on a targeted vocabulary provides direct interpretability and clear relevance to domain-specific sentiment indicators, though it may lack sensitivity to nuanced or emerging expressions not covered in the lexicon.

[5] This might be mitigated by means of using TF-idf (Term frequency – Inverse document frequency) when accounting for the words used in the dictionary.

As mentioned before, BERT is a deep learning architecture for NLP analysis developed by Google which harness the notion of self-attention to weigh-in the context in the computation of word embedding. It was developed in 2018, with the goal of provide contextual understanding on unlabeled data (Devlin et al. (2019)).[6] Unlike previous Large Language Models (LLMs) relying on Feed-Forward Neural Networks and Convolutional Neural Networks, Transformers do not process the input sequence sequentially over time (Amatriain et al. 2023). Instead, they process the entire sentence at once weighting the relevance of words based on the self-attention mechanism Vaswani et al. (2017).

In particular, for this paper, we use the version known as RoBERTuito (Yang et al. (2020)), which is a financial domain-specific language model based on BERT, pre-trained using a large scale of financial news corpora, such as 5,000 tweets written in Spanish. This bidirectional approach enables RoBERTuito to understand sentiment more precisely by contextualizing words according to surrounding terms, capturing subtle language shifts and financial-specific jargon common in social media discussions. This makes RoBERTuito particularly adept at identifying sentiment in real-time and informal text environments, where nuanced expressions can be key to understanding sentiment dynamics in finance.

The sentiment output for each analyzed piece of text is a probability distribution over the two possible classes, negative and positive. It is therefore possible to translate it to the range -1 and 1 with a transformation such as:

$$Sentiment = Prob\,(positive) - Prob\,(negative)$$

3.2.4. Anomalies Detection

Mining potential distressful companies in a fast-changing business environment is crucial for timely intervention, but it is also a very challenging task computationally which can be tackled as an anomaly detection problem (Zhu et al. 2021; Yıldız et al. 2022). In the realm of supervisory technology (Suptech), anomaly detection in sentiment analysis could serve as a proactive tool for financial authorities. By continuously monitoring sentiment trends, Suptech applications can provide early warnings of potential financial distress or systemic risks, as shown by previous studies suchs as Guerra et al. (2022); Guerra and Castelli (2021); Prenio (2019); Zeranski and Sancak (2020) and Maheshwari and Chatnani (2023).

Anomaly detection in sentiment analysis involves identifying deviations from typical sentiment patterns within textual data. By analyzing sentiment data from various sources, such as news articles, social media, and financial reports, supervisors can detect unexpected sentiment shifts that warrant further investigation. For instance, a sudden surge in negative sentiment surrounding a particular stock could signal potential credit risk alerts with implications at either systemic or idiosyncratic level. However, anomalous instances in a dataset are very rare in general, which leads to imbalanced distribution of classes in the dataset, which poses a great empirical challenge (Kansal and Pandey 2022).

Our approach would enable authorities to respond swiftly to emerging threats, thereby enhancing the stability and integrity of financial markets. In this vein, several methodologies have been explored in various studies. For example, Bakumenko and Elragal (2022) discusses the application of machine learning techniques to identify

[6] The original task was to learn to predict words that might appear before and after other text, hence the term bidirectional, with the aim of translating sentences from German into English.

anomalies in financial datasets, highlighting the importance of such methods in enhancing financial supervision. Additionally, Crépey et al. (2022) presents a methodology combining principal component analysis and neural networks to improve anomaly detection in financial time series, demonstrating the effectiveness of advanced analytical approaches in this domain. Similarly to our study, Park (2024) tackles the longstanding challenge of manually verifying system-generated anomaly alerts and how this technology could support financial markets monitoring. Though, as importantly remarked by Su et al. (2024) the transformative impact that new NLP techniques could have on anomaly detection should always be accompanied by the need for continuous innovation, ethical considerations, and practical solutions involving human-machine interaction.

3.3. *Results*

For illustrative purposes, we first pre-select a group of corporations which ex-post have experienced a series of corporate events which derived mainly in stock returns declining, and finally showing in a particular period of time abnormal low correlation with market indices[7]. In particular, we showcase the results of three particular stocks which are either ranked high in any centrality metric in our previous network analysis or have displayed a clear pattern of abnormal returns due to idiosyncratic risk. Our results will consist on detecting anomalies by using a traffic lights system. To deploy this, we will identify those moments in time where the point-in-time sentiment in a particular corporate increases more than two times the standard deviation of the moving average of its sentiment (known as Bollinger bands, as shown in studies like Devarasetty (2021) or Milstein et al. (2024)).

First, on Almirall, as shown in Figure 5 we are able to identify red flags in sentiment precisely in times of distress, i.e.: when the particular stock prices prices declines while the market index does not.

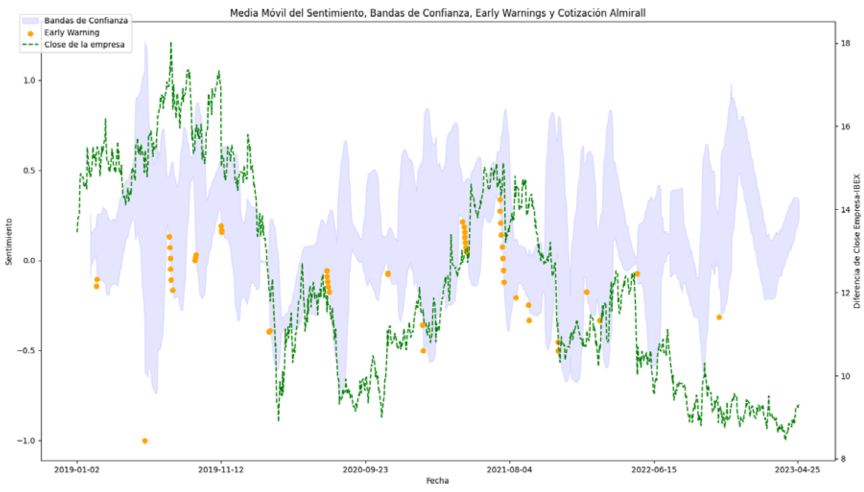


Figure 5.: Red flags in Almirall sentiment.

This same analysis is repeated for two more instances, such as Abengoa and Pescanova (see Figure 6 and Figure 7 respectively). In all three cases, our mixture of BERT-dictionary-based sentiment seems to capture timely the distress of both com-

[7]See in the Appendix an exploratory analysis of correlation between Almirall and Ibex returns, in Figure A1, including a scatter plot between sentiment based on dictionaries in Figure A3 or BERT in Figure A2, versus company returns.

panies, fulfilling the goal of an early warning system. Though, not all draw-downs in the stock market are captured, and it also remains work for further research to investigate the statistical significance of this sentiment series as predictive variable of the probability of default of these companies.

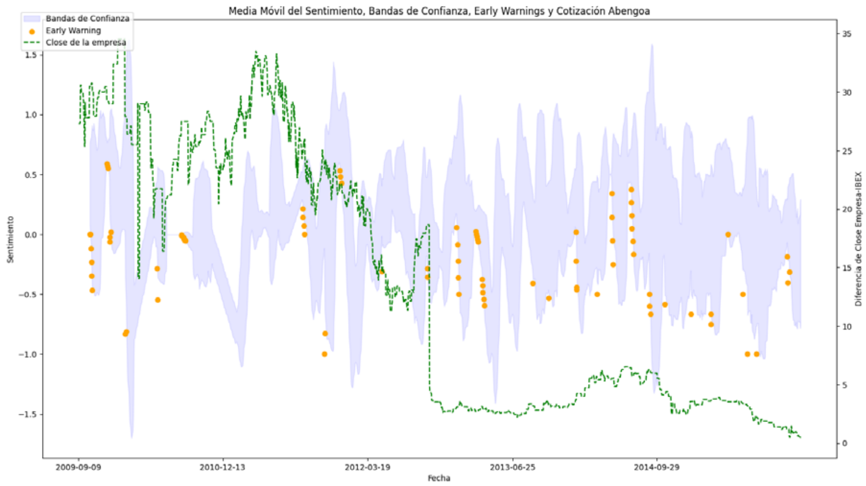


Figure 6.: Red flags in Abengoa sentiment.

A decision-support system such as this would provide an enhanced risk assessment perspective to supervisors, which could also serve for the purpose of classifying corporations in a range of low-to-mid and high potential risk. Previous studies like Guerra et al. (2022) use this sentiment as input to further explore its predictive value on the distance-to-default of this companies.

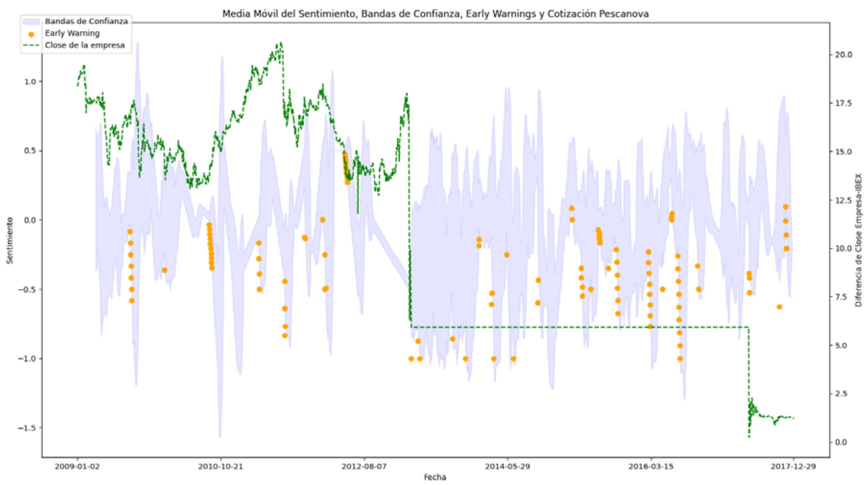


Figure 7.: Red flags in Pescanova sentiment.

4. Conclusions and Further Research

In this study we have covered the construction of an experimental early warning systems harnessing different machine learning techniques. We conclude a successful proof-of-concept of what could later become a SupTech tool to monitor useful information in news for supervisory purposes.

We identify two main building blocks in this innovative exercise. First, underpinning the selection of key or representative corporations to be monitored, there is a network analysis carried out from a raw set of financial news. We measure different interconnection metrics, and we assess their relationship with stock market volatility. Besides, the use of network analysis may serve us to monitor corporate relationships (e.g.: geopolitical, business model, legal aspects...).

Then, we elaborate a method to extract a sentiment metric of the different sets of news articles, per corporation. We create a model to flag outliers which in some cases may be related to financial distress, either at idiosyncratic or systemic level. To understand its potential, we showcase three potential examples that suffered periods of instability (i.e.: decorrelated with the main stock index) during our sample period. We evidence the power of our EWS to flag alerts during the downturns of these stocks, although with some limitations.

There remains several venues for further exploration and research. Some promising lines of investigation relate to using different data sources, such as the open source project GDELT. Additionally, we could explore other unstructured information sources such as social media posts. On top of this, methodologically, it could be explored the potential value of using word embeddings from the news such as dimensionality reduction or clustering algorithms in order to extract more information on sentiment trends.

In short, we consider that with this work we contribute to the nascent field of research and experimentation in the SupTech space, leveraging on more work from other Central Banks and Supervisors (Packard and Prenio 2023; Hertig 2021). All in all, this may serve financial supervisors to complement more traditional balance-sheet type of information as included in confidential reports, such as direct loans or other forms of investments.

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Appendix A. Appendix – Additional figures and tables

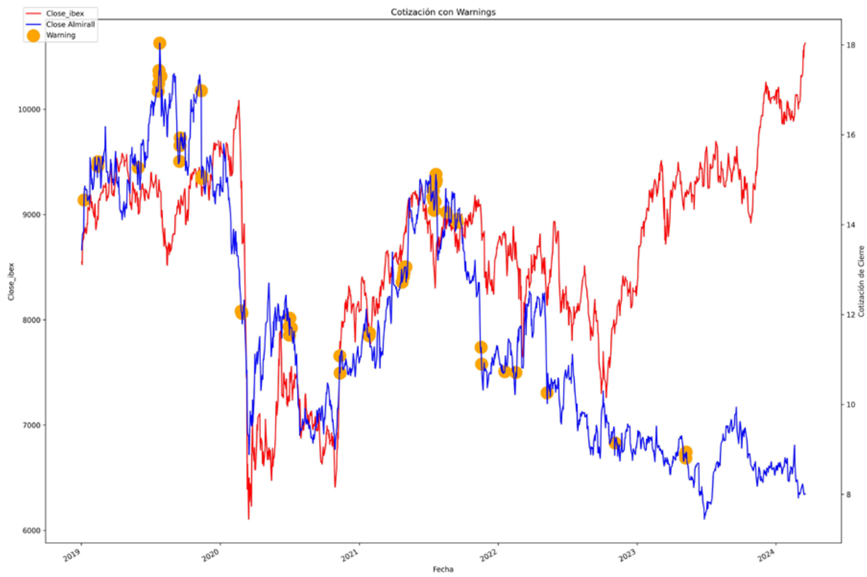

Figure A1.: Correlation between Almirall and Ibex returns, and red flags.

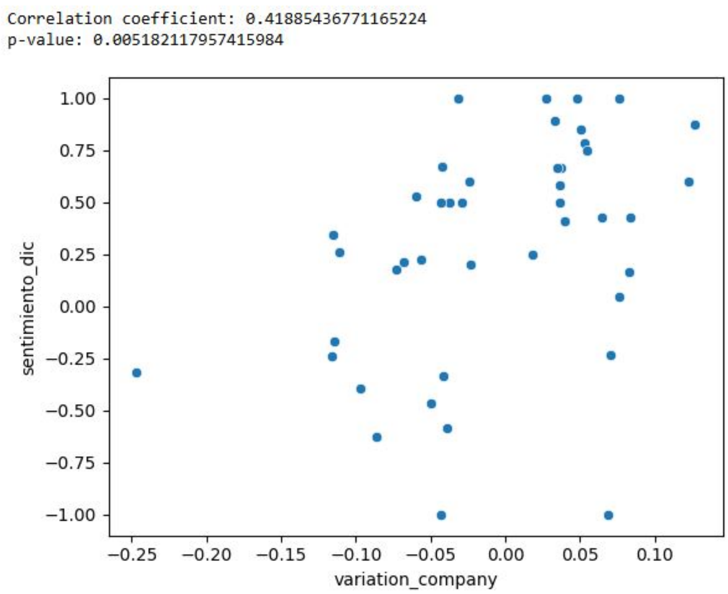

Figure A2.: Correlation between Almirall sentiment dictionary-based and company returns.

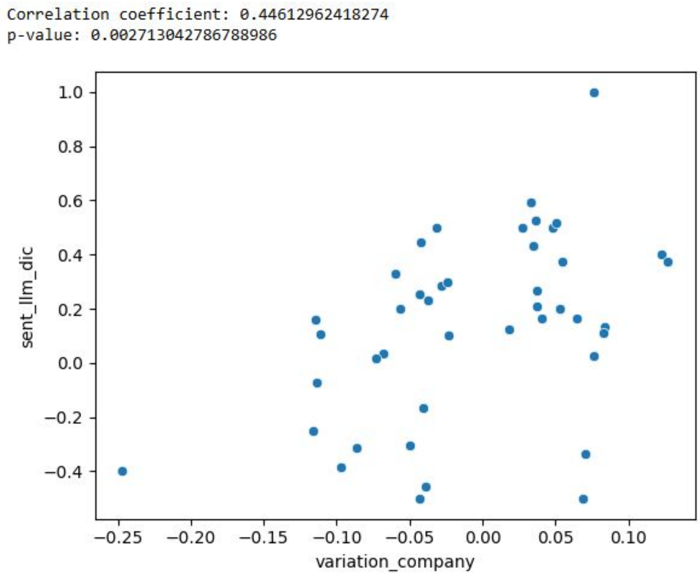

Figure A3.: Correlation between Almirall sentiment BERT-based and company returns.

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