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Corruption Detection Through Textual Analysis: Evidence From Eurozone Banks

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ABSTRACT

This research investigates the disclosure of banking institutions by analyzing their annual reports to identify the determinants capable of signaling possible corruption scandals. A textual analysis was conducted on the financial reports of 42 Eurozone banks from the period 2013 to 2022. Drawing on impression management theory, we combine an advanced large language model (LLM) and dictionary approach to extract and analyze the governance-related textual content of the banks in the sample. Machine learning algorithms—including random forests, support vector machines, gradient boosting, and naive Bayes classifiers—and logistic regression have been employed to verify whether disclosure indicators allow for the identification of corruption scandals from a preventive perspective. Our findings show that specific textual measures can be used to analyze the association between disclosure and corruption events and as predictive tools to detect corruption scandals before they become public domain. Our study has several implications, particularly for supervisors and investors who can proactively leverage our findings to identify possible corruption scandals in banks by analyzing their financial disclosures.

1 | Introduction

One of the most pressing challenges of our time is addressing the phenomenon of corruption, including its detection and prevention. While much relevant literature has been produced on the phenomenon of corruption, there is currently little research on how it can be predicted and prevented, particularly in the fields of accounting and finance. Defined as "the abuse of entrusted power for private gain" (Cuervo-Cazurra 2016, 36), corruption undermines democracy, violates human rights, and leads to market distortions (United Nations 2004). The consequences on economic development are multiple, such as a disincentive to investments of entrepreneurs, an increase in the prices of goods and services, an unequal distribution of wealth in the economy, and an altered composition of government expenditure (Rabbiosi and Santangelo 2019; Sartor and Beamish 2020; Spyromitros and Panagiotidis 2022), which can lead to inefficiencies in the financial system (Cooray and Schneider 2018).

These consequences imply that corruption negatively affects global GDP and that pursuing Sustainable Development Goals is more arduous (Uddin and Rahman 2023; United Nations 2018). For these reasons, corruption has been considered a "wicked problem" (Reinecke and Ansari 2016).

Corruption is particularly relevant in the banking sector due to its interactions with the financial system. Banking corruption scandals have resulted in the bankruptcy of financial institutions, such as the cases of Washington Mutual, Bear Stearns, and Lehman Brothers, all of which failed in 2008 with disastrous consequences on the international financial system. In this regard, the International Monetary Fund (2023) has pointed out that corruption scandals pose a risk to financial stability.

Corruption can jeopardize the effectiveness of bank lending (Weill 2011) and the performance of banking institutions (Chen et al. 2015), thus increasing the probability of a banking crisis (Ben Ali et al. 2020), resulting in a 'domino effect' that can compromise the stability of the banking system at worldwide level. A recent study by Abuzayed et al. (2024) finds that corruption practices negatively impact banks' profits and increase risks. Considering the global importance of these phenomena, scholars have increasingly focused in recent years on investigating corruption in the banking sector (Bahoo 2020).

Corruption events are closely linked to the concept of Environmental, Social, and Governance (ESG), particularly the governance pillar, as they represent a failure of corporate governance mechanisms (Boateng et al. 2021; Weismann 2009). In this regard, it is noteworthy to mention that implementing effective corporate governance practices is associated with lower levels of corruption and, consequently, higher levels of financial stability in the banking sector (Toader et al. 2018).

In this context, the issue of corruption in the banking sector associated with bank disclosure is particularly relevant. Various stakeholders demand that banks disclose any misconduct that can lead to corruption scandals and the anti-corruption systems adopted to prevent the onset of corruption-associated phenomena, such as fraud, extortion, collusion, and bribery (Chen et al. 2015). Although the disclosure of corruption-related issues in the banking sector holds significant theoretical and practical implications, a limited body of literature focuses on such a topic. There are relatively few studies that have focused on the study of corruption in banking institutions together with their disclosure (Chantziaras et al. 2020; Elamer et al. 2019; Hashmi et al. 2022; Nobanee et al. 2020; Vilar and Simão 2015). Furthermore, none of these studies address corruption detection through disclosure analysis. Corruption research in the banking system mainly focuses on the negative consequences of corruption (e.g., Abuzayed et al. 2024; Asteriou et al. 2021; Bermpei et al. 2021; Fan et al. 2008) and the link between this phenomenon and governance mechanisms (e.g., Arshad and Rizvi 2013; Toader et al. 2018). de Andrés et al. (2024) provide one of the first studies on this topic. The authors conduct empirical research on corruption-related disclosure within the banking sector to understand the motivations behind financial institutions' inclusion of corruption information in their financial reports. While providing an excellent basis for the disclosure analysis for detecting and preventing corruption, neither this study directly addresses this issue. Thus, to our knowledge, no research has studied how bank disclosures can be analyzed to identify indicators capable of detecting potential corruption scandals. This is surprising because the banking and accounting literature has widely employed textual analysis techniques for a variety of reasons, including the measurement of the probability of default and fraud detection (Cecchini et al. 2010; Shirata et al. 2011; Tennyson et al. 1990). In particular, starting from the assumption that models based only on financial ratios and market variables can be subject to severe limitations due to the purely backward-looking and going-concern nature of such measures (Li 2012; Lopatta et al. 2017), Cecchini et al. (2010) obtain encouraging results in both bankruptcy and fraud prediction using textual analysis on annual reports. Specifically, their textual measures performed better in predicting bankruptcy and fraud than models based on quantitative measures (i.e., Altman 1968; Beneish 1999) and even better when combined.

In light of this research gap, we try to answer the following research question: *what type of early warning indicators can be computed using disclosures to detect the occurrence of a banking corruption scandal in advance?*

To answer this research question, we adopted a textual analysis methodology by drawing upon a Large Language Model (LLM) called FinBERT (Huang et al. 2023) and the dictionary approach (Loughran and McDonald 2011) to extract and analyze texts related to bank governance. The texts analyzed were extracted from the financial and non-financial reports of Eurozone banks whose data were present in the Refinitiv database and whose reports were available in English on their institutional websites.

We investigate banks' behavior in reporting governance-related information based on alternative theories, namely signaling theory (Spence 1973) and impression management (Goffman 1959; Merkl-Davies and Brennan 2011). According to signaling theory, banks not involved in corruption scandals should disclose more governance information. Indeed, from an ex-ante perspective, banks implementing better anti-corruption practices should tend to disclose more information to demonstrate their superiority in preventing corruption than their competitors. According to impression management theory, banks involved in corruption scandals should disclose more governance information to make their audience perceive them as non-corrupted.

We contribute to the literature by using predictive techniques, specifically machine learning algorithms—random forests, support vector machines, gradient boosting, and naive Bayes classifier—and logistic regression, adopting a wide range of advanced textual measures and control variables to detect corruption events in the banking industry. Further, we compute the SHAP values to make our results more interpretable in light of our theoretical framework and research hypothesis. SHAP values are a unified measure of variable importance that attributes the changes in the expected model prediction to each variable included in the model (Lundberg and Lee 2017). In other words, SHAP values provide information on the importance and direction (positive or negative) of each variable contribution to the prediction (Komisarczyk et al. 2024; Lundberg and Lee 2017).

This contribution is particularly relevant and original not only considering the paucity of the literature focusing on the determinants of corruption events but also because, to the best of our knowledge, we are the first to attempt to predict bank corruption events before they become public domain by using bank-specific and textual measures. Notably, this work advances the finance and accounting literature using disclosure as a source of incremental information by demonstrating its potential to provide relevant insights for predicting corruption events. By introducing this novelty to the literature, we suggest that future research can build on the insights of this study to further explore this critical topic, which is essential for the sake of the economic and social system.

The remainder of this paper is organized as follows. Section 2 addresses the research background, reviews the literature, describes our theoretical framework, and develops the research hypotheses. Section 3 thoroughly explains our empirical methodology, while Section 4 presents the results and robustness tests. Lastly, Section 5 discusses our results and concludes by proving practical implications for organizations, managers, and policymakers as well as theoretical ones.

2 | Research Background

2.1 | Corruption in Banking

The literature on bank corruption has captured the attention of scholars and policymakers at the international level due to its theoretical and practical importance, although several gaps still exist, leaving relevant avenues for future research (Bahoo 2020). This literature has extensively explored the economic consequences of corruption by investigating the banking system's role as a channel for its perpetuation and analyzing the impact of such events on the financial industry.

Amongst the most relevant channels through which banks are involved in corruption events and can significantly impact the economy, it is noteworthy to mention the lending activity (Akins et al. 2017). Previous studies have highlighted the negative consequences of corruption, which can result in lower levels of bank lending through higher levels of information asymmetries in the lending market (Abuzayed et al. 2024; Bermpei et al. 2021; Fan et al. 2008). According to Weill (2011), although corruption generally hampers bank lending, it can also have a 'greasing effect' whenever bribery incentivizes bank employees to grant new loans.

Other studies attempt to identify those factors that can reduce corruption in bank lending. For instance, Barth et al. (2009) and Barry et al. (2016) show that the structure of the banking industry, corporate governance mechanisms, and the legal environment at the country level are relevant determinants of corruption in bank lending. Banking supervision and disclosure also play a role, as fostering private monitoring by pushing banks to disclose detailed information in their annual financial reports results in a weaker effect of corruption in terms of reduction in lending (Beck et al. 2006).

The negative consequences of corruption are not just associated with their lending activities. The extant literature has shown that bank corruption events and ineffective anti-corruption mechanisms are associated with higher levels of risk-taking, potentially resulting in a less stable and sound banking system (Ben Ali et al. 2020; Chen et al. 2015; Jenkins et al. 2023). Corruption may also have a 'grease the wheel' effect as it is associated with higher levels of bank profitability (Arshad and Rizvi 2013), although unsustainable levels of risk may still jeopardize the correct functioning of the banking sector. However, the literature is not unanimous in this regard, as Asteriou et al. (2021) find that corruption has a negative effect on both bank stability and profitability.

Corruption practices in the banking industry are also associated with unethical and opaque accounting manipulation practices, including income smoothing, potentially resulting in a lack of credibility of financial reporting and jeopardizing the ability of current and potential investors to make rational and conscious economic and financial decisions (Ozili 2019). Such a type of accounting manipulation strategy is associated with fraudulent behavior by bank managers (Nyakarimi 2022). More broadly, analogous findings have been observed in the literature focusing on non-financial firms (Lewellyn and Bao 2017; Liu 2016; Xu et al. 2019).

Based on the idea that corruption events can be considered a failure of corporate governance mechanisms (Boateng et al. 2021; Weismann 2009), several studies have remarked on the link between the governance pillar of the ESG paradigm. Among these studies, Toader et al. (2018) argue that implementing effective corporate governance practices is associated with lower levels of corruption and, consequently, higher levels of financial stability in the banking sector. According to Arshad and Rizvi (2013), adequate corporate governance mechanisms are crucial to reducing corruption levels in the banking industry. Along the same lines, Khan et al. (2024) shed light on the beneficial effect of rigorous corporate governance by showing that specific characteristics of bank boards of directors (i.e., size of the board, high academic qualifications, and presence of females) mitigate the negative relationship between corruption and bank stability.

Although several aspects of corruption in the banking industry have been widely analyzed, and the importance of bank transparency has been considered as a potential countermeasure to mitigate its negative financial consequences (e.g., Beck et al. 2006), the literature analyzing the relationship between disclosure and bank corruption events is remarkably scant (de Andrés et al. 2024). In addition, no study has hitherto analyzed the role of disclosure in identifying 'corrupted' and 'non-corrupted' banks and, potentially, in detecting corruption events in the banking industry in advance. Furthermore, the development of tools and techniques to detect and predict entity-specific corruption events is virtually nonexistent. To the best of our knowledge, Lima and Delen's (2020) study is amongst the few attempts to predict the levels of corruption, and they do so by focusing on corruption perception. However, our research is substantially different as we focus on bank-specific determinants that can provide warning signals to predict the occurrence of corruption events at the entity level.

2.2 | Disclosure in Banking

An important area of research related to the banking industry focuses on the topic of disclosure, particularly addressing financial (Kahl and Belkaoui 1981; Nier and Baumann 2006; Tabash 2019; Wieczorek 2022; Zelenyuk et al. 2021) and risk disclosure (Altunbaş et al. 2022; Bischof et al. 2021; Chen and Du 2020; Firoozi and Mohsni 2023).

Recent research has increasingly focused on analyzing bank disclosure from a non-financial perspective. For instance, Wang (2023) demonstrates that banks subject to stricter ESG disclosure requirements are more likely to impose environmental covenants in loan agreements and terminate relationships with borrowers with poor environmental and social records, illustrating how ESG disclosures enhance banks' due diligence and risk management processes. Khan et al. (2021) find a positive effect of green banking disclosures on banks' market value, moderated by the presence of non-performing loans.

In this context, the role of governance mechanisms in understanding the effects of non-financial disclosure in the banking sector is fundamental. Indeed, Gunardi et al. (2022), focusing on the determinants of Islamic Corporate Social Responsibility (CSR) bank disclosure, emphasize the importance of governance structures in shaping disclosure practices and highlight the role of CSR in aligning financial activities with ethical and social values. In this regard, Zhang et al. (2020) demonstrate that banks with higher social responsibility and corporate governance disclosure scores tend to report lower percentages of Level 3 fair-value assets, which are associated with higher risk and less transparency. Adu et al. (2022), delving into the effects of corporate governance on executive compensation and sustainable banking, reveal that executive compensation can enhance sustainable banking disclosures, although it has a negative association with environmental performance. Further exploring the role of governance, Adu et al. (2023) focus on the impact of bank ownership structures on sustainable banking disclosures, highlighting that institutional and foreign ownership positively influence sustainable banking disclosures, whereas government ownership has a negative effect. They also demonstrate that the relationship between bank ownership structures and sustainable disclosures is positively moderated by the quality of corporate governance mechanisms, suggesting that good governance practices are essential for fostering transparency and sustainability in banking.

Scholarly research has also focused on the key role of governance-related disclosure. For instance, Grassa and Chakroun (2016) focus on the corporate governance determinants of governance-related disclosure and find that board size and independence are associated with higher levels of disclosure. Hence, these authors emphasize the close interrelationship between strong corporate governance practices and corporate governance disclosure. Similar findings have also been obtained by Abdullah et al. (2015). However, other determinants also play a key role. Grassa (2018) examines the role of several bank- and country-level characteristics in shaping governance-related disclosure practices in the banking industry. Their findings show that leverage and size are the main determinants of governance-related disclosure. Other studies provide evidence of a strong relationship between governance-related disclosure and financial performance (Abdo and Fisher 2007; Abdul Rahim et al. 2024), although the literature is not unanimous in this regard, as other authors have found an insignificant relationship (Elgattani and Hussainey 2021; Nobanee and Ellili 2022).

These studies underscore the multifaceted role of disclosure in the banking sector, pointing out that effective disclosure practices enhance transparency and accountability and are crucial in promoting sustainable and ethical banking practices. In particular, corporate governance is pivotal in shaping disclosure practices in the banking industry, revealing insights for policymakers, banking practitioners, and regulators aiming to enhance disclosure standards and promote sustainable banking practices.

More recently, scholars have analyzed the tone of bank disclosure through sentiment analysis for various research purposes. For example, Beretta et al. (2023), through a tone analysis conducted on the disclosure of Italian banks, find a significant impact of board composition on the textual attributes of bank non-financial disclosure. In this context, most of the studies in this field have proposed textual sentiment analyses of banking disclosure, taking dictionary analyses as a methodological reference under Loughran and McDonald (2011, 2016). In this regard, Berger et al. (2024), analyzing 10-K reports of banks, find that negative sentiment among bank managers leads to increased liquidity hoarding beyond what is warranted by the bank's fundamental conditions and highlight the significant role of managerial sentiment in determining the liquidity that banks provide. Moreover, Hassan et al. (2022), examining the interplay between disclosure tone, financial risk, and readability of annual reports of Arab banks, find that reports with positive tones are easier to read. In contrast, those with negative tone are more comprehensive, underscoring the need for plain language and neutral tones in financial reporting to enhance transparency and comprehension. The study by Mousa et al. (2022) analyzes the textual contents of annual reports of listed banks from emerging markets. It employs machine learning to predict financial performance by incorporating disclosure tone to demonstrate that sentiment analysis of annual report narratives significantly enhances the predictive accuracy of financial performance models. Focusing on the tone of environmental disclosure, Gambacorta et al. (2024) analyze the relationship between environmental disclosure and brown lending in the European banking industry and find that banks' more positive and less negative tone is associated with lower levels of environmental responsibility. Finally, Azmi Shabestari et al. (2020) investigate the timeliness and informativeness of risk factor disclosures during the 2008 financial crisis, finding that although banks increased the quantity of risk disclosures and adopted a more negative tone during the crisis, the disclosures were not timely. In particular, banks that disclosed risks earlier managed their operations more effectively throughout the crisis, emphasizing the importance of timely and proactive risk communication in mitigating the impacts of financial turbulence.

The above-mentioned studies have utilized the Loughran and McDonald's (2011, 2016) dictionary for sentiment analysis to understand the dynamics of bank disclosures. However, our study introduces a novel approach to this area of research by employing a pre-trained contextual language learning model, specifically BERT (Devlin et al. 2019), which has significantly advanced natural language processing capabilities (Bhattacharya and Mickovic 2024). One of the main novelties of our study lies in adopting this innovative methodology, as, to the best of our knowledge, we are the first to utilize BERT to analyze bank disclosures for predicting bank corruption through text analysis. This advanced model allows for a more nuanced and context-aware understanding of disclosure narratives, potentially leading to more accurate predictions and insights than traditional sentiment analysis tools. By leveraging these cutting-edge techniques, our research provides deeper insights and contributes to developing more robust models for risk prediction in the banking sector.

2.3 | Theoretical Framework and Hypothesis Development

As already mentioned, the literature focusing on the entity-specific factors associated with the occurrence of corruption events in the banking industry is remarkably scant. Thus, we cannot rely on previous empirical studies that conduct similar analyses to develop our research hypotheses and theoretical framework. However, by drawing upon the empirical banking literature (e.g., Avignone et al. 2021; Fortin et al. 2010) and previous studies focusing on corruption (e.g., Lima and Delen 2020), we can identify the group of variables that are potentially associated with corruption events.

Specifically, aside from country-level, corporate governance, and other bank-specific characteristics,[1] we argue that disclosure measures might be associated with corruption events and may play a relevant role in identifying in advance such scandals before they become public domain. Different competing theoretical frameworks support the idea that disclosure is associated with corruption events (Blanc et al. 2017, 2019; de Andrés et al. 2024). According to the impression management theory (Goffman 1959), disclosure practice can be employed to deceptively give the impression that corruption events are perfectly under control and do not represent an urgent and pressing threat that can jeopardize a bank's reputation. On the other hand, the signaling theory (Spence 1973) provides another interesting ex-ante argument on the relationship between corruption and disclosure. This theoretical framework posits that banks are willing to provide higher levels of disclosure if they have developed and implemented reliable and effective anti-corruption mechanisms. This argument is in line with the idea that non-financial information can be used as a means to communicate more effectively with current and potential investors (Cho et al. 2015) and inform them about the superior performance and effectiveness of the anti-corruption mechanisms (i.e., within a signaling disclosure strategy). This theoretical argument is further reinforced by existing literature, which has widely acknowledged the significance of signaling theory in interpreting the disclosure behavior of banks and firms (Morris 1987; Neifar and Jarboui 2018).

In sum, although these theories are in stark contrast regarding the sign of the relationship between corruption events and bank disclosures, they agree that there is a strong association between the two. Building on these theoretical arguments, we aim to examine the potential role of disclosure in identifying corruption events. Particularly, we contend that this relationship is not only held when we consider concurrent disclosure strategies and corruption events but also when disclosure can be used to predict corruption events in advance before they become public domain. This argument is supported by the idea that textual analysis techniques have been widely employed as predictive tools, primarily when supported by machine learning algorithms (Chan et al. 2021; Schumaker and Chen 2009). If this argument is correct, we should observe an association between past disclosures (i.e., observed in year *t-1*) and present corruption events (i.e., that become public domain in year *t*). Thus, we state our first and main research hypothesis as follows:

Hypothesis 1. *There is an association between present and past disclosure and corruption events.*

Digging deeper into the theoretical basis of this relationship, we argue that two specific characteristics of bank disclosures are closely associated with corruption events, namely (i) the governance topic within bank disclosures and (ii) the tone of such governance-related disclosures. The tight relationship between corruption and corporate governance is due to the fact that the latter is generally considered a failure of the former (Boateng et al. 2021; Weismann 2009). More broadly, banks and firms that are in line with the ESG paradigm are supposed to avoid any type of involvement in corruption events and, specifically, they should be mainly focused on the G pillar of ESG, further confirming the strong relationship between governance and corruption (Hoang 2022; Zhang and So 2024). In this regard, Wu (2005) has shown that effective corporate governance mechanisms play a significant role in corruption prevention and anti-corruption campaigns. With specific reference to the banking industry, Arshad and Rizvi (2013) and Toader et al. (2018) have shown that adequate corporate governance mechanisms are crucial to reducing corruption levels. Along the same lines, Ghazwani et al. (2024) demonstrate that specific corporate governance dimensions (e.g., board gender diversity and independence) are strongly associated not only with more effective anticorruption practices but also with higher levels of transparency regarding such practices, further confirming the strong relationship between corruption, corporate governance, and disclosure. Hence, relying on the above-mentioned theories, according to signaling theory, non-corrupted banks are supposed to rely on governance-related disclosure to remark on the effectiveness of their anticorruption systems, disclosing more information regarding them compared to their corrupted counterparts. Conversely, relying on impression management theory, corrupted banks could provide more governance-related disclosure than their non-corrupted counterparts to appear efficient and hide their problems from their stakeholders. Overall, these theories suggest that the extent to which banks disclose governance-related sentences could significantly vary depending on whether they are corrupted or not. Thus, based on these theoretical arguments, we develop our second research hypothesis:

Hypothesis 2. *There is an association between present and past extent of governance-related disclosure and corruption events.*

Another crucial characteristic of disclosure—in general—and of governance-related disclosures—in particular—is their tone (del Gaudio et al. 2020; Rogers et al. 2011). One remarkable finding of this strand of literature is the strict relationship between disclosure tone and corporate governance (Alwani and Mousa 2022; Bassyouny et al. 2020). Henry's (2008) study is amongst the first attempts to systematically measure the tone of financial disclosures by using specific tailor-made dictionaries of positive and negative keywords. After this seminal study, other contributions have followed the same approach to provide more comprehensive dictionaries and deeper examinations of disclosure tones (Bassyouny et al. 2022). Loughran and McDonald (2011) have proposed a range of dictionaries to measure various components of disclosure tone that have become a standard in the literature. Specifically, these authors provide three different dictionaries to measure the degree of negativity, positivity, and litigiousness of disclosures. These characteristics might play a prominent role in identifying associations of elements that could allow the prediction of corruption events. For instance, within the signaling strategy (Spence 1973), non-corrupted banks may use a more positive and less negative tone in their governance disclosures to highlight the effectiveness of their anticorruption systems. Furthermore, while several previous studies focused on the positive and negative tone of texts, we posit that a litigious tone could also play a relevant role in the specific case of corruption events. Indeed, the litigious tone is defined by Loughran and McDonald (2011) as the level to which disclosure reflects the propensity of a firm to disclose information regarding the legal context and events likely to affect its operations. Specifically, banks uninvolved (or unlikely to be involved) in corruption events would use a less litigious tone because they are not expected to be entangled in a lawsuit. Thus, a higher or lower presence of a litigious tone could provide incremental information in the corruption investigation. On the other hand, the impression management theory (Goffman 1959) can reveal that corrupted banks could bias the tone of their governance-related disclosure positively and use less negative and litigious terms to impress their audience. Based on these theoretical considerations, we develop our third research hypothesis:

Hypothesis 3. *There is an association between present and past tone of governance-related disclosure and corruption events.*

Our three research hypotheses are graphically represented in Figure 1.

3 | Methodology

3.1 | Data Collection

We rely on different data sources to construct our dataset. First, we identify corruption scandal events in the banking industry by searching the most reputable economic and financial newspapers at the European level[2] and the Nexis Uni database, which provides an up-to-date archive of industry information (including the banking and financial sectors) and the latest economic news with worldwide coverage.[3] Following de Andrés et al. (2024), we adopt an exact definition of corruption to identify such scandals. In particular, we rely upon Nye (1967, 419), who defines corruption as "behavior which deviates from the formal duties of a given role because of private-regarding (personal, close family, private clique) pecuniary or status gains; or violates rules against the exercise of certain types of private-regarding influence. This includes such behavior as bribery (use of a reward to pervert the judgment of a person in a position of trust); nepotism (bestowal of patronage by reason of ascriptive relationship rather than merit); and misappropriation (illegal appropriation of public resources for private-regarding uses)." Using this definition, we identify 21 corruption cases in the Eurozone.[4]

Second, aside from identifying corruption scandals and the computation of textual analysis measures, our primary data source is Eikon, a comprehensive database provided by the London Stock Exchange Group (LSEG data & analytics), from which we collect financial statements and ESG data. We restrict our analysis to those banks in Eikon whose headquarters are in Eurozone countries[5]. In doing so, we analyze a highly homogeneous and comparable sample of banks and ensure a high level of standardization of regulatory and supervisory practices, as well as financial reporting standards, in light of the establishment of the European Banking Union and enforcement of International Accounting Standards/International Financial Reporting Standards (IAS/IFRS) (Agostino et al. 2011; Avignone et al. 2021). To further enrich our dataset and mitigate the problem of missing values, we complement the accounting bank-level data collected from LSEG with Moody's Analytics BankFocus (Bureau Van Dijk), widely employed in the banking literature[6] (Miller et al. 2021; Overesch and Wolff 2021).

Third, we collect country-level and macroeconomic variables from the World Development Indicator database provided by the World Bank.

For all banks in our sample, we manually collect the annual financial reports from the investor relation section of their institutional websites. Following previous studies (Altunbaş et al. 2022, 2023), we restrict our analysis to English versions of such reports, and we also require that financial reports are audited to ensure the reliability of the disclosures.

Regarding the textual analysis measures, we extract sentences related to the governance topic using the FinBERT LLM (Huang et al. 2023) from the selected banks' reports. We calculate the percentage of sentences related to governance based on the total sentences in the reports. Further, we use the Loughran and McDonald (2011) to compute the number of positive, negative, and litigious words within these governance-related sentences.

Given that we need a comparable group of banks that have not been involved in corruption events, we adopt simple matching criteria using bank size measured by total assets (Altunbaş et al. 2022) and select 21 comparable 'non-corrupted' banks (i.e., not involved in corruption events that are public domain) so that we have a balanced sample including 50% of 'corrupted' and 50% of 'non-corrupted' banks. This feature of the sample is necessary to prevent our machine learning algorithm from achieving high accuracy by simply assuming that all banks are not 'corrupted' if, for instance, the share of 'non-corrupted' banks would be higher than 50%. Hence, our final sample consists of 42 banks. The retrieved sample includes only banks operating in civil law countries. This shared

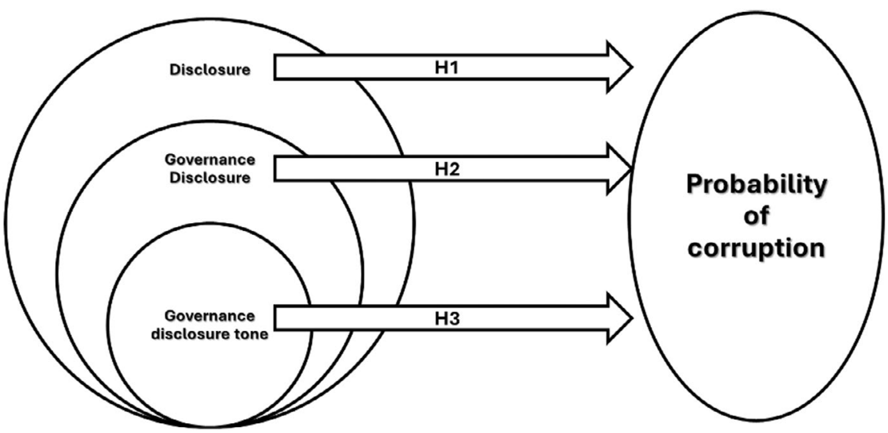

FIGURE 1 | Theoretical framework and hypotheses. The figure graphically represents our research hypotheses.

characteristic fits our research, allowing us to investigate a homogeneous sample. Indeed, common and civil law country banks could significantly differ in their investment business activities, and considering such a peculiarity would necessitate retrieving larger and more stratified samples. We analyze these banks over the 2013–2022 time horizon to cover the period in which such scandals have occurred.[7]

3.2 | Textual Analysis

We use two different textual analysis approaches to analyze bank disclosures, namely, the Bidirectional Encoder Representations from Transformers adapted to the finance domain to categorize ESG sentences (called FinBERT) (Huang et al. 2023) and dictionary approach-based sentiment analysis (Loughran and McDonald 2011).

FinBERT is an LLM, a natural language processing algorithm based on deep learning, capable of locating ESG-related sentences within a text (Chan et al. 2021). Specifically, the algorithm can classify each sentence as environmental, social, or governance-related since the model is pre-trained on a large corpus of financial texts containing sentences pre-classified into environmental, social, and governance-related categories by expert human coders. The LLM then uses the labeled dataset to learn how sentences should be categorized. The model demonstrates high levels of accuracy in identifying ESG-related sentences while emulating the human coders' judgment. For our specific purposes, we use FinBERT to detect sentences in bank disclosures within the governance category (the G pillar of ESG) to count the percentage of sentences focusing on governance-related topics within bank disclosures.

In addition, we isolate these governance-related sentences from the text and measure their sentiment. To perform this second task, we employ the sentiment analysis approach Loughran and McDonald (2011) propose to measure bank disclosures' positive, negative, and litigious tone. This approach is based on a simple word count of words within a text. The Loughran and McDonald's (2011) dictionary consists of lists of words with a positive, negative, or litigious connotation when appearing in a financial text. Therefore, this analysis simply consists of counting the words that appear in the positive, negative, and litigious wordlists proposed in the Loughran and McDonald's (2011) dictionary within banks' reports. Particularly, we count the occurrences of these words in the governance-related sentences identified by FinBERT. Thus, by combining these two methodologies, we compute the following text measures:

- *% governance sentences*: computed as the total number of governance-related sentences identified by FinBERT divided by the total number of sentences in the annual financial report.
- *Positive tone*: computed as the ratio between the occurrences of positive keywords within governance-related sentences and the total number of words in governance-related sentences.
- *Negative tone*: computed as the ratio between the occurrences of negative keywords within governance-related sentences and the total number of words in governance-related sentences.
- *Litigious tone*: computed as the ratio between the occurrences of litigious keywords within governance-related sentences and the total number of words in governance-related sentences.

3.3 | Machine Learning and Logit Methodology

The empirical analyses in this work are performed using the R software (R Core Team 2024). To analyze the association between bank disclosures and corruption events, we draw upon two different methodologies: machine learning algorithms and logistic regression. First, regarding the machine learning algorithms, we use random forests (Liaw and Wiener 2002), support vector machine (Meyer et al. 2023), gradient boosting (Ridgeway 2024), and naive Bayes classifier (Meyer et al. 2023). These advanced machine learning algorithms are widely utilized in the accounting and finance literature for diverse purposes, such as estimating the likelihood of a firm obtaining corporate social responsibility assurance (Thompson and Buertey 2023) or predicting bankruptcy probability (Mai et al. 2019; Nguyen and Huynh 2022).

Specifically, random forest independently constructs multiple decision trees in parallel using training data to identify correlations between explanatory variables and the response variable. This approach enables us to deliver more accurate and stable predictions than individual decision trees (Breiman 2001).

Support vector machine maps training observations into an n-dimensional space, identifies the optimal function to separate these observations into predefined classification categories, and applies this function to new observations for classification tasks (Cortes and Vapnik 1995; Hefner and Ousley 2014).

Gradient boosting constructs multiple decision trees sequentially (Friedman 2001). Using training data, each tree is constructed to correct the errors made by the preceding ones. This incremental process allows the algorithm to improve its predictive power at every iteration.

Lastly, the naive Bayes classifier is based on Bayes' theorem, which calculates the probability of an observation belonging to a specific class under the assumption of variable independence. It evaluates the likelihood of the observation belonging to each class using Bayes' theorem, and the class with the highest probability is selected as the predicted outcome.

To conduct the analysis using machine learning algorithms, the data must be divided into training and test sets. The training data consists of observations provided to the algorithms to enable them to 'learn' the relationships between explanatory variables and the response variable. Conversely, the test data comprises observations for which the response variable is unknown to the algorithms. Based on the patterns learned from the training data, the algorithms attempt to predict the response variable for the test data (Abu-Mostafa et al. 2012; Choudhury et al. 2021; Thompson and Buertey 2023).

Such a split between training and test data can be performed in several ways, using different percentages of the original data as training and test sets. A widely used approach to split training and test data is known as k-fold cross-validation, which involves partitioning the data into multiple k subsets (also defined as 'folds') and training the model on the overall number of these subsets minus one (k-1). Then, the fold left out is used as a test set (Abu-Mostafa et al. 2012; Choudhury et al. 2021; Thompson and Buertey 2023). Then, this procedure is iteratively repeated until every fold has been used as training and test data.

In this study, we employ a form of cross-validation known as leave-one-out. This method uses all but one observation as the training set, with the excluded observation serving as the test set. The process is repeated iteratively until each observation has been used both as part of the training set and as the test data. Leave-one-out cross-validation is particularly suited to our research context, as it maximizes the data available for training while ensuring effective model validation, especially given the size of our dataset (Hawkins et al. 2003).

Furthermore, a branch of machine learning research strongly advocates for stratified cross-validation, which ensures that the training and test sets preserve the same proportion of classes to predict. In line with this approach, we adapt the leave-one-out method by excluding a pair of observations (one corrupted and one non-corrupted bank) at each iteration instead of a single observation. This adjustment allows us to maintain a perfect balance between corrupted and non-corrupted observations in both the training and test sets.[8]

For our empirical analysis, these machine learning algorithms can identify banks involved in corruption scandals by leveraging input variables potentially linked to such events. Compared to conventional regression analyses, these algorithms offer several advantages, including the absence of a linear assumption for regression parameters and a data-driven approach that does not rely on specific theoretical frameworks to interpret or justify the sign of a regression coefficient (Jarmulska 2022). While this data-driven characteristic is a key advantage of the machine learning approach, often outperforming conventional regression methods in terms of accuracy, it also poses a limitation, as these algorithms provide no insight into the linearity or type of nonlinearity (e.g., convex or concave) between input and output variables, nor the direction of this relationship.

In other words, these algorithms function as 'black boxes': while they achieve high predictive accuracy, their results are difficult to interpret (Óskarsdóttir et al. 2022; Zhao and Hastie 2021). Consequently, it becomes challenging to identify which variables contribute to the model's accuracy and how they influence its performance. Nonetheless, a specific line of machine learning research has focused on 'opening up these black boxes,' aiming to make their heuristics more interpretable for human users. A particularly noteworthy study is Lundberg and Lee (2017), which introduces SHapley Additive exPlanations, a method that provides SHAP values to interpret the results of machine learning algorithms. Derived from Shapley values in game theory (Roth 1988; Shapley 1951), SHAP values make it possible to explain how each variable in a machine learning model contributes to the obtained predictions. This study leverages SHAP values to derive meaningful theoretical insights from our empirical results.

Although machine learning algorithms do not enable testing the statistical significance of our variables of interest using p-values, SHAP values provide a means to interpret whether and how textual measures contribute to the predictions of these algorithms (Komisarczyk et al. 2024). Specifically, SHAP values enable the evaluation of individual variables' impact on model performance. They offer a robust method for interpreting machine learning algorithms by quantifying and visualizing the contribution of variables to predictions. Furthermore, SHAP values provide both local and global interpretability, enhancing the understanding of machine learning results.

It is possible to use two plots to interpret the models' behavior (Mayer 2024; Wickham 2009). First, the feature importance plot displays the mean absolute SHAP values for each variable, representing its relevance to the predictions. Variables with higher mean absolute SHAP values are more influential in the predictive task. The second visualization, known as the 'beeswarm plot,' shows the variables used by the predictive model on the vertical axis. Then, the SHAP values are displayed on the horizontal axis, quantifying each feature's contribution to the model's prediction. Positive SHAP values indicate that a variable pushes the prediction toward the corrupted class, while negative values pull it toward the non-corrupted class. Each point on the beeswarm plot represents a specific observation in the dataset, with the point's color indicating the value of the variable for that observation and its location representing the corresponding SHAP value.

Additionally, we use a conventional logistic regression model to test the robustness of the machine learning algorithms in identifying the key textual factors influencing the likelihood of a bank being involved in a corruption scandal.

The variables used in the machine learning algorithms and the logistic models are:

- $\mathrm{CORRUPT}_{ijt}$ is a dummy variable equal to 1 if bank i in country j at time t is involved in a corruption scandal and 0 otherwise. This is the response variable of the employed models.
- *% governance sentences*$_{ijt}$ is the total number of governance-related sentences divided by the total number of sentences in the annual financial report.
- *Positive tone*$_{ijt}$ is the ratio between the occurrences of positive keywords within governance-related sentences and the total number of words in governance-related sentences.
- *Negative tone*$_{ijt}$ is the ratio between the occurrences of negative keywords within governance-related sentences and the total number of words in governance-related sentences.
- *Litigious tone*$_{ijt}$ is the ratio between the occurrences of litigious keywords within governance-related sentences

and the total number of words in governance-related sentences.

- $Bank_{ijt}$ represents bank-level controls based on accounting data.
- ESG_{ijt} represents bank-level controls based on ESG data and corporate governance variables.
- $Country_{jt}$ represents country-level controls.

Initially, these variables were used in machine learning and logistic regression models to examine the association between disclosure and corruption events. However, since all dependent and independent variables are observed simultaneously at time *t*, they cannot be employed for predictive purposes. To address this limitation, in a second step, all variables—except for the response variable—were lagged by 1 year, enabling an evaluation of the capability of our textual measures to detect corruption events before they enter the public domain.

Following Thompson and Buertey (2023), we include the same textual and control variables in both models for consistency and to enhance the comparability of machine learning and logit methodologies. However, given that some variables might be linearly correlated (which would violate one of the assumptions of logistic regression) and to ensure the convergency of the models, we collapse all accounting, ESG, and country-level variables into three aggregated variables by using principal component analysis (Bruce Ho and Wu 2009; Kassambara and Mundt 2020; Lê et al. 2008) (named *Accounting PCA*, *ESG PCA*, and *Country PCA*, respectively). In doing so, we also overcome multicollinearity concerns in our logistic regression models. In this regard, we perform a sensitivity analysis to ensure that the predictions' results are not driven by the specific set of controls chosen in the generation of the principal components.[9] Also, we repeat the analyses by computing different Accounting, ESG, and Country PCAs at each iteration by randomly selecting only 3/4 of the original variables. This test confirms the robustness of our results.

4 | Results

4.1 | Descriptive Analysis Results

Table 1 presents the descriptive statistics of the variables used in the models for both the non-corrupted and corrupted groups. In terms of textual measures, non-corrupted banks, on average, provide less governance-related disclosure compared to corrupted entities. Furthermore, the table indicates that non-corrupted banks tend to use a more litigious tone and exhibit less negative and positive tone on average compared to their corrupted counterparts. Notably, the median negative tone of non-corrupted banks is higher than that of corrupted banks. Regarding the control variables, non-corrupted banks exhibit lower levels of accounting and country PCA, while their ESG PCA is higher on average compared to corrupted entities. Consequently, Table 1 highlights significant differences in the control variables between the two groups, suggesting that this heterogeneity can be leveraged to enhance the performance of our machine learning and logit corruption detection tools.

The correlation matrix (Table 2) indicates that the independent variables exhibit low correlation, making them suitable for inclusion in the machine learning and logistic regression models.

TABLE 1 | Descriptive statistics of the variables included in the model for the non-corrupted and corrupted group.

	Accounting PCA	ESG PCA	Country PCA	% governance sentences	Litigious tone	Negative tone	Positive tone
Non-corrupted							
Min.	−5.24E+11	−36.825	−2.60E+12	0.05021	0.003577	0.002704	0.002704
1stQu.	−4.49E+11	−4.633	−5.91E+11	0.0691	0.008666	0.007979	0.004654
Median	−4.29E+11	6.788	−2.38E+10	0.09826	0.011943	0.00883	0.006129
Mean	−3.18E+11	1.555	−1.07E+11	0.10979	0.012755	0.008918	0.005902
3rdQu.	−3.69E+11	12.749	9.53E+11	0.1187	0.016375	0.01077	0.007622
Max.	6.94E+11	27.059	1.27E+12	0.27048	0.027695	0.012913	0.009032
Corrupted							
Min.	−4.91E+11	−36.424	−2.60E+12	0.04808	0.00447	0.005849	0.003279
1stQu.	−3.63E+11	−14.9318	−5.91E+11	0.07314	0.007154	0.007665	0.005511
Median	−1.68E+11	0.2341	4.60E+11	0.12879	0.008991	0.008146	0.006582
Mean	3.18E+11	−1.5547	1.07E+11	0.11367	0.009937	0.009067	0.006708
3rdQu.	8.49E+11	8.7702	1.13E+12	0.14569	0.011703	0.010205	0.007729
Max.	2.39E+12	29.8015	1.35E+12	0.22029	0.017008	0.014741	0.011953

Note: This table shows the descriptive statistics of the independent variables included in the analysis, differentiating between corrupted and non-corrupted banks. Variables are defined in Section 4.

TABLE 2 | Correlation matrix.

	Accounting PCA	ESG PCA	Country PCA	Litigious tone	% governance sentences	Negative tone	Positive tone
Accounting PCA	1.000						
ESG PCA	−0.160	1.000					
Country PCA	−0.352	0.149	1.000				
Litigious tone	−0.176	0.495	−0.303	1.000			
% governance sentences	0.219	−0.242	−0.200	−0.286	1.000		
Negative tone	0.020	−0.057	−0.256	0.302	0.052	1.000	
Positive tone	0.076	0.042	−0.026	−0.013	0.168	0.474	1.000

Note: This table shows the correlation coefficients of the independent variables included in the model (1). Variables are defined in Section 4.

TABLE 3 | Confusion matrices of baseline machine learning estimation.

Random forests	0	1
0	14	7
1	6	15
Accuracy	**0.69**	
Support vector machine		
0	10	11
1	7	14
Accuracy	**0.57**	
Gradient boosting		
0	14	7
1	5	16
Accuracy	**0.71**	
Naive Bayes		
0	13	8
1	12	9
Accuracy	**0.52**	

Note: This table shows the confusion matrix of the baseline machine learning estimations (i.e., with input variables at time *t*). 1 indicates that the bank is involved in corruption events, while 0 indicates that the bank is not involved in corruption events. Accuracy levels in bold.

4.2 | Machine Learning Analyses Results

Our baseline results are summarized in the confusion matrices reported in Table 3. The rows of the matrices indicate whether the bank has been involved in corruption events (i.e., the output variable CORRUPT is equal to 1) or not (i.e., the output variable CORRUPT is equal to 0), whilst the columns represent the classification of the employed algorithms (i.e., 1 when the bank is expected to be corrupted, and 0 when it is expected not to be corrupted) (Hasnain et al. 2020). Thus, the figures in the diagonal represent the corruption/non-corruption cases that have been correctly identified.

Using random forests, 14 out of 21 banks are correctly identified as non-corrupted, while 15 out of 21 are correctly identified as corrupted. Similarly, gradient boosting correctly identifies 14 out of 21 banks as non-corrupted and 16 out of 21 as corrupted. These results demonstrate that our models effectively classify both types of banks based on the textual measures and control variables. The accuracy of the random forests and gradient boosting models, as reported in Table 3, is 0.69 and 0.71, respectively, indicating that the models correctly classify 69% and 71% of corrupted and non-corrupted banks. Conversely, the naive Bayes and support vector machine algorithms exhibit lower performance, with accuracies of 0.57 and 0.52, respectively, though both still exceed the 50% threshold. Given the notable performance of our corruption detection tool, we find partial confirmation of research Hypothesis H1.

To test our research hypotheses more in-depth, we need information regarding the relevance and the impact—positive or negative—of the various textual measures in assessing bank corruption events within such a machine-learning approach. Figure 2 reports the SHAP values of all input variables for the models with the highest accuracy levels—random forests and the gradient boosting algorithm. Specifically, the top section of Figure 2 displays the feature importance and beeswarm plots for the random forest algorithm, while the bottom section presents these plots for the gradient boosting algorithm.

First, from the random forests model, it emerges that among our variables of interest, the textual variables of *litigious tone* and *% governance sentences* play a relevant role in our model. Specifically, both variables have mean absolute SHAP values of approximately 0.05. The contribution of these variables is inferior only to that of accounting and country measures. However, the SHAP values of these textual variables are comparable to those of the country-level variable. Overall, these results validate Hypotheses H1–H3, affirming the association between corruption events and present disclosure. Then, as regards the beeswarm plot of the random forests, it shows that lower values of *litigious tone* mainly push the prediction to the corrupted

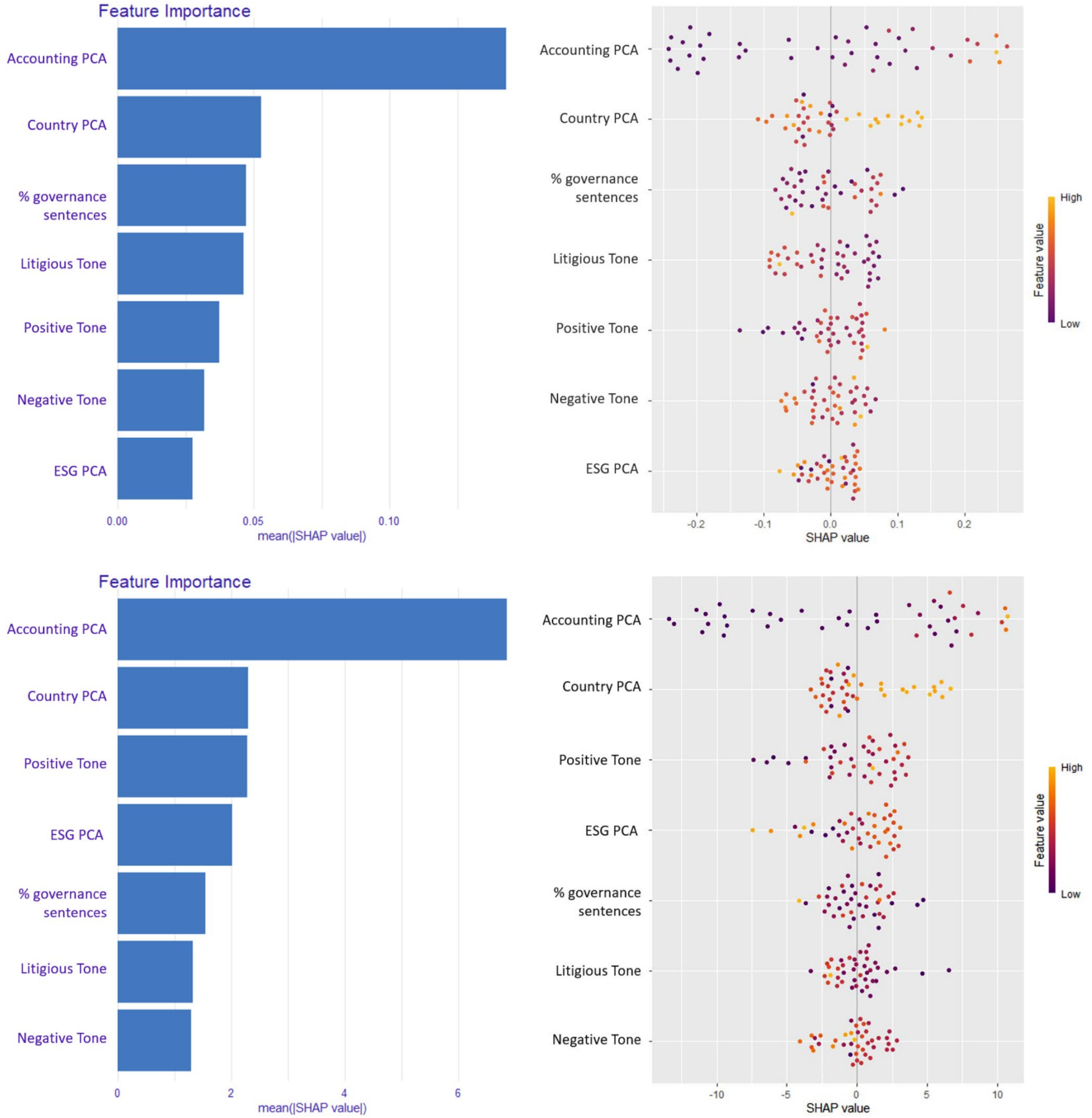

FIGURE 2 | SHAP values variable importance of baseline random forests and gradient boosting estimation. This figure shows the variable importance coefficients of the input variables of the baseline random forests (upper image) and gradient boosting (lower image) estimation (i.e., with input variables at time *t*) using SHAP values. Variables are defined in section 4. [Colour figure can be viewed at wileyonlinelibrary.com]

class. On the contrary, a higher *% governance sentences* mainly push the prediction toward the corrupted class.

As for the other textual variables, although they are less significant than the previously discussed ones, the plot reveals that a higher frequency of positive words and a lower frequency of negative words push predictions toward the corrupted class. These insights also provide a theoretical basis for interpreting our results. These findings align with the impression management theory (Goffman 1959), according to which corrupted banks tend to manage the impressions of their audience by attenuating the usage of litigious and negative terms to disclose more about their governance mechanisms in a more positive fashion. As for the gradient boosting algorithm, textual variables also appear relevant in improving the model accuracy. However, this model privileged the count of positive terms within governance-related disclosure sentences. In particular, the beeswarm plot shows that, as in the case of the random forest, the higher use of positive words pushes the prevision toward the corrupted class. This result also supports our research hypotheses and the theoretical explanation of impression management.

However, given that we are not lagging our input variables, we are just measuring the association between present disclosures and concurrent corruption events. Thus, we are not assessing the predictive power of our model and the associated textual measures. In order to address this, we lag our input variables by 1 year so that we can assess the predictive power of our models. The confusion matrices reported in Table 4 show that random forests and gradient boosting models correctly classify 65%. As could reasonably be expected, the model accuracy is lower than that of the previous ones. However, accuracy is still significantly higher than 50%, indicating that their predictive powers are better than a random assignment of banks in the corrupt and non-corrupt categories.

As for variable importance, Figure 3 shows that the SHAP values of the random forest model associated with *litigious tone* and *negative tone* are even higher than before, making these variables comparatively more important with respect to all the others included in the model. Although the importance of the variable *% governance sentences* is lower than the baseline model, this result is partially compensated by the relatively higher importance of the variable *negative tone*. As regards the beeswarm plot of this random forest model, in this case, lower values of litigious and negative tone also push the prediction toward the corrupted class. Similarly, the SHAP values of the gradient boosting algorithm are comparatively higher than those of the other variables when we lag them, and as in the case of the random forest, lower values of litigious and negative tone push the prediction toward the corrupted class. Hence, these results support our research hypotheses regarding the association between past disclosures and subsequent corruption events in banking,[10] confirming the predictive power of our textual measures and hypotheses H1, H2, and H3 in line with impression management theory.

TABLE 4 | Confusion matrices of predictive machine learning estimation.

Random forests	0	1
0	9	4
1	5	8
Accuracy	**0.65**	
Support vector machine		
0	8	5
1	8	5
Accuracy	**0.5**	
Gradient boosting		
0	9	4
1	5	8
Accuracy	**0.65**	
Naive Bayes		
0	7	6
1	3	10
Accuracy	**0.65**	

Note: This table shows the confusion matrix of the predictive machine learning estimations (i.e., with input variables at time *t-1*). 1 indicates that the bank is involved in corruption events, while 0 indicates that the bank is not involved in corruption events. Accuracy levels in bold.

4.3 | Additional Analyses and Robustness

To test the robustness of the results of our machine learning algorithms, we repeat the analysis by recalculating the PCA included in the model at each cross-validation iteration to ensure that the specific set of controls chosen does not drive the results. Specifically, we calculate the alternative PCAs by randomly selecting 75% of the original input variables at every iteration. This procedure allows us to obtain different Accounting, ESG, and Country PCA at every iteration to perform the classification task. On the other hand, the textual variables have not been changed. Tables 5 and 6 show the classification results of the different machine learning algorithms using these randomly calculated PCAs.

The results of the robustness check are consistent with those of the main analysis of this work for both the lagged and non-lagged models. Further, we also show the results of the logistic regression models performed during the cross-validation process. Tables 7 and 8 present the distribution of the estimates and *p*-values of the regression models. The results corroborate the findings of the machine learning algorithms. Indeed, as it is possible to check from the tables, the textual variables are significant in several models. Furthermore, the model estimates confirm the main findings highlighted by the SHAP values, indicating that a lower usage of negative and litigious tones and a higher usage of positive tones is significantly associated with the corrupted class.

5 | Discussion and Conclusion

Our results answer the research question regarding the association between corruption events and bank disclosures. Notably, we find support for our research hypotheses on the presence of an association between present and past disclosure and corruption events, thereby confirming our first research hypothesis. More specifically, disclosure tone and the percentage of governance-related sentences are associated with the probability of being involved in a corruption event.

Specifically, from a theoretical perspective, our results are in line with the impression management theory (Goffman 1959), showing that banks involved in corruption events tend to be less transparent when it comes to governance-related matters and use a less litigious and negative tone and a more positive tone, likely in an attempt to divert the attention of the readers of their annual financial reports, thereby conveying a deceptive positive message. These findings are corroborated by our predictive models, which reveal that banks involved in corruption events tend to adopt a less negative and more positive tone in their disclosures prior to their scandals becoming public. This behavior likely reflects an impression management

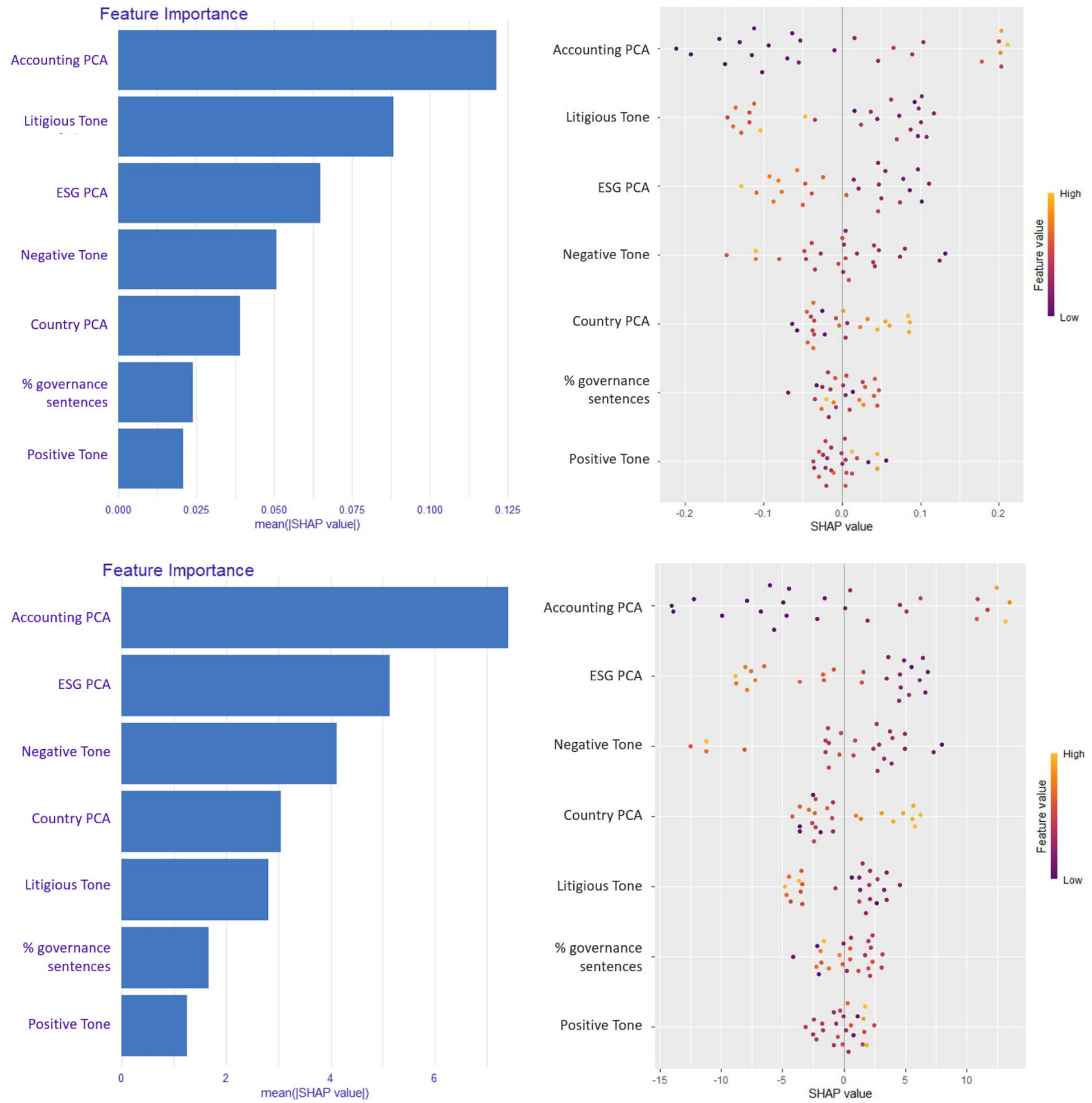

FIGURE 3 | SHAP value variable importance of predictive random forests and gradient boosting estimation. This figure shows the variable importance coefficients of the input variables of the predictive random forests (upper image) and gradient boosting (lower image) estimation (i.e., with input variables at time *t*-1). Variables are defined in section 4. [Colour figure can be viewed at wileyonlinelibrary.com]

strategy designed to emphasize positive aspects of their corporate governance while concealing its failures associated with corruption.

Recent finance and accounting research has increasingly focused on analyzing bank disclosure from a non-financial perspective (Khan et al. 2021; Wang 2023). The focus on governance mechanisms described in these disclosures has been stressed (Adu et al. 2022; Gunardi et al. 2022; Zhang et al. 2020). These studies underscore the multifaceted role of disclosure in the banking sector, pointing out that effective disclosure practices enhance transparency and accountability and promote sustainable and ethical banking practices.

In this context, most of the studies in this field have proposed textual sentiment analyses of banking disclosure, taking dictionary analyses as a methodological reference under Loughran and McDonald (2011, 2016). Scholars have analyzed the tone of bank disclosure through such a technique, finding significant relationships between sentiment and bank characteristics

TABLE 5 | Confusion matrices of baseline machine learning estimation using randomly calculated PCAs.

Random forests	0	1
0	14	7
1	6	15
Accuracy	**0.69**	
Support vector machine		
0	7	13
1	4	16
Accuracy	**0.57**	
Gradient boosting		
0	14	7
1	5	16
Accuracy	**0.71**	
Naive Bayes		
0	14	7
1	10	11
Accuracy	**0.59**	

Note: This table shows the confusion matrix of the baseline machine learning estimations (i.e., with input variables at time *t*). 1 indicates that the bank is involved in corruption events, while 0 indicates that the bank is not involved in corruption events. Accuracy levels in bold.

TABLE 6 | Confusion matrix of predictive machine learning estimation using randomly calculated PCAs.

Random forests	0	1
0	8	5
1	5	8
Accuracy	**0.61**	
Support vector machine		
0	9	4
1	8	5
Accuracy	**0.54**	
Gradient boosting		
0	7	6
1	4	9
Accuracy	**0.61**	
Naive Bayes		
0	7	6
1	4	9
Accuracy	**0.61**	

Note: This table shows the confusion matrix of the predictive machine learning estimations (i.e., with input variables at time *t-1*). 1 indicates that the bank is involved in corruption events, while 0 indicates that the bank is not involved in corruption events. Accuracy levels in bold.

such as board composition, liquidity, and financial risk (Beretta et al. 2023; Berger et al. 2024; Hassan et al. 2022). A particularly relevant study in this branch of research is that of Mousa et al. (2022), which, employing machine learning algorithms on disclosure tone, demonstrated that sentiment analysis of banks' reports significantly enhances the predictive accuracy of financial performance models.

These studies have emphasized the key role of textual measures as determinants of bank performance and going concern. Our study adds evidence to this literature that such measures can also help predict corruption events. Although several aspects of corruption in the banking industry have been widely analyzed, and the importance of bank transparency has been considered as a potential countermeasure to mitigate its negative financial consequences (e.g., Beck et al. 2006), to the best of our knowledge the literature analyzing the relationship between disclosure and bank corruption events is remarkably scant (de Andrés et al. 2024). In addition, no study has hitherto analyzed the role of disclosure in identifying 'corrupted' and 'non-corrupted' banks and, potentially, in detecting corruption events in the banking industry in advance. Specifically, the development of tools and techniques to detect and predict entity-specific corruption events is virtually nonexistent. Furthermore, our paper introduces a novel approach to this area of research by not only relying on sentiment analysis but also employing a pre-trained contextual LLM, specifically FinBERT, which has significantly advanced natural language processing capabilities in recent years (Bhattacharya and Mickovic 2024). The usage of this LLM allowed us not only to focus on the sentiment of the overall document but also to address governance-related sentences specifically.

In providing such new insights, our study also contributes to the branch of studies investigating bank corruption. Specifically, this study adds to previous studies attempting to identify corruption-related factors in the banking sector (Barry et al. 2016; Barth et al. 2009; Beck et al. 2006). Starting from the theoretical insight that corruption events can be considered a failure of corporate governance mechanisms (Arshad and Rizvi 2013; Boateng et al. 2021; Khan et al. 2024; Toader et al. 2018; Weismann 2009), the study demonstrates that textual measures regarding governance-related sentences can support analysts in predicting corruption events in the banking sector.

This paper analyzed the relationship between disclosure and corruption events in the banking sector. Specifically, by using both advanced machine learning algorithms (particularly random forests and gradient boosting) and conventional econometric techniques (logistic regressions) and combining advanced LLM based on artificial intelligence (FinBert) (Huang et al. 2023) with conventional dictionary approaches to conduct a sentiment analysis (Loughran and McDonald 2011), we provide robust evidence of the association between disclosure and the occurrence of corruption events. In addition, we test the predictive power of our textual measures and show that disclosures can be employed to detect banks potentially involved in corruption events before such scandals become public domain.

Overall, our findings have important practical policy and economic implications, as we show that advanced textual

TABLE 7 | Distribution of the estimates and *p*-values of the baseline logistic regression models.

Estimate						
	Min	**1qrt**	**Median**	**Mean**	**3qrt**	**Max**
(Intercept)	−3.27E−01	6.24E−01	7.70E−01	9.37E−01	1.16E+00	2.90E+00
Accounting PCA	2.29E−12	2.40E−12	2.47E−12	2.65E−12	2.72E−12	5.00E−12
ESG PCA	−3.88E−03	1.56E−02	1.84E−02	2.06E−02	2.02E−02	6.38E−02
Country PCA	2.91E−13	3.93E−13	4.57E−13	5.02E−13	5.30E−13	1.10E−12
Litigious tone	−4.85E+02	−2.13E+02	−2.03E+02	−2.14E+02	−1.88E+02	−6.50E+01
% governance sentences	−1.40E+01	−8.63E+00	−7.82E+00	−8.31E+00	−7.54E+00	−4.68E−01
Negative tone	−2.37E+02	1.03E+02	1.26E+02	1.27E+02	1.43E+02	4.58E+02
Positive tone	5.41E+01	1.29E+02	1.99E+02	2.11E+02	2.21E+02	7.03E+02
Number of Id = 40						
Pr(>|t|)						
	Min	**1qrt**	**Median**	**Mean**	**3qrt**	**Max**
(Intercept)	0.28017048	0.60208067	0.72946924	0.69393269	0.82111887	0.91190898
Accounting PCA	0.01247489**	0.01568022**	0.01913555**	0.02015577**	0.02244675**	0.04437651**
ESG PCA	0.16102769§	0.5166562	0.55766406	0.55732476	0.61420686	0.90931753
Country PCA	0.13212323§§	0.26948928	0.33129902	0.33402593	0.39363671	0.572546
Litigious tone	0.03009722**	0.1837282§	0.19744593§	0.22387867	0.22353139	0.68330969
% governance sentences	0.16437124§	0.29103617	0.33381906	0.35007527	0.36153033	0.96249544
Negative tone	0.1257228§§	0.51609175	0.56464994	0.55107259	0.59207199	0.89892604
Positive tone	0.06600849*	0.38940945	0.43684969	0.47366435	0.62124611	0.84047956
Number of Id = 40						

Note: This table shows the distribution of the estimates and *p*-values of the baseline logit models employed in the cross-validation process. ***, **, *, §§, and § indicate statistical significance at the 1%, 5%, 10%, 15%, and 20% levels, respectively. Variables are defined in Section 4.

measures can be used to detect in advance a potential involvement of a bank in a corruption event before becoming public domain. Given that such a type of scandal may have a detrimental impact on a bank's image and reputation and, consequently, negative financial consequences, supervisors and policymakers can rely on our models to detect in advance corruption events to preserve financial stability and make rational and conscious financial decisions, respectively. More specifically, supervisory authorities might benefit from our corruption detection tool in several ways. First, within the second pillar of Basel regulation, supervisors might demand that banks include the reputational risk associated with potential corruption scandals in their Internal Capital Adequacy Assessment Process (ICAAP) if they are likely to be involved in corruption scandals. Second, supervisors can prioritize on-site inspections and carry out reinforced Supervisory Review and Evaluation Process (SREP) assessments for banks potentially involved in corruption scandals. Third, within the third pillar of Basel regulation, supervisors might push banks to be more transparent in their corporate governance and anti-corruption disclosure so that investors and stakeholders can exercise market discipline more effectively by penalizing banks more potentially exposed to corruption events.

Our empirical analysis does not come without limitations. First, the random forests approach adopted in this paper does not allow us to exploit the time series dimension of our panel data. Unfortunately, to the best of our knowledge, the development of machine learning methodologies for panel data is at the frontier of research, and therefore, these methodologies are not yet employed in the empirical banking and accounting literature as they are not yet corroborated. We leave to future research the use of more advanced machine learning methodologies for panel data to analyze larger international samples. Second, although we analyze a wide range of countries covering the entire Eurozone over a time horizon covering the 2013–2022 period, our sample size of 42 banks is still limited and may not fully represent the whole European banking industry. Moreover, the analyzed sample concerns only banks operating in civil law countries. While such a feature makes our sample homogeneous, it could also limit the generalizability of our findings. In this respect, future studies should

TABLE 8 | Distribution of the estimates and p-values of the lagged logistic regression models.

Estimate						
	Min	**1qrt**	**Median**	**Mean**	**3qrt**	**Max**
(Intercept)	1.30E+00	2.80E+00	3.14E+00	2.98E+00	3.37E+00	3.83E+00
Accounting PCA	4.37E−12	4.73E−12	4.74E−12	4.75E−12	4.92E−12	4.97E−12
ESG PCA	−1.77E−01	−1.62E−01	−1.58E−01	−1.54E−01	−1.45E−01	−1.28E−01
Country PCA	5.98E−13	6.09E−13	6.23E−13	6.37E−13	6.47E−13	7.66E−13
Litigious tone	2.43E+02	3.84E+02	4.41E+02	4.19E+02	4.70E+02	5.52E+02
% governance sentences	−6.70E+00	−2.47E+00	−2.34E+00	−1.66E+00	−2.32E+00	8.40E+00
Negative tone	−1.40E+03	−1.39E+03	−1.36E+03	−1.33E+03	−1.32E+03	−1.11E+03
Positive tone	6.56E+02	7.98E+02	8.30E+02	8.00E+02	8.41E+02	8.84E+02
Number of Id = 24						
Pr(>|t|)						
	Min	**1qrt**	**Median**	**Mean**	**3qrt**	**Max**
(Intercept)	0.52980385	0.63478307	0.65252659	0.66752104	0.68228057	0.87266606
Accounting PCA	0.04457313**	0.04824222**	0.05430489*	0.05424153*	0.05783311*	0.06790144*
ESG PCA	0.30379155	0.33164651	0.33252521	0.34868772	0.36391938	0.4282669
Country PCA	0.34709299	0.3731486	0.3930916	0.38418279	0.39631756	0.42355202
Litigious tone	0.52508138	0.55946416	0.5792278	0.59816117	0.63694361	0.70242735
% governance sentences	0.73010243	0.82853332	0.86756354	0.84513694	0.87813348	0.92229947
Negative tone	0.09854359*	0.09927863*	0.10613736§§	0.11761644§§	0.12494403§§	0.1783628§
Positive tone	0.1888056§	0.18985923§	0.19874414§	0.21430033	0.23117008	0.27664231
Number of Id = 24						

Note: This table shows the distribution of the estimates and p-values of the baseline logit models employed in the cross-validation process. ***, **, *, §§, and § indicate statistical significance at 1%, 5%, 10%, 15%, and 20% levels, respectively. Variables are defined in Section 4.

retrieve and analyze more extensive and stratified samples, considering common law countries.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Research data are not shared.

Endnotes

[1] These variables are included in our regression models as control variables.

[2] Such newspapers include City A.M., Financial Times, Reuters and The Economist.

[3] For further information, see the institutional website of the data provider, Lexis Nexis: https://www.lexisnexis.com/en-int/products/nexis-uni.

[4] We wish to remark that we analyze banks' potential involvement in corruption scandals by looking at the news in the public domain (i.e., available on reputable news publication websites). Thus, we cannot guarantee that the 'corrupted' banks of our sample are actually guilty of corruption, nor that 'non-corrupted' banks are not involved in any corruption event that is not yet in the public domain. However, given that just spreading the news of corruption scandals brings negative reputational and financial consequences (de Andrés et al. 2024), we contend that analyzing only corruption events in the public domain is particularly meaningful from a theoretical and practical perspective.

[5] The selection of a sample of Eurozone banks allows us to focus on a homogeneous group of countries mainly characterized by civil law and a bank-centered system. This aspect makes our analysis even more relevant as traditional commercial banks play a more relevant role in lending for firms than common law and market-centered countries (Levine 2002). Hence, corruption scandals and the associated lack of trust in the banking system would be particularly detrimental to the real economy and the allocative efficiency of bank lending.

[6] To further attenuate the problem of missing data and to ensure that we can effectively use our random forests methodology, we impute missing data using median values following the procedure suggested by Shmueli et al. (2017).

[7] Although three of these corruption events occurred in 2012, the reports published by the banks in 2013 are the first to include information regarding these scandals, given that the annual financial reports and the sustainability/non-financial reports published in 2013 referred to the year 2012.

[8] Before implementing this balanced leave-one-out, we also performed the traditional non-stratified one and obtained similar results. Such a finding supports the robustness of the analysis.

[9] We conducted a sensitivity analysis for each PCA (Camargo, 2024) employing 1000 bootstrap replicates and 1000 random permutations. The results showed strong significance (i. Accounting PCA: empirical Psi of 2136.0780, max null Psi = 156.9997, p value < 0.05; empirical Phi of 0.5340, max null Phi = 0.1632, p value < 0.05; ii. ESG PCA: empirical Psi of 4.0962, max null Psi = 2.1782, p value < 0.05; empirical Phi of 0.3123, max null Phi = 0.2277, p value < 0.05; iii. Country PCA: empirical Psi of 59.2195, max null Psi = 12.6724, p value < 0.05; empirical Phi of 0.3948, max null Phi = 0.1826, p value < 0.05) indicating that the principal components are statistically significant and that there is a non-random correlational structure between the analyzed variables. Further, the tests indicated that most of the variables used have significant loadings contributing to the PCA results (98% for the Accounting PCA, 71% for the ESG PCA, and 90% for the Country PCA), indicating the absence of a specific set of controls variables capable of driving the results. The full list of variables included in the three principal component analysis variables is reported in the online appendix S1.

[10] We wish to remark that these results should be interpreted with caution because the number of observations of the predictive model is lower because corruption events occurring at the beginning of the sample period cannot be taken into consideration in the predictive model, as well as those banks for which we lack observations for the two subsequent years of interest.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.