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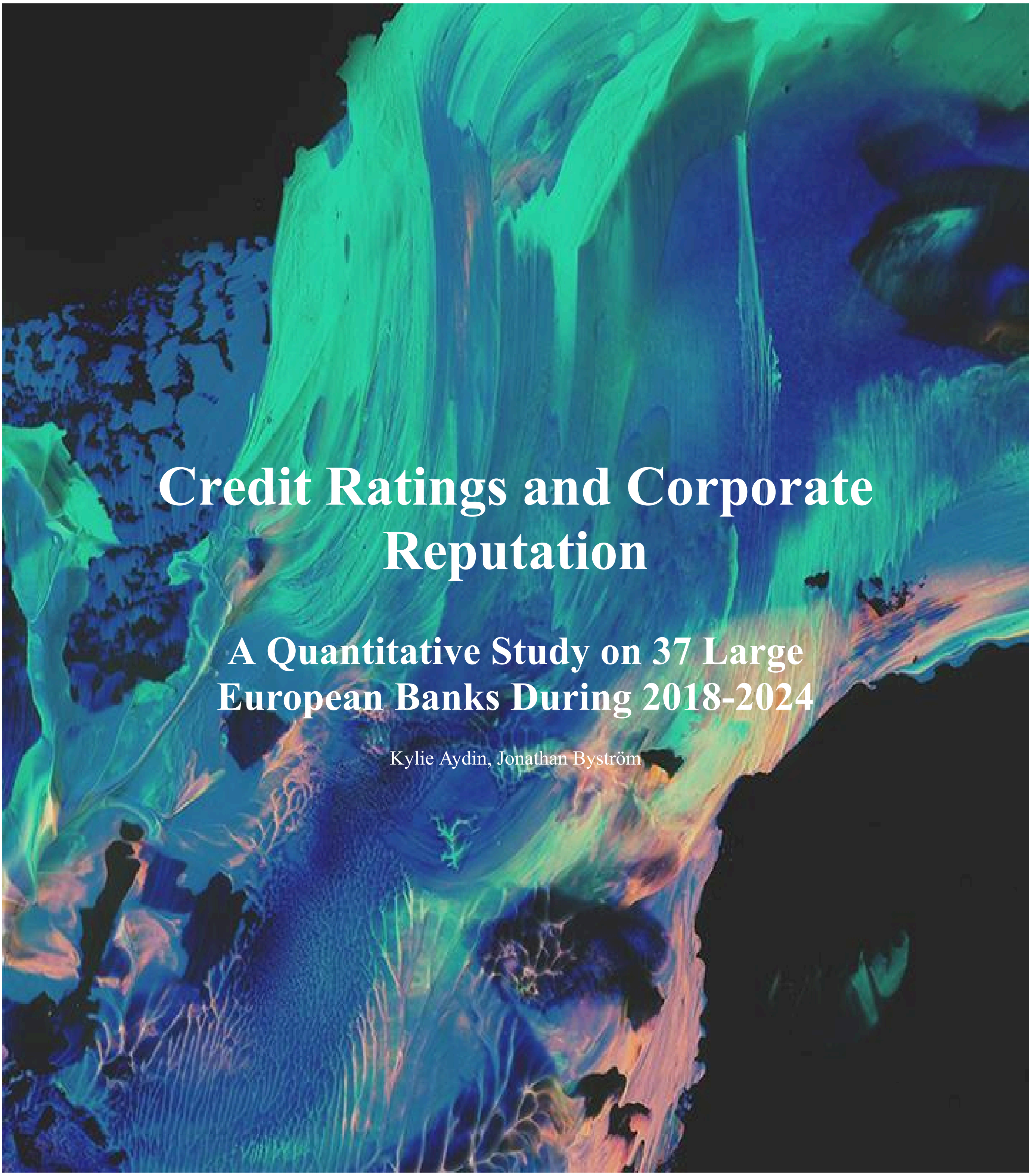

Credit Ratings and Corporate Reputation

A Quantitative Study on 37 Large European Banks During 2018-2024

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Abstract

This thesis aims to investigate whether corporate reputation indicators provide explanatory value in credit ratings beyond traditional financial indicators among the largest European banks during the period 2018-2024. Credit ratings play an important role in financial markets by summarizing the creditworthiness of institutions and influence both investment decisions and regulatory frameworks. However, previous research suggests that credit ratings might not fully capture all relevant factors, such as reputation.

The study applies a quantitative research approach using panel data for a sample of 37 large European banks rated by Fitch Ratings. The thesis conducts a fixed effects multiple regression analysis with Ordinary Least Squares (OLS) estimates using credit ratings as the dependent variable and reputation indicators as independent variables, along with using credit risk indicators and size of banks as control variables. Reputation is measured through Search Interest Volatility, measuring fluctuations in market attention and Scandal Severity, capturing the intensity of negative events affecting banks. The traditional financial indicators include Return on Risk-Weighted Assets (RoRWA), Tier 1 Ratio, Expected Credit Loss (ECL) Ratio, Liquidity Coverage Ratio (LCR) and total assets.

The results show that the selected reputation indicators do not provide statistically significant evidence that they provide additional explanatory value for credit ratings, after financial variables are included in the model. In contrast, financial indicators, particularly the ECL Ratio and Tier 1 Ratio, are statistically significant which is consistent with how credit risk is typically measured. These findings suggest that credit ratings in the sample primarily reflect financial information rather than the chosen reputation indicators. This is consistent with the theories used to form the hypothesis as the Theoretical Framework of the study indicates a research gap where the importance of corporate reputation and its potential effect on triggering financial instability might not be reflected in the assessment of credit risk.

Keywords:
Credit Ratings, Corporate Reputation, Credit Risk, Market Attention, Search Interest, Scandal Severity, Fitch Ratings, Basel Frameworks

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Abbreviations

BCBS - Basel Committee on Banking Supervision
ECL - Expected credit losses
IFRS9 - International Financial Reporting Standard 9
LCR - Liquidity Coverage Ratio
NSFR - Net Stable Funding Ratio
OLS - Ordinary Least Squares
RoRWA - Return on Risk-Weighted Assets
RWA - Risk-Weighted Assets

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1. Introduction

The Introduction Chapter starts with presenting the role of banks, credit ratings and credit rating agencies which establishes the background of the study. Then, limitations of credit ratings and the importance of corporate reputation for banks are introduced. Moreover, the chapter discusses prior research and problematization to show a research gap regarding credit ratings and corporate reputation, leading to the study's research question. Lastly, the purpose and contribution of the study are discussed.

1.1. Background

Banks are essential to the functioning of the economy because they provide credit, ensure access to funds and manage different types of financial risk through a wide range of financial activities (Berger et al., 2020, p. 1). Because of this important role, assessing the creditworthiness of banks is important for regulators, investors, depositors, banks and other market participants. One of the most widely used tools for this purpose is credit ratings, which summarize an institution's relative creditworthiness and influence both market behavior and regulatory decision making (White, 2010, pp. 212-215).

Credit ratings are important because they transform complex financial and non-financial information into a simplified ranking that can be used by market participants when evaluating issuers and securities. In this way, ratings help reduce information asymmetries between issuers and investors and support decision making in capital markets (White, 2010, pp. 212-213). Moreover, their role extends beyond information alone. Ratings are also part of the institutional and regulatory framework of the financial system, where rating categories may affect capital requirements, investment suitability and risk-weights (White, 2010, pp. 213-215). Consequently, changes in credit ratings may influence funding conditions, investor behavior and the willingness or ability of investors to hold a given security. Credit ratings therefore play an important role in functioning as signals of creditworthiness.

Standard & Poor's (S&P) Global Ratings define credit ratings as "forward-looking opinions about an issuer's relative creditworthiness" (S&P Global Ratings, n.d.). This definition suggests that ratings are intended to reflect future repayment capacity rather than only current financial conditions. In the case of banks, rating agencies use structured analytical frameworks that combine qualitative assessments with financial indicators to evaluate overall resilience. Fitch Ratings, for example, assesses banks through key rating drivers such as business profile, risk profile, asset quality, earnings and profitability, capitalization and leverage and funding and liquidity (Fitch Ratings, 2025b, pp. 1-3). These dimensions allow for an evaluation of whether a bank can continue meeting its obligations over time, including under less favourable economic conditions and periods of uncertainty.

Even so, whether credit ratings fully capture all relevant sources of credit risk has been increasingly questioned, especially after the Global Financial Crisis (Afik & Galil, 2025, p. 1). While ratings are meant to summarize creditworthiness, it remains unclear whether they also reflect more fast-moving signals that can affect confidence in banks, such as governance concerns, repeated scandals or negative public information. If reputation shocks are capable of influencing stakeholder behavior and contributing to funding pressure or broader financial stress, it becomes important to ask whether such signals are sufficiently reflected in credit ratings.

1.2. Limitations of Credit Ratings

Even with their widespread use in financial markets, the informational value of credit ratings has been broadly examined in academic research. A large part of the literature focuses on how well ratings reflect underlying financial fundamentals such as leverage, profitability, liquidity, capital structure and default probabilities. Although credit ratings are useful indicators of relative creditworthiness, research suggests that they do not map directly onto short-term default probabilities and explain only part of the variation in realized default risk. Hilscher and Wilson (2017, pp. 3414-3417) show that market-based and model-based measures of default probability outperform credit ratings when predicting short-term failures. Their study also finds that a large portion of variation in default probabilities occurs within rating categories instead of across them, meaning that firms with the same credit rating can still differ significantly in their underlying risk levels (Hilscher & Wilson, 2017, p. 3422). This suggests that while ratings capture broad differences in creditworthiness, they may be less precise in reflecting shorter-term changes in risk. Instead, they appear to be more effective at indicating relative exposure to wider macroeconomic shocks than at predicting exact default outcomes over short horizons (Hilscher & Wilson, 2017, p. 3423).

Another commonly discussed limitation concerns the timing of rating adjustments. Empirical studies show that credit ratings often adjust slowly to weakening financial conditions, especially during periods of stress (White, 2010, pp. 212-219). For example, van de Ven et al. (2018, pp. 478-480) found that sovereign credit ratings in the Eurozone adjusted slowly during the financial crisis, with rating downgrades often occurring only after major market disruptions had already taken place. Their findings suggest that credit ratings may fail to provide timely signals when risk develops rapidly. Although bank rating methodologies combine financial and qualitative assessments, they are still largely built around structured frameworks and relatively stable indicators (Fitch Ratings, 2025b, pp. 1-3). As a result, they may be less responsive to fast-moving reputation-related signals, such as sudden negative public information, governance concerns or rapid shifts in stakeholder confidence.

1.3. Corporate Reputation

Corporate reputation can be understood as an overall evaluation of a firm that is shaped by its past behavior and by how stakeholders interpret that behavior over time (Weigelt & Camerer, 1988, pp. 443-444). A strong reputation may lead stakeholders to view a firm more positively, while repeated scandals, weak governance, or negative public information may weaken that view. In banking, this is especially important because banks depend heavily on trust and confidence. When stakeholders do not have complete information, reputation becomes more important in shaping how a bank is perceived (Weigelt & Camerer, 1988, p. 447).

This is relevant because reputation might influence financial stability indirectly through stakeholder behavior. Diamond and Dybvig (1983, pp. 401-403) show that even fundamentally solvent banks can be under severe pressure if depositors lose confidence and withdraw funds at the same time. Stakeholders form views of firms not only from information disclosed by the firms themselves, but also from media and other public sources (Fombrun & Shanley, 1990, p. 234). This suggests that reputation-related information may be important in banking because it can influence trust and confidence that are important for the stability of banks.

More recent banking cases also indicate that factors such as repeated scandals, negative media attention and rapid information spread can intensify depositor concern and increase pressure on already vulnerable institutions, see Table 1. It becomes relevant to examine whether these factors are also reflected in credit ratings.

Table 1: Summary of the Examples of Bank Failures in Europe

Bank	Cause
Credit Suisse - Switzerland, 2023	Negative media coverage, repeated scandals and ongoing governance concerns contributed to further deterioration in confidence during an already fragile period (Swiss Financial Market Supervisory Authority FINMA, 2023). This intensified pressure on the bank and increased concerns about its broader financial stability.
Sberbank CZ - Czech Republic, 2022	Geopolitical developments and loss of trust were associated with large withdrawals of funds. This created severe liquidity pressure and contributed to the bank's collapse (Polach & Chalupa, 2025).
ABLV Bank - Latvia, 2018	Money laundering accusations triggered serious confidence loss and large withdrawals, which contributed to the collapse of ABLV Bank (Coppola, 2018).

Consequently, the study aims to develop two indicators for measuring corporate reputation that include Search Interest Volatility, focusing on market attention and availability of information and Scandal Severity, capturing the intensity of new information. To allow the model of the study to focus specifically on the association between credit ratings and reputation indicators, the control variables, Return on Risk-Weighted Assets (RoRWA), Tier 1 Ratio, Expected Credit Loss (ECL) Ratio, Liquidity Coverage Ratio (LCR) and total assets are used to represent the "traditional financial indicators."

1.4. Problematization and Research Gap

Previous research suggests that credit ratings are important for assessing creditworthiness, but also that they may not fully capture all relevant dimensions of credit risk (Hau et al., 2012, pp. 4-8). This becomes a problem when risk develops through factors that are not immediately visible in traditional financial indicators. In banking, potential factors also include reputation, confidence and public perception.

While credit ratings are mainly assessed through traditional financial indicators such as profitability, leverage and liquidity, recent studies show that the inclusion of qualitative information makes rating downgrades more informative (Bozanic et al., 2023, pp. 799-800). Moreover, Donovan et al. (2021, pp. 815-818) showed that qualitative information from annual reports and conference calls can improve the prediction of credit events beyond traditional financial measures.

In addition, there have been certain studies focusing on reputation as an important risk for banks. Adeabah et al. (2023, p. 344) explain that reputational risk is a relevant risk for banks, although ways of measuring it are not fully developed, suggesting that some important aspects of risk might be difficult to capture (Adeabah et al., 2023, pp. 344-345).

In line with this, many studies point out the influence of social media and news sources on bank failures. The study conducted by Cookson et al. (2026, p. 1) showed that when information spread through social media that Silicon Valley Bank might collapse, depositors rushed to withdraw their funds which also contributed to concerns about spillover effects on other banks and industries. Moreover, another study showed that bank-level measures of banks do not directly explain public confidence or reputation (Chernykh et al., 2023, p. 2).

Regardless, fewer studies clearly examine whether ratings also capture fast-moving reputational developments in a systematic way. This points to a possible gap, since standardized rating methodologies are primarily designed to assess broader creditworthiness over time, but may be less sensitive to sudden non-financial developments that can still affect confidence in banks. This thesis addresses that issue by examining whether reputation-related indicators provide additional explanatory value, beyond traditional financial indicators when analysing bank credit ratings.

To study this issue, the thesis focuses on the period 2018-2024. This period includes different market conditions, including the years before, during and after the Covid-19 pandemic. As a result, the period makes it possible to analyze banks across both more stable and more stressed conditions, which strengthens the relevance of the study.

1.5. Research Question

"To what extent do corporate reputation indicators provide additional explanatory value for credit ratings, beyond traditional financial indicators, among the largest European banks during 2018-2024?"

1.6. Purpose of the Thesis

The purpose of this thesis is to examine whether reputation-related indicators provide additional explanatory value, beyond traditional financial indicators when analysing credit ratings based on Fitch Ratings in a sample of the largest European banks by total assets during 2018-2024. More specifically, the study aims to assess whether reputation-related signals, specifically within market attention and scandal intensity, are associated with credit ratings.

This issue is particularly relevant in banking because confidence-related shocks can matter even before they appear clearly in traditional financial measures. Negative public information, repeated scandals, governance concerns or sharp changes in stakeholder trust may contribute to credit risk, especially during periods of uncertainty. Previous studies also show that the spread of negative information can result in spillover effects, affecting the other banks and industries.

Moreover, the study does not imply that credit ratings should react to every short-term panic event, but instead, it aims to show that the reputation of banks may contain information that becomes relevant for the broader risk profile and can be an important dimension for the stability of banks. If credit ratings are intended to reflect a bank's overall creditworthiness and ability to withstand stress, it becomes relevant to examine whether reputation-related indicators provide additional explanatory value, beyond traditional financial indicators when analysing ratings.

1.7. Theoretical and Practical Contributions

This study contributes to business administration research through its focus on credit ratings and credit risk assessment in the banking sector. More specifically, it examines whether reputation indicators provide additional explanatory value beyond traditional financial indicators when analysing bank credit ratings. As a result, the study contributes to the research gap on the association between credit ratings and non-financial indicators such as corporate reputation.

The study contributes theoretically by discussing prior studies and theories related to credit ratings, credit risk and reputation. The previous literature suggests certain limitations to credit ratings and the potential importance of non-financial indicators such as reputation. In addition, theories and concepts including the bank run theory, herding behavior and informational cascades, asymmetric information and the signaling theory are discussed in the Theory Chapter for explaining the importance and the role of corporate reputation and credit ratings for banks. Therefore, the study aims to provide relevant literature, theories and concepts on whether credit ratings mainly focus on financial indicators and that credit ratings might not directly reflect reputation indicators.

This study also contributes practically by applying measurable proxies for corporate reputation that includes Search Interest Volatility and Scandal Severity. This is relevant as reputation is difficult to measure and is relatively underdeveloped, according to previous studies and regulatory frameworks discussed in the following chapter. Search Interest Volatility is constructed using Google Trends while Scandal Severity is constructed through a criteria that ranks the scandals that the banks in the sample were involved in. Therefore, the study provides a criteria that can be used to assess the severity of scandals.

As a result, the study can be theoretically and practically relevant for depositors, investors, regulators and banks as it highlights the importance of reputation for banks using previous studies, theories and concepts, along with providing measures for capturing certain aspects of reputation. The findings of the study aim to provide a perspective on whether selected reputation indicators are associated with credit rating outcomes, after traditional financial indicators are accounted for. This, then, can be used for decision-making in terms of investments, suggesting additional ways of measuring potential credit risk and instability, as well as for regulatory frameworks.

1.8. Delimitations

There are certain limits to the study that allow for answering the research question. These limits include the following:

1. The study focuses on credit ratings assessed by Fitch Ratings. The reasoning for this choice is due to Fitch Ratings providing publicly available credit ratings for the banks in the sample for the whole time horizon. However, different rating agencies might have different methods and therefore, different credit ratings for the banks in the sample. As a result, the findings apply to ratings specifically assessed by Fitch Ratings, which might affect the generalizability of the results to other rating agencies.
2. The population of the study is 50 largest European banks by total assets in 2024, ranked by S&P (Mones & Hayes, 2024). As a result, the sample is limited to 37 banks in this category that are rated by Fitch Ratings. While the sample size can be considered small, it still allows for conclusions on associations between variables. Moreover, this approach allows the study to focus on banks with available credit ratings in order to have a dataset without missing observations. Regardless, this limits the generalizability as the findings focus on a sample of large European banks rated by Fitch Ratings, without including smaller or regional banks that are not rated by the credit rating agency.
3. The time horizon of the study is limited to 2018 to 2024. While this makes the study more focused and relevant for the period of before, during and after the Covid-19 pandemic, it affects generalizability as other periods are not accounted for.
4. The chosen indicators for measuring corporate reputation focus on two aspects of reputation that are market attention and scandal intensity. This allows for a more specific and focused study, however, other dimensions of reputation are not captured. As a result, these indicators alone might not capture corporate reputation fully. Similarly, the chosen control variables that represent the "traditional financial indicators" might not capture all financial dimensions used in assessing credit ratings as they mainly focus on risk-adjusted profitability, capital strength, asset quality, liquidity and size. Regardless, these indicators allow for a more specific and focused study.

2. Theory

This chapter starts by reviewing previous literature. Then, the main theories are introduced: the bank run theory, behavioral finance including herding behavior and informational cascades, asymmetric information and the signaling theory. These theories are defined and discussed with the relevant implications to the study. Moreover, the chapter discusses credit ratings and credit risk, focusing on Basel Regulations and the measures used for assessing credit risk. These theories and concepts set the Theoretical Framework for the thesis that will be used to answer the research question.

2.1. Prior Research

Credit ratings play a central role in financial markets because they provide a simplified assessment of creditworthiness that can be used by investors, regulators and other market participants. In the banking sector, this becomes even more important since banks rely on external funding and are closely connected to the broader financial system. Moreover, banks are often harder to assess than non-financial firms because it is more difficult to get a clear and complete picture of their underlying risk. They are exposed to many different types of risks and are characterized by information asymmetries between the bank and external stakeholders. In this way, credit rating agencies play an important role in interpreting available information (Hau et al., 2012, pp. 7-8).

A growing part of the literature shows that credit ratings do not fully reflect underlying credit risks. Earlier research suggests that ratings may only be partly aligned with future default probabilities and that meaningful differences in risk can still exist within the same rating category. This becomes especially relevant in banking, where information asymmetry and differences in institutional quality can affect how financial information is understood and assessed. Shen et al. (2012, pp. 171-172) showed, for example, that banks with similar financial ratios may still receive different ratings depending on the information environment and country-specific setting. Hau et al. (2012, pp. 4-5) find that bank credit ratings can have relatively low information content in relation to future distress risk, especially within the higher investment-grade range and that ratings might also be systematically more favourable for larger banks.

While traditional credit risk analysis mainly focuses on financial indicators such as leverage, profitability and liquidity, more recent research has started to pay more attention to qualitative and non-financial information. Bozanic et al. (2023, pp. 780-781) showed that credit analysts use qualitative disclosures when forming their assessments through soft adjustments, meaning that they go beyond the initial quantitative model and reflect non-financial information. Their results also show that when more credit-risk focused qualitative information is reflected in ratings, rating downgrades become more informative (Bozanic et al., 2023, pp. 799-800). In line with this, Donovan et al. (2021, pp. 815- 818) show that qualitative information from sources such as annual reports and conference calls can improve the prediction of credit events beyond traditional measures, including bankruptcies, private debt spreads and credit rating downgrades.

Furthermore, the banking literature has increasingly focused on reputational risks as an important part of overall risk. Adeabah et al. (2023, p. 344) argue that following the Global Financial Crisis, reputational risk has become one of the most significant risks facing banks. They also show that the way reputational risk is measured and incorporated into more formal frameworks remains relatively underdeveloped, which suggests that some important aspects of bank risk may still be difficult to capture in a structured way (Adeabah et al., 2023, pp. 344-345).

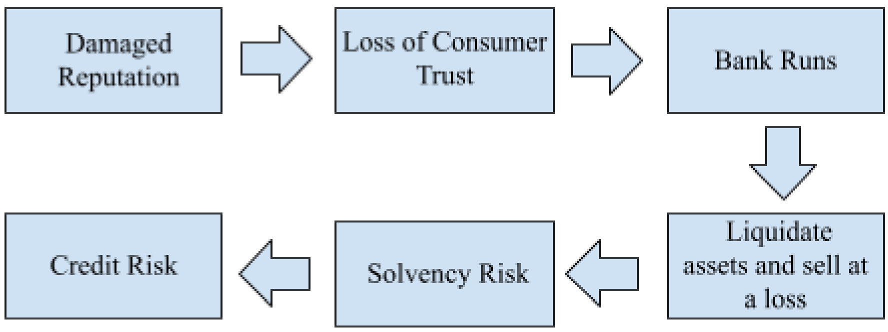
With this in mind, previous research suggests that credit ratings are useful, but that they do not fully reflect all relevant aspects of credit risk. Research also shows that qualitative disclosures and other non-financial information can matter for credit risk assessment, while the banking literature highlights that reputational risk may also become important for how bank risk develops and is perceived. However, there is still limited research that more clearly examines whether these broader signals are sufficiently reflected in bank credit ratings. Therefore, theories and concepts will be used in the next sections to highlight the importance of reputation and the gap between the role of reputation and the assessment of credit ratings.

2.2. Bank Run Theory

Bank runs have played a central role in many financial crises. Diamond and Dybvig (1983, p. 402) developed a model explaining how banks transfer illiquid assets into liquid liabilities. Through this model, they show that bank runs, where depositors rapidly withdraw their funds as they anticipate a bank failure, force banks to liquidate assets and sell them at a loss (Diamond and Dybvig, 1983, pp. 401-403).

Diamond and Dybvig (1983, p. 403) demonstrated that when confidence is not sustained, banks are unable to efficiently distribute the risk which can trigger a bank run. Even stable and healthy banks might collapse due to insolvency (Diamond and Dybvig, 1983, pp. 402-403).

The bank run theory shows that reputation and confidence are important factors that increase the vulnerability of a bank. As the bank run theory suggests, even stable banks might fail due to a loss of trust which would lead to insolvency and expose the bank to credit risk.



(Source: Diamond and Dybvig, 1983, pp. 401-403)

Figure 1: The Effects of Damaged Reputation

Figure 1 illustrates the effects of damaged reputation that is adapted from Diamond and Dybvig’s model (1983, pp. 401-403) and shows how damaged reputation might influence the model which, as a result, affects credit risk. When confidence deteriorates, depositors might withdraw funds rapidly, triggering a bank run. As described in the bank run theory, banks are then forced to liquidate assets at a loss. These losses can lead to solvency risk due to the failure of meeting obligations. Consequently, this exposes the bank to credit risk. This suggests that reputation can provide early signs of credit risk and bank failure.

When reputation is not strong due to scandals or investigations, uncertainty and panic can cause bank runs that might be severe enough to lead to credit risk and the failure of a bank. Hence, reputation plays a central role in bank runs and has spillover effects on other types of risks, indicating that it can be used as an important indicator for the scope and severity of a bank failure.

2.3. Herding Behavior and Informational Cascades

Herding behavior and information cascades are key concepts in behavioral finance. As described by Banerjee (1992, p. 798), herding behavior refers to individuals following the action of others, regardless of their own personal information and opinions. The study suggests that even if a person has private information, they might choose what the previous person or majority has chosen and therefore "join the herd" (Banerjee, 1992, p. 799).

Informational cascades, on the other hand, explain how a small amount of new information can influence decisions and form suspicions (Bikhchandani et al., 1992, p. 994). Bikhchandani et al. (1992, p. 994) developed a model that illustrates how small shocks can result in large shifts in behavior and opinions. Their study shows that individuals are likely to ignore their own signals and act accordingly to any new information (Bikhchandani et al., 1992, p. 994).

Moreover, Bikhchandani et al. (1998, p. 168) describes informational cascades as "pervasive but fragile herd behavior," meaning that such behaviors spread across individuals but are sensitive to any new information. Moreover, the authors mention that collective behavior/actions such as bank runs can be classified as informational cascades since they are vulnerable to shocks and often get triggered by new information (Bikhchandani et al., 1998, pp. 167-168).

Building on these theories, exposure on social media has played a significant role in recent financial crises. Evidence from the collapse of Silicon Valley Bank (SVB) in early 2023 illustrates the importance of social media on the effect of bank runs (Cookson et al., 2026, p. 1). The wide and rapid spread of information on social media about the possibility of SVB's failure on the platform X (formerly known as Twitter) contributed to a rapid withdrawal of deposits and increased concerns about spillover effects on other banks and industries (Cookson et al., 2026, p. 1). Exposure on social media might therefore trigger bank runs not only at the bank expected to fail, but also at other banks, especially the ones with "large market-to-market losses and a large percentage of uninsured deposits" (Cookson et al., 2026, p. 23).

Similarly, other empirical evidence shows that social media influenced bank runs in both the U.S. and in Europe, including the collapse of three large banks in the U.S. and the failure of Credit Suisse (Dosumu et al., 2023, pp. 1-3). The negative effects were reflected in stock market returns and spillover effects on other sectors in Europe (Dosumu et al., 2023, p. 3). A similar study conducted by Chernykh et al. (2023, p. 1) showed the relationship between financial stability and public confidence in Russian banks. The authors found that bank-level measures, including Public Confidence in Bank Rate (PCBR), do not independently explain public confidence or its relation to bank failures (Chernykh et al., 2023, p. 2). This is because depositors are unlikely to track financial statements and annual reports. Instead, they are more likely to follow bank-related information on social media and news reports (Chernykh et al., 2023, p. 13). Therefore, exposure on news articles and social media can be a relevant indicator for corporate reputation.

Herding behavior and information cascades theories help explain why confidence can deteriorate quickly and spread across individuals. New information on social media or in the news might trigger panic and despite having private information, depositors might withdraw funds due to uncertainty. As a result, if one depositor withdraws funds, others might follow, causing severe bank runs. Moreover, empirical evidence suggests that social media has a significant influence on bank runs, exposing financial institutions to credit risk. This can be another important reason why reputation should be one of the key measures in credit ratings and shows that exposure on social media/internet can be a way of measuring corporate reputation which acts as early signals of financial stress and credit risk.

2.4. Asymmetric Information and the Signaling Theory

Asymmetric information is one of the main concerns of many different stakeholders. Akerlof (1970, p. 489) explains asymmetric information with the famous “lemons” example that describes a faulty car. Akerlof (1970, p. 489), in his study, argues that a car buyer does not have sufficient information before the purchase on whether the car is good or faulty, unlike sellers that know more about the car. As a result, asymmetric information arises where sellers know more than buyers, allowing them to sell faulty cars at the same price as good-quality cars (Akerlof, 1970, p. 489). This then leads to a situation where sellers only sell faulty cars because they are better off selling lower-quality products for a higher price, which is a direct consequence of asymmetric information (Akerlof, 1970, pp. 489-490).

Banks possess more detailed information about their risk exposures and financial performance than investors and depositors which then results in asymmetric information. Calomiris and Gorton (1991, p. 111) argue that when depositors do not have sufficient information about a bank's portfolio, they are likely to withdraw deposits if they expect the bank to fail. This can also be related to information cascades as when depositors do not have enough information, any new signal can trigger panics and stress. As they receive this information, depositors might not know which banks will be affected and therefore, withdraw funds from different banks (Calomiris & Gorton, 1991, p. 124), suggesting a spillover effect across institutions. This explains why bank runs and consumer trust is important for all financial institutions as financial stress in one bank can lead to problems for other banks, including subsidiaries of that bank.

Additionally, the signaling theory as described by Spence (1973, p. 357) introduces signals as noticeable indicators that can be adjusted by the party sending them. In the cases of asymmetric information, signals provide insight to a situation which gets updated as new information arrives (Spence, 1973, pp. 357-359). Corporate reputation can be seen as a signal of a firm’s activity (Fombrun & Shanley, 1990, p. 234) as it is observable and is subject to changes depending on firms’ activities and behavior. Using reputation as a signal, the severity of reactions from stakeholders might change with availability of new information, under periods of uncertainty and lack of perfect information. This also suggests that any new information might trigger bank runs, especially if the scandals are severe and impact the bank's activities. Therefore, involvement in scandals and investigations might damage corporate reputation which can trigger bank runs and lead to an exposure of credit risk.

Similarly, credit ratings can be used as a signal as it provides useful information about a firm's creditworthiness. Due to the asymmetric information surrounding banks, depositors, investors and regulators might depend on external rating agencies to monitor banks and assess credit risk. However, whether credit ratings are associated with different aspects of reputation that can influence credit ratings is the main question of the study. Regardless, the Basel II framework, specifically the first pillar on minimum capital requirements, relied heavily on credit rating agencies.

2.5. Basel Frameworks

The Basel Committee on Banking Supervision (BCBS) was established to improve regulation, supervision and the overall soundness of financial institutions (Basel Committee on Banking Supervision, 2018a).

The Basel framework is important for financial stability and covers risks that banks face. Basel frameworks, especially Basel II, use external credit ratings as a measure of credit risk. Therefore, the accuracy and validity of ratings are important not only for regulatory capital requirements but also for investors, depositors and stakeholders.

2.5.1. Basel II Framework

Basel II Framework was designed in 2004 by the BCBS and further developed the Basel I Framework, implemented in 1988, which primarily focused on capital requirements and credit risk measurements (European Central Bank, 2004, p. 139). The Basel I framework followed a simple standardized approach and required banks to hold 8% of Risk-Weighted Assets (RWA) using on four risk-weights: 0%, 20%, 50% and 100%, depending on the category of the debt (European Central Bank, 2004, p. 139).

However, the standardized approach assumed identical credit risk within the given category and ignored individual differences across borrowers, while also insufficiently assessing other risks banks face (European Central Bank, 2004, p. 139). Consequently, BCBS introduced the Basel II framework, which focused on three pillars (Basel Committee on Banking Supervision, 2006, p. 2):

1. Minimum capital requirements
2. Supervisory review
3. Market discipline

The first pillar addresses credit, operational and market risks. The pillar defines regulatory capital requirements and introduces a capital ratio which must be equal or greater than 8% of RWA and defines Tier 1 and Tier 2 capital, where Tier 2 capital cannot exceed Tier 1 Capital (Basel Committee on Banking Supervision, 2006, p. 13).

Two approaches are introduced: The Standardized Approach and Internal Ratings-Based (IRB) Approach (Basel Committee on Banking Supervision, 2006, p. 19). The IRB

Approach allows banks to develop their own credit risk rating models after being approved by supervisors (Basel Committee on Banking Supervision, 2006, p. 19). The IRB Approach focuses on probability of default (PD), loss given default (LGD), exposure at default (EAD) and maturity of the exposure (European Central Bank, 2004, p. 141).

In contrast, the Standardized Approach relies on external credit ratings agencies and applies different risk-weights depending on the external rating of the counterparty, suggesting that regulatory capital becomes directly dependent on these ratings (Basel Committee on Banking Supervision, 2006, pp. 19-23).

The second pillar focuses on the importance of supervisory review and addresses the importance of supervision, risk assessment and internal management control (Basel Committee on Banking Supervision, 2006, pp. 205-207). Moreover, the pillar mentions the risks faced by banks:

- ❖ Credit risk
- ❖ Operational risk
- ❖ Market risk
- ❖ Interest rate risk
- ❖ Liquidity risk
- ❖ Other risks that include risks such as reputational and strategic risks.

The BCBS states that risks such as reputational and strategic risks are difficult to measure and require further development and research (Basel Committee on Banking Supervision, 2006, p. 208). This suggests that although reputational risk is recognized, it is not quantified as a part of the regulatory capital.

The third pillar introduces disclosure requirements and focuses on transparency. Its main objective is to support Pillars 1 and 2 through disclosure requirements regarding capital adequacy, risk exposures and risk processes (Basel Committee on Banking Supervision, 2006, p. 226). Pillar 3 suggests that stakeholders use disclosed information to evaluate banks. Therefore, transparency is important not only for regulatory purposes, but also for reducing asymmetric information for stakeholders.

2.5.2. Basel II and the Global Financial Crisis

Basel II relied heavily on credit ratings from agencies such as Fitch Ratings, Moody's and S&P. The weaknesses of this reliance were that ratings are generally subjective toward counterparty risk, differ depending on the agency's method of measuring credit risk and under Basel II, unrated institutions were assigned a default risk-weight (Van Roy, 2005, p. 5).

Additionally, the Financial Crisis Inquiry Commission (2011, p. xxv) stated that "the three credit rating agencies (Fitch Ratings, Moody's and S&P) were key enablers of the financial meltdown," as highly rated securities were considered low-risk and investors along with regulatory capital heavily relied on these ratings. Although this is stated mainly for credit ratings on securities, it still suggests that credit ratings might not always be a reliable measure of credit risk, particularly as they may not be sufficiently forward-looking to account for panics and financial stress.

Moreover, the lack of transparency of financial institutions and the collapse of major banks caused panic and uncertainty among investors and depositors, which then spread across other financial institutions that were considered stable and “too big to fail” (Financial Crisis Inquiry Commission, 2011, p. xvi). This suggested that the crisis was not an outcome only based on balance sheet activities and operational structures, but also from the loss of public confidence and panic across stakeholders.

2.5.3. Basel III

Under Basel III, credit risk and capital requirements are established under two approaches: Standardized Credit Risk Assessment Approach (SCRA), applied to unrated banks and banks in countries that do not allow external ratings and External Credit Risk Assessment Approach (ECRA) that applies risk-weights based on rating from external agencies (Basel Committee on Banking Supervision, 2017b, pp. 7-8). ECRA suggests that Basel III continues to rely on external ratings for regulatory purposes.

However, in response to the Global Financial Crisis, Basel III introduced an eligibility criteria for external credit assessment institutions (ECAI) where only the agencies that fulfill the standards of objectivity, independence, transparency, disclosure and credibility are recognized (Basel Committee on Banking Supervision, 2017b, pp. 28-29). This shows that Basel III regulations aim to strengthen the transparency and credibility of external ratings used for regulatory capital.

Moreover, Basel III framework introduced new key measures for regulatory capital to strengthen capital adequacy (Basel Committee on Banking Supervision, 2017b, pp. 137). These include:

- ❖ Tier 1 Capital of a minimum 6% of RWA
- ❖ Total Capital of a minimum 8% of RWA

Considering that the Global Financial Crisis exposed limitations in liquidity risk measures, Basel III introduced the following ratios: Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR) (European Central Bank, 2010, p. 129). LCR measures the short-term liquidity of banks that is required to survive financial distress while the NSFR measures the long-term liquidity through assets that are financed through liabilities or equity (European Central Bank, 2010, pp. 129-130).

In Basel III, Expected Credit Loss (ECL) is mentioned in detail. ECL is introduced by the International Financial Reporting Standard 9 (IFRS9) and is a forward-looking measure for expected losses that is constructed using past and current events, along with predicting losses that might arise in the future (Basel Committee on Banking Supervision, 2017a, p. 1). ECL framework has three stages and total ECL is constructed by adding all three stages that include 12-month ECL and lifetime ECL (Basel Committee on Banking Supervision, 2017a, pp. 1-2). ECL can be used to measure how an asset’s credit risk changes (Basel Committee on Banking Supervision, 2017a, p. 1) and therefore can be used to measure asset quality in terms of risk.

Basel regulations introduce many different indicators and ratios for measuring a bank’s credit risk, including RWA, Tier 1 Capital, ECL, LCR and NSFR. However, it can be concluded that the indicators mainly focus on financial measures with very limited focus on corporate reputation. Basel Regulations also suggest the importance of credit ratings and their role in regulation, which also primarily focus on financial measures.

2.6. The Fitch Rating Criteria Framework

According to Fitch Ratings, credit ratings solely focus on credit risk and do not assess other types of risk such as interest rate risk or liquidity risk (Fitch Ratings, 2025a, pp. 2-3). However, credit ratings measure different dimensions such as liquidity, profitability and capital that influence credit risk.

Fitch Ratings provides a detailed Banking Rating Framework that outlines the central dimensions used to evaluate a bank's credit risk (Fitch Ratings, 2024, p. 1), see Table 2 below:

Table 2: Fitch Ratings Criteria Dimensions

Dimension	Description
Operating Environment (OE) Score	Measure the risk of the bank's business environment
Key Rating Drivers (KRDs)	Evaluate both quantitative and qualitative factors, including: 1. Asset Quality: Measured by Non-Performing Loan (NPL) ratio that is impaired loans divided by gross loans 2. Earnings and Profitability: Measured by Operating profit/RWA 3. Capitalisation and Leverage: Measured by Core Capital Ratio (Tier 1 Ratio)
Viability Rating (VR)	Measure the credit profile of a bank that primarily focuses on indicators introduced under Basel III regulations

(Source: Fitch Ratings, 2024, p. 1)

While financial factors are evaluated in detail, there are no individual and specific dimensions that measure confidence and reputation. In addition, the BCBS states that "the revised standards (in Basel III) will make banks more resilient and restore confidence in banking systems" (Basel Committee on Banking Supervision, n.d.), suggesting that enhancing stability and soundness of financial systems would strengthen consumer trust. However, considering the severity of bank runs and the behavioral theories and studies behind it, financial ratios might not be sufficient to address confidence.

Based on the bank run theory, behavioral finance, asymmetric information and signaling theory, along with the overview of the dependence of Basel II on credit ratings, information availability and transparency play an important role for stakeholders since uncertainty can trigger panic and bank runs.

Credit ratings can be used to reduce asymmetric information as it provides additional information for risk exposure. However, they might not include the early signs of collapse that corporate reputation captures. Credit ratings mainly focus on financial stability and do not independently measure public trust and reputation, even though a deterioration in these dimensions can trigger severe bank runs. As a result, it is important to investigate whether credit ratings are associated by reputational factors.

2.7. Evidence from European Bank Collapses and Scandals

Over the years, numerous European banks have experienced bank failures and scandals. These examples show that different underlying issues such as repeated scandals, governance issues, geopolitical tensions and legal problems lead to uncertainty and trigger bank runs. This exposes the banks to liquidity and solvency risk which as a result, spills over to credit risk.

1. Credit Suisse

The collapse of Credit Suisse in March 2023 is considered to be the first large bank failure since the Global Financial Crisis in 2007-2009 (Stuart, 2023). Credit Suisse was one of the largest banks in Switzerland and collapsed due to poor governance and multiple scandals that deteriorated the bank's reputation and led to a loss of confidence (Swiss Financial Market Supervisory Authority FINMA, 2023).

The Swiss Financial Market Supervisory Authority, FINMA, reported that "owing to the inadequate implementation of its strategic focus areas, repeated scandals and management errors, Credit Suisse lost the confidence of its clients, investors and the markets. The resulting high level of withdrawals of client funds led to the risk of immediate insolvency in mid-March 2023" (Swiss Financial Market Supervisory Authority FINMA, 2023).

After a journalist made a social media post about Credit Suisse being close to a collapse, consumers withdrew their deposits quickly and the share price declined rapidly (Stuart, 2023). Even though the bank met the regulatory requirements concerning liquidity in 2022, the damage to reputation exposed the bank to a collapse (Swiss Financial Market Supervisory Authority FINMA, 2023).

Credit Suisse is an example of governance issues increasing reputational risk and how it can lead to credit risk even though the bank meets the regulatory requirements. This also reflects that reputational risk increases over time with repeated scandals and exposes banks to credit risk due to bank runs.

2. Sberbank CZ

Sberbank CZ was the tenth largest bank in the Czech Republic and a subsidiary of a Russian bank (Polach & Chalupa, 2025). The bank collapsed and filed for bankruptcy in the first half of 2022 due to the Russia-Ukraine war affecting consumer trust, leading to insolvency and credit risk (Polach & Chalupa, 2025).

The Czech National Bank, CNB, reported that Sberbank CZ faced serious liquidity issues due to the worsening situation of the geopolitical tensions between Russia and Ukraine which caused rapid withdrawal of deposits (CNB, 2022). Moreover, in the beginning of 2022, the U.S. imposed sanctions on two of Russia's largest banks, including Sberbank and its subsidiaries, in response to Russia's attacks on Ukraine (U.S. Department of the Treasury, 2022). Consequently, the rapid withdrawals of deposits resulted in liquidity problems, which then led to Sberbank CZ being unable to meet its obligations (Polach & Chalupa, 2025).

Sberbank is an example of how external geopolitical tensions can lead to a loss of confidence. Consequently, this exposes the bank to credit risk. This case shows that while a bank might not have any visible financial issues, increasing exposure related to reputation can trigger financial distress caused by a rapid withdrawal of deposits.

3. ABLV Bank

ABLV Bank, one of Latvia's largest banks, collapsed in 2018 after the U.S. Treasury announced serious money laundering concerns which quickly led to a withdrawal of deposits (Coppola, 2018).

On the 16th of February 2018, the U.S. Treasury Department's Financial Crimes Enforcement Network (FinCEN) published a notice stating its findings on money laundering concerns related to ABLV Bank (U.S. Mission Latvia, 2025). This notice resulted in strong liquidity issues due to the immediate withdrawal of deposits (European Central Bank, 2018). Consequently, one week later, on the 23rd of February 2018, the European Central Bank (ECB) stated that ABLV Bank is close to failing (European Central Bank, 2018).

The collapse of ABLV Bank demonstrates that a financial institution's activities must be transparent, as a lack of transparency can expose it to money laundering or similar concerns that can damage its reputation.

The cases of Credit Suisse, Sberbank CZ and ABLV Bank clearly show that different risks such as governance, geopolitical and legal issues can significantly deteriorate consumer trust. When reputation is damaged, the banks face liquidity risk due to the rapid withdrawal of deposits. This then results in credit risk as the bank is likely to default due to bank runs. Based on these examples and theoretical reasoning discussed in previous sections, it can be concluded that reputation develops over time, acting as a signal of potential bank failure and credit risk as new information becomes available.

2.8. Theoretical Framework and Hypothesis

As discussed in the previous sections, there are many theories and studies on bank runs and its severity. However, when assessing credit risk, corporate reputation does not play a significant role. This suggests a research gap between the importance of reputation and the way of assessing credit risk.

The bank run theory developed by Diamond and Dybvig (1983, pp. 401-403) explains what bank runs are and why they should be important for banks' risk exposures as they have severe spillover effects on other types of risk.

The behavioral finance theories including herding behavior and informational cascades developed by Banerjee (1992, pp. 798-799) and Bikhchandani et al. (1992, p. 994; 1998, pp. 167-168) explain behavioral mechanisms that can cause bank runs, exposing banks to vulnerability. The empirical evidence from other studies shows the effect of social media on the availability and spread of new information and how that information might trigger bank runs (Cookson et al., 2026, p. 1; Dosumu et al., 2023, p. 1). This indicates that market attention and scandal intensity might reflect reputation. As a result, the study will measure reputation through Search Interest Volatility to measure fluctuations in market attention and Scandal Severity to capture how severe new information might be.

The asymmetric information theory explained by Akerlof (1970, pp. 489-490) and Calomiris and Gorton (1991, p. 111) illustrates that two parties having different levels of information can lead to uncertainty and as a result trigger bank runs. This was further supported in the signaling theory, explained by Spence (1973, pp. 357-359), as in certain situations where uncertainty or asymmetric information are present, signals provide new perspectives and affect the available information. Because of the uncertainty around banks, credit ratings play a central role in adding additional information for stakeholders and regulators.

However, as shown in the statements from the Financial Crisis Inquiry Commission (2011, p. xxv), credit ratings might not be a fully sufficient and reliable measure. Moreover, the Basel II Framework suggests that reputation is not fully developed (Basel Committee on Banking Supervision, 2006, p. 208) while Fitch Rating Criteria shows that reputation is not a specific dimension (Fitch Ratings, 2024, pp. 1-2), suggesting a research gap with the theories and literature discussed. Therefore, the study aims to contribute to the research gap by providing empirical evidence on whether reputational factors provide explanatory value to credit ratings of banks.

Consequently, the study answers the research question: "To what extent do corporate reputation indicators provide additional explanatory value for credit ratings, beyond traditional financial indicators, among the largest European banks during 2018-2024?"

To answer the research question, the study formulates the following hypotheses:
H_a: Corporate reputation indicators, Search Interest Volatility and Scandal Severity, provide additional explanatory value for credit ratings, beyond financial indicators.

H_0: Corporate reputation indicators, Search Interest Volatility and Scandal Severity, do not provide additional explanatory value for credit ratings, beyond financial indicators.

Where:
H_a: Alternative hypothesis
H_0: Null hypothesis

3. Theoretical Methodology

The Theoretical Methodology Chapter outlines the study's research philosophy, approach and strategy, while comparing and evaluating other methods. Then, the literature and data collection sources are evaluated in terms of relevancy, transparency and reliability. Moreover, different sampling methods are discussed which sets an outline for the next chapter.

3.1. Research Philosophy

This thesis is based on critical realism. Critical realism means that reality exists whether we observe it or not, but the understanding of reality is never complete and is always shaped by theory (Lauzier-Jobin et al., 2022, pp. 4-6). This is suitable for the thesis since the study looks at observable indicators, such as financial measures and reputation-related proxies, while also recognizing that these indicators do not fully explain bank risk on their own. Instead, they can be seen as signs of deeper processes linked to reputation and financial vulnerability (Easton, 2010, pp. 119-120).

The ontological position is about how reality is understood. In social research, two common positions are objectivism and constructionism. Constructionism puts more emphasis on how reality is shaped through social interaction (Bell et al., 2022, pp. 27-30). This thesis is closer to a critical realist ontological position, since it assumes that there are underlying structures and mechanisms beyond what can be directly observed, even if they are not always fully visible (Lauzier-Jobin et al., 2022, pp. 4-5). In this study, bank risk is not seen as something that can be fully captured by one variable on its own. Measures such as capital and liquidity ratios, along with reputation-related indicators are therefore treated as observable signs of broader underlying conditions rather than full explanations by themselves (Easton, 2010, pp. 119-120).

The epistemological position then concerns how that reality can be understood. This thesis does not follow a strictly positivist view where knowledge is treated as fully objective and final (Bell et al., 2022, pp. 30-34). Instead, knowledge is seen as partly theory-informed and open to revision (Lauzier-Jobin et al., 2022, p. 6). This means that empirical analysis can identify patterns, but theory is still needed to help explain what those patterns may reflect. For this thesis, that matters because the study is not only interested in whether statistical relationships exist, but also in whether those relationships may reflect deeper mechanisms discussed in the Theoretical Framework, such as bank runs (Easton, 2010, pp. 119-120).

This also links to the axiological position, which is about the role of values and judgments in research. The thesis recognises that research is not completely value-free (Lauzier-Jobin et al., 2022, pp. 7-8). The choice to study reputation-related indicators together with traditional financial measures already reflects a judgment that standard approaches may not capture all relevant parts of bank risk. At the same time, the study still aims to be systematic and transparent in how variables are selected, how data is collected and how findings are interpreted. Therefore, the point is not to remove all judgment, but to make the important choices clear and well grounded (Lauzier-Jobin et al., 2022, pp. 7-8).

Together, this makes critical realism a suitable foundation for the thesis. It allows the study to combine quantitative empirical analysis with theoretical interpretation

(Lauzier-Jobin et al., 2022, pp. 6-7). The thesis uses structured numerical data to examine whether reputation-related indicators provide additional explanatory value beyond traditional financial indicators, but it does not treat the statistical results as complete explanations on their own. Instead the findings are interpreted as possible signs of deeper mechanisms affecting credit risk and stability (Easton, 2010, pp. 119-120).

3.2. Research Approach

This thesis mainly follows a deductive research approach. This means that the study starts from an existing theory and then uses empirical analysis to examine whether the expectations developed from that theory are supported by the data (Lo et al., 2020, p. 221). A deductive approach is suitable for this thesis as the purpose is not to create a completely new theory, but to examine whether reputation-related indicators may provide additional explanatory value beyond traditional indicators when analysing credit risk. The thesis therefore begins with the Theoretical Framework and uses it as a basis for forming expectations that can later be tested with observable data.

More specifically, the study builds on theory related to credit risk, information asymmetry and reputation in financial markets as discussed in Chapter 2. Akerlof (1970, pp. 488-490) explains that information asymmetry can arise when one party has more information than another. Calomiris and Gorton (1991, pp. 124-127) explain that when depositors and investors cannot fully observe bank-specific risks, reactions to new information may contribute to withdrawals of funds and broader financial instability. Other theories also suggest that new public information can influence how people react during periods of uncertainty. Especially when individuals begin to follow the behavior and reactions of others instead of relying on their own information (Bikhchandani et al., 1992, pp. 992-995). Signaling theory also suggests that publicly available information and signals may influence how stakeholders view risk and financial stability (Spence, 1973, pp. 355-359). Based on these theoretical starting points, the thesis develops expectations about the association between reputation indicators and selected measures of credit risk. These expectations are then translated into measurable variables and tested through empirical analysis.

Moreover, the deductive approach in this thesis is shaped by the critical realism position presented in the previous section. From that perspective, theory testing is not only about identifying statistical relationships, but also about considering whether the findings may reflect deeper underlying mechanisms. Miller and Tsang (2010, p. 139) argue that theory testing should not rely only on statistical relationships. They also stress that researchers should consider whether the suggested mechanisms appear to work in the expected way (Miller & Tsang, 2010, p. 147). They also point out that empirical support does not provide complete certainty, since theory testing remains provisional rather than final (Miller & Tsang, 2010, p. 140).

In this thesis, that means the findings are interpreted in relation to the wider Theoretical Framework instead of being treated as complete explanations on their own. Even though the thesis is mainly deductive, there is still a limited inductive element in the interpretation of the findings. During the empirical analysis, patterns may appear that were not fully expected from the beginning and if that happens, the theoretical interpretation may need to be adjusted in light of the results. But this still remains secondary, since the main direction of the study is deductive and the hypotheses are derived from existing theory and then tested empirically. Therefore, a deductive approach suits the thesis because it allows the study to move from theory to measurable expectations and then to empirical testing in a structured way.

3.3. Research Strategies

This thesis follows a quantitative research strategy. This means that the study uses structured, numerical data to examine associations between measurable variables. A quantitative strategy fits this thesis because the purpose is to examine whether reputation-related indicators provide additional explanatory value beyond traditional financial indicators when analysing credit risk. The research strategy therefore gives the study a practical structure and helps connect the Theoretical Framework to the empirical analysis (Fletcher, 2017, pp. 181-182). Since the thesis looks at observable indicators across a sample of banks over several years, a quantitative strategy makes it possible to examine these relationships in a structured and comparable way (Demirbaga, 2024, pp. 292-294).

A quantitative strategy is also suitable because the thesis uses both numerical and ordinal variables collected across banks and over time. These include financial ratios, credit ratings and reputation-related proxies. This makes it possible to examine whether the selected reputation indicators are associated with credit ratings while traditional financial indicators are included in the analysis. Quantitative methods are mainly used in finance and accounting research when relationships between risk-related variables are analyzed across companies and time periods (Hasan et al. 2023, pp. 1-3). The strategy also allows the study to apply statistical analysis in a structured and transparent way (Cheng & Neamtiu, 2009, pp. 108-110).

3.4. Literature Sources

When reviewing literature, theories and methods, one of the first key steps is to identify keywords (Creswell & Guetterman, 2021, pp. 106-107). For the thesis, the main keywords included:

- ❖ Credit ratings
- ❖ Corporate Reputation
- ❖ Bank Runs
- ❖ Bank Run Theory
- ❖ Behavioral Finance
- ❖ Asymmetric Information
- ❖ Signaling theory
- ❖ Social Media
- ❖ News exposure

The other steps include, finding good-quality, reliable and relevant sources using the key terms listed (Creswell & Guetterman, 2021, pp. 106-108). The thesis includes journal articles found in Umeå University’s Library or articles from journals listed in the ABS Journal Ranking System. The literature is peer-reviewed, allowing for reliable information.

The theories used for the Theoretical Framework are also obtained from journal articles listed in the ABS Journal Ranking System. For reviewing real-life bank examples in the Theory Chapter, the government published reports and news articles were used, which give a balanced discussion on real-life events while also acknowledging that information on news articles might not be reliable. However, news sources were only used for reflecting the information that spread out to the public and were not included for constructing the theory or methodology of the thesis.

Moreover, the Methodology Chapter includes articles found in Umeå University's Library and ABS Journal Ranking system, along with course literature and textbooks. The sources were carefully evaluated, making sure they are peer-reviewed and relevant for the thesis.

3.5. Data Collection Sources

Data collection sources can depend on whether the study adopts quantitative or qualitative research strategies. Quantitative studies include numerical data for conducting data analyses while qualitative studies focus on data that is not numerical (Collis & Hussey, 2021, p. 6). The data can be primary data where it is collected directly from the main source or secondary data where other already established sources are used (Collis & Hussey, 2021, p. 20).

Qualitative data allow interpretations using a given context which ensures that the study focuses on the event being investigated (Collis & Hussey, 2021, p. 117). This can make the data collected more focused and relevant to the research topic. However, it might limit generalizability, which refers to how applicable the results of the study are to other populations (Collis & Hussey, 2021, p. 48). Quantitative data, on the other hand, are collected from different periods and settings (Collis & Hussey, 2021, p. 117). This allows comparisons across time or within subjects and can be used to investigate multiple entities over time.

Considering this, the data collection source most relevant for this study is secondary quantitative data. The dependent variable, credit ratings, is obtained from Fitch Ratings for the years 2018-2024. Fitch Ratings is one of the credit rating agencies that provides credit ratings used under Basel Frameworks. It is accessible for the public, making data collection for the sample more consistent and reduces the possibility of missing data.

The independent variables, Search Interest Volatility and Scandal Severity, are obtained from Google Trends and news sources, including the Financial Times and Reuters. These proxies illustrate how stakeholders are exposed to information about banks, which might influence their view of the bank's reputation. While qualitative primary data sources could provide a more personal and direct view of stakeholders' opinions, collecting such data for multiple European banks would be limited by access, scope and time availability. Therefore, secondary quantitative data enables broader and more consistent data availability in a way that can measure stakeholders' exposure to new information across countries.

In addition, the study includes control variables including credit risk measures such as Return on RWA (RoRWA), Tier 1 Ratio, ECL Ratio, LCR and total assets that are collected from annual reports, registration documents and Basel III regulatory disclosure reports of the banks in the sample. Including credit risk measures as control variables, allows the study to test whether credit ratings are associated with reputation, beyond credit risk measures.

3.6. Sampling Methods

For data collection, different sampling methods include random sampling and non-random sampling. Random sampling ensures that all subjects have equal chance of selection, reducing biases and improving generalizability (Collis & Hussey, 2021, p. 185). The different random sampling methods include the following:

- ❖ Simple random sampling where every subject in the population has the same chance of being selected, reducing bias and giving each subject a chance (Agresti, 2018, pp. 26-27).
- ❖ Systematic sampling randomly chooses a subject in the population and uses fixed intervals to choose other subjects which can impose biases and underrepresentation issues if there is a set order (Collis & Hussey, 2021, p. 185).
- ❖ Stratified sampling divides the population into groups based on characteristics. Then, the percentage that each group or strata makes up within the population is calculated and subjects are randomly selected until the required number is reached, reducing underrepresentation issues (Collis & Hussey, 2021, p. 186).
- ❖ Cluster sampling involves randomly selecting entire groups from the population instead of sampling individual groups which is beneficial in studies with limited time (Collis & Hussey, 2021, p. 187).

In contrast, non-random sampling methods focus on accessibility which limits generalizability (Collis & Hussey, 2021, p. 118). The different non-random sampling methods include:

- ❖ Volunteer sampling refers to individuals volunteering to be a part of the sample which can cause under-representation as volunteers might not represent the population accurately (Agresti, 2018, p. 30). However, this method increases availability of data as volunteers choose to participate and can be relevant if the study aims to investigate a specific part of the population.
- ❖ Networking uses researcher contacts to collect data, allowing for accessibility (Collis & Hussey, 2021, p. 118). This method can also result in under-representation and only focuses on the researchers' environment. However, different settings can be achieved and the researcher can get contacts that might be valuable for the investigation.
- ❖ Snowball sampling is finding an individual in the sample and asking them if they have any contacts with similar characteristics or experience (Collis & Hussey, 2021, pp. 118-119), prioritizing accessibility.
- ❖ Purposive sampling focuses on finding subjects related to a specific characteristic or experience. (Collis & Hussey, 2021, p. 119). It can be useful for when researchers are aiming to investigate a specific and focused sample.

Based on these methods, it can be concluded that non-random sampling is mainly used to investigate specific populations that are most relevant for the study, while also accounting for accessibility and availability.

Considering that the study adopts a quantitative, deductive approach, random sampling methods might be better for generalizability and reliability purposes. However, since the study focuses on Fitch credit ratings and therefore, chooses the sample based on whether the large European banks are rated by Fitch Ratings during 2018-2024, purposive sampling is the most suitable for this study. While the sampling method limits generalizability, it ensures that the study can collect credit ratings data for all banks. This allows the study to conduct a focused study that uses the most relevant subjects in order to answer the research question.

4. Practical Methodology

The chapter starts with introducing the population, sample and the time horizon of the study. Then, the dependent, independent and control variables are constructed with explanations on what they measure, their purpose and limitations. Moreover, the model of the thesis is discussed, followed by explanations on data validity issues such as endogeneity, reverse causality, heteroskedasticity, autocorrelation and multicollinearity. Finally, reliability, validity and ethical considerations of the study are explained, with a section on the use of Artificial Intelligence.

4.1. Population and Sample

Population refers to the main group investigated for a study, while a sample is a smaller section of that population (Collis & Hussey, 2021, p. 46). For the thesis, the population consists of the 50 largest European banks by total assets in 2024, categorized by S&P (Mones & Hayes, 2024). This ensures that the study focuses on banks that have large scale activities which are more likely to have all the data required for constructing the study, such as being rated by Fitch Ratings during the whole time horizon and disclosing the required regulatory information.

The sample of the study consists of 37 banks from the chosen population that have been rated by Fitch Ratings between 2018 and 2024, see Appendix 1. The sample includes banks with a variety of credit ratings, ranging from AAA to B-. While the variety of ratings might strengthen the generalizability of the study, purposive sampling might introduce sampling biases and limit the application of the results to other populations. The study acknowledges that there might be generalizability limitations, however, the results can still be applicable for testing the association between credit ratings and reputation indicators.

Moreover, the variables form a panel data, as it includes observations across multiple banks over a given time horizon (Stock & Watson, 2015, p. 397). Although 37 banks might be considered a small sample, it yields 259 observations which can be used to form conclusions about associations between variables and answer the research question.

4.2. Time Horizon

According to the Theory Chapter, periods of increased uncertainty might raise stakeholders' sensitivity to new information and potentially trigger bank runs. To account for this effect, the study examines the period 2018 to 2024, which includes both pre and post COVID-19 pandemic years, representing uncertainty shocks related to the pandemic.

This time horizon allows for an analysis of how new information, in periods of uncertainty, might affect confidence and trust of stakeholders in banks. By including both pre and post shock effects, the study can also take into account the effect of availability and severity of new information through reputation indicators during periods of stability and financial stress.

4.3. Dependent, Independent and Control Variables of the Study

There are different types of variables, including discrete and continuous variables. Discrete variables take specific and separate values while continuous variables can take decimal values (Agresti, 2018, p. 25). The different variables and their measurement methods include the following:

- ❖ Ratio variables are measured on a numerical scale with consistent intervals (Collis & Hussey, 2021, p. 187). This allows for accurate comparisons across observations.
- ❖ Interval variables specify an interval scale and group the variables based on this scale (Collis & Hussey, 2021, p. 188). This can be practical if there are many interval groups, however, it reduces accuracy as it groups variables with different values.
- ❖ Ordinal variables are categorical variables where the observations are coded or ranked numerically (Collis & Hussey, 2021, p. 188). This method transforms categorical observations into numerical values, but it can impose biases and subjectivity if the identification method is not clear.
- ❖ Nominal variables categorize observations using codes for specific names. (Collis & Hussey, 2021, p. 188). While this is a simple way of identifying the observations, the categories might be interpreted differently by respondents or researchers.

As a result, the most suitable choices for the variables include discrete, ordinal variables for credit ratings and Scandal Severity, as they are based on transforming categories into numerical values based on criteria. Then, continuous, ratio variables are used for Search Interest Volatility and all of the control variables as they are measured on a numerical scale. The sections below further discuss the variables with their purposes and limitations, also considering the different types of measurement methods.

4.3.1. Dependent Variable

The dependent variable, credit ratings, is derived from Fitch Ratings for each bank in the sample, between 2018-2024, allowing for accessibility of data for the banks within the chosen time horizon. Fitch Ratings provide 20 categories for credit ratings as shown in the following table:

Table 3: Long-term Ratings based on Fitch Ratings

Rank	Rating	Rank	Rating
20	AAA	9	BB
19	AA+	8	BB-
18	AA	7	B+
17	AA-	6	B
16	A+	5	B-
15	A	4	CCC+/CCC/CCC-

14	A-	3	CC
13	BBB+	2	C
12	BBB	1	RD/D
11	BBB-		
10	BB+		

(Source: Fitch Ratings, 2025a, p. 11)

Credit ratings are discrete, ordinal values that are transformed into numerical values where each rating is assigned a number. This is a common practice in previous studies that use credit ratings as a variable and conduct regression analysis to examine a relationship/association between credit ratings and other variables (Baghai et al., 2014, p. 1965; Panta et al., 2023, p. 2; Sajjad & Zakaria, 2018, p. 16).

This method ensures easier interpretation of credit ratings, as it clearly assigns each rating a specific number and the ratings are in descending order where higher values represent better credit ratings.

A limitation of treating credit ratings as numerical variables is that differences between ratings are not equal. For example, the difference between AAA and AA+ is not the same as BBB- and BB+ or that a bank can be a high A+ while the other can be a low A+. However, to be able to conduct a regression analysis, the study assumes equal distances between different ratings.

4.3.2. Independent Variables

As mentioned in the Theoretical Framework section, availability of new information during periods of uncertainty can lead to severe bank runs which can affect credit risk. When measuring reputation, the study aims to replicate the different ways that stakeholders might receive new information about a bank that may influence their private information, potentially triggering panic.

Moreover, to minimize endogeneity and reverse causality, see Section 4.5., the reputation indicators are lagged by one year. To account for this effect, data for these indicators are collected between 2017 to 2023. One of the limitations of using annual data for the chosen reputation indicators is that corporate reputation can be considered as a fast-moving signal that captures shocks and fluctuations in firms' activities. As a result, data could have been calculated using quarterly or semiannually data to account for this effect. However, this would require all variables to be collected quarterly or semi-annually which would put a constraint on time availability and data accessibility. Therefore, the independent variables were collected annually.

1. **Search Interest Volatility**

To replicate how stakeholders might react to new and negative information, the first dependent variable is Search Interest Volatility using data from Google Trends. Google Trends can be used to measure how frequently a bank is researched. For the data collection, the name of the bank is searched on Google Trends by individually adding the three keywords "scandal," "investigation," and "failure" that captures the different negative aspects of reputational damages. Then, the volatility of monthly search interest for each year is calculated by taking the standard deviation of the values. Using the standard deviation rather than the yearly average allows for analyzing the fluctuations within each year and accounting for negative and damaging reputational events.

Moreover, Search Interest Volatility is a continuous, ratio variable as it can take decimal points and is based on a numerical scale of 0 to 100. The purpose of this independent variable is to measure the volatility of negative exposure of banks and account for the effect of potential new information that can lead to uncertainty and panic.

One limitation of using Google Trends is that not all stakeholders might be using Google to search for information. However, Google is widely used and has data availability, making the study replicable and consistent across banks. Another limitation is that Google Trends only provides monthly search interest when using data longer than 5 years. Nevertheless, monthly data will still provide insight on fluctuations, even though it is slightly broader than taking daily data. It is also important to add that only negative exposure of Search Interest Volatility is used and therefore, positive market attention is not included to ensure that the variable only focuses on information that might trigger panic.

2. Scandal Severity

Scandals are key contributors to reputational damage. In the study, banking scandals are defined as events related to a bank's operations, governance and regulatory alignment. These include unethical acts in the business environment and/or internal management conflicts, investigations, accusations, regulatory breaches and criminal charges. However, not all scandals have the same reputational effect. Unethical actions against employees might not trigger a bank run compared to if a bank was involved in fraud or money laundering investigations. Therefore, the severity of the scandals are measured to account for the impact of different scandals.

To measure severity, two news platforms are used: Financial Times and Reuters. Both sources are widely used news platforms that allow access to their archive with a list of articles, providing availability and coverage. One limitation is that Reuters only provides articles from 2020 and onwards. As a result, articles from 2017-2019 cannot be accessed through their archive. The articles from this period can still be reached through manual searches, however, for replicability and consistency, only articles from the archives were used. Nevertheless, Financial Times gives access to articles for the whole time horizon, allowing the study to have a source that covers all years. Despite this limitation, Reuters still provides valuable articles that contribute to the study.

Moreover, Scandal Severity is a discrete, ordinal variable as the severity is ranked between 0 to 5. For the ranks, the study constructs a Scandal Severity Criteria where different numerical values are assigned based on the severity of the reported scandal, see Table 4. The criteria is structured by gathering all scandals reported on Financial Times and Reuters, which allows the study to generate a set of categories that gathers the common scandals banks face.

Table 4: Scandal Severity Criteria

<table>
<tr><td>Rank</td><td>Description</td></tr>
<tr><td>0</td><td>No news exposure on Financial Times or Reuters that fits the criteria</td></tr>
<tr><td>1</td><td>If the article fits <u>one</u> of the two categories listed, it ranks 1:
1. Unethical acts against employees and customers, including:
a. Assault
b. Discrimination
c. Mistreatment
2. Internal management conflicts, including:
a. Lawsuits between employees
b. Lawsuits between employees and the bank</td></tr>
<tr><td>2</td><td>If the article fits <u>one</u> of the three categories listed, it ranks 2:
1. Accusations, warnings or threats of potential investigation or regulatory action related to:
a. Misconduct
b. Regulatory breaches including antitrust laws (bond cartels, market abuse)
c. Criminal activities
2. Ongoing investigations on activities, including:
a. Fraud
b. Money laundering
3. Setting a sum for a legal case
<u>Without a formal regulatory or legal outcome or official charges</u></td></tr>
<tr><td>3</td><td>If the article fits <u>both</u> of the categories listed, it ranks 3:
1. Confirmed regulatory actions, including:
a. Fines
b. Reprimands
c. Sanctions
d. Seizing assets
2. Related to regulatory and risk management controls, including:
a. Regulatory breaches including antitrust laws (bond cartels, market abuse)
b. Control failure
c. Lack of risk management procedures</td></tr>
<tr><td>4</td><td>If the article fits <u>both</u> of the categories listed, it ranks 4:
1. Confirmed regulatory or legal actions, including:
a. Fines
b. Penalties
c. Sanctions
2. Related to criminal activities, including:
a. Money laundering
b. Fraud
c. Accounting and reporting misalignment
d. Deceptive activities (manipulation, rate-rigging)
<u>Without formal convictions</u></td></tr>
</table>

5	If the article fits the category listed, it ranks 5: **1. Confirmed financial or non-financial criminal activities that result in:** a. Pleading guilty b. Conviction c. Prison sentences

Using the criteria, the articles were ranked and only the highest rank was kept for the given year to account for the most significant shocks related to the severity, see Appendix 2. One limitation of measuring Scandal Severity is subjectivity, as different readers might view the seriousness of the scandals differently. The study aims to reduce this issue and the potential biases that come from the use of ordinal variables by making a clearly defined, strict criteria where the articles and their rankings are provided in Appendix 2 for transparency. Moreover, both of the authors have gone through the sample separately using the criteria in order to test subjectivity and adjust the criteria for consistency.

4.3.3. Control Variables

The control variables used in the study account for credit risk and bank size, allowing the analysis to focus specifically on the association between credit ratings and reputation indicators. The control variables related to credit risk are continuous, ratio variables which accurately control for credit risk, allowing for comparisons across banks with different currencies and scales. The total assets variable, used for controlling size, is also a continuous, ratio variable. However, for comparability, it is converted to the Euro (€), using Excel functions to obtain the exchange rate for the end of each year.

1. **RoRWA**

Return on Assets (ROA) measures efficiency of assets in terms of profitability, calculated by dividing net income by average total assets (Horngren et al., 2014, p. 167). However, for measuring credit risk of financial institutions, accounting for risk of assets can give a more reliable profitability measure. Therefore, for this study, one of the control variables is RoRWA, as shown below.

$$\text{RoRWA} = \frac{\text{Net income}}{\text{RWA}}$$

Figure 2: RoRWA

Other profitability measures such as Operating Profit divided by RWA, could also have been used for this study, as it is widely used by Fitch Ratings (Fitch Ratings, 2024, p. 1). However, operating profit is not consistently reported across banks. While operating profit can be computed using annual reports, to ensure transparency and replicability, the study uses RoRWA, as it is a risk-adjusted profitability ratio based on commonly disclosed information.

2. **Tier 1 Ratio**

Tier 1 Capital, also known as core capital, is a key indicator used in both Basel Frameworks and Fitch Ratings. Fitch Ratings applies a high risk-weight to core capital (Fitch Ratings, 2024, p. 1), suggesting its significance and use for assessing credit risk.

Tier 1 Capital is calculated by adding the Common Equity Tier 1 (CET1) Capital, a bank's high quality capital and Additional Tier 1 (AT1) Capital, other capital that is not included (Eurostat, 2025). This is then divided by RWA to compute the Tier 1 Ratio, which as a result reflects how a bank handles losses while continuing its operations (Eurostat, 2025), as shown in Figure 3 below. As a result, the ratio is useful for assessing credit risk and shows how a bank can withstand financial stress.

$$\text{Tier 1 Ratio} = \frac{\text{CET1 Capital} + \text{AT1 Capital}}{\text{RWA}}$$

(Source: Eurostat, 2025)

Figure 3: Tier 1 Ratio

3. **ECL Ratio**

ECL Ratio is a forward-looking ratio that measures asset quality as it reflects the level of expected credit risk of loans (Frykström & Li, 2018, pp. 1-2). ECL is generally disclosed by European banks, making it an available source for measuring asset quality. IFRS9 suggests that ECL is calculated through 3 stages that measure risks on loans which is a direct measure of credit risk (Frykström & Li, 2018, pp. 2-3).

$$\text{ECL Ratio} = \frac{\text{ECL Provisions on loans to customers}}{\text{Gross loans to customers}}$$

Figure 4: ECL Ratio

By using the above formula, the study focuses on ECL on loans granted to customers, as customer lending is one of the core businesses for banks and accounting for potential losses is important for a bank's financial stability. Therefore, the ECL Ratio reflects the asset quality of loans to customers and its exposure to expected losses.

The other options that can be considered for measuring asset quality are NPL ratio and Loan Loss Provision (LLP) Ratio. These two ratios can be used for assessing asset quality and Fitch Ratings specifically uses NPL ratio, applying a 20% risk-weight (Fitch Ratings, 2024, p. 1). Although these are widely recognized for asset quality and credit risk, not all banks disclose these ratios or information required to compute these ratios such as impaired loans or loan loss provisions. Therefore, to ensure consistency and transparency of the data collection, the ECL Ratio is used, as the information required is disclosed by a majority of European banks, allowing for a more reliable comparison.

4. LCR

LCR and NSFR are liquidity measures that are two of the key ratios introduced in the Basel III framework in response to the Global Finance Crisis. One of the main differences between LCR and NSFR is that LCR measures the short-term liquidity and the bank's ability to react under financial stress while NSFR is a long-term measure of liquidity that ensures the stability of a bank's operations (Basel Committee on Banking Supervision, 2018b, p. 1).

Both of these ratios give valuable information when assessing credit risk through the liquidity dimension. However, since LCR measures how the bank handles liquidity shocks, it can be a more relevant measure for the study, considering that shocks and rapid withdrawal of funds can affect the short-term liquidity leading to credit risk.

Moreover, the disclosure of NSFR became mandatory for all banks in the EU in 2021 (European Commission, 2025). As a result, not all European banks disclosed the NSFR between 2018 to 2021. Since the time horizon of the thesis is 2018 to 2024, using the NSFR would result in missing data which can lead to uninformative results. Therefore, LCR is more suitable for the study as it is generally disclosed by European banks between 2018 and 2024.

5. Total assets

Firm size is often added as a control variable to investigate dependent variables that are company specific (Loughran & McDonald, 2024, p. 2487). The thesis focuses on credit ratings and reputation which varies across banks. Larger banks might have more risk exposure or more scandals which might impose biases. Therefore, firm size can be used to account for the differences between these banks. Firm size is commonly measured through total assets (Loughran & McDonald, 2024, p. 2487), therefore, the study will use total assets as a control variable and all numbers will be converted to million euros (€) to ensure comparability across banks. By controlling for total assets, the study can better isolate whether changes in the dependent variables are associated with the reputation proxies rather than difference in size alone.

4.4. Model of the Thesis

Multiple regression analysis is a simple linear model that includes two or more independent variables for explaining a dependent variable (Agresti, 2018, pp. 319-322). Bivariate regression analysis, on the other hand, includes only one independent variable, allowing for even a simpler way of analyzing models and is easier to interpret, however, does not account for other potential independent variables (Agresti, 2018, p. 322). The study conducts a multiple regression analysis as it aims to test the two independent variables that capture different aspects of reputation.

Moreover, the panel data of the study is balanced, meaning that there are no missing values across banks and time horizon, unlike an unbalanced panel dataset (Stock & Watson, 2015, p. 397). In regression analysis with panel datasets, entity (α_i) and time (λ_t) fixed effects can be used to account for unknown variables in the model that differ between entities or over time (Stock & Watson, 2015, pp. 403-408). In certain situations where unobserved observations are present both types of fixed effects are relevant to include in the regression model (Stock & Watson, 2015, p. 409).

This leads to the model of the study, which is a fixed effects multiple regression model using Ordinary Least Squares (OLS) estimates where OLS estimators are defined as "estimators of coefficients that minimize the sum of squared mistakes" (Stock & Watson, 2015, p. 239).

Some previous studies that used credit ratings as a dependent variable, estimated regression analysis using OLS (Panta et al., 2023, p. 3; Baghai et al., 2014, p. 1973). However, probit or logit regression models are particularly used for models with binary dependent variables, where the dependent variable takes the values 0 or 1 (Stock & Watson, 2015, p. 437). For ordinal variables, ordered probit or ordered logit models are used that extend the binary variables to ordinal variables (Wooldridge, 2013, p. 684). While ordered logit models allow for differences between categories, when entity fixed effects are used, the estimates can become "biased and inconsistent" (Baghai et al., 2014, p. 1973). Considering that the study has panel data with entity fixed effects, using OLS estimation is more suitable for the model of the study.

Considering the variables, OLS estimates and fixed effects, the model for the study is as shown below:

Equation 1: Multiple regression model with panel data

$$CR_{it} = \beta_0 + \beta_1 SIV_{i(t-1)} + \beta_2 SS_{i(t-1)} + \beta_3 ECLR_{it} + \beta_4 T1R_{it}$$
$$\beta_5 RoRWA_{it} + \beta_6 LCR_{it} + \beta_7 TA_{it} + \alpha_i + \lambda_t + \mu_{it}$$

Where:

CR_{it}: Credit ratings for bank i at time t

β_0: The constant/intercept

β_1 to β_7: Coefficients

$SIV_{i(t-1)}$: Search Interest Volatility, lagged by one period

$SS_{i(t-1)}$: Scandal Severity, lagged by one period

$ECLR_{it}$: ECL Ratio

$T1R_{it}$: Tier 1 Ratio

$RoRWA_{it}$: RoRWA

LCR_{it}: LCR

TA_{it}: Total assets

α_i: Entity Fixed Effects

λ_t: Time Fixed Effects

μ_{it}: Error term

The OLS assumptions for fixed effects models include linear model specification, random sampling, independent variables that vary over time, strict exogeneity, homoskedasticity and no serial correlation (Wooldridge, 2013, p. 509). The study does not use a random sampling method as it adopts purposive sampling in order to focus on a specific population for answering the research question, which limits external validity of the findings that will be discussed further in Section 4.8. Nevertheless, the model is linear, as outlined above and the independent variables vary over the time horizon. The other OLS assumptions are discussed in the next sections.

4.5. Endogeneity and Reverse Causality

Endogeneity occurs when the independent variables are correlated with the error term (μ_{it}) that influences the dependent variable (Roberts & Whited, 2013, pp. 494-495), which goes against the assumption of exogeneity. This is a severe issue because the parameters can become uninformative and unreliable due to biases (Roberts & Whited, 2013, pp. 494-495).

Potential endogeneity might occur in this study because the independent variables that measure reputation could include unobserved characteristics related to the dependent variable, which are captured in the error term. One of the ways of responding to potential endogeneity is through the use of "panel data models such as fixed or random effects" (Roberts & Whited, 2013, p. 495). While random effects might be more commonly used due to its effectiveness, if the error term has a relationship with the dependent variables, fixed effects would produce more reliable results (Longhi & Nandi, 2015, p. 190). In the study, the error term might include unobservable characteristics that influence reputation proxies while also affecting credit ratings. Considering that variables also vary with time, using both entity fixed effects and time fixed effects are more appropriate for the study.

Another issue is reverse causality, which is a type of endogeneity that illustrates how the dependent variable might influence the independent variable (Spiegler, 2022, p. 1). This results in biases and as a result, the regression analysis might become uninformative. In this study, reverse causality could occur if changes in credit ratings influence the reputation variables. To minimize this risk, the reputation measures are constructed in a highly specific way that measures reputation only. For example, the Search Interest Volatility is obtained by the bank's name plus keywords related to different aspects of scandals and Scandal Severity is only assessed through bank-specific scandals and investigations. This ensures that the reputation proxies are not influenced by changes in credit ratings, mitigating the potential for reverse causality. Moreover, control variables measuring credit risk and total assets ensure that the study focuses on the association between credit ratings and reputation variables only.

Another way of addressing endogeneity and reverse causality is using lagged variables which is commonly used for studies in finance as it assumes that the lagged variables influence the dependent variable indirectly through the impact on the endogenous variables (Roberts & Whited, 2013, pp. 517-518). For the study, the reputation variables are lagged by one year to reduce endogeneity.

Consequently, the study attempts to mitigate endogeneity and reverse causality through using fixed effects, lagged variables and control variables. While endogeneity and reverse causality concerns cannot be fully fixed, these approaches improve the reliability and validity of the findings.

4.6. Heteroskedasticity and Autocorrelation

Homoskedasticity assumes that the error term has constant variance and when this condition is not met, heteroskedasticity arises (Stock & Watson, 2015, pp. 204-205). In data where heteroskedasticity becomes a concern, cluster-robust standard errors can be applied which allow different variances of errors among groups while treating the groups as independent (MacKinnon et al., 2023, p. 273). Moreover, cluster-robust standard errors can also be used in OLS models when autocorrelation or serial correlation arises (Wooldridge, 2013, p. 431), which refers to the error terms for one year being correlated with another year (Wooldridge, 2013, p. 353).

Heteroskedasticity might arise in the study as the sample includes banks in different countries that likely differ in terms of variance while autocorrelation might be present as each bank is observed over 7 years where similar and bank-specific observations might lead to correlation in error terms over the years. Therefore, cluster-robust standard errors are used in the model for more informative and reliable conclusions.

4.7. Multicollinearity

Multicollinearity refers to high correlation between independent variables, resulting in less reliable estimation of parameters (Stock & Watson, 2015, p. 248). Perfect multicollinearity occurs if one independent variable can be expressed through a linear relationship using other independent variables, whereas imperfect multicollinearity occurs if one or two independent variables are not exactly but significantly correlated (Stock & Watson, 2015, pp. 248-251).

Although the independent variables both measure aspects of reputation, they measure different dimensions. Search Interest Volatility measures market attention and the accessibility of new information through searches, while Scandal Severity measures the intensity of that information. Even though scandals might influence search interest, neither variable is fully captured by the other variable as high search interest might be the result of other information beyond scandals and the severity of scandals do not reflect market attention. Nevertheless, the study checks for multicollinearity between independent variables and control variables in the next chapter.

4.8. Reliability and Validity

Reliability means that the data collection should be accurate and replicable in a way that if the same study is conducted, the results should be the same (Collis & Hussey, 2021, p. 47). The study uses available information from Fitch Ratings, Financial Times and Reuters, Google Trends and banks' financial reports. The variable construction and data collection choices are explicitly stated to ensure transparency and replicability. Moreover, all the data was double-checked to ensure reliable data and trustworthy results.

Validity, on the other hand, suggests whether the study observes relevant variables in relation to the aim of the investigation and makes conclusions that accurately represent a relationship (Collis & Hussey, 2021, p. 48). Internal validity ensures that the investigators can motivate for the relationship between the independent and dependent variables to be causal (Roe & Just, 2009, p. 1266). The thesis aims to improve internal validity by selecting variables that are relevant and measure corporate reputation. Moreover, including credit risk indicators and total assets as control variables minimizes biases that might arise due to differences in credit risk management and bank size, allowing the study to focus on the association between credit ratings and reputation.

External validity refers to the generalizability of the results of the study to other populations and situations (Roe & Just, 2009, p. 1267). Since the study uses a purposive sampling method, generalizability is limited due to sampling biases that arise with the use of non-probability sampling methods. However, since the study aims to examine whether reputation indicators are associated with credit ratings, only the most relevant subjects were included in the sample. To minimize generalizability issues, the thesis uses credit ratings data that are commonly disclosed and reputation indicators that are accessible to the public, along with conducting a transparent study with strict criteria and fully disclosed data collection methods.

4.9. Ethical Considerations

Research integrity is an important part of conducting studies to ensure quality, accuracy and transparency (ALLEA, 2023, pp. 3-5). The core values for research integrity include the following:

Table 5: Research Integrity Core Values

Core Values	**Description**
Reliability	Ensuring that the method, data and analysis are consistent and replicable
Honesty	Conducting a transparent, accurate and objective research
Respect	Respecting the rights, integrity and well-being of researchers, research subjects and society
Accountability	Taking responsibility for the whole study and its societal outcomes

(Source: ALLEA, 2023, p. 5)

The study aims to ensure research integrity through documenting the research methods, data collection sources, variable construction, results and analysis in a transparent and consistent way. As mentioned in the previous section, the data is collected from publicly available sources, which allows replicability and transparency. Although the names, annual reports, credit ratings from Fitch Ratings and news articles related to the banks in the sample are reported in Appendix 1 and 2, these sources are published by the banks in the sample, Fitch Ratings and the news agencies, therefore, do not include personal or sensitive information.

Furthermore, sources used for theories and methodology are based on peer-reviewed sources and textbooks, where all of them are referenced for transparency and fairness. Moreover, responsibility has been taken into account throughout the whole research process and the contribution/impact of the findings on whether reputation indicators are associated with credit ratings are discussed in relation to stakeholders and society, without including personal opinions, but rather interpretations based on the findings.

4.10. The Use of Artificial Intelligence (AI)

The authors of this thesis confirm that the ideas for the study, data collection, analysis, interpretations and all of the content were constructed and formulated by the authors. The AI tool, ChatGPT, was used for getting feedback on the text that was already written. This includes checking the grammar and language of the text for readability and ensuring that the written text made logical sense.

The reasoning behind this use is to ensure that the flow and language of the text are correct. The content and graphs/tables are constructed and written by the authors where if external sources are used, they are cited properly using the APA 7th referencing style. AI was not used to collect data, select sources or create empirical results. The authors were responsible for finding the sources, data collection, conducting statistical analyzes, interpretations and analysis of the findings and conclusions shown in the study.

5. Data

This chapter introduces the data and the variables through the use of descriptive statistics. Then, the chapter includes the reasoning behind logarithmic transformation of certain variables. Moreover, heteroskedasticity and multicollinearity of the data are discussed.

5.1. Descriptive Statistics

Since the dataset is balanced, there are no missing values and therefore, no additional observations were calculated or estimated. The following table shows the variables used in the model with their mean, standard deviation, minimum and maximum values.

Table 6: Descriptive Statistics

Variable	Mean	Standard Deviation	Min	Max
Credit Ratings	14.5444	2.650318	5	20
Search Interest Volatility	4.478185	7.576613	0	30.5034
Scandal Severity	.8339768	1.405776	0	5
ECL Ratio	.0167283	.0130115	.0001566	.0987327
Tier 1 Ratio	.1712311	.0224068	.1213	.227
RoRWA	.0162971	.0106067	-.0338479	.0548099
LCR	1.664142	.6509616	.8086	7.56
Log of Total Assets	13.20861	.8989322	11.16528	14.88499

The mean of 14.5 for credit ratings suggests that banks in the sample are, on average, rated around A and A-. The minimum and maximum values suggest that the range is between AAA to B-, indicating variation across banks.

Variables including Search Interest Volatility, LCR, RoRWA and potentially ECL Ratio show wide ranges between minimum and maximum values, suggesting possible outliers and the need for variable transformations that will be discussed in the following section. Similarly, total assets have already been logarithmically transformed to address differences in size across banks.

Moreover, the mean value for Scandal Severity indicates that on average, the scandals for banks in the sample are low, with severity ranging from 0 to 5. In addition, the reputation variables had a significant amount of zeros as not all banks had scandals or search interest for every year. In contrast, Tier 1 Ratio and RoRWA are relatively stable, indicating similar and consistent observations across banks.

5.2. Logarithmic Transformation of Total Assets Variable

Normal distribution is not required for OLS and does not impact the validity of the estimations as OLS estimates are "asymptotically" normal, meaning, the distribution of the estimates becomes normal when the sample size increases (Wooldridge, 2013, p. 175). The Central Limit Theorem (CLT) suggests that sampling distribution can be considered approximately normal when the sample size is large and while there is no specific rule, the distribution can be approximately normal for sample sizes that are 30 or higher (Stock & Watson, 2015, pp. 98-99). This is relevant for the thesis, as the sample size is 37 banks with 259 observations and the parameters are estimated using fixed effect OLS. However, the study acknowledges that the sample size can be considered small.

Nevertheless, if some variables are skewed or have many outliers, the results might be unreliable (Lee, 2020, pp. 503-504). Therefore, in such situations, logarithmic transformation can be used on variables where there are huge differences between the lowest and the highest observations (Lee, 2020, p. 505).

In the model, total assets have huge differences between observations, causing outliers. As a result, the variable is transformed logarithmically and the potential influence of extreme observations is minimized, see Figure 5 below:

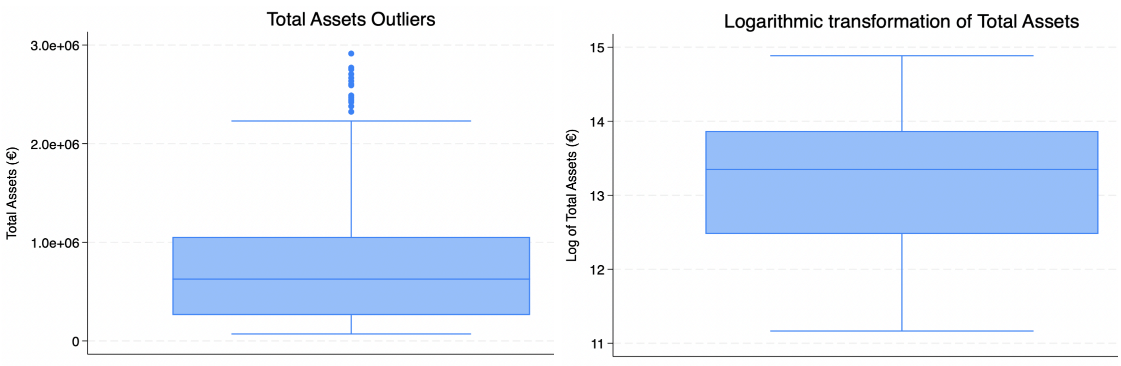


Figure 5: Before and After the Logarithmic Transformation of Total Assets

Other variables were also visualized, see Appendix 3. Certain variables such as Search Interest Volatility, LCR and RoRWA showed more extreme outliers which were tested in Section 6.6.2. For variables including, Scandal Severity and Tier 1 Ratio, there were no visible outliers unlike in variables credit ratings and ECL Ratio. However, variable transformations were not conducted for these indicators as differences between high and low values show shocks/changes that would not be accounted for if transformations were implemented.

5.3. Heteroskedasticity in the Model

As mentioned in Section 4.6., there is a high probability of heteroskedasticity due to the nature of the observations within banks and countries in the sample. To test whether the data is heteroskedastic, first the residuals are plotted against predicted values, see Appendix 4. As expected, the results indicate a clear pattern that can be due to the use of ordinal variables in the model, but it might also indicate heteroskedasticity as it is shaped upwards and not spread evenly around 0. As a result, a modified Wald test is used to confirm for heteroskedasticity within entities for fixed effects regression analysis (Baum, 2001, p. 101).

Table 7: Modified Wald Test

Modified Wald test for groupwise heteroskedasticity in fixed effect regression model	
chi2 (37)	10120.93
Prob > chi2	0.0000

The null hypothesis is rejected as the p-value of the test is 0.000, suggesting there is heteroskedasticity within entities (Baum, 2001, p. 104). The results confirm that the use of cluster-robust standard errors are necessary to minimize heteroskedasticity and produce more reliable results.

5.4. Multicollinearity in the Model

To test for correlation across variables, a pairwise correlation matrix was constructed which shows that there are no extreme correlations between variables.

Table 8: Pairwise Correlation Matrix

	Credit Ratings	Search Interest Volatility	Scandal Severity	ECL Ratio	Tier 1 Ratio	RoRWA	LCR	Log of Total Assets
Credit Ratings	1							
Search Interest Volatility	0.0712	1						
Scandal Severity	-0.0922	0.0641	1					
ECL Ratio	-0.7050	-0.1726	0.1579	1				
Tier 1 Ratio	0.4751	0.0490	-0.2205	-0.4796	1			
RoRWA	0.1692	-0.0857	-0.1477	-0.2371	0.3197	1		
LCR	-0.0775	-0.0887	-0.1000	0.1289	0.2427	0.0735	1	
Log of Total Assets	0.3429	0.3033	0.1089	-0.1538	-0.1184	-0.1104	-0.2268	1

Based on the correlation matrix, the strongest correlations are between credit ratings and ECL Ratio (-0.7050), ECL Ratio and Tier 1 Ratio (-0.4796) and credit ratings and Tier 1 Ratio (0.4751). Considering that these ratios are commonly used for assessing credit risk and credit ratings, correlation between these variables are expected.

To check multicollinearity, the Variance Inflation Factor (VIF) is calculated. VIF is widely used for multicollinearity and shows whether the independent variables are correlated with each other (Wooldridge, 2013, p. 98). Multicollinearity becomes a concern if the VIF values are high, e.g. if VIF > 10 (Wooldridge, 2013, p. 98). However, as seen in the table below, the VIF of independent and control variables are low, suggesting that multicollinearity is not a concern for the variables used.

Table 9: VIF Table

Variable	VIF	1/VIF
Search Interest Volatility	1.14	0.879077
Scandal Severity	1.08	0.927784
ECL Ratio	1.52	0.655811
Tier 1 Ratio	1.61	0.622874
RoRWA	1.15	0.866431
LCR	1.19	0.841705
Log of Total Assets	1.20	0.830105
Mean VIF	1.27	

6. Empirical Results

This chapter presents the results of the study using different models. The main model is first tested with control variables to see the influence of traditional financial indicators. Then, the independent variables are added individually to assess the effects of reputation on credit ratings. After the models are introduced, robustness tests are conducted to check the stability and consistency of the model.

6.1. Model with control variables

To investigate whether corporate reputation indicators provide additional explanatory value to credit ratings, beyond traditional financial indicators, the model is first tested with only the control variables. Table 10 shows the variables' coefficients, robust standard deviations, t-values and the p-values.

Table 10: Model with Control Variables

	Coefficient	Robust Standard Deviation	t-value	P>t (p-value)
ECL Ratio	-16.2395	6.357991	-2.55	0.015
Tier 1 Ratio	9.320107	4.102005	2.27	0.029
RoRWA	12.19476	10.42525	1.17	0.250
LCR	-.112602	.0791026	-1.42	0.163
Log of Total assets	.0913923	.4130809	0.22	0.826
R-squared: Within	0.2614			
R-squared: Between	0.6312			
R-squared: Overall	0.4886			

The results indicate that the control variables, ECL Ratio and Tier 1 Ratio, provide significant evidence at the 5% significance level that they contribute to credit ratings. The results show that the negative coefficient of ECL Ratio suggests a negative relationship while the positive coefficient of Tier 1 Ratio implies a positive relationship with credit ratings.

Moreover, the other control variables, including RoRWA, LCR and log of total assets do not have significance at the 5% confidence level. Even though there is no statistical evidence that these variables influence credit ratings, the coefficients show that credit ratings are positively associated with RoRWA and log of total assets while being negatively associated with LCR.

To measure how effectively the model fits to the data, in other terms the "measure of fit", R^2, can be used which shows the percentage of the variance of the dependent variable that is explained through the independent variables (Stock & Watson, 2015, p. 167). However, in fixed effects models, R^2 might not be as straightforward and therefore, the "within" R^2 is used to explain the proportion of variation in the dependent variable over time that is explained through the variation of the independent variables (Wooldridge, 2013, p. 487). The within R^2 of the model is 26.14%, suggesting that 26.14% of the variation in credit ratings within the banks in the sample during 2018-2024 can be explained through the variation in the control variables.

6.2. Model with the Independent Variable Search Interest Volatility

The first independent variable is added to the model to evaluate the influence of Search Interest Volatility on credit ratings.

Table 11: Model with Search Interest Volatility

	Coefficient	Robust Standard Deviation	t-value	P>t (p-value)
Search Interest Volatility	-.0037676	.0053092	-0.71	0.483
ECL Ratio	-16.4119	6.325626	-2.59	0.014
Tier 1 Ratio	9.380331	4.138196	2.27	0.030
RoRWA	12.20973	10.39685	1.17	0.248
LCR	-.1129096	.0782423	-1.44	0.158
Log of Total assets	.1154069	.41996	0.27	0.785
R-squared: Within	0.2631			
R-squared: Between	0.6537			
R-squared: Overall	0.5060			

The coefficient of the Search Interest Volatility is -.0037676, suggesting that a one unit increase in Search Interest Volatility is associated with a -.0038 unit decrease in credit ratings which can be considered as a small impact. However, the p-value is insignificant at 5% significance level, suggesting that the coefficient is not significant and that there is no evidence of an association between Search Interest Volatility and credit ratings in the sample.

The within R^2 for the model is 26.31%, suggesting a small increase of 0.65% compared to the model with only control variables. Moreover, the coefficients and the signs of the control variables do not significantly change, suggesting that the model is stable and robust to changes in the model.

6.3. Model with the Independent Variable Scandal Severity

The second independent variable is added to the model to evaluate the effect of Scandal Severity on credit ratings.

Table 12: Model with Scandal Severity

	Coefficient	Robust Standard Deviation	t-value	P>t (p-value)
Scandal Severity	-.0019416	.0242738	-0.08	0.937
ECL Ratio	-16.19863	6.458866	-2.51	0.017
Tier 1 Ratio	9.306513	4.050685	2.30	0.028
RoRWA	12.19994	10.4639	1.17	0.251
LCR	-.1128313	.07981	-1.41	0.166
Log of Total assets	.0921349	.4105046	0.22	0.824
R-squared: Within	0.2614			
R-squared: Between	0.6309			
R-squared: Overall	0.4884			

The coefficient of the Scandal Severity is -.0019416, suggesting that a one unit increase in Search Interest Volatility is associated with a -.002 unit decrease in credit ratings. Moreover, the p-value is also insignificant at 5% significance level, suggesting insignificance of the coefficient and no evidence of an association between Scandal Severity and credit ratings in the sample.

The within R^2 for the model is 26.14%, suggesting a small decrease of 0.65% from the model with Search Interest Volatility and no change from the model with only control variables. Additionally, the coefficients and the signs of the control variables remain stable.

6.4. Main Model: Fixed Effects Multiple Regression Model using OLS Estimates

Finally, the main model of the study is presented in Table 13 that includes both of the independent variables and control variables, see results below:

Table 13: Results of Fixed Effects Multiple Regression Model using OLS Estimates

	Coefficient	Robust Standard Deviation	t-value	P>t (p-value)
Search Interest Volatility	-.0037715	.0053184	-0.71	0.483
Scandal Severity	-.0020999	.0245264	-0.09	0.932
ECL Ratio	-16.36787	6.424166	-2.55	0.015
Tier 1 Ratio	9.36569	4.087251	2.29	0.028
RoRWA	12.21535	10.43512	1.17	0.249
LCR	-.1131579	.0789509	-1.43	0.160
Log of Total assets	.116235	.4171331	0.28	0.782
R-squared: Within	0.2632			
R-squared: Between	0.6533			
R-squared: Overall	0.5057			

Adding both of the independent variables, Search Interest Volatility and Scandal Severity, does not significantly change the coefficients or the signs of the variables, implying stability of the model. The p-value of the independent variables in the final model remain insignificant at 5% significance level, indicating that there is no significant evidence that Search Interest Volatility and Scandal Severity provide additional explanatory value for credit ratings, beyond traditional financial indicators. As a result, the null hypothesis cannot be rejected.

The within R^2 for the model is 26.32%, suggesting that 26.32% of the variation in credit ratings within banks over 2018-2024 can be explained through the variation in the independent and control variables. This is higher than all the previous models, even though there is only 1% change between the second model and the final model, showing that the inclusion of all independent and control variables increase the efficiency of how the model applies the data.

6.5. Results with the Hypothesis

To summarize the results, at 5% significance level, the study fails to reject the null hypothesis and concludes that the chosen reputation indicators, Search Interest Volatility and Scandal Severity, do not provide additional explanatory value for credit ratings, after including financial indicators as control variables in the model.

Table 14: Conclusion with the Null Hypothesis

Hypothesis	Conclusion
H_0: Corporate reputation indicators, Search Interest Volatility and Scandal Severity, do not provide additional explanatory value for credit ratings, beyond financial indicators.	Failed to reject the null hypothesis at 5% significance level.

6.6. Robustness tests

A few robustness tests were conducted to test the reliability and stability of the model, which include testing the model without control variables and transforming the variables with extreme observations and outliers.

6.6.1. The Model without Control Variables

The use of control variables are important for the model to focus solely on the association between credit ratings and reputation indicators. To check this, the model is first tested without control variables:

Table 15: The Model without Control Variables

	Coefficient	Robust Standard Deviation	t-value	P>t (p-value)
Search Interest Volatility	-.0012884	.0048035	-0.27	0.790
Scandal Severity	-.019453	.0334321	-0.58	0.564
R-squared: Within	0.0968			
R-squared: Between	0.0066			
R-squared: Overall	0.0044			

The results show that the signs of the coefficients and the p-value change slightly but the results remain stable, suggesting the model is robust to changes. However, it is clear that the within R^2 decreases significantly when the control variables are excluded, suggesting that only 9.68% of the variation in credit ratings within banks over 2018-2024 can be explained through the variation in the independent variables.

6.6.2. Further Variable Transformations

Since Search Interest Volatility is based on a numerical scale of 0 to 100, the variable has huge differences between the highest and the lowest observations. Therefore, the model was tested through logarithmically transforming Search Interest Volatility.

Table 16: The Model with Logarithmic Transformation of Search Interest Volatility

	Coefficient	Robust Standard Deviation	t-value	P>t (p-value)
Log of Search Interest Volatility	-.0018664	.0360326	-0.05	0.959
Scandal Severity	-.001925	.024374	-0.08	0.937
ECL Ratio	-16.20531	6.461696	-2.51	0.017
Tier 1 Ratio	9.310018	4.058242	2.29	0.028
RoRWA	12.20906	10.48682	1.16	0.252
LCR	-.112891	.0794171	-1.42	0.164
Log of Total Assets	.0935999	.4184265	0.22	0.824
R-squared: Within	0.2614			
R-squared: Between	0.6325			
R-squared: Overall	0.4895			

The results show that the coefficients or the signs of the variables did not change significantly, suggesting that the extreme observations within Search Interest Volatility did not influence the model. However, it can be said the p-value for Search Interest Volatility becomes less insignificant. The variable also becomes harder to interpret as reducing the differences between observations removes the shocks related to market attention.

Moreover, winsorization can be used on variables to reduce the influence of extreme outliers (Mohammed et al., 2025, p. 157). Different winsorization percentages can be used such as 1% of the variables (Mohammed et al., 2025, p. 160). Variables, other than total assets and Search Interest Volatility, that could have been potentially influenced by extreme outliers were RoRWA and LCR. As a result, these variables were winsorized at 1% individually, see Appendix 5 and Appendix 6. Results of both the winsorized RoRWA and LCR show that the p-value remained insignificant and the effect of the winsorization on other variables was limited. This suggests that the extreme observations of RoRWA and LCR do not necessarily influence the model. It can be concluded that the model is robust to changes in extreme outliers.

To summarize the robustness tests, the model stays consistent and stable when the model is adjusted in terms of the exclusion of control variables, the logarithmic transformation of Search Interest Volatility and the winsorization of RoRWA and LCR. This shows that the results of the study are not sensitive to variable choices, transformation or the influence of outliers.

7. Analysis and Discussion

This chapter analyzes and discusses the findings of the study in relation to the research question. The control and independent variables are then analyzed and evaluated with their interpretations and limitations. This is followed by a discussion of the results in relation to the theories and concepts presented in the Theory Chapter. Lastly, overall interpretations are discussed to summarize the main findings of the study.

7.1. Answering the Research Question

The study answers the Research Question: "To what extent do corporate reputation indicators provide additional explanatory value for credit ratings, beyond traditional financial indicators, among the largest European banks during 2018-2024?"

The results show that, at the 5% significance level, there is not enough empirical evidence that the chosen reputation indicators, Search Interest Volatility and Scandal Severity, provide additional explanatory value for credit ratings beyond traditional financial indicators.

This suggests that after accounting for credit risk indicators and the asset size of banks in the sample, the different reputation aspects, as measured in the study, are not directly associated with credit ratings based on Fitch Ratings.

7.2. Analysis of Control Variables

The results suggest that at the 5% significance level, the control variables, ECL Ratio and Tier 1 Ratio, provide additional explanatory value for credit ratings. The negative coefficient of ECL Ratio suggests that higher expected credit losses are associated with higher credit risk and lower credit ratings. The positive coefficient of Tier 1 Ratio shows that stronger capital is associated with higher credit ratings. These results confirm that asset quality and capital strength are key dimensions used in assessing credit risk and align with the theory, as both ratios are indicators used in Basel Frameworks and Fitch Ratings.

In contrast, other control variables, including RoRWA, LCR and the log of total assets, are not significant. This indicates that in a sample of 37 European banks that were selected from a population of 50 largest European banks, risk-adjusted profitability or asset size might not contribute additional information to credit ratings. In addition, considering that banks are required to maintain a minimum LCR of 100%, the insignificant result suggests that, beyond meeting the requirements, the level of LCR does not provide additional information to credit ratings.

7.3. Analysis of Independent Variables

The independent variables were constructed based on theory and prior studies. Search Interest Volatility measures the fluctuations in market attention related to the keywords "scandal," "investigation," and "failure" while Scandal Severity measures the intensity of scandals related to the banks in the sample. These indicators reflect the availability and severity of new information that can be considered as the theoretical factors that lead to bank runs.

The results provide no statistically significant evidence that Search Interest Volatility and Scandal Severity play a role in explaining credit ratings. The negative coefficients of both variables indicate that there could be a negative association between the variables and credit ratings which is expected as increased negative market attention and more severe scandals might lead to lower ratings in theory due to the possibility of increased risk. However, this association is not supported by empirical evidence.

Moreover, another interesting finding is that the measure of fit (within R^2) of the second model, where control variables and Search Interest Volatility was tested, was the second highest, after the main model. This potentially suggests that Search Interest Volatility might contribute more explanatory value to credit ratings, compared to Scandal Severity, even though both variables are not statistically associated with ratings. An explanation for this could be that market attention could be more relevant for credit ratings as it might influence credit risk indicators, such as capital and expected credit losses, through bank activities or stakeholder concerns, which are key contributors to credit ratings in the sample, according to the results.

It was also seen that the measure of fit for the model with Scandal Severity was the same as the model with only the control variables. This might indicate that Scandal Severity could already be reflected within credit risk indicators and therefore does not provide additional explanatory value. This could potentially suggest that credit ratings react to scandals after they affect credit risk indicators, which could also be one of the reasons why the coefficients of the reputation variables are statistically small, as they do not contribute any additional information to credit ratings.

Another potential reasoning behind the statistically insignificant results could be because credit ratings are forward-looking measures and adjust slowly over time. On the other hand, the reputation indicators used in the study capture the fluctuations in market attention and severity of bank scandals, which focus on the possibility of shocks and panic based on new information. As a result, they might be measuring the short-term impact of availability and severity of new information, even when the variables are lagged by one period.

Consequently, the lagged reputation indicators might not be fully accounted for in credit ratings due to the nature of the variables. This then opens up a future research possibility on whether the results would change if the same study was conducted using reputation indicators lagged by two or more periods.

7.4. Results with Theory

In the Theory Chapter, several theories were mentioned: the bank run theory, behavioral finance including herding behavior and informational cascades, asymmetric information and the signaling theory.

The bank run theory and behavioral finance explain bank runs and the underlying mechanisms behind the severity of bank runs. Therefore, corporate reputation and its impact on the potential bank runs imposed significant credit risk and vulnerability to banks. Moreover, previous studies suggested that corporate reputation can be measured through market attention and scandal intensity that focuses on the availability of new information and its potential effects on triggering bank runs.

The other theories, asymmetric information and the signaling theory explain how different parties having different information can lead to uncertainty and therefore, signals play a role in minimizing the information gap. Due to the uncertainty around banks, credit ratings play a central role in providing additional information.

However, based on the discussions regarding the Basel Frameworks and Fitch Ratings criteria, credit risk is mainly assessed through balance sheet indicators without having reputation as a specific dimension.

The results are consistent with the Theoretical Framework that credit risk indicators play a bigger role in explaining credit ratings compared to reputation indicators as the study provides evidence that asset quality and capital strength is directly reflected in credit ratings while there is no evidence for an association between credit ratings and reputation indicators used in the study.

It was also mentioned in the previous section that credit ratings might react to severity of scandals after they start influencing credit risk. Theories suggested that damage to reputation leads to loss of consumer trust. This triggers bank runs and consequently affects credit risk. Considering that results also suggest that credit ratings are mainly influenced by credit risk indicators such as capital strength and asset quality, scandals might affect credit risk and indirectly affect credit ratings, which can be one of the reasons Scandal Severity is statistically insignificant as there is no direct association between the variable and credit ratings.

Moreover, the results do not provide evidence that reputation is not incorporated in credit ratings or that it is not important, rather the aspects of reputation chosen for the study do not provide additional information in explaining credit ratings. Therefore, future research can be conducted on analyzing the association between different aspects of reputation and credit ratings to assess whether other dimensions in reputation such as past scandals influence ratings.

7.5. Overall Interpretation

As a result, the findings suggest a few potential conclusions and interpretations based on the results of the study.

Firstly, the results indicate that the reputation indicators chosen for the study might not be fully captured in credit ratings due to the nature of the variables. This interpretation follows the theory which suggested a research gap where the importance of corporate reputation and its potential effect on triggering bank runs during periods of uncertainty were not reflected in the assessment of credit ratings. Consequently, this indicates that Fitch Ratings might focus mainly on traditional financial indicators rather than measures capturing the availability and severity of new information.

Considering that the coefficients of the reputation indicators, especially Scandal Severity, are statistically small and the within R^2 was unchanged between the models with only control variables and Scandal Severity, scandals do not provide additional explanatory power, beyond traditional financial indicators. As a result, another interpretation can be that corporate reputation might be accounted for when it affects the credit risk indicators. The theory suggested that damaged reputation is likely to lead to credit risk. Consequently, credit ratings might reflect reputation indicators after they influence credit risk.

Moreover, the findings suggest that the chosen independent variables might not fully capture reputation. Since the study focused on two aspects of reputation, market attention and scandal intensity, other aspects were not captured which potentially suggests that corporate reputation might not be fully represented. This indicates that different dimensions of reputation could still be reflected in credit ratings.

To summarize, these interpretations show that the statistically significant results suggest that reputation indicators chosen for the study are not directly reflected in Fitch Ratings, after accounting for credit risk and size of banks in the sample. This does not mean that reputation is irrelevant for credit ratings or credit risk, instead, the results show that Search Interest Volatility and Scandal Severity do not provide direct additional explanatory value for Fitch Ratings beyond the traditional financial indicators used in this study. Consequently, the findings suggest that credit ratings focus mainly on credit risk indicators such as capital strength and asset quality which might react to corporate reputation after it visibly affects credit risk indicators.

8. Conclusion

The Conclusion Chapter summarizes the findings and explains how the study contributes to the research gap and stakeholders. Moreover, the quality of the results is discussed in relation to validity, generalizability and reliability. Then, recommendations, ethical and societal implications, along with limitations and future research opportunities are discussed.

8.1. Findings and Contribution

The thesis examines whether corporate reputation indicators provide additional explanatory value for credit ratings beyond traditional financial indicators among the largest European banks during 2018-2024. The empirical results show that the selected reputation indicators, Search Interest Volatility and Scandal Severity, are not statistically significant when financial variables are included in the model. On the other hand, financial indicators especially the ECL Ratio and Tier 1 Ratio are statistically significant and consistent with how credit risk is usually assessed. These results suggest that credit ratings in this sample primarily reflect financial information, rather than the selected reputation indicators.

Nevertheless, this should not be interpreted as evidence that reputation is not considered in credit rating processes. Instead, the findings suggest that the chosen reputation indicators do not provide additional explanatory value to credit rating. This could be due to the chosen proxies not fully capturing corporate reputation or it may be that reputation only becomes relevant once it affects measurable financial indicators. This may suggest that credit ratings focus more on broader and more stable assessments of creditworthiness rather than short-term changes in public attention or scandals.

These findings help explain how credit risk is mainly evaluated within a sample of large European banks and why financial indicators appear to play a larger role than the selected reputation indicators. While previous research suggests that qualitative and non-financial information can influence credit risk assessments, the results of this study indicate that such effects are not easily captured through observable proxies such as search interest or scandal rankings. This suggests that reputation may affect credit risk indirectly, for example through its impact on stakeholder behavior. In this way, the study explains whether measurable reputation-related indicators provide additional explanatory value beyond traditional financial indicators when analysing credit ratings, based on Fitch Ratings.

8.2. Quality of the Results

- **Validity and Generalizability**

Internal validity of the results of the study was improved through different methods. The model includes time and entity fixed effects, lagged independent variables, relevant control variables and cluster-robust standard errors. These approaches help mitigate concerns related to endogeneity, reverse causality, heteroskedasticity and autocorrelation. As a result, the results become more reliable and less biased.

External validity or generalizability, on the other hand, might be limited as the sample is based on purposive sampling and focuses only on large European banks rated by Fitch Ratings during 2018-2024. This might limit how well the result applies to smaller banks or other regions. However, as mentioned in Section 4.8., the study focuses on a specific sample, that is banks rated by Fitch Ratings for data availability. This allowed the study to have a balanced panel data and to primarily examine whether the chosen reputation indicators influenced credit ratings. Therefore, even though the results might not be fully applicable to all populations, it still provides useful insight into the role of the chosen reputation variables in explaining credit ratings within the given sample.

- **Reliability**

The results can be considered reliable and trustworthy as all the data was double-checked. Reliability could have been limited in terms of the independent variable, Scandal Severity, as it can be considered subjective. However, the variable is constructed using a strict criteria as shown in Table 4. To strengthen the reliability further, both of the authors went through the articles in Appendix 2 for the whole sample and used the criteria to rank the articles for consistency.

Moreover, robustness tests show that changes in model specification and extreme outliers do not significantly affect the results. This suggests that the findings are stable and not significantly influenced by specific model choices which strengthens reliability as the results are consistent across different methods.

In terms of replicability, the variables are constructed in a transparent way with all the methods and equations explained in Chapter 4, along with a list of banks in the sample and articles used with their ranks in Appendix 1 and 2. Moreover, the study can be replicated as it mainly focuses on publicly available information, transparently constructed variables and strict criteria for certain variables.

8.3. Recommendations for Stakeholders

For stakeholders including investors and depositors, the findings show that credit ratings may not immediately reflect all dimensions of corporate reputation and might react to these types of risks after they affect credit risk. Therefore, investors and depositors should interpret credit ratings in relation to other sources of information, such as media coverage and news exposure, public attention or other qualitative information, to provide a broader understanding of credit risk in the banking sector. This may be especially important during periods of financial uncertainty and increased market stress, such as pandemics, where confidence-related developments can become more relevant for financial stability.

For credit rating agencies, the results suggest that credit ratings primarily reflect financial information and may be less responsive to fast-moving reputational events, such as sudden changes in public confidence or negative media exposure. As a result, credit rating agencies could consider explicitly mentioning and incorporating non-financial indicators, including corporate reputation as a dimension in their credit rating frameworks.

For banks, the study shows the importance of scandals and market attention that might negatively affect corporate reputation, exposing banks to financial instability and credit risk. In this context, the findings show that the chosen reputation indicators might indirectly affect credit ratings once they visibly influence credit risk. As a result, banks could consider potential actions for preventing scandals such as monitoring bank activities, including the actions of subsidiaries. It is also relevant for banks to incorporate strengthening corporate reputation as a risk management method.

For regulators, it is important to consider that credit ratings have been the center of debates in terms of their accuracy and whether they fully reflect all relevant information. From this perspective, the study shows that, based on the sample, Fitch credit ratings might be more focused on capturing capital strength and asset quality rather than the chosen reputation indicators. Consequently, it could be important for regulators to develop frameworks that include corporate reputation and its different aspects that might lead to financial instability.

8.4. Societal and Ethical Implications

More broadly, the findings also highlight potential implications for financial stability. Banks are highly dependent on trust and confidence, meaning that negative information or sudden changes in public perception may contribute to liquidity pressure and financial stress even before such effects become clearly visible in traditional financial indicators.

If confidence-related shocks are not fully and immediately reflected in credit risk assessments, there may be a risk that stakeholders, including depositors, taxpayers, investors and regulators might underestimate vulnerabilities in the short-term, especially in situations where trust and liquidity play a central role. From a societal perspective, this is particularly important because banks play a significant role in the economy and financial stability. As a result, instability in the financial sector would result in certain issues such as unemployment and inflation that would affect everyone in the economy, also considering spill-over effects of bank runs and failures to other banks and industries.

Moreover, reputation is particularly important socially and ethically since bank scandals include unethical and harmful events that might trigger or negatively affect depositors, employees, investors and the general public trust. These are important to consider as even if a bank is profitable and scores high in traditional financial indicators, it might cause severe damage to society through its unethical acts which are captured in corporate reputation. Therefore, it becomes relevant to evaluate the creditworthiness of firms based on corporate reputation and unethical activities, as in a way creditworthiness should also capture trust and stability. Consequently, this topic is not only relevant for depositors, banks and credit ratings but also the whole society and the economy.

8.5. Limitations and Future Research

This study has several limitations that are important to consider when interpreting the findings. The sample size is relatively limited, even if it still allows for certain conclusions across banks and over time. In addition, the use of purposive sampling may affect how well the findings can be applied to other contexts or to smaller financial institutions.

Additionally, one limitation is that the sample of the study only focuses on the largest European banks, rated by Fitch Ratings and therefore, does not include smaller or regional banks that are not rated by the rating agency. This also imposes another limitation as only data from Fitch Ratings is used and other rating agencies are not included in the data collection which might further limit generalizability of the results.

Another limitation concerns the selected reputation indicators, which may mainly capture short-term changes in public attention, even when lagged and therefore might not fully reflect how reputation develops over time or how it is assessed by credit rating agencies. Furthermore, annual data is collected for the independent variables for time and data accessibility purposes which might not capture the reputational shocks and fluctuations compared to semi-annual data. Lastly, the Scandal Severity variable included two news article sources, where only one of the sources had an archive with articles from the whole time horizon.

These limitations open up several directions for future research. One approach is to examine both shorter and longer lag structures for reputation variables to better capture delayed effects. Future studies could also explore alternative measures of reputation that more closely reflect stakeholder perceptions or how institutions assess reputation in practice. Expanding the sample further and also including ratings from other rating agencies, smaller or medium-sized banks, or banks in other regions, could provide further insight into how reputation interacts with credit risk across different contexts.

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Appendix

Appendix 1: Banks in the Sample

	Bank	Ratings between 2018- 2024 (taking the last rating of each year)
1	Svenska Handelsbanken AB, https://www.handelsbanken.com/en/investor-relations/reports-and-presentations	2018: AA 2019: AA 2020: AA 2021: AA 2022: AA 2023: AA 2024: AA https://www.fitchratings.com/entity/svenska-handelsbanken-ab-80359527#ratings
2	Swedbank AB, https://www.swedbank.com/investor-relations/reports-and-presentations/annual-reports.html	2018: AA- 2019: AA- 2020: A+ 2021: A+ 2022: AA- 2023: AA- 2024: AA- https://www.fitchratings.com/entity/swedbank-ab-80359928#ratings
3	ING Groep N.V., https://ing.com/investors/financial-performance/annual-reports/2024	2018: A+ 2019: A+ 2020: A+ 2021: A+ 2022: A+ 2023: A+ 2024: A+ https://www.fitchratings.com/entity/ing-groep-nv-85271275#ratings
4	Banco Santander S.A., https://www.santander.com/en/shareholders-and-investors/financial-and-economic-information#annual-report	2018: A- 2019: A- 2020: A- 2021: A- 2022: A- 2023: A- 2024: A- https://www.fitchratings.com/entity/banco-santander-sa-80360562

		#ratings
5	Danske Bank A/S, https://danskebank.com/file-cloud?filters=Investor%20relations	2018: A 2019: A 2020: A 2021: A 2022: A 2023: A+ 2024: A+ https://www.fitchratings.com/entity/danske-bank-a-s-80359690#ratings
6	UBS Group AG, https://www.ubs.com/global/en/investor-relations/financial-information/annual-reporting/ar-archive.html	2018: AA- 2019: AA- 2020: AA- 2021: AA- 2022: AA- 2023: A+ 2024: A+ https://www.fitchratings.com/entity/ubs-ag-80359520#ratings
7	Skandinaviska Enskilda Banken AB (SEB), https://sebgroup.com/our-offering/reports-and-publications/annual-and-sustainability-reports	2018: AA- 2019: AA- 2020: AA- 2021: AA- 2022: AA- 2023: AA- 2024: AA- https://www.fitchratings.com/entity/skandinaviska-enskilda-banken-ab-publ-80359927#ratings
8	Deutsche Bank, https://investor-relations.db.com/reports-and-events/annual-reports/#tab-container-1-2024-2022-2	2018: BBB+ 2019: BBB 2020: BBB 2021: BBB+ 2022: BBB+ 2023: A- 2024: A- https://www.fitchratings.com/entity/deutsche-bank-ag-80089261#ratings
9	CaixaBank S.A., https://www.caixabank.com/en/shareholders-investors/economic-financial-information/annual-half-year-statements.html	2018: BBB+ 2019: BBB+ 2020: BBB+ 2021: BBB+ 2022: BBB+

		2023: BBB+ 2024: A- https://www.fitchratings.com/entity/caixabank-sa-90522281#ratings
10	UniCredit Bank S.p.A., https://www.unicreditgroup.eu/en/investors/financial-reporting/financial-reports.html	BBB+ to BB+ 2018: BBB 2019: BBB 2020: BBB- 2021: BBB 2022: BBB 2023: BBB 2024: BBB+ https://www.fitchratings.com/entity/unicredit-spa-80360405#ratings
11	Bank of Ireland Group PLC, https://investorrelations.bankofireland.com/results-centre/#panel2-3	2018: BBB 2019: BBB 2020: BBB 2021: BBB 2022: BBB 2023: BBB+ 2024: BBB+ https://www.fitchratings.com/entity/bank-of-ireland-group-public-limited-company-96483709#ratings
12	HSBC Holdings PLC, https://www.hsbc.com/investors/results-and-announcements/all-reporting/group?page=1&take=20&years=2024%7C2023%7C2022%7C2021%7C2020%7C2019%7C2018&reporting-type=annual	2018: AA- 2019: A+ 2020: A+ 2021: A+ 2022: A+ 2023: A+ 2024: A+ https://www.fitchratings.com/entity/hsbc-holdings-plc-80359989#ratings
13	ABN AMRO Bank N.V., https://www.abnamro.com/en/investor-relations/information/all-financial-reports?selectedTab=2024	2018: A+ 2019: A+ 2020: A 2021: A 2022: A 2023: A 2024: A https://www.fitchratings.com/entity/abn-amro-bank-nv-88846058

		#ratings
14	Standard Chartered PLC, https://www.sc.com/en/investors/financial-results/	2018: A 2019: A 2020: A 2021: A 2022: A 2023: A 2024: A https://www.fitchratings.com/entity/standard-chartered-plc-84253875#ratings
15	Crédit Agricole Group, https://www.credit-agricole.com/en/finance/financial-publications#	2018: A+ 2019: A+ 2020: A+ 2021: A+ 2022: A+ 2023: A+ 2024: A+ https://www.fitchratings.com/entity/credit-agricole-sa-80360059#ratings
16	Banca Monte dei Paschi di Siena SpA (BMPS), https://www.gruppomps.it/en/investor-relations/financial-results/financial-results-year-2024.html	2018: B 2019: B 2020: B 2021: B 2022: B+ 2023: BB 2024: BB+ https://www.fitchratings.com/entity/banca-monte-dei-paschi-di-siena-spa-80359663#ratings
17	Barclays PLC, https://home.barclays/investor-relations/reports-and-events/financial-results/financial-results-2024/	2018: A 2019: A 2020: A 2021: A 2022: A 2023: A 2024: A https://www.fitchratings.com/entity/barclays-plc-86198905#ratings
18	Lloyds Banking Group PLC ,https://www.lloydsbankinggroup.com/investors/financial-downloads.html	2018: A+ 2019: A+ 2020: A+ 2021: A

		2022: A 2023: A 2024: A+ https://www.fitchratings.com/entity/lloyds-banking-group-plc-80359546#ratings
19	Société Générale SA, https://investors.societegenerale.com/en/publications-documents?&theme=finance&category%5Bresultats-financiers%5D&category%5Bpilier-iii-et-autres-publications-prudentielles%5D&year%5B2025%5D&year%5B2024%5D&year%5B2023%5D&year%5B2022%5D&year%5B2021%5D&year%5B2020%5D&year%5B2019%5D	2018: A 2019: A 2020: A- 2021: A- 2022: A- 2023: A- 2024: A- https://www.fitchratings.com/entity/societe-generale-sa-80359523#ratings
20	Banco Bilbao Vizcaya Argentaria (BBVA), https://shareholdersandinvestors.bbva.com/financials/financial-reports/#2024	A- to BBB 2018: A- 2019: A- 2020: BBB+ 2021: BBB+ 2022: BBB+ 2023: BBB+ 2024: BBB+ https://www.fitchratings.com/entity/banco-bilbao-vizcaya-argentaria-sa-80360670#ratings
21	Intesa Sanpaolo S.p.A., https://group.intesasanpaolo.com/en/investor-relations/financial-reports/2024	2018: BBB 2019: BBB 2020: BBB- 2021: BBB 2022: BBB 2023: BBB 2024: BBB https://www.fitchratings.com/entity/intesa-sanpaolo-spa-80360476#ratings
22	BPER Banca S.p.A., https://group.bper.it/en/investor-relations/group-results/financial-statements-reports	2018: BB 2019: BB 2020: BB 2021: BB+ 2022: BB+ 2023: BBB- 2024: BBB- https://www.fitchratings.com/entity/bper-banca-spa-80359996

23	Erste Group Bank, https://www.erstegroup.com/en/investors/reports/financial-reports	2018: A- 2019: A 2020: A 2021: A 2022: A 2023: A 2024: A https://www.fitchratings.com/entity/erste-group-bank-ag-80359908#ratings
24	Rabobank, https://www.rabobank.com/about-us/organization/results-and-reports/downloads	2018: AA- 2019: AA- 2020: A+ 2021: A+ 2022: A+ 2023: A+ 2024: A+ https://www.fitchratings.com/entity/cooperatieve-rabobank-ua-90485080#ratings
25	NatWest Group PLC, https://investors.natwestgroup.com/results-centre	2018: A 2019: A 2020: A 2021: A 2022: A 2023: A 2024: A https://www.fitchratings.com/entity/natwest-group-plc-80089671#ratings
26	Türkiye Cumhuriyeti Ziraat Bankasi AS, https://www.ziraatbank.com.tr/en/investor-relations/financials/annual-reports	2018: B+ 2019: B+ 2020: B+ 2021: B+ 2022: B- 2023: B- 2024: B+ https://www.fitchratings.com/entity/turkiye-cumhuriyeti-ziraat-bankasi-as-80089907#ratings
27	Belifius Bank SA/NV, https://www.belfius.be/about-us/en/investors/results-reports/reports	2018: A- 2019: A- 2020: A- 2021: A- 2022: A- 2023: A-

		2024: A- https://www.fitchratings.com/entity/belfius-bank-sa-nv-80360509#ratings
28	Crédit Mutuel Group, https://www.creditmutuel.com/en/publications/annual-report.html	2018: A+ 2019: A+ 2020: A+ 2021: A+ 2022: A+ 2023: A+ 2024: A+ https://www.fitchratings.com/entity/credit-mutuel-alliance-federale-80361291#ratings
29	Nykredit A/S, https://www.nykredit.com/en-gb/filarkiv/?searchText=&documentTypeCategories=&legalEntities=78&documentTypes=83&years=	2018: A 2019: A 2020: A 2021: A 2022: A 2023: A 2024: A+ https://www.fitchratings.com/entity/nykredit-bank-a-s-91732090#ratings
30	DZ Bank AG, https://www.dzbank.com/content/dzbank/en/home/we-are-dz-bank/investor-relations/reports/report-archive.html	2018: AA- 2019: AA- 2020: AA- 2021: AA- 2022: AA- 2023: AA- 2024: AA- https://www.fitchratings.com/entity/dz-bank-ag-deutsche-zentral-genossenschaftsbank-80359643#ratings
31	BNP Paribas SA, https://invest.bnpparibas/en/search/reports/documents/financial-reports?s%5Bsubthemes%5D%5B%5D=17&s%5Blocale%5D%5B%5D=en&s%5Byear%5D%5B%5D=2024&s%5Byear%5D%5B%5D=2023&s%5Byear%5D%5B%5D=2022&s%5Byear%5D%5B%5D=2021&s%5Byear%5D%5B%5D=2020&s%5Byear%5D%5B%5D=2019&s%5Byear%5D%5B%5D=2018	2018: A+ 2019: A+ 2020: A+ 2021: A+ 2022: A+ 2023: A+ 2024: A+ https://www.fitchratings.com/entity/bnp-paribas-sa-80359629#ratings

32	Groupe BPCE, https://www.groupebpce.com/en/the-group/our-publications/	2018: A+ 2019: A+ 2020: A+ 2021: A+ 2022: A+ 2023: A 2024: A https://www.fitchratings.com/entity/groupe-bpce-88193055#ratings
33	La Banque Postale S.A., https://www.labanquepostale.com/en/investors/regulatory-information/universal-registration-document.html	2018: A- 2019: A- 2020: A- 2021: A 2022: A 2023: A 2024: A https://www.fitchratings.com/entity/la-banque-postale-sa-82694877#ratings
34	KBC Group NV, https://www.kbc.com/en/investor-relations/reports/annual-reports.html	2018: A 2019: A 2020: A 2021: A 2022: A 2023: A 2024: A https://www.fitchratings.com/entity/kbc-group-nv-80360667#ratings
35	Landesbank Baden-Wuerttemberg, https://www.lbbw.de/group/news-and-service/investor-relations/financial-reports/financial-reports_7u12dygoe_e.html	2018: A- 2019: A- 2020: A- 2021: A- 2022: A- 2023: A- 2024: A+ https://www.fitchratings.com/entity/landesbank-baden-wuerttemberg-81203650#ratings
36	Bayerische Landesbank, https://www.bayernlb.com/internet/en/blb/resp/meta_6/about_us/investor_relations_7/veroeffentlichungen_1/finanzberichte_1/financial_reports.jsp	2018: A- 2019: A- 2020: A- 2021: A- 2022: A- 2023: A-

		2024: A+ https://www.fitchratings.com/entity/bayerische-landesbank-81203048#ratings
37	Zurcher Kantonalbank, https://www.zkb.ch/en/lps/corporate/berichterstattung/downloads.html	2018: AAA 2019: AAA 2020: AAA 2021: AAA 2022: AAA 2023: AAA 2024: AAA https://www.fitchratings.com/entity/zuercher-kantonalbank-87593175

Appendix 2: News Articles for the Banks in the Sample

	Bank	Highest ranked articles in the given year
1	Svenska Handelsbanken AB	2017: 2 - Handelsbanken chairman questioned in bribery probe 2018: 3 - Five Scandinavian banks fined €2.5m for unauthorised credit ratings1 2019: No news exposure 2020: No news exposure 2021: No news exposure 2022: No news exposure 2023: No news exposure
2	Swedbank AB	2017: No news exposure 2018: 3 - Five Scandinavian banks fined €2.5m for unauthorised credit ratings 2019: 2 - Swedbank chief accused of not telling truth on suspicious money 2020: 4 - Swedbank fined $400m over weak money-laundering controls 2021: No news exposure 2022: 2 - Sweden announces charges against Swedbank ex-CEO over Baltic scandal 2023: 3 - Swedbank receives $82 mln administrative fine over lack of IT control
3	ING Groep N.V.	2017: 2 - ING Bank says criminal investigation could lead to “significant” fines 2018: 4 - Money laundering fine pushes down profits at ING 2019: 2 - ING backs EU anti-money laundering

		push following scandals 2020: No news exposure 2021: No news exposure 2022: No news exposure 2023: No news exposure
4	Banco Santander S.A.	2017: No news exposure 2018: 3 - Santander fined £33m for failing to pass on inheritances 2019: 1 - Santander is willing to fight Orcel in court over CEO job 2020: 4 - Santander unit agrees $550m deceptive lending settlement 2021: 1 - Santander ordered to pay €68m to Andrea Orcel over U-turn 2022: 4 - Santander UK fined £108mn for anti-money laundering failures 2023: No news exposure
5	Danske Bank A/S	2017: 2 - French probe Danske Bank link to alleged Russian fraud 2018: 4 - Danske Bank charged over €200bn money-laundering scandal 2019: 2 - Estonian scandal forces Danske out of the Baltics and Russia 2020: 2 - Danske Bank, Deutsche Bank channelled suspicious money through Lithuania - Danish media 2021: 2 - Danske Bank faces preliminary charges related to market abuse 2022: 5 - Danske Bank pleads guilty to resolve long-running Estonia money-laundering probe 2023: No news exposure
6	UBS Group AG	2017: 3 - UBS gets reprimand from Swiss regulator over role in 1MDB scandal 2018: No news exposure 2019: No news exposure 2020: 2 - Dutch prosecutors to investigate UBS chief over ING money laundering case 2021: 3 - Hong Kong regulator fines UBS $1.5 mln for compliance breaches 2022: No news exposure 2023: 5 - UBS fails to overturn guilty verdict in French tax evasion case
7	Skandinaviska Enskilda Banken AB (SEB)	2017: No news exposure 2018: 3 - Five Scandinavian banks fined €2.5m for unauthorised credit ratings 2019: 2 - SEB shares slide over money laundering concerns

		2020: 4 - SEB fined for Baltic money laundering deficiencies 2021: No news exposure 2022: No news exposure 2023: No news exposure
8	Deutsche Bank	2017: 4 - FCA fines Deutsche Bank £163m for 'serious anti money laundering failings' 2018: 2 - Deutsche Bank offices raided in German money-laundering probe 2019: 4 - Deutsche Bank pays €15m in money laundering settlement 2020: 3 - Deutsche Bank fined for Jeffrey Epstein 'compliance failures' 2021: 4 - Deutsche Bank to pay nearly $125 million to resolve U.S. bribery, metals charges 2022: 2 - BaFin threatens Deutsche Bank with fines as deadlines to fix controls approach 2023: 3 - Fed fines Deutsche Bank $186mn over failure to fix control flaws
9	CaixaBank S.A,	2017: No news exposure 2018: No news exposure 2019: No news exposure 2020: No news exposure 2021: No news exposure 2022: 1 - Brazil's Caixa CEO, close Bolsonaro ally, resigns over sexual harassment scandal 2023: No news exposure
10	UniCredit Bank S.p.A.	2017: No news exposure 2018: No news exposure 2019: No news exposure 2020: No news exposure 2021: 3 - EU fines UBS, Nomura, UniCredit $452 mln over bond cartel 2022: No news exposure 2023: No news exposure
11	Bank of Ireland Group PLC	2017: No news exposure 2018: No news exposure 2019: No news exposure 2020: No news exposure 2021: 3 - Bank of Ireland fined 24.5 mln euros over IT failures 2022: No news exposure 2023: No news exposure
12	HSBC Holdings PLC	2017: 2 - HSBC faces fresh suit alleging forex manipulation

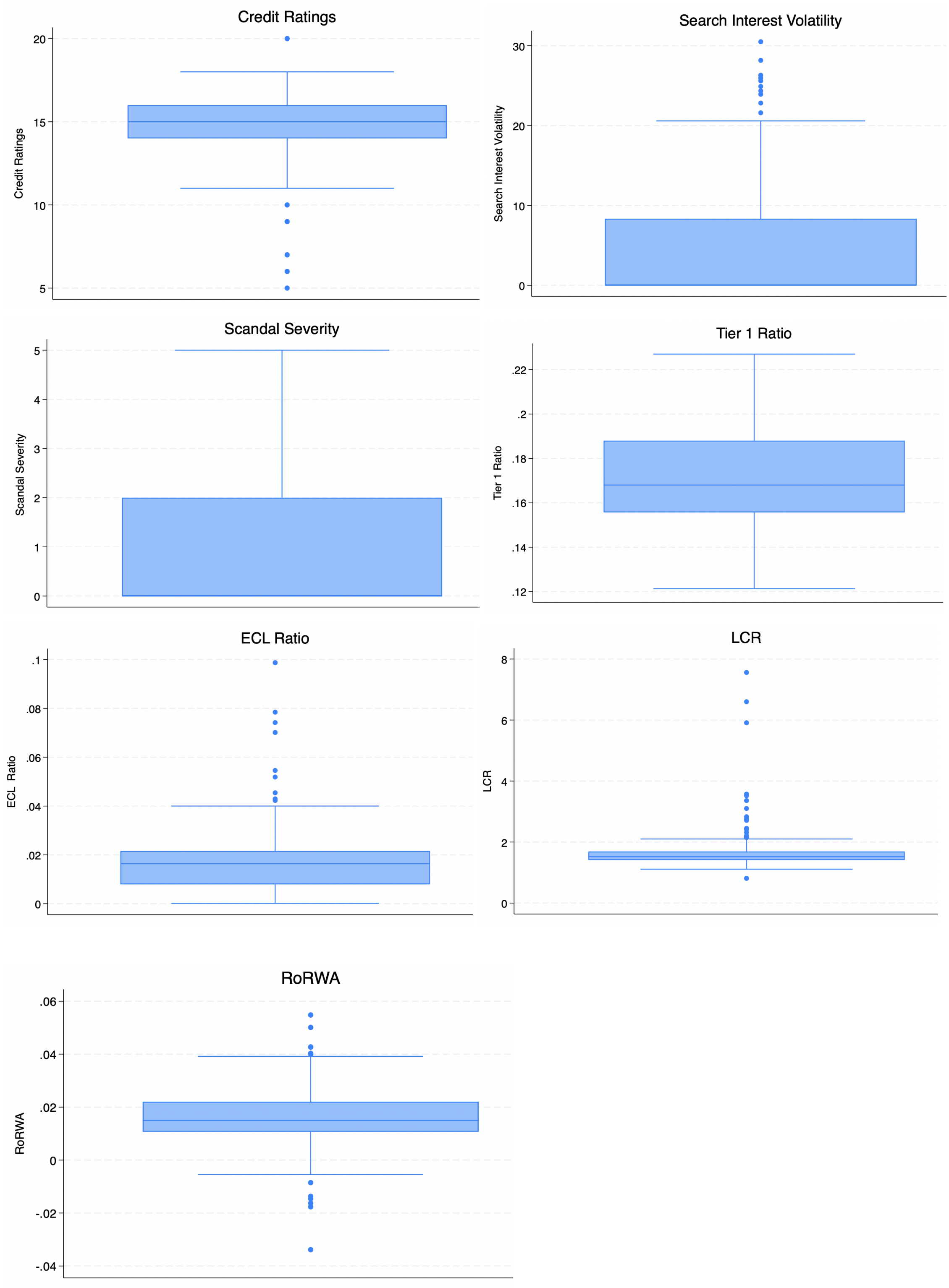
		2018: No news exposure 2019: No news exposure 2020: No news exposure 2021: 4 - HSBC fined $85 mln for UK anti-money laundering failings 2022: No news exposure 2023: No news exposure
13	ABN AMRO Bank N.V.	2017: No news exposure 2018: No news exposure 2019: 2 - ABN Amro under investigation for money laundering 2020: No news exposure 2021: 4 - ABN Amro reaches €480m anti-money laundering settlement 2022: No news exposure 2023: No news exposure
14	Standard Chartered PLC	2017: No news exposure 2018: No news exposure 2019: 4 - Standard Chartered to pay $1bn to settle Iran sanctions probe April 2019 2020: No news exposure 2021: 3 - Standard Chartered fined £46m over regulatory reporting failures 2022: No news exposure 2023: No news exposure
15	Crédit Agricole Group	2017: No news exposure 2018: No news exposure 2019: No news exposure 2020: No news exposure 2021: 3 - BAML, C.Agricole, C.Suisse fined $34 mln over bond cartel 2022: 4 - Crédit Agricole will pay $55 mln in interest rate-rigging settlement 2023: No news exposure
16	Banca Monte dei Paschi di Siena SpA (BMPS)	2017: No news exposure 2018: No news exposure 2019: 5 - Jail terms for 13 bankers over Monte Paschi scandal 2020: No news exposure 2021: 2 - Exclusive: Italy prosecutors seek mass trial in diamond fraud probe 2022: No news exposure 2023: No news exposure
17	Barclays PLC	2017: 2 - Barclays and former executives charged with crisis-era fraud

		2018: 3 - Barclays fined $15m by US regulator over whistleblowing scandal 2019: No news exposure 2020: No news exposure 2021: 2 - Barclays CEO Staley departs after Epstein probe 2022: 3 - Barclays faces $590 million hit, scrutiny over sales slip-up 2023: No news exposure
18	Lloyds Banking Group PLC	2017: 2 - Lloyds was repeatedly warned of criminality at HBOS 2018: No news exposure 2019: 2 - Lloyds: how HBOS whistleblower exposed failings in UK regulation 2020: No news exposure 2021: No news exposure 2022: No news exposure 2023: No news exposure
19	Société Générale SA	2017: No news exposure 2018: 4 - Société Générale fined $1.3bn for US sanctions violations 2019: No news exposure 2020: No news exposure 2021: No news exposure 2022: No news exposure 2023: No news exposure
20	Banco Bilbao Vizcaya Argentaria (BBVA)	2017: No news exposure 2018: No news exposure 2019: 2 - BBVA officially under investigation in spying probe at the bank 2020: 4 - BBVA paid 10 million euros for services of police chief in alleged spying case - court document 2021: No news exposure 2022: No news exposure 2023: 2 - BBVA chair called to testify as witness in alleged spying
21	Intesa Sanpaolo S.p.A.	2017: No news exposure 2018: No news exposure 2019: No news exposure 2020: No news exposure 2021: 2 - Italy prosecutors seek mass trial in diamond fraud probe 2022: No news exposure 2023: No news exposure

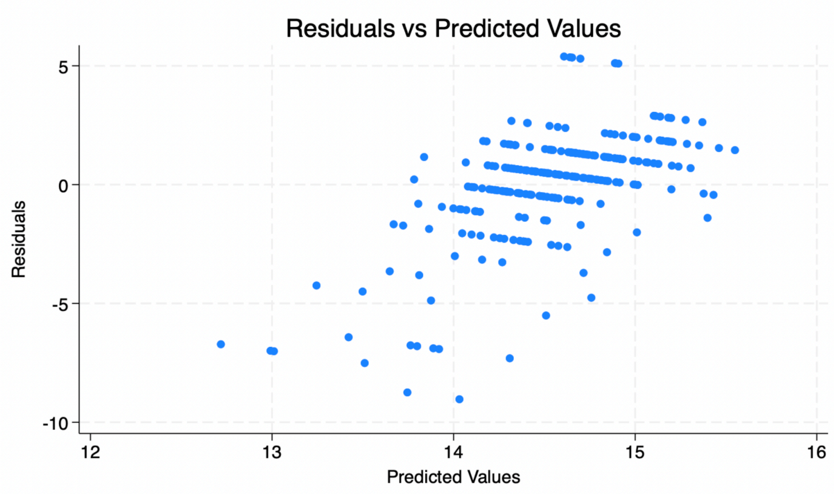
22	BPER Banca S.p.A.	No news exposure between 2017-2023
23	Erste Group Bank	2017: No news exposure 2018: No news exposure 2019: No news exposure 2020: No news exposure 2021: No news exposure 2022: No news exposure 2023: No news exposure
24	Rabobank	2017: No news exposure 2018: 4 - Rabobank to pay US $369m over cover-up in Mexico drug money case 2019: No news exposure 2020: No news exposure 2021: 2 - Rabobank faces punishment over customer anti-money-laundering checks 2022: 2 - Rabobank investigated for suspected Dutch money laundering violations 2023: 3 - Rabobank hit with $29 mln EU fine over 2006-16 bond cartel
25	NatWest Group PLC	2017: No news exposure 2018: No news exposure 2019: No news exposure 2020: No news exposure 2021: 5 - NatWest pleads guilty to failing to stop alleged money laundering 2022: 2 - FCA aims to use criminal powers in anti-money laundering probes 2023: 2 - NatWest 'debanking' review finds potential breaches of FCA rules
26	Türkiye Cumhuriyeti Ziraat Bankasi AS	2017: No news exposure 2018: No news exposure 2019: No news exposure 2020: No news exposure 2021: No news exposure 2022: 2 - Bank regulator puts German unit of Turkey's Ziraat under supervision 2023: No news exposure
27	Belifius Bank SA/NV	No news exposure between 2017-2023
28	Crédit Mutuel Group	No news exposure between 2017-2023
29	Nykredit A/S	No news exposure between 2017-2023
30	DZ Bank AG	No news exposure between 2017-2023
31	BNP Paribas SA	2017: 2 - BNP Paribas under investigation over role

		in Rwanda genocide 2018: 5 - BNP Paribas' US unit pleads guilty to FX price-fixing conspiracy 2019: 1 - Tribunal exposes gender gap in banking culture and pay 2020: 2 - BNP Paribas faces anti-corruption questions over Deutsche prime brokerage deal 2021: No news exposure 2022: 1 - Ex-BNP banker wins £2mn payout for gender discrimination 2023: 3 - Wall Street groups fined $555mn by regulators over messaging violations
32	Groupe BPCE	2017: No news exposure 2018: No news exposure 2019: No news exposure 2020: No news exposure 2021: No news exposure 2022: No news exposure 2023: No news exposure
33	La Banque Postale S.A.	No news exposure between 2017-2023
34	KBC Group NV	No news exposure between 2017-2023
35	Landesbank Baden-Wuerttemberg	2017: No news exposure 2018: No news exposure 2019: No news exposure 2020: No news exposure 2021: No news exposure 2022: 2 - 100 banks, 1,000 suspects: German fraud probe puts Scholz on the spot 2023: No news exposure
36	Bayerische Landesbank	No news exposure between 2017-2023
37	Zurcher Kantonalbank	No news exposure between 2017-2023

Appendix 3: Box Plots for the other Variables



Appendix 4: Residuals vs Predicted Values



Appendix 5: The Model with Winsorized RoRWA

	Coefficient	Robust Standard Deviation	t-value	P>t (p-value)
Search Interest Volatility	-.0035714	.0053426	-0.67	0.508
Scandal Severity	-.0033542	.0249189	-0.13	0.894
ECL Ratio	-15.57898	6.398643	-2.43	0.020
Tier 1 Ratio	9.400854	4.189117	2.24	0.031
Winsorized RoRWA	14.33092	10.96205	1.31	0.199
LCR	-.1137758	.0791486	-1.44	0.159
Log of Total assets	.1304244	.4177544	0.31	0.757
R-squared: Within	0.2671			
R-squared: Between	0.6434			
R-squared: Overall	0.4971			

Appendix 6: The Model with Winsorized LCR

	Coefficient	Robust Standard Deviation	t-value	P>t (p-value)
Search Interest Volatility	-.0037457	.0052971	-0.71	0.484
Scandal Severity	-.0024207	.0246672	-0.10	0.922
ECL Ratio	-16.23802	6.402325	-2.54	0.016
Tier 1 Ratio	9.359778	4.06979	2.30	0.027
RoRWA	12.25788	10.40211	1.18	0.246
Winsorized LCR	-.1570764	.0948021	-1.66	0.106
Log of Total assets	.1266277	.4137301	0.31	0.761
R-squared: Within	0.2649			
R-squared: Between	0.6572			
R-squared: Overall	0.5112			