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Narrative Disclosure Tone and Bank Risk: The Role of Economic Policy Uncertainty

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ABSTRACT

This study examines the impact of narrative disclosure tone (NDT) on bank riskiness, particularly in the context of heightened economic policy uncertainty (EPU). Utilizing data from 114 banks across 2052 bank-year observations between 2005 and 2022, our findings reveal a significant positive relationship between NDT and various measures of bank risk, including credit, liquidity, operational, and market risks. The results demonstrate that a negative tone in narrative disclosures heightens perceived and actual risk, with this effect being further amplified during periods of high EPU. Our study highlights the strategic importance of narrative disclosures in managing stakeholder perceptions and highlights the need for banks to carefully consider their communication strategies in volatile economic environments. These findings offer practical insights for banking institutions, regulators, and investors in understanding the complex dynamics between narrative tone, economic uncertainty, and financial risk.

JEL Classification: G21, G28, G32

1 | Introduction

The banking industry has undergone significant changes in recent years due to a series of global economic shocks, including the global financial crisis of 2007–2008, the COVID-19 pandemic, and the Russia–Ukraine war. These events have profoundly impacted the banking sector, particularly in Europe, by increasing risk and uncertainty. The global financial crisis highlighted systemic vulnerabilities within the banking sector, prompting a thorough review of risk management procedures. European banks, already dealing with national debt concerns, faced additional strain. The subsequent COVID-19 pandemic exacerbated these issues by disrupting economic activity, increasing credit risk, and necessitating large loan loss provisions (Çolak and Öztekin 2021). More recently, geopolitical tensions from the Russia–Ukraine conflict have introduced new layers of risk, such as market volatility, supply chain interruptions, and sanctions impacting financial operations (Rose et al. 2023; Zhang et al. 2023). These events highlight the need for banks to understand, manage, and effectively communicate their risk exposure to stakeholders to reduce information asymmetry and maintain investor confidence.

One key mechanism banks use to address information asymmetry and communicate their risk exposure is narrative disclosure in annual reports (Bassyouny et al. 2020; Elsayed and Elshandidy 2020). Narrative disclosure refers to the qualitative information presented in annual reports, offering stakeholders additional insights and context beyond numerical data (Merkl-Davies and Brennan 2007). Unlike conventional financial reports that focus on quantitative data, narrative disclosures provide a comprehensive examination of a bank's risk exposure, management framework, and overall financial health (Wu et al. 2022; Yekini et al. 2016). This qualitative information

helps stakeholders understand the context and implications of the presented data, particularly during periods of significant uncertainty. Through narrative disclosures, banks can effectively communicate their risk management strategies and the potential impacts of external shocks.

The tone of narrative disclosures, referred to as NDT, has become critical for conveying substantive information about firms due to its influence on stakeholder perception and decision-making (Bai et al. 2022; Bassyouny et al. 2020; Henry 2008). By strategically crafting the tone and wording of these disclosures, banks can influence risk perceptions and demonstrate their resilience in the face of economic challenges. NDT is grounded in several well-established theories. Agency theory suggests that managers can reduce agency costs and conflicts of interest with stakeholders by providing clear and transparent narrative disclosures that explain risks and the measures taken to manage them (Jensen and Meckling 1976). Signaling theory posits that narrative disclosures can reduce information asymmetry and enhance credibility by sharing private information with the market. In the banking context, narrative disclosures can signal management's confidence in their risk mitigation strategies and preparedness to handle adverse events. Additionally, impression management theory indicates that managers may use narrative disclosures to shape stakeholder perceptions and present their organizations in a favorable light. By carefully selecting the language and tone, banks can influence stakeholders' perceptions of risk and foster a more positive view of their risk management and financial stability.

EPU adds another layer of risk that banks must manage. EPU arises from changes in government policies, geopolitical events, regulatory modifications, and other external factors that impact economic conditions (Wen et al. 2021). These uncertainties can disrupt financial markets, erode investor confidence, and alter the risk environment for banks. A recent PwC survey (Annual Global CEO) reports that CEOs view economic uncertainty as the greatest threat to bank stability, surpassing concerns over protectionism and geopolitical uncertainty (PwC 2019). EPU has become a growing concern, particularly following the financial crisis (Baker and Bloom 2013), Brexit (Belke et al. 2018), and the COVID-19 pandemic (Altig et al. 2020). In times of high EPU, banks may increase their risk-taking and experiment with new financial instruments, potentially raising their risk exposure (Fang et al. 2014). Additionally, high EPU can reduce the effectiveness of monetary policy and exacerbate economic shocks (Fernández-Villaverde et al. 2011), further strengthening the impact of NDT on bank risk. Studies have shown that EPU has adverse effects on the financial stability of banks (Gulen and Ion 2016), with increased uncertainties reducing loan proportions and shrinking credit supply (Liu and Zhang 2015). Other research has explored how bank lending responds to specific uncertainties, such as political and regulatory risks, focusing on changes in credit volume (e.g., Biswas and Zhai 2021; Hu and Gong 2019; Wen et al. 2021).

Moreover, EPU can significantly affect the effectiveness of narrative disclosures. During periods of elevated EPU, there is an increased demand for comprehensive and transparent disclosures. Stakeholders seek reassurance through detailed narratives that explain how banks are adapting to changing economic policies and regulatory environments (Baker et al. 2016). Effective narrative disclosures with the appropriate tone can bolster investor confidence and stabilize perceptions of bank riskiness. Recent studies indicate that banks providing more comprehensive and transparent narrative disclosures are associated with lower risk perceptions and increased investor confidence (Elshandidy and Acheampong 2021). This is particularly relevant in the European banking sector, where regulatory expectations for transparency have increased following the financial crisis. The European Central Bank (ECB) and other regulatory bodies have emphasized the need for improved disclosure practices to foster market discipline and enhance financial stability (ECB 2024).

NDT has garnered significant interest in academic literature, with prior studies highlighting its importance in corporate transactions and stock market characteristics. For example, Ahmed and Elshandidy (2016) found that companies with a conservative approach and negative sentiments in their annual reports are less likely to engage in mergers and acquisitions. Conversely, Cho and Kim (2021) observed that companies with an optimistic tone in their reports tend to have higher stock liquidity. Yekini et al. (2016) emphasized the predictive power of tone concerning stock returns, while Del Gaudio et al. (2020) discovered that the tone of mandated disclosures can explain the risk of bank failure. Other research has examined the relationship between NDT and various aspects of a company, such as earnings volatility (Borochin et al. 2018; Donelson et al. 2012), performance (Mayew et al. 2015; Patelli and Pedrini 2014), board and CEO characteristics (Davis et al. 2015), stock market responses (Henry 2008; Kimbrough and Wang 2014), and shareholder lawsuits (Rogers et al. 2011).

While the literature acknowledges that banks increase their forward-looking narrative disclosures during times of economic uncertainty to communicate future prospects (Beretta and Bozzolan 2008; Krause et al. 2017), there is a lack of evidence on the influence of EPU on the relationship between NDT and bank risks. This study aims to fill this gap by examining the relationship between NDT and bank risks,[1] with a particular focus on the moderating effect of EPU. We hypothesize that high EPU amplifies the impact of NDT on bank risk. Our analysis, based on 2052 bank-year observations across 114 banks from 2005 to 2022, demonstrates that NDT significantly increases all risk measures, with this positive relationship intensifying during periods of high economic policy uncertainty. Our results are robust across various sensitivity and endogeneity checks, confirming the consistency and reliability of our findings.

This study contributes to the literature in several ways. First, it enhances our understanding of the impact of narrative disclosure tone on bank risks. Using a comprehensive dataset of 2052 bank-year observations from 114 banks over the period 2005 to 2022, we find that a more negative tone in annual reports significantly raises the perceived level of risk associated with banks. This is consistent with the principles of agency theory, signaling theory, and impression management theory, which suggest that effective narrative disclosures can reduce information asymmetry and improve stakeholder perceptions (Jensen and Meckling 1976; Merkl-Davies and Brennan 2007). Second, we highlight the critical role of economic policy uncertainty in moderating the relationship between NDT and bank risk. We

show that high EPU exacerbates the impact of NDT on bank risk, with banks that strategically disclose more positive information in their narrative reports potentially mitigating the negative effects of EPU on the perception of bank stability. Finally, we offer new insights into the role of bank regulation and supervision in shaping the relationship between NDT, EPU, and bank risk. Our findings suggest that stringent capital regulations, strong supervisory frameworks, and enhanced private monitoring can effectively reduce the adverse effects of EPU on bank stability. These findings align with the work of Nguyen (2021) and Anginer et al. (2018).

Our paper has practical implications for various stakeholders in the banking industry. First, it highlights the importance of narrative disclosure as a tool for informing stakeholders about potential risks and promoting transparency. Banks should recognize the strategic value of NDT, especially during periods of heightened economic policy uncertainty, and carefully select the tone of their disclosures to effectively communicate their risk management strategies. Second, our study highlights the need for policymakers and regulatory bodies to incorporate NDT into their risk assessment frameworks. By integrating narrative analysis methodologies, regulators can gain a deeper understanding of banks' risk profiles and better assess their readiness to confront economic uncertainties. This information can enhance regulatory supervision and inform policy decisions aimed at promoting financial stability and investor confidence. Finally, for investors and market analysts, our study demonstrates the value of critically examining the narrative sections of bank annual reports. By analyzing the tone and content of these disclosures, investors can better gauge the level of risk exposure and make more informed investment decisions.

The remainder of this paper is structured as follows: Section 2 reviews related literature and outlines the hypotheses, while Section 3 describes the data and methodology used. Section 4 discusses the findings, and Section 5 reports the results of further analysis and robustness checks. Section 6 provides the conclusion.

2 | Literature Review and Hypothesis Development

2.1 | Narrative Disclosure Tone and Bank Risk

The banking sector plays a pivotal role in the global financial system, acting as a crucial intermediary that facilitates the flow of capital and supports economic growth. However, the inherent risks faced by banks, such as credit risk, market risk, and operational risk, are exacerbated by the dynamic and often unpredictable global financial environment. These risks necessitate effective communication strategies to ensure that stakeholders are adequately informed about the financial health and risk exposure of banks. Among the various communication tools available, NDT has emerged as a critical factor in shaping stakeholder perceptions and influencing bank risk.

NDT refers to the sentiment or tone conveyed through the qualitative information presented in banks' annual reports. Unlike quantitative financial data, which can be systematically analyzed and compared, narrative disclosures provide a more nuanced understanding of a bank's operations, risk management practices, and overall financial well-being. The tone of these disclosures whether positive, neutral, or negative—can significantly impact how stakeholders interpret the information, thereby influencing their perceptions of the bank's risk profile. The theoretical underpinnings of NDT's impact on bank risk can be traced to agency theory and signaling theory. According to agency theory, the separation of ownership and control in corporations leads to potential conflicts of interest between managers and shareholders. Managers, who possess more information about the firm's operations, may use narrative disclosures to reduce information asymmetry and align the interests of stakeholders with those of the firm (Jensen and Meckling 1976). By clearly articulating the risks and the measures taken to mitigate them, managers can build trust with stakeholders, thereby reducing perceived risk. For example, a positive tone in narrative disclosures might signal that the bank is effectively managing its risks, leading to increased stakeholder confidence and lower perceived risk. Signaling theory, on the other hand, suggests that companies use narrative disclosures as a means to convey private information to the market, thus reducing information asymmetry and enhancing the firm's credibility. In the context of banking, a positive NDT may signal the management's confidence in their risk management strategies, thereby reassuring stakeholders and potentially lowering the perceived risk. Conversely, a negative tone may signal underlying problems or vulnerabilities, leading to higher perceived risk and potentially adverse market reactions.

Empirical studies have provided substantial evidence on the importance of NDT in shaping financial outcomes. For instance, Ahmed and Elshandidy (2016) explored the impact of NDT on corporate transactions, particularly mergers and acquisitions (M&A). They found that companies with a conservative tone in their reports were less likely to engage in M&A activities, suggesting that NDT can serve as an indicator of a company's risk appetite and strategic intentions. This finding is particularly relevant for banks, where strategic decisions such as mergers or acquisitions can have significant implications for risk exposure and financial stability. Similarly, Del Gaudio et al. (2020) examined the role of NDT in mandatory disclosures and its impact on bank insolvency risk. Their study demonstrated that the tone of narrative disclosures could influence variations in the risk of insolvency, highlighting the critical role of NDT in assessing the financial stability of banks. These findings highlight the importance of carefully crafting the tone of narrative disclosures to manage stakeholder perceptions and mitigate potential risks.

The relationship between NDT and market perceptions is well-documented in the literature, with numerous studies showing that the tone of disclosures can significantly influence investor behavior and market outcomes. For example, Martikainen et al. (2023) found that a positive tone in narrative disclosures could enhance investor confidence, leading to higher stock prices, improved market liquidity, and reduced borrowing costs for banks. On the other hand, a negative tone might raise concerns among investors, resulting in increased perceived risk, heightened regulatory scrutiny, and potential reputational damage (Bassyouny et al. 2020). Yekini

et al. (2016) further explored the predictive power of NDT concerning stock returns, demonstrating that the tone of narrative disclosures could serve as a leading indicator of future financial performance. This finding is particularly relevant for banks, where market perceptions of risk can have immediate and far-reaching consequences. For instance, a negative NDT might trigger a decline in stock prices, increase volatility, and lead to a higher cost of capital, all of which could exacerbate the bank's risk profile.

Based on the discussion above it is evident that a more negative tone in narrative disclosures is likely to increase perceived risk, which in turn could lead to higher actual risk as stakeholders, including investors and regulators. We therefore formulate our first hypothesis which states that:

H1. *NDT is positively associated with increased bank risk.*

2.2 | The Role of EPU in the Relationship Between Narrative Disclosure Tone and Bank Risk

The impact of EPU on bank risk is a topic of growing importance, particularly in the aftermath of significant global events such as the financial crisis, Brexit, and the COVID-19 pandemic. EPU refers to the uncertainty surrounding economic policies, including fiscal, monetary, and regulatory measures, which can create an unpredictable environment for financial institutions. In such an environment, the tone of narrative disclosures becomes even more critical, as stakeholders seek clarity and reassurance from banks about their risk management strategies.

Gulen and Ion (2016) provided compelling evidence that EPU exacerbates the impact of various shocks on financial stability. Their study showed that during periods of high EPU, firms tend to become more risk-averse, leading to reduced investment, lower growth prospects, and higher perceived risk. For banks, this heightened uncertainty can result in more cautious lending practices, reduced access to credit, and increased volatility in financial markets. Liu and Zhang (2015) examined the impact of EPU on bank lending, finding that increased uncertainty leads to a decrease in loan proportions and limited credit availability, particularly for banks with higher leverage. This suggests that during times of high EPU, the tone of narrative disclosures plays a crucial role in shaping stakeholders' perceptions of risk. A negative NDT in such an environment may further amplify perceived risk, leading to more significant market reactions and potentially higher actual risk.

Banks may also alter their risk-taking behavior in response to EPU. Fang et al. (2014) found that banks might increase their risk appetite during uncertain economic conditions, experimenting with new financial instruments, revising lending criteria, and exploring alternative investment strategies. This proactive approach, while intended to mitigate potential losses and capitalize on emerging opportunities, could inadvertently increase the bank's risk exposure, especially if coupled with a negative NDT. The interaction between EPU and NDT is particularly relevant in the context of regulatory changes. Fernández-Villaverde et al. (2011) highlighted how increased EPU might weaken the effectiveness of conventional monetary policy measures, limiting the ability of central banks to stabilize economic conditions and alleviate the consequences of adverse shocks. In such a scenario, the tone of narrative disclosures can either mitigate or exacerbate stakeholder concerns, depending on whether the tone is perceived as reassuring or alarming.

Based on these insights, it is clear that EPU intensifies the relationship between NDT and bank risk, making the tone of disclosures even more influential in shaping risk perceptions and outcomes during periods of heightened economic uncertainty. We therefore formulate our second hypothesis:

H2. *The association between NDT and bank riskiness is further heightened by high levels of EPU.*

3 | Data and Method

3.1 | Data Samples and Sources

We employed 114 banks across Europe from the period of 2005 to 2022, resulting in a total of 2052 bank-year observations. We employ European context because of the persistent policy uncertainty in the European regions, as illustrated in Figure 1, caused by factors like escalating trade tensions between China and the United States, the uncertainty surrounding Brexit, fiscal integration with the EU, the US election, the COVID-19 pandemic, and the Russia–Ukraine war (Nguyen 2021). Our choice of specific countries is based on the availability of EPU data. We began in 2005 to consider the disclosure impact of IFRS adoption (Acheampong and Elshandidy 2021). Put together, focusing on the EU context makes it an interesting setting to study in order to provide deeper insights for policymakers, regulators, and market participants.

3.2 | Variables Measurement

3.2.1 | Risk Measures

We employed different measures for bank risk as our main dependent variables, which include both accounting-based and market-based risk measures. The accounting-based risk measures we employed are credit risk (CR), liquidity risk (LR), operation risk (OR), insolvency risk (IR), and asset risk (AR), whereas the market-based risk measures employed in this study are total risk (TR), systematic risk (SR), and unsystematic risk (UR). According to Elnahass et al. (2021), we measure CR by scaling non-performing loans by total assets. *We calculate LR as the ratio of liquid assets to the sum of short-term funding and deposits*. The standard deviation of return on assets quantifies OR. *IR* is measured by scaling the sum of return on assets and equity to assets by the standard deviation of return on assets. *AR* represents the ratio of return on assets to the standard deviation of return on assets. Following Elshandidy et al. (2013), *TR* is measured using the volatility of market returns, and beta is used to measure *SR*. The standard error of CAPM is used to measure *UR*. All risk indicators represent the overall financial stability of the banking sector (Trinh et al. 2020).

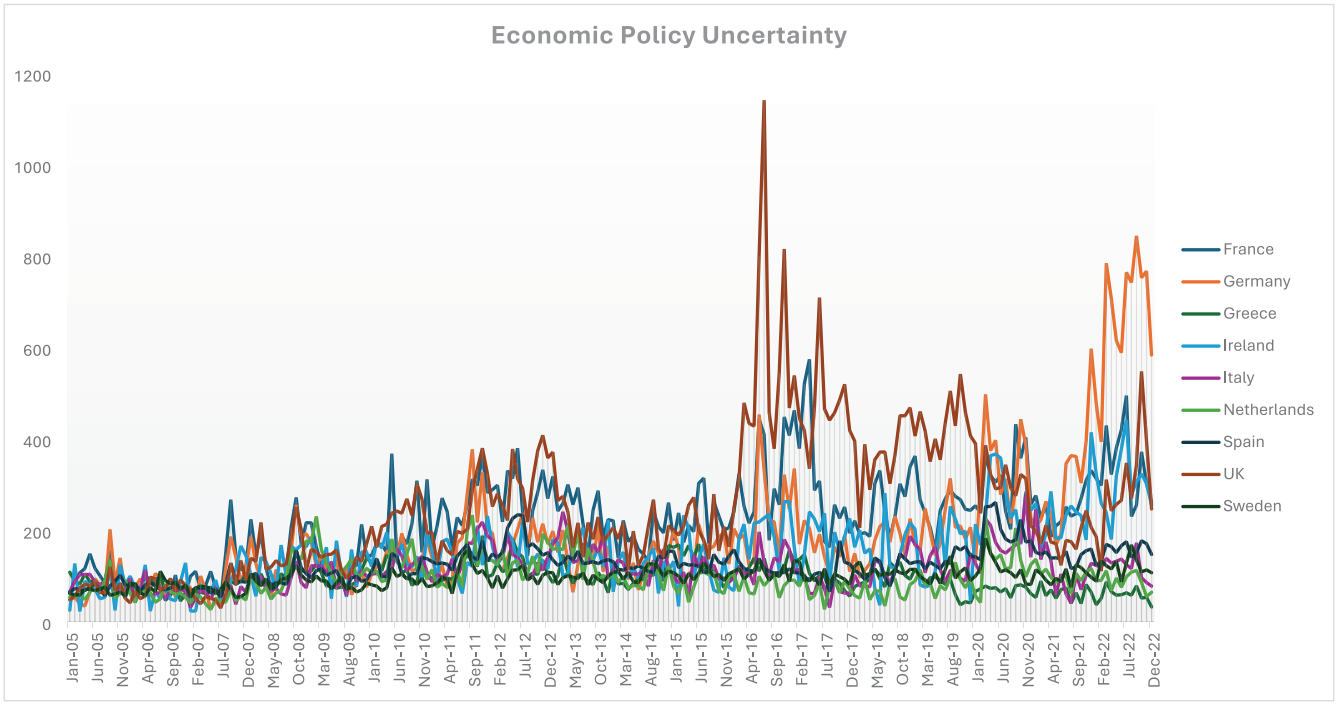

FIGURE 1 | Economic policy uncertainty.

3.2.2 | Narrative Disclosure Tone

Using a computerized textual analysis approach, Loughran and McDonald's (2011) wordlist is employed on the annual reports (narratives) of all sample banks to measure narrative disclosure tone. We employed the wordlist developed by Loughran and McDonald (2011) because it originates from financial documents, rendering it particularly suitable for studies involving financial reporting and business communication research (Loughran and McDonald, 2016). Moreover, this wordlist offers extensive coverage with 345 positive and 2329 negative words, as opposed to Henry's (2008) wordlist, which includes 104 positive and 85 negative words. Our emphasis on annual reports stems from their continued significance as the primary means of communication with investors (Acheampong and Elshandidy 2021).

By employing Loughran and McDonald's (2011) terms, we proceed through these sequential actions. We follow the following steps to determine the NDT: Using Python software, we install the following libraries: "pandas," "nltk," and "scikit-learn." Once these are loaded, we load the wordlist for Loughran and McDonald. Next, we conduct pre-processing of the texts, which entails tokenizing, converting text to lowercase, and removing stopwords and punctuation. The next step involves tone analysis. This is where we count the frequency of words in each Loughran and McDonald's category (positive, negative, uncertain). We then normalize the counts. By the total number of words. Consequently, we aggregate the rates for each major interpretation, specifically positive, negative, and uncertain. In essence, this concept is based on the idea that a greater occurrence of these terms signifies a more pronounced alignment of a bank's emphasis on the associated key significance, be it positive or negative. Next, following Del Gaudio et al. (2020), we compute our tone measure, which we label "NDT," by subtracting the frequency of positive words from the frequency of negative words and dividing the result by the sum of the two frequencies. By this construction, a higher score reflects a more negative tone in the annual report, and vice versa. Figure 2 presents the process.

3.2.3 | Economic Policy Uncertainty (EPU)

EPU is captured using the economic policy uncertainty index developed by Baker et al. (2016).[2] This index aims to evaluate the changes in a nation's policy uncertainty over time by analyzing newspaper articles that address economic uncertainties associated with policies. The main advantage is that media and government data are used instead of focusing on questionable individual occurrences. Comprehensive audit studies verify the accuracy of the index by incorporating both human evaluations of newspaper items and computer-generated indices. Our study shares similarities with Wu et al. (2020) in investigating the influence of economic uncertainty on bank stability. However, our analysis specifically concentrates on policy-related economic uncertainty. In our paper, EPU, unlike other studies, specifically refers to the unpredictability of results associated with fiscal, regulatory, monetary, and trade policies (Kostka and Van Roye 2017; Ng et al. 2020).

3.2.4 | Control Variables (Bank-Level and Country-Level)

ROA is a measure of profitability. Higher profits are a positive sign, as they suggest a lower level of risk. This is due to the strong growth projections and the ability to withstand any potential setbacks. According to Ghosh (2015), highly profitable banks have minimal motivation to partake in riskier operations. According to Berger and DeYoung (1997), non-profitable

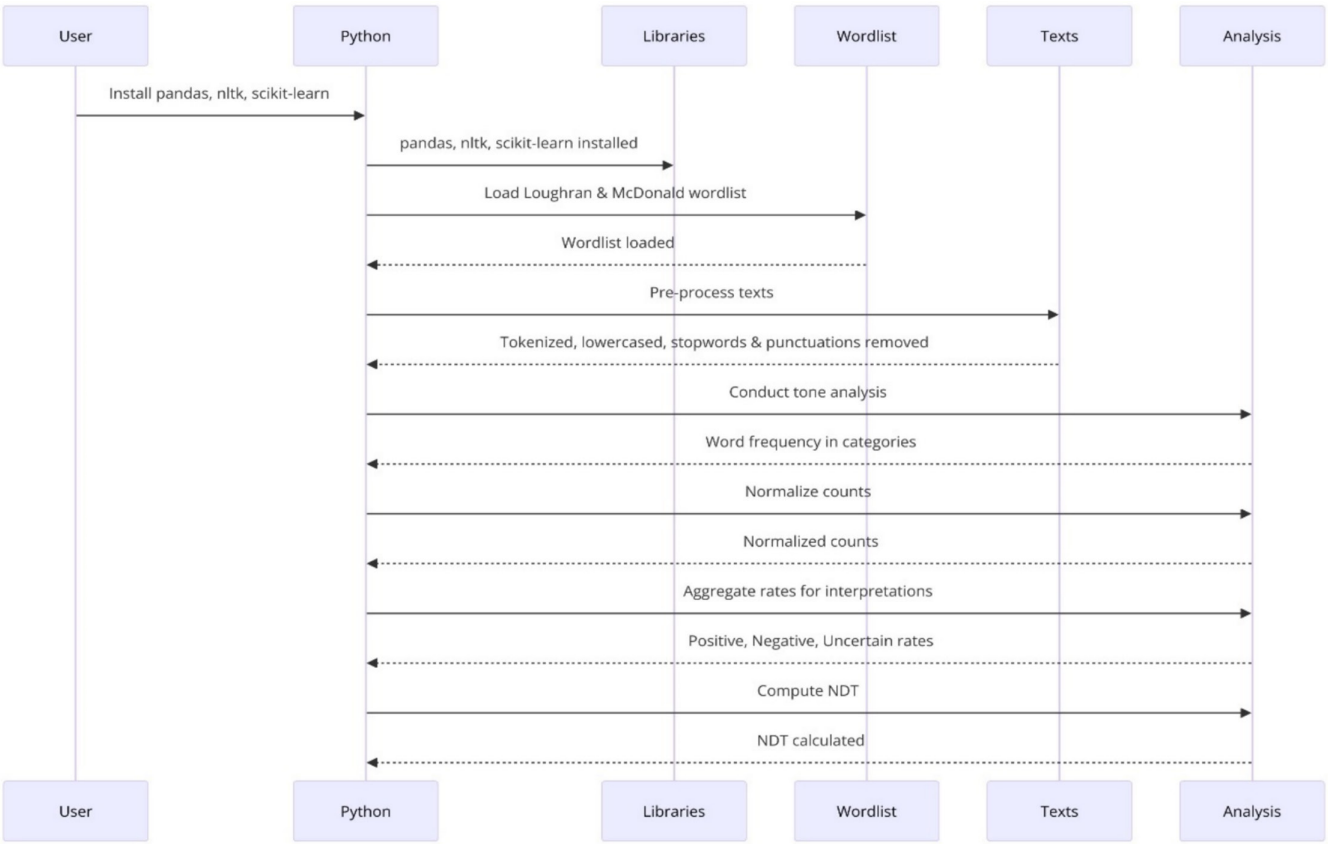

FIGURE 2 | NDT process. This figure presents the process we employed to capture narrative disclosure tone from the annual reports of EU banks using Python.

banks tend to have high levels of risk and are more likely to default. This suggests a possible link to the "bad management hypothesis." On the other hand, García-Marco and Robles-Fernández (2008) find that banks with high profitability often face high levels of non-performing loans due to their tendency to take on risky activities. We, therefore, expect either a positive or negative relationship between ROA and bank risk. SIZE is measured as the natural logarithm of total assets (Acheampong and Elshandidy 2021; Elnahass et al. 2021). Large banks often assume greater risk due to the perception that they are too big to fail. However, larger banks often prioritize strong corporate governance and protecting their reputation, which can deter them from engaging in excessive risk-taking. Chang et al. (2018) find a positive correlation between bank size and the cost of debt. On the other hand, Gay et al. (2011) observed a negative correlation between size and the cost of equity capital. We anticipate either a positive or negative correlation between bank size and bank risk. Firms with higher leverage are more likely to engage in risk management activities to reduce their risk exposure. LEV is defined as the total debt relative to total assets (Acheampong and Elshandidy 2021; Elnahass et al. 2021). Non-interest income (DINCOME) represents the portion of total revenue that comes from sources other than interest. These sources can include trading activities, fees, and commissions (Acheampong and Elshandidy 2021; Demir and Danisman 2021). Generally, increasing diversification can lead to reduced bank risk and more consistent returns. However, various empirical studies have produced contradictory findings. We therefore expect either a positive or negative relationship between DINCOME and bank risk.

We employed the law index created by Djankov et al. (2008) to assess the level of legal protection for minority shareholders against expropriation by company insiders. This index takes into account various aspects of corporate governance, such as the rights of oppressed minorities, cumulative voting, voting by mail, pre-emptive rights, unblocked shares, and capital requirements for calling meetings.[3] We grade the law on a scale of 0 to 5, with a lower number indicating a greater degree of self-dealing. A strong emphasis on compliance and regulations could signify an effective response to the needs and expectations of citizens and stakeholders. Thus, a negative sign is anticipated for the LAW and bank risk relationship. According to Park (2012), there is a clear relationship between corruption and the occurrence of problematic loans in the banking sector. We assess corruption levels using Transparency International's Corruption Perception Index (CPI). We chose this index because of its comprehensive coverage of corruption, rigorous assessment process, and extensive track record, among other things. The index ranges from 0 to 10, with higher scores indicating lower levels of corruption. Park's (2012) research determines corruption by subtracting a country's actual CPI from the maximum CPI score (10). This calculation allows for a lower CI, indicating lower levels of corruption. Studies have demonstrated that reducing corruption levels positively affects loan quality and is associated with more moderate growth (Chen et al. 2015; Park 2012). Therefore, we expect a positive correlation between corruption and bank risk. We measure GDP as the natural logarithm of gross domestic products per capita (Acheampong

and Elshandidy 2021; Demir and Danisman 2021; Elnahass et al. 2021). A decrease in the GDP growth rate hinders progress in debt servicing and, at the same time, leads to increased risk. It is worth noting that the situation is completely different when an economy goes through a period of economic growth (Ali and Daly 2010; Salas and Saurina 2002). Therefore, we anticipate a negative relationship between GDP and bank risk. Inflation refers to the percentage variation in the consumer price index (e.g., Acheampong and Elshandidy 2021; Jankowitsch et al. 2007). This measure considers the impact of monetary instability on banks' resource allocation (Boyd et al. 2001). When inflation rises, it becomes easier to repay loans because their value decreases over time. On the other hand, Jankowitsch et al. (2007) find that borrowers' net income and ability to service debt decrease when inflation increases, which ultimately raises the risk for banks. Thus, we anticipate that there will be either a positive or negative relationship between inflation and bank risk.

3.3 | Empirical Model

Based on prior literature, this paper aims to assess the impact of NDT on bank riskiness, potentially raising three main issues. The first issue, as indicated by Bermpei et al. (2018), has to do with the likelihood of a time-persistent occurrence of bank stability. That is, the present bank risk variables can be predicted easily from previous values, indicating the pressing need to include lagged dependent variables to mitigate omitted variable bias. The second issue has to do with the likelihood of a lack of independence among independent variables; an example is that higher levels of EPU can predict a fall in economic growth (Baker et al. 2016). In addition, as indicated by Nier and Baumann (2006), implementing more stringent regulations may have a favorable impact on the capital of banks. The third and final issue concerns the likelihood of endogeneity that arises from the reciprocal causal link between bank risk and its independent variables. To overcome these issues, we examine the following dynamic model with fixed effects at the individual level to investigate the evident impact of NDT on bank risk level:

$$Risk_{i,t} = \beta_1 NDT_{i,t-1} + \beta_2 EPU_{j,t} + \beta_3 NDT_{i,t-1} * EPU_{j,t} + \sum_{n=1}^{Nr} Xbv_{i,t} + \sum_{n=1}^{Nc} Xcv_t + \varepsilon_{i,t} \quad (1)$$

where Risk represents both accounting-based (i.e., credit, liquidity, operational, insolvency, and asset risks) and market-based (total, systematic, and unsystematic risk). *NDT* represents the disclosure tone captured using the Loughran and McDonald (2011) wordlist. EPU represents economic policy uncertainty. $Xbv_{i,t}$ represents the collection of bank-specific variables comprising bank size (*SIZE*), liquidity (*LIQUID*), profitability (*ROA*), diversified income (*DINCOME)*, and leverage (*LEV*). Xcv_t represents the set of country-level variables consisting of the corruption index (*CORRUPTION*), GDP per capita (*GDP*), inflation rate (INFLATION), and rule of law (*R-LAW)*. is the error term. All variables are winsorized in our models. Appendix A describes all the variables.

We concentrate on capturing bank-specific effects through fixed-effects or random-effects models. However, these models may not be reliable because they include lagged dependent variables, leading to dynamic panel bias, even when considering longer time periods. In order to tackle this issue, two techniques are commonly employed: the bias-corrected method, which is appropriate for limited data sets and brief time periods, and the instrumental variables method employing generalized method of moments (GMM) specifications. We employ the latter because it is more effective for large data sets and a defined time range (i.e., 2005–2022). Arellano and Bond (1991) pioneered the use of the first-differenced GMM estimator to handle the dynamic effects present in panel data. However, it is important to note that this estimate can be susceptible to finite sample bias, which can impact the accuracy of the results even when using large samples. In order to address this issue, the GMM model employed by Arellano and Bover (1995) and Blundell and Bond (1998) utilizes a two-step GMM estimator, which offers improved asymptotic efficiency and increased GMM diagnostic tests. Nevertheless, the standard errors of two-step GMM estimators frequently exhibit a downward bias, therefore requiring the use of Windmeijer-corrected standard errors. This estimator classifies independent variables as either exogenous, predefined, or endogenous. In accordance with Bermpei et al. (2018), we employed the second lag of dependent variables (bank risk factors) and bank-level variables as instruments, considering them to be endogenous. On the other hand, we treated country-level variables as exogenous, following the approach of Delis (2012). Minimizing the number of endogenous and preset variables reduces the proliferation of instruments. The validity of GMM estimates is verified by doing the Arellano–Bond tests for first- and second-order autocorrelation, as well as Hansen's J test for overidentifying constraints.

4 | Empirical Findings

4.1 | Descriptive Statistics

We report descriptive statistics in Table 1 and the correlation matrix in Table 2. The mean of the accounting-based risk measures indicates a moderate level of risk across EU banks, with credit risk (5.77), liquidity risk (28.34), and operational risk (0.44). Asset risk and insolvency risk indicate a balance of asset performance and insolvency concerns among EU banks. Market-based risk measures generally exhibit lower means. For instance, unsystematic risk is quite low at −1.733, which indicates less variability than might be expected given market conditions. The mean EPU is 0.474, with a standard deviation of 0.448, indicating that EPU in Europe is generally moderately high on average, with minor fluctuations. This is further depicted in Figure 1. The mean of leverage and profitability reports 0.155 and 0.080, respectively. Bank size and diversification income also have a mean of 20.905 and 0.383, respectively, indicating that on average, EU banks in our sample are large and more diversified in terms of their income streams to overcome any unprecedented financial shocks. Moving to the country variables, the mean values of corruption and rule of law indicate that, on average, EU countries within our sample reflect good governance levels. The mean GDP (0.063) and inflation (0.160) also indicate a more stable economic condition. From the correlation matrix (Table 2), the positive association between NDT

TABLE 1 | Descriptive statistics.

	Ex. sig	Obs.	1st qu.	3rd qu.	Mean	Std. dev.
Accounting-based risk measures						
CR		2052	1.544	9.285	5.766	5.755
LR		2052	14.96	41.81	28.34	19.70
OR		2052	0.081	0.767	0.438	0.503
AR		2052	1.433	2.764	2.117	1.010
IR		2052	−1.350	−0.290	−0.833	0.596
Market-based risk measures						
TR		2052	0.013	0.021	0.017	0.010
SR		2052	0.420	1.175	0.789	0.533
UR		2052	−1.774	−1.733	−1.733	0.305
Main independent variable						
NDT_{t-1}	(+)	2052	−0.682	0.549	−0.040	0.904
Bank-level controls						
LEV	(+)	2052	0.097	0.192	0.155	0.078
ROA	(+/−)	2052	0.034	0.129	0.080	0.089
SIZE	(+/−)	2052	18.098	24.427	20.905	4.527
DINCOME	(+/−)	2052	0.189	0.516	0.383	0.238
Country-level controls						
R-LAW	(−)	2052	−0.569	0.352	−0.115	0.669
CORRUPTION	(+)	2052	0.322	0.799	0.552	0.334
GDP	(−)	2052	0.011	0.052	0.063	0.091
INFLATION	(+/−)	2052	0.069	0.232	0.160	0.109
EPU	(+)	2052	0.192	0.600	0.474	0.448

Note: This table presents the descriptive statistics of all the variables employed in the analysis. All variables are winsorized at the 95th percentile. Table 1 describes all the variables.

and most of the risk measures provides preliminary evidence that supports our first hypothesis.

4.2 | How Does NDT Affect Bank Riskiness?

Table 3 provides a detailed analysis of the relationship between Narrative Disclosure Tone (NDT) and various measures of bank riskiness, revealing a consistent and significant positive impact across both accounting-based and market-based risk measures. This finding highlights the critical role that NDT plays in shaping stakeholder perceptions and, consequently, influencing the risk profile of banks. The results indicate that NDT significantly contributes to explaining bank risk exposure. The positive coefficients observed across all risk measures suggest that a more negative tone in narrative disclosures is associated with heightened perceptions of risk, which in turn translates into increased actual risk. This aligns with the notion that soft information—qualitative insights embedded in narrative sections of annual reports—can be as influential as quantitative data in informing stakeholder decisions and perceptions (Acheampong and Elshandidy 2021).

The economic significance of these findings is particularly notable. A 1 % standard deviation increase in NDT corresponds to substantial increases in various types of risks: 0.396 in credit risk, 0.115 in liquidity risk, 0.354 in operational risk, 0.908 in asset risk, and 0.114 in insolvency risk, all of which are statistically significant at the 1% level. Additionally, market-based risks also exhibit significant sensitivity to NDT, with increases of 0.025, 0.597, and 0.495 in total risk, systematic risk, and unsystematic risk, respectively. These findings suggest that NDT not only influences perceptions but has a tangible impact on the risk levels of banks, reinforcing the importance of tone in financial disclosures. The positive association between NDT and bank risk across all these measures indicates that stakeholders interpret a negative tone as a signal of underlying vulnerabilities or challenges, which may prompt more conservative or risk-averse behavior. This is particularly important in the context of banks, where perceptions of risk can have immediate and profound effects on market behavior, regulatory scrutiny, and overall financial stability.

In addition to NDT, other variables such as SIZE, LEV, corruption, and inflation also play significant roles in influencing

TABLE 2 | Correlation matrix.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
CR	1.00	0.01	0.01	−0.01	**0.06**	**−0.02**	0.01	0.02	**0.43**	**−0.08**	0.03	**−0.04**	**0.12**	0.01	**0.15**	**0.05**	**−0.07**	**0.04**
LR		1.00	**0.01**	**0.01**	0.02	0.02	−0.01	0.001	0.02	0.01	0.02	0.01	−0.02	**−0.03**	**0.01**	−0.01	0.01	0.01
OR			1.00	0.03	−0.02	**0.05**	**−0.01**	**−0.01**	**0.04**	−0.04	**0.01**	**−0.01**	0.02	0.01	0.02	0.01	0.04	**0.05**
AR				1.00	−0.02	0.001	−0.04	**−0.01**	**−0.05**	−0.02	0.01	0.02	0.01	**0.02**	**0.04**	**0.01**	−0.01	**0.05**
IR					1.00	0.01	**−0.01**	−0.04	**0.07**	**−0.04**	**0.09**	**−0.19**	**−0.03**	0.01	−0.02	0.04	−0.04	0.03
TR						1.00	0.02	−0.01	0.01	0.01	0.01	0.01	−0.05	0.01	−0.01	−0.01	0.03	0.03
SR							1.00	**0.02**	**0.03**	−0.03	**−0.02**	**−0.04**	**−0.01**	**−0.02**	**0.01**	0.04	−0.03	0.06
UR								1.00	−0.03	−0.03	−0.02	−0.04	−0.01	−0.02	0.01	0.04	−0.06	0.03
NDT									1.00	**0.10**	0.07	−0.04	**−0.07**	**−0.21**	**−0.44**	0.09	**−0.13**	**0.02**
LEV										1.00	**−0.26**	**0.51**	**−0.12**	0.01	**−0.15**	**−0.07**	**0.09**	**−0.06**
ROA											1.00	**−0.13**	**0.01**	0.02	−0.03	0.01	0.01	**0.03**
SIZE												1.00	**0.05**	−0.01	**0.03**	0.01	−0.01	−0.01
DINCOME													1.00	−0.01	**0.09**	**0.07**	**−0.05**	**0.03**
R-LAW														1.00	**−0.04**	**−0.05**	0.03	**−0.05**
CORRUPTION															1.00	**0.19**	**−0.15**	0.05
GDP																1.00	**0.38**	**0.16**
INFLATION																	1.00	**−0.19**
EPU																		1.00

Note: This table reports the correlation matrix of all the variables employed in our analysis. Significant correlations are highlighted in bold.. Table 1 describes all the variables.

TABLE 3 | The impact of NDT and bank riskiness.

		Panel A					Panel B		
		Accounting-based risk measures					Market-based risk measures		
	Ex. Sig.	CR	LR	OR	AR	IR	TR	SR	UR
NDT_{t-1}	(+)	0.439***	0.127***	0.392***	1.005***	0.127***	0.028***	0.661***	0.548**
		(0.000)	(0.006)	(0.000)	(0.000)	(0.006)	(0.000)	(0.000)	(0.029)
LEV	(+)	−3.931**	0.208	−0.484	1.218***	0.208	0.012***	0.299	0.052***
		(0.029)	(0.456)	(0.174)	(0.000)	(0.456)	(0.001)	(0.134)	(0.008)
ROA	(+/−)	−3.194***	−0.563***	−0.477*	7.052***	−0.563***	−0.010***	−0.609***	−0.094***
		(0.006)	(0.007)	(0.089)	(0.000)	(0.007)	(0.000)	(0.001)	(0.000)
SIZE	(+/−)	0.132***	0.017***	0.006	0.037***	0.017***	0.004***	−0.016***	0.011***
		(0.000)	(0.006)	(0.328)	(0.000)	(0.006)	(0.000)	(0.000)	(0.004)
DINCOME	(+/−)	2.098***	0.052	0.045	−2.513***	0.052	−0.001	−0.019	−0.029*
		(0.000)	(0.332)	(0.963)	(0.000)	(0.332)	(0.889)	(0.717)	(0.056)
R-LAW	(−)	0.300**	−0.015	0.027	0.016	−0.015	−0.006**	0.022	0.486**
		(0.049)	(0.441)	(0.404)	(0.319)	(0.441)	(0.022)	(0.240)	(0.041)
CORRUPTION	(+)	0.552	0.173***	0.236**	0.769***	0.173***	0.002**	−0.097*	0.002**
		(0.168)	(0.003)	(0.010)	(0.000)	(0.003)	(0.017)	(0.060)	(0.017)
GDP	(−)	2.098	0.850***	−1.088***	0.292*	0.850***	0.015***	5.377***	0.228***
		(0.106)	(0.002)	(0.000)	(0.064)	(0.002)	(0.000)	(0.000)	(0.000)
INFLATION	(+/−)	−2.147**	−0.355	0.661***	0.426***	−0.355	−0.010***	5.377***	−0.025***
		(0.022)	(0.106)	(0.008)	(0.001)	(0.106)	(0.000)	(0.000)	(0.004)
Constant	(?)	0.583**	−0.070**	1.939***	−2.166**	−0.070**	0.996***	−1.086**	−0.190**
		(0.032)	(0.012)	(0.001)	(0.024)	(0.012)	(0.000)	(0.019)	(0.022)
Model-fit statistics									
Adjusted R^2		5%	4%	7%	22%	4%	7%	5%	16%
Year FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(Continues)

TABLE 3 | (Continued)

	Panel A					Panel B		
Wald test	63.25***	200.12***	92.58***	62.35***	71.23***	100.85***	63.25***	98.22***
Hasen J.	0.389	0.154	0.233	0.241	0.136	0.245	0.152	0.227
Obs.	2052	2052	2052	2052	2052	2052	2052	2052

Note: This table presents the impact of NDT on bank riskiness. The dependent variables are credit risk (CR), operational risk (OR), asset risk (AR), insolvency risk (IR), and liquidity risk (LR) which represent accounting-based measures in panel A, and total risk (TR), systematic risk (SR), and unsystematic risk (UR) which represents market-based measures in panel B. Fixed effects contain bank and year-fixed effects. *p* Values are reported in parenthesis. All variables are winsorized at the 95th percentile. Appendix A describes all the variables employed.
$^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

bank risk. The positive and significant association between bank size (SIZE) and all risk measures, except for systematic risk, suggests that larger banks, while benefiting from diversification and economies of scale, also face greater complexity and potential risk exposure. This finding contrasts with the traditional view that larger banks are inherently safer due to their diversified portfolios (Bermpei et al. 2018). Instead, it suggests that the complexities associated with managing a larger institution may introduce additional risks, particularly in the context of narrative disclosures that might reflect these complexities. Leverage (LEV) also shows a positive and significant association with all risk measures except credit risk (CR), indicating that higher levels of debt financing are generally associated with greater risk. This aligns with the understanding that highly leveraged banks are more vulnerable to market fluctuations and economic downturns, as they have less financial flexibility to absorb shocks.

Country-specific factors such as corruption and inflation further contribute to the risk profile of banks. The positive coefficient for corruption implies that higher levels of corruption exacerbate bank risk, likely due to the erosion of institutional integrity and the increased likelihood of regulatory and compliance challenges (Acheampong and Elshandidy 2021). Inflation, particularly in more developed economies, also contributes to increased bank risk, complementing findings from previous studies (e.g., Anginer et al. 2014; Demirgüç-Kunt and Detragiache 2002; Demirgüç-Kunt and Huizinga 2010). Rising inflation can lead to higher interest rates, which increase the cost of borrowing and the risk of default, thus elevating overall risk levels.

4.3 | Impact of NDT on Bank Riskiness: The Role of EPU

Table 4 explores the moderating role of Economic Policy Uncertainty (EPU) in the relationship between NDT and bank riskiness, revealing that EPU amplifies the impact of NDT on bank risk. The coefficients for NDT remain positive and significant across all risk measures, but with increased magnitude, particularly in operational and asset risks, where coefficients reach 1.196 and 1.014, respectively. This suggests that in times of heightened economic uncertainty, the tone of narrative disclosures becomes even more influential in determining bank risk.

The interaction between NDT and EPU further highlights this relationship. The positive and significant coefficients of the interaction term for all bank risk measures, except liquidity risk, indicate that EPU enhances the sensitivity of bank risks to NDT. Specifically, there is a marginal increase of 0.156, 0.109, and 0.043 in credit risk, operational risk, and asset risk, respectively. For market-based risks, the marginal increases due to EPU are observed at 0.001, 0.037, and 0.046 for total risk, systematic risk, and unsystematic risk, respectively. These findings provide strong evidence that economic uncertainties heighten the influence of NDT on bank risk, consistent with prior studies that have shown how heightened EPU can limit the effectiveness of monetary policies and lead to increased risk-taking behaviors among banks (e.g., Fernández-Villaverde et al. 2011; Gulen and Ion 2016; Raunig et al. 2017).

TABLE 4 | The impact of NDT and bank riskiness—the role of EPU.

		Panel A					Panel B		
		Accounting-based risk measures					Market-based risk measures		
	Ex. Sig.	CR	LR	OR	AR	IR	TR	SR	UR
NDT_{t-1}	(+)	0.482**	0.307***	1.196***	1.014***	0.307***	0.048***	0.812***	0.011**
		(0.016)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.031)
LEV	(+)	−3.816**	0.973***	−0.498	1.234***	0.973***	0.197***	0.418**	0.09**
		(0.011)	(0.002)	(0.121)	(0.000)	(0.002)	(0.000)	(0.383)	(0.010)
ROA	(+/−)	−3.208***	−1.139***	−2.240***	7.112***	−1.139***	−0.158***	−0.735***	−0.109***
		(0.006)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SIZE	(+/−)	0.131***	0.037***	0.0013	0.037***	0.037***	−0.056***	−0.019***	−0.523***
		(0.000)	(0.000)	(0.808)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DINCOME	(+/−)	2.095***	0.113**	0.088	−2.540***	0.113**	0.005	−0.021	0.005*
		(0.000)	(0.039)	(0.319)	(0.000)	(0.039)	(0.418)	(0.688)	(0.081)
R-LAW	(−)	0.331*	−0.047**	0.071**	0.019	−0.047**	−0.009***	0.035*	−0.009
		(0.053)	(0.024)	(0.019)	(0.257)	(0.024)	(0.000)	(0.062)	(0.670)
CORRUPTION	(+)	0.507	0.298***	0.515***	0.779***	0.298***	0.033***	−0.127**	0.104***
		(0.206)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.015)	(0.000)
GDP	(−)	1.920	1.438***	−5.641***	0.194	1.438***	0.206***	6.642***	0.206***
		(0.140)	(0.000)	(0.000)	(0.227)	(0.000)	(0.000)	(0.000)	(0.000)
INFLATION	(+/−)	−1.905**	−0.967***	2.375***	0.452***	−0.967***	−0.161***	5.117***	−0.731***
		(0.044)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EPU	(+)	0.979**	0.502***	5.374***	0.272***	0.502***	0.049***	0.3773***	0.109**
		(0.042)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.003)	(0.038)
NDT*EPU	(+/−)	0.030*	−0.044	0.240**	0.047*	−0.044**	0.010*	0.077**	0.105*
		(0.094)	(0.367)	(0.000)	(0.088)	(0.036)	(0.059)	(0.043	(0.060)
Constant	(?)	0.159**	−0.798**	0.217***	−2.166**	−0.798**	0.387***	−1.068**	−0.350**
		(0.023)	(0.045)	(0.002)	(0.012)	(0.045)	(0.000)	(0.033)	(0.021)

(Continues)

TABLE 4 | (Continued)

	Panel A				Panel B			
Model-fit statistics								
Adjusted R^2	10%	22%	24%	23%	19%	29%	19%	22%
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wald test	53.11***	108.12***	78.03***	52.36***	81.26***	103.55***	66.27***	90.25***
Hasen J.	0.490	0.364	0.137	0.201	0.139	0.340	0.184	0.245
Obs.	2052	2052	2052	2052	2052	2052	2052	2052

Note: This table presents the moderation role of EPU on the impact of NDT on bank riskiness. The dependent variables are credit risk (CR), operational risk (OR), asset risk (AR), insolvency risk (IR), and liquidity risk (LR) which represent accounting-based measures in panel A, and total risk (TR), systematic risk (SR) and unsystematic risk (UR) which represents market-based measures in panel B. Fixed effects contain bank and year-fixed effects. *p* Values are reported in parenthesis. All variables are winsorized at the 95th percentile. Appendix A describes all the variables employed.
$^*p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$.

The findings from Table 4 suggest that during periods of high EPU, stakeholders place greater weight on the tone of narrative disclosures, using them as a critical tool for assessing a bank's ability to navigate uncertain economic landscapes. The increased risk sensitivity to NDT under high EPU conditions implies that banks need to be particularly cautious in how they frame their disclosures during such times. A negative NDT in an environment of high EPU could exacerbate market perceptions of risk, leading to more severe consequences such as increased volatility, higher funding costs, and greater regulatory scrutiny. Conversely, a well-crafted, positive NDT could help mitigate some of the adverse effects of EPU by reassuring stakeholders and maintaining confidence in the bank's stability and risk management strategies. These results highlight the strategic importance of narrative disclosures in managing stakeholder perceptions and risk, particularly in uncertain economic times.

Overall, the findings from Tables 3 and 4 collectively highlight the critical role that NDT plays in influencing bank risk, particularly in the context of economic uncertainties. They suggest that narrative disclosures are not just a form of communication, but a strategic tool that banks can use to manage perceptions, build transparency, and navigate the complex risk landscape.

5 | Further Analysis and Robustness Checks

5.1 | Alternative Measures for Bank Risk

In this section, we conduct a series of analyses to assess the degree to which our estimate findings are reliable. First, we employ alternative measures for bank risk that are widely employed in prior literature. We employ two risk measures for accounting-based and two risk measures for market-based. For accounting-based risk measures, we employ net charge-offs as a percentage of gross loans. An increase in the percentage of gross loans comprised of net charge-offs directly reflects an ex-post worsening in the riskiness of banks. Net charge-offs are the operational losses that are recognized and written down by banks. Next, we employ the Sharpe ratio, which is defined as the return on equity divided by the standard deviation of ROE. Higher values of the Sharpe ratio reflect the greater stability of banks (Demirgüç-Kunt and Huizinga 2010). The Sharpe ratio is often considered a measure of the risk-adjusted returns of banks. Shifting to market-based risk measures, we employ market data to construct Merton's (1974) "distance to default" in such a way that a larger number indicates a greater distance to default or a higher degree of stability. Using Merton's risk index significantly reduces the number of banks included in our assessment. According to Bharath and Shumway (2008), it is possible that Merton's measure of "distance to default" may not perform as well in out-of-sample projections. This contrasts with a suggested "naïve distance to default" measure. Based on this, we employ the latter measure as an alternative risk measure.

From Table 5 (panel A), we find the estimated coefficients of NDT are positive and significantly associated with both the net charge-off and Sharpe ratio at *p* values of 0.059 and 0.032, respectively. Most importantly, EPU exhibits positive signs for both risk indicators and is statistically significant. This is also true for the interaction term, which shows a further increase in bank risk with

TABLE 5 | Alternative bank risk measures.

		Panel A		Panel B		Panel C	
		Accounting-based measures		Market-based measures		Aggregate risk measures	
	Ex. sig.	Net charge-off	Sharpe ratio	Merton	Naive	ABM	MBM
NDT_{t-1}	(+)	2.870**	0.137*	2.654**	0.125	6.683**	0.673***
		(0.028)	(0.079)	(0.041)	(0.103)	(0.011)	(0.004)
LEV	(+)	4.919**	0.166***	1.809***	0.301***	6.001***	0.911***
		(0.011)	(0.016)	(0.000)	(0.004)	(0.000)	(0.000)
ROA	(+/−)	−0.604	−0.041**	−0.583	−0.049**	0.062**	0.376**
		(0.129)	(0.035)	(0.424)	(0.057)	(0.018)	(0.001)
SIZE	(+/−)	0.246***	1.578***	0.264**	0.914**	1.910***	1.052***
		(0.000)	(0.000)	(0.003)	(0.012)	(0.000)	(0.000)
DINCOME	(+/−)	−6.454***	0.192***	−1.208	−0.073	−1.872***	0.045***
		(0.000)	(0.025)	(0.552)	(0.337)	(0.000)	(0.000)
R-LAW	(−)	−1.368	0.066	−3.800**	0.094	1.315***	0.813**
		(0.273)	(0.221)	(0.034)	(0.173)	(0.000)	(0.031)
CORRUPTION	(+)	0.830**	0.014	0.552	−0.041	−1.301	0.801*
		(0.018)	(0.303)	(0.487)	(0.178)	(0.278)	(0.072)
GDP	(−)	−2.478	−0.078	0.892	−0.081	4.457***	1.175***
		(0.630)	(0.104)	(0.906)	(0.751)	(0.000)	(0.000)
INFLATION	(+/−)	1.821***	−0.597***	1.689**	0.603***	1.568**	0.846*
		(0.000)	(0.000)	(0.034)	(0.000)	(0.014)	(0.053)
EPU	(+)	0.385***	0.478***	4.634**	0.506***	0.188*	0.045**
		(0.000)	(0.000)	(0.016)	(0.000)	(0.073)	(0.031)
NDT_{t-1}*EPU	(+/−)	0.302***	0.314***	0.365***	0.232**	0.456***	0.589**
		(0.000)	(0.000)	(0.000)	(0.019)	(0.000)	(0.013)
Constant	(?)	3.455**	0.897*	1.788**	0.470*	1.950**	2.565**
		(0.035)	(0.055)	(0.034)	(0.092)	(0.032)	(0.014)
Model-fit statistics							
Adjusted R^2		16%	14%	19%	9%	10%	16%
Year FE		Yes	Yes	Yes	Yes	Yes	Yes
Bank FE		Yes	Yes	Yes	Yes	Yes	Yes
Wald test		108.11***	74.33***	94.03***	67.32***	90.34***	59.93***
Hasen *J*.		0.136	0.221	0.105	0.288	0.118	0.191
Obs.		2052	2052	2052	2052	2052	2052

Note: This table presents the impact of NDT on bank riskiness. We use alternative bank risk measures. The dependent variables we employed are net charge-off and Sharpe ratio in panel A, Merton and naïve distance to default in panel B, and aggregate accounting and market-based measures in panel C. Fixed effects contain bank and year-fixed effects. *p* Values are reported in parenthesis. Appendix A describes all the variables employed.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

higher economic uncertainties. This suggests favorable evidence for reduced risk-adjusted returns in banks with increased economic uncertainty. As reported in Table 5 (panel B), NDT is positive and significantly associated with Merton distance to default and only marginally insignificant with naïve distance to default. While we see an insignificant coefficient for EPU using naïve distance to default, surprisingly, the interaction term turns out to be positive and significant. These results, put together, indicate that bank risk increases with higher economic policy uncertainty and are thus qualitatively consistent with our main findings.

We further test the reliability of our main findings using various bank risk measures. We conduct a rerun of our primary analysis, utilizing the aggregate metrics of the risk measures. We aggregate all accounting-based risk measures and label them as ABM, and we do the same for market-based risk measures and label them as MBM. Table 5 (panel C) reports the results. Findings reveal a positive and significant relationship between aggregate accounting-based risk measures and NDT. This is also true for aggregate market-based risk measures. These results are consistent with our main findings, which confirm hypothesis 1. We also note that the moderation role of EPU remains positive, which indicates that instances of high economic uncertainty further heighten the relationship existing between NDT and bank risk.[4]

TABLE 6 | Robustness check—quantile regression.

		Panel A					Panel B		
		Accounting-based risk measures					Market-based risk measures		
	Ex. Sg	CR	LR	OR	AR	IR	TR	SR	UR
NDT_{t-1}	(+)	0.939**	0.122***	0.408***	0.803***	0.110***	0.106***	0.611***	0.809**
		(0.045)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.020)
LEV	(+)	−1.033**	0.652	−0.484**	1.018***	0.304	−0.098**	1.076***	−1.356**
		(0.040)	(0.897)	(0.026)	(0.000)	(0.150)	(0.016)	(0.000)	(0.018)
ROA	(+/−)	−0.993***	−0.632***	−0.477**	4.602***	−0.432***	−0.408***	0.402***	−0.793***
		(0.000)	(0.000)	(0.041)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
SIZE	(+/−)	0.452**	0.037***	0.086	0.107***	0.044***	0.013	0.608***	0.392**
		(0.011)	(0.004)	(0.124)	(0.000)	(0.003)	(0.821)	(0.000)	(0.031)
DINCOME	(+/−)	1.048***	0.052	0.082	−1.500***	0.203	0.066	−1.090***	1.048**
		(0.000)	(0.983)	(0.393)	(0.000)	(0.391)	(0.190)	(0.000)	(0.028)
R-LAW	(−)	0.174*	−0.087	0.068	0.306	−0.094	0.118*	0.603	0.384**
		(0.063)	(0.378)	(0.321)	(0.909)	(0.323)	(0.081)	(0.789)	(0.033)
CORRUPTION	(+)	0.623	0.389*	0.633**	0.849***	0.456***	0.603**	0.709***	0.503
		(0.262)	(0.062)	(0.044)	(0.000)	(0.000)	(0.020)	(0.000)	(0.108)
GDP	(−)	1.194	0.945***	−1.005***	0.452**	0.492***	−0.985***	0.392**	0.794*
		(0.840)	(0.002)	(0.002)	(0.010)	(0.000)	(0.000)	(0.034)	(0.090)
INFLATION	(+/−)	−0.937**	−0.378	0.238***	0.396***	−0.633	0.406***	0.599***	−0.637**
		(0.047)	(0.298)	(0.000)	(0.001)	(0.293)	(0.000)	(0.000)	(0.028)
EPU	(+)	0.475**	0.422***	2.450***	0.204***	0.418***	1.650***	0.204***	0.475**
		(0.032)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.032)
NDT_{t-1}*EPU	(+/−)	0.072*	−0.108	0.124**	0.083*	−0.054	0.117***	0.069*	0.059*
		(0.054)	(0.265)	(0.000)	(0.073)	(0.234)	(0.000)	(0.061)	(0.077)
Constant	(?)	0.349**	−0.644**	0.202***	−1.343**	−0.559**	0.800***	−1.007**	0.479**
		(0.011)	(0.031)	(0.000)	(0.020)	(0.041)	(0.000)	(0.011)	(0.042)
Model-fit statistics									
Adjusted R^2		14%	20%	24%	21%	18%	18%	20%	16%
Year FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.		2052	2052	2052	2052	2052	2052	2052	2052

Note: This table presents the robustness checks for our main analysis. Panel A and panel B reports the lag analysis for accounting-based and market-based risk measures respectively. Fixed effects contain bank and year-fixed effects. *p* Values are reported in parenthesis. All variables are winsorized at the 95th percentile. Table 1 describes all the variables employed.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

5.2 | An Alternative Econometric Approach

Here, we employ a different econometric approach to estimate and explore the relationship between narrative disclosure tone and bank riskiness, considering the impact of economic policy uncertainty. We employ the quantile regression estimator developed by Parente and Santos Silva (2016). The quantile regression estimator is used to estimate the median of the dependent variable based on the values of the independent variables. This estimator is robust to non-normal errors and outliers, and it also addresses the "Moulton problem" that occurs when estimating the impact of aggregate variables on microunits (Moulton 1990). According to the information presented in Table 6, the outcomes are essentially identical in terms of quality. As shown by positive and statistically significant coefficients like the credit risk coefficient of 0.939 and the liquidity risk coefficient of 0.122, it seems that when narrative disclosure from EU banks' annual reports increases in the years before, so does the risk for those banks in the following year. This can be attributed to the influence of the material revealed in the banks' annual reports, namely in the narrative portion. This statement validates our primary discoveries. The control variables' coefficients display reasonable indications. Thus, this enhances the economic importance of NDT in elucidating bank risk. Our findings indicate that economic uncertainty has a detrimental effect on banks' stability, leading to significant financial consequences.

5.3 | Propensity Score Matching

In addition to using the instrumental variables method with the GMM model definition, we also employed propensity score matching (PSM) to mitigate any endogeneity concerns (To

TABLE 7 | Robustness checks—propensity score matching.

		Panel A					Panel B		
		Accounting-based risk measures					Market-based risk measures		
	Ex. Sig.	CR	LR	OR	AR	IR	TR	SR	UR
NDT_{t-1}	(+)	0.134**	0.107*	0.432**	0.803	0.820	0.182*	0.451	0.308**
		(0.032)	(0.054)	(0.010)	(0.230)	(0.262)	(0.064)	(0.134)	(0.045)
LEV	(+)	−1.901*	0.103	−0.264	1.119***	0.198	0.034***	0.598	0.043***
		(0.065)	(0.150)	(0.571)	(0.000)	(0.350)	(0.001)	(0.454)	(0.003)
ROA	(+/−)	−2.004***	−0.361*	−0.370*	5.042***	−0.423***	−0.024***	−0.509***	−0.081**
		(0.000)	(0.081)	(0.069)	(0.000)	(0.002)	(0.000)	(0.000)	(0.040)
SIZE	(+/−)	0.032***	0.302**	0.012	0.062***	0.090***	0.004***	−0.034**	0.041**
		(0.000)	(0.021)	(0.125)	(0.000)	(0.002)	(0.000)	(0.010)	(0.026)
DINCOME	(+/−)	0.991***	0.021	0.051	−2.010***	0.049	−0.001	−0.098	−0.029*
		(0.000)	(0.633)	(0.703)	(0.000)	(0.302)	(0.349)	(0.457)	(0.086)
R-LAW	(−)	0.110***	−0.185	0.042	0.042	−0.051	−0.006**	0.052*	0.436**
		(0.001)	(0.243)	(0.103)	(0.209)	(0.071)	(0.012)	(0.090)	(0.030)
CORRUPTION	(+)	0.292	0.097***	0.335**	0.419***	0.053***	0.009**	−0.073*	0.001**
		(0.938)	(0.001)	(0.022)	(0.000)	(0.002)	(0.026)	(0.030)	(0.037)
GDP	(−)	1.191	0.850***	−1.031***	0.190*	0.690***	0.075***	2.075***	0.128***
		(0.402)	(0.002)	(0.000)	(0.034)	(0.001)	(0.000)	(0.000)	(0.000)
INFLATION	(+/−)	−1.107*	−0.525	0.365***	0.320***	−0.250	−0.045***	2.807***	−0.045***
		(0.062)	(0.204)	(0.003)	(0.000)	(0.206)	(0.000)	(0.000)	(0.009)
Constant	(?)	0.338**	−0.092*	0.834***	−1.060**	−0.100**	0.571***	−1.060**	−0.494**
		(0.011)	(0.052)	(0.000)	(0.012)	(0.031)	(0.000)	(0.034)	(0.012)
Model-fit statistics									
Adjusted R^2		8%	6%	6%	16%	9%	7%	5%	13%
Obs.		2052	2052	2052	2052	2052	2052	2052	2052

Note: This table presents the moderation role of EPU on the impact of NDT on bank riskiness using GMM. The dependent variables are credit risk (CR), operational risk (OR), asset risk (AR), insolvency risk (IR), and liquidity risk (LR) which represent accounting-based measures in panel A, and total risk (TR), systematic risk (SR), and unsystematic risk (UR) which represents market-based measures in panel B. Fixed effects contain bank and year-fixed effects. *p* Values are reported in parenthesis. All variables are winsorized at the 95th percentile. Appendix A describes all the variables employed.
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

et al. 2018). PSM enables us to compare banks based on their projected probability of narrative disclosure tone, rather than relying on a multitude of specific bank criteria for comparison. More precisely, we employ a logit model to estimate the propensity score for each observation in order to match the treatment group (high NDT) with the control group (low NDT). We then use this propensity score to predict the probability of receiving treatment based on the bank-level data. We employ nearest neighbor matching to pair each instance of high NDT with banks in the control group that have the most similar score to the treatment group (Bonaventura et al. 2018). We employ a technique known as common support to reduce extreme borders. This involves removing banks from the control group whose scores are higher than the maximum or lower than the lowest propensity score among high NDT in the treatment group. The outcomes derived from the PSM models, as presented in Table 7, demonstrate qualitatively similar results to the main findings (refer to Tables 3 and 4). Specifically, NDT exhibits a favorable and statistically significant correlation with the majority of bank risk variables. There is a strong link between the EPU measure and NDT. Notably, the direction of the coefficient for the interaction terms shows that bank risk rises as economic uncertainty rises. This suggests that endogeneity issues do not affect our findings.

6 | Conclusion

In prior literature, the impact of NDT on bank riskiness has received limited empirical attention. Capturing NDT through computerized textual analysis, our paper sheds new light on this area and, most importantly, examines the influence of EPU on banks from Europe over the period between 2005 and 2022. Based on 2052 bank-year observations, we show that NDT has a significant impact on bank risks. Importantly, we find that this relationship between NDT and bank risks is stronger in times of high EPU, indicating that stakeholders place greater reliance on NDT when faced with heightened uncertainty. Our results suggest that narrative disclosures in the annual reports of banks contain valuable information that helps them explain their risk exposure to stakeholders. It also shows how important the tone and content of these narrative disclosures are in providing stakeholders with insights into banks' risk management practices, future outlooks, and responses to economic conditions. Our results are robust across various sensitivity checks, confirming the consistency and reliability of our findings.

The findings of our study have several practical implications for various stakeholders in the banking industry. First and foremost, our findings highlight the significance of narrative disclosure as a mechanism for informing stakeholders about potential risks and promoting openness. Particularly during periods of heightened economic policy uncertainty, banks should recognize the potential of strategic narrative disclosure and select the appropriate tone when communicating their risk management strategies to their stakeholders. Second, our study emphasizes the need for policymakers and regulatory bodies to incorporate NDT into their risk assessment frameworks. By integrating narrative analysis methodologies, regulatory bodies can gain a deeper understanding of banks' risk profiles and more effectively assess their readiness to confront economic uncertainties. The potential of this information lies in its ability to improve regulatory supervision and direct policy decisions aimed at promoting investor confidence and financial stability. Finally, for investors and market analysts, our study highlights the value of closely examining the narrative sections of bank annual reports. By critically analyzing the tone and content employed in narrative disclosures, investors can potentially gauge the level of risk exposure and make more informed investment decisions.

While our study provides valuable insights into the relationship between NDT, bank riskiness, and EPU, it has certain limitations that create avenues for future research. Our study focused only on banks in Europe. Future research could extend the analysis to other geographical regions and countries to explore potential cultural, regulatory, or institutional factors that may influence the relationship between NDT, bank riskiness, and EPU. Cross-country comparisons could provide valuable insights into the role of varying regulatory environments and cultural norms in shaping narrative disclosure practices, as well as their impact on risk communication. Furthermore, our study examined a relatively broad time period (2005–2022). However, future research could delve deeper into specific time periods or events to explore how NDT and its impact on bank riskiness evolve over time. For instance, studies could investigate the role of NDT during specific financial crises, regulatory changes, or other significant economic events to understand how banks adapt their risk communication strategies in response to such circumstances.

Author Contributions

Acheampong Albert conceptualized the study and led the drafting of the manuscript. Ngozi Ibeji and Thuy Nguyen contributed to data analysis and interpretation. Freeman Owusu provided critical revisions and additional insights into the theoretical framework. All authors read and approved the final manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Endnotes

[1] We employ a wide range of accounting-based and market-based risk measures and provide a more holistic view of banks' risk exposure from accounting and capital market perspectives. These risks capture the full financial stability of banks (Trinh et al. 2020). As argued by Gentry and Shen (2010), accounting-based and market-based measures convey different information. Accounting-based measures reflect the past or short-term exposure, whereas market-based measures offer insight into the future or long-term exposure of banks. Additionally, as the use of accounting-based risk measures can be affected by certain accounting standards, such as IFRS 9 Financial Instruments, the use of market-based measures provides alternative insight.

[2] You can find economic policy uncertainty at www.policyuncertainty.com.

[3] The index for law was developed by Djankov et al. (2008), and the data file can be downloaded from http://post.economics.harvard.edu/faculty/shleifer/data.html.

[4]In an untabulated result, we employ interest rate risk as an alternative measure of bank risks, and we find consistent results with our main findings indicating the informativeness of narrative disclosure in the annual reports of banks and how EPU further heightens this association.

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Appendix A

Variables description.

Variable	Abbreviation	Description
Risk variables		
Credit risk	CR	Captured as non-performing loans scaled by total assets (NPL/TA)
Liquidity risk	LR	Liquid assets divided by the sum of short-term funding and deposits
Operational risk	OR	The standard deviation of return on assets.
Asset risk	AR	Return on assets divided by standard deviation of return on assets
Insolvency risk	IR	This measure describes the probability of default; it quantifies the comprehensive return on assets and equity relative to assets, adjusted by the standard deviation of return on assets.
Total risk	TR	Volatility of market returns
Systematic risk	SR	Beta
Unsystematic risk	UR	Standard error of CAPM
Narrative disclosure tone	NDT	Calculated using the Loughran and McDonald dictionary, this measure represents the ratio of the difference between negative and positive words to the combined count of positive and negative words.
Economic policy uncertainty	EPU	Economic Policy Uncertainty Index
Bank-level variables		
Financial leverage	LEV	Total debt divided by total assets, representing a change in financial leverage
Profitability	ROA	Net income divided by total assets represents bank's the profitability.
Bank size	SIZE	Natural logarithm of total assets.
Diversification income	DINCOME	Non-interest income divided by total income.
Country-level variables		
Rule of law	R-LAW	A measure of legal safeguards to protect minority shareholders from unjust actions by insiders. The measure examines various aspects of corporate governance, including protecting oppressed minority shareholders, cumulative voting, remote voting, pre-emptive rights, unblocked shares, and the capital needed to hold meetings.
Corruption	CORRUPTION	The initial score of Transparency International's Corruption Perception Index (TI index) which reflects the perceived extent of existing corruption, is rated on a scale from 0 to 10. A greater score implies stronger economic and political integrity. It is calculated as 10 – TI, where a higher value signifies a greater prevalence of corruption.
GDP per capita	GDP	An indicator of the economic environment within which a bank functions, calculated as the actual increase in real GDP.
Inflation	INFLATION	The yearly inflation rate is calculated as the percentage change in the consumer price index.

Note: This table describes all the variables employed.