LUND UNIVERSITY

SCHOOL OF ECONOMICS AND MANAGEMENT

Master's Programme in Finance

ESG Metrics: Exploring their Role in Predicting Systemic Risks in the European Financial System

May 2024

Trang Nguyen (19990412-T762)

Ibad Bayramov (20000611-T298)

Supervisor: Anders Vilhelmsson

Abstract

The study aims to explore the relationship between European financial banks' ESG pillars and their contribution to systemic risk, with a focus on the Eurozone banking industry. Utilizing the €ΔCoVaR metric to capture systemic risk, we analyzed a sample of 35 publicly listed banks across 12 European Union countries for the period of 2019 to 2023. The methodology consists of three steps. The first step is estimating VaR for each bank using the Basic Historical Simulation method. The VaR results will allow for the computation of CoVaR, ΔCoVaR, and €ΔCoVar. The last step is to analyze the relationship between ESG and €ΔCoVaR.

Our primary hypothesis (H0) posited that banks with higher ESG would contribute less to systemic risk; however, our findings indicate a positive correlation, diverging from pre-pandemic studies which generally reported a negative link. Our secondary hypothesis (H1) examined the distinct impacts of individual ESG pillars on systemic risk, revealing that while the environmental and social pillars have positive impact on systemic risk, the governance pillar shows a comparatively weaker association with systemic risk.

Keywords: ESG, systemic risk, European Union, financial stability, Value at Risk (VaR), CoVaR, ΔCoVaR, quantile regression, basic historical simulation.

Acknowledgements

During the writing process, we would like to express our deepest gratitude to our supervisor, Professor Vilhelmsson, for his invaluable guidance. Moreover, special thanks to our families for their tremendous support. Lastly, we are grateful to Lund University and the Swedish Institute for providing opportunities and resources that have significantly enriched our academic journey.

Table of Contents

1. Introduction

The integration of Environmental, Social, and Governance (ESG) metrics into the financial sector has emerged as a strategic move for enhancing the reputation and credibility of banks, signaling a shift towards sustainability (Schultz, Castelló, and Morsing, 2013). Specifically, ESG scores are aggregate measures calculated from weighting various heterogeneous indexes:

- Environmental (E), indicating sustainable resource management, emissions reduction, and innovative approaches to minimize environmental impact;
- Social (S), including factors such as employee satisfaction, workplace well-being, diversity, and human rights;
- And Governance (G) involves compliance, transparency, and fair treatment of shareholders.

In the financial industry, the common thought is that prioritizing social and environmental performance might compromise shareholder value, leading to increased costs and reduced competitiveness (Walley and Whitehead, 1994). However, counterarguments by Porter and Van der Linde (1995) propose that well-designed environmental regulations can yield benefits that outweigh costs, fostering resource efficiency. The escalating demand for ESG data underscores its significance in informing financial decisions, prompting regulatory interventions such as the European Banking Authority's mandate for major banks to disclose their ESG exposure from 2023 (EBA, 2022).

- Systemic risks, as defined by the International Monetary Fund (2008), denote *threats to financial stability arising from disruptions within the financial system with potentially severe consequences for the real economy*.
- While putting it in the context of the European financial system, the European Central Bank (ECB) describes it as the *risk of experiencing a strong systemic event that adversely affects several systemically important intermediaries or markets*. In other words, the collapse of one bank can trigger the failure of another, even if the latter appeared financially stable initially.

In the spring of 2023, the global finance industry witnessed the sudden collapses of high-profile banks, including Silicon Valley Bank (SVB), Signature Bank, and First Republic Bank, which reverberated across financial markets, precipitating uncertainty and concern. These incidents, characterized by their geographic diversity and multifaceted causes, further highlighted the importance of dealing with systemic risk within the banking sector. The ensuing market turmoil and public unease highlighted fears of financial contagion, wherein disruptions in one sector propagate across an economy or region, potentially leading to widespread consequences. The fate of the busted American banks spilled over the continent of Europe, too. The demise and the ultimate bankruptcy of Credit Suisse led to a significant increase in total extreme credit risk spillover within and without the European banking sector (Nekhili et al., 2023). Martins (2023) points out that the failure of Credit Suisse undermines agents' confidence regarding the soundness of the banking system.

With the EU banking industry taking a leading position compared to those based in other regions (Ho, Wang, and Vitell, 2012), we focus on the banking sector, specifically with the selection of large banks by market capitalization in the region. The heterogeneity of banking systems across the European financial market further complicates the interpretation of sustainability on financial market stability. Moreover, the emergence of the COVID-19 pandemic has introduced new challenges and uncertainties to banking market dynamics. The pandemic has disrupted financial markets, strained banking systems, and altered economic outlooks across the Eurozone (Elnahass et al. 2021). As these financial failures could have been predicted and prevented with a better emphasis on ESG by the management boards, understanding the direct relationship between ESG metrics and systemic risk has, therefore, become increasingly important.

This study emphasizes the Eurozone financial market particularly, as numerous countries in this area were early adopters of sustainability initiatives. The European Commission's commitment to reviewing non-financial reporting provisions aligns with the goals outlined in the European Green Deal, which seeks to transition the Union towards a resource-efficient, competitive, and climate-neutral economy by 2050. As it is predominantly a negative screening approach, involving the exclusion of companies failing to meet ESG criteria from investment portfolios (Amel-Zadeh et al., 2018). Firms operating in European financial markets were urged to disclose their ESG data, consequently ensuring the high availability and quality of this data. Additionally, the Eurozone market illustrates the intricate interconnectedness of financial institutions, where the fortunes of banks and investment firms intertwine amidst shared economic challenges and opportunities. Interbank markets, particularly vulnerable during crises, exemplify this systemic risk, where liquidity shocks can propagate through lending relationships, as evidenced by the research of Rochet and Tirole (1996).

The importance of each pillar over the financial banks also varies. The OECD report (2022) found that the governance pillar has a more substantial and more immediate influence over the financial sector. This is because the effects of governance changes tend to be more visible and quicker to materialize, whereas environmental and social changes may take longer to show their full impact (Monteiro et al., 2021). The chair of the European Risk Management Council, Evgueni Ivantsov, indicates that the governance pillar of the ESG metrics is the common root cause of their downfall. The most important issues faced by both were toxic culture and mismanagement of strategic risk. On the other hand, Chiaramonte et al. (2022) found that all individual pillars reduce bank fragility, with a higher impact from the social dimension. Accordingly, this research thus aims to explore the joint and individual ESG pillar (Environmental, Social, Governance) influence on systemic risk. Accordingly, the research hypotheses emerge as follows:

H0: Banks with higher ESG contribute relatively less to overall systemic risk, and

H1: Individual ESG pillars have separate effects on systemic risk.

While there has been a rise in discussions comprising different opinions and perspectives about ESG activities from financial experts, none of these assertions have been empirically and thoroughly examined, specifically on banking stability and within the pandemic periods. Our research makes two significant contributions to current literature. First, this study uses the CoVaR method, which, unlike traditional risk measures, accounts for the asymmetry of risk, particularly in tail events, providing a more nuanced understanding of systemic vulnerabilities. Integrating ESG considerations into the CoVaR framework enables a comprehensive assessment of how environmental, social, and governance practices may affect systemic stability. Secondly, given its unique characteristics and importance in the global financial system, we focus specifically on the Eurozone market. The research methodology involves gathering financial data from the Thomson Reuters Eikon database for 35 European financial banks with headquarters in the Eurozone area from 2019 to 2023. This study helps policymakers, regulators, and market participants better understand and mitigate the systemic risks in one of the world's most interconnected financial markets.

Outline

The remainder of this paper is organized as follows. *Chapter 2* presents a basis of the theoretical frameworks, introducing the concept of ESG and its individual pillars alongside an overview of systemic risk measurements. In *Chapter 3*, the literature review examines relevant empirical research on the association between ESG and systemic risk. *Chapter 4* outlines the quantitative methodology used in the paper, comprising the estimation of VaR, quantile regression for CoVaR and ΔCoVaR, and constructing a fixed effects model for panel regression. The data and control variables selection process are described with the addition of descriptive statistics in *Chapter 5*. The authors discuss empirical results and analysis in *Chapter 6* and thus draw conclusions, address research limitations and future suggestions in the final section – *Chapter 7*.

2. Theoretical Frameworks

Chapter 2 will review the fundamental theories and concepts regarding the field of study. We begin by examining the ESG concept's evolutionary trajectory and its components. Subsequently, we establish precise definitions for risk and systemic risk, delineating their conceptual boundaries. Following this, this section will present a detailed explanation of the selected risk measures, offering readers a formal description of how VaR and ES serve as indicators of risk and the calculations of selected Risk Measures. Lastly, systemic risk measurements are introduced to explain how systemic risk is assessed conceptually.

2.1 Definition of ESG and ESG Pillars

In today's society, investors and regulators are interested in more than just standard financial information. An example of this comes from the world's leading investment fund, BlackRock, which shifted its strategy to focus on sustainable development as the investors now recognize 'that climate risk is investment risk' (Mrchkovska et al., 2023). Subsequently, many other firms have embraced the trend, and as a result, environmental, social, and governance issues have become at the forefront of corporate reporting and performance (Arvidsson & Dumay, 2022). Through its Sustainable Development Goals, the United Nations encourages everyone to act on these issues—including companies (United Nations Development Programme [UNDP], 2015). Addressing these issues is often referred to as Environmental, Social, and Governance (ESG) or Corporate Social Responsibility (CSR) (Garzón-Jiménez, R., and Zorio-Grima, A., 2021).

According to Gillan et al. (2021), ESG refers to how companies and investors include environmental, social, and governance issues in their business practices. As mentioned before, ESG comprises environmental, social, and governance pillars. The environmental pillar examines how a company's actions affect the environment (PWC, 2023). This includes looking at workplace safety and health, adequate remuneration, inequality, social cohesion, and developing opportunities (Barangă and Țanea, 2022). The focus of the social pillar is how the company interacts with society and engages with its employees, clients, and other stakeholders (Arvidsson & Dumay, 2022). This includes looking at safety and health at work, adequate remuneration, inequality, social cohesion, and developing opportunities (Gillan et al., 2021). Of all the social factors, Diversity, equality, and non-discrimination have become inseparable from the corporations (Gillan et al., 2021). The governance pillar of ESG focuses on corporate management and behavior, encompassing aspects such as board structure, management compensation, adherence to ethical business practices, data protection, and transparency standards (Barangă and Țanea, 2022).

2.2 Definition of Systemic Risk

The research by Galati and Moessner (2010) concludes that there is no exact definition of systemic risk. On the other hand, (Adrian and Brunnermeier, 2016) define systemic risk as the risk that has the potential to impair the capacities of economic and financial systems and the production industries. Thus, a breakdown in aggregate financial intermediation stemming from shortages in both capital and liquidity across the financial system exacerbates systemic risk (Richardson et al., 2018). Regardless of the definition of systemic risk, it is widely acknowledged that the presence of systemic risk in the financial system poses significant threats to financial stability (Ostalecka, 2012).

Systemic risk, a concept that was already familiar before the 2008 financial crisis, has gained even more prominence in the years following the crisis (Smaga, 2014). The regulatory framework in place during the 2008 financial crisis was found to be inadequate in dealing with systemic risk. This realization has led policymakers to increasingly focus on systemic risk and its control mechanisms, driven by the severe adverse effects of systemic risk crises (Richardson et al., 2018).

Unlike other types of risks, market risk can only be indirectly attributed to a given institution (Smaga, 2014). Dow (2000) has identified the four most common factors for systemic risk:

1. Hazardous actions of individuals or groups of traders
2. An aggressive organizational culture focused on short-term gains
3. Failures in management across banks or the entire financial system leading to inertia
4. An inability to adapt to economic shifts and banks being overly exposed to the same type of risk, resulting in symmetric shocks across the entire system.

2.3. Measuring Risk

The early 1990s saw several spectacular company failures due to the inappropriate use of derivatives and a lack of sufficient internal controls. The most notable failures are Orange County (1994, losses of US$1.8 billion), Metallgesellschaft (1994, US$1.3 billion), Barings (1995, US$1.3 billion), and Daiwa (1995, US$1.1 billion) (Jadhav and Ramanathan, 2009). In response to these events, Basel I, also called the Basel Accord, was created. The Basel Accord provides recommendations on banking regulations with regard to credit, market, and operational risks. Its purpose is to ensure that financial institutions hold enough capital on account to meet obligations and absorb unexpected losses (Abad et al., 2014). Chapter 2.3 introduces two standard measures of firm-level risk: Value at Risk (VaR) and Expected Shortfall (ES) measures (Acharya et al., 2016). Both risk measures aim to provide a single number for the total risk in a portfolio (Hull, 2023).

2.3.1. Definition and Calculation of Value at Risk

Value at Risk (VaR) is a statistical measure used to evaluate a company's or investment portfolio's financial risk within a given timeframe. It is one of the most common risk measures used in finance. The correct estimation of VaR is essential for any financial institution in order to arrive at accurate capital requirements and meet the adverse movements of the market (Jadhav and Ramanathan, 2009). It calculates the maximum anticipated loss at a certain confidence level (Hull, 2023). Financial managers estimate the quantile of the left lower-sided tail as a representation of worst losses for a given α (Jadhav and Ramanathan, 2009). VaR requires two crucial parameters to be determined: the time horizon for estimating risk and the associated confidence level (Ball and Fang, 2006). The selected time horizon should account for the maximum duration needed to liquidate the portfolio or allow management sufficient time to address any issues (Jorion, 2002). Likewise, the chosen confidence level should align with the organization's risk aversion. Ceteris paribus, longer time horizons, and higher confidence levels result in higher VaR estimates, all else equal (Jorion, 2002). **Equation 1** is the formula of VaR_α for continuous loss distribution at the α confidence level:

$$Pr\ (L_t > VaR_\alpha) = 1 - \alpha \tag{1}$$

Where:

L_t - the maximum expected loss in period t,

α = the designated confidence level

Equation 1 implies that the probability of the portfolio losing more than VaR_α is 1 - α. If the loss distribution is discrete, the definition is adjusted because there might not be a specific loss l that precisely corresponds to the desired probability 1 - α to the right of l. Instead, we select the smallest loss l such that the probability does not exceed 1-α. **Equation 2** is the formula of VaR_α for both continuous and discrete loss distributions:

$$VaR_\alpha = \min \{l: \Pr(L > l) \leq 1-\alpha\} \quad (2)$$

Equation 2 implies that Value at Risk indicates the highest potential loss within a specified time frame that will not be exceeded with a probability of $1 - \alpha\%$ (Hull, 2012). One of VaR_α's benefits is that it applies to any financial instrument and is expressed uniformly in terms of '*lost money*' (Duffie and Pan, 1997). VaR's clear economic meaning has cemented the risk measure as a household name for portfolio risk management and capital allocation (Gao and Song, 2008). VaR's strengths, such as its accessibility for expression in price units, enable straightforward interpretation of risk extent (Acerbi et al., 2008). Due to the gap between theoretical models and regulators' practical needs, initially designed as an individual institutional-level risk measurement, VaRα has persisted in regulation-assessing risks of the financial system as a whole (Allen and Saunders, 2002). The other examples of the VaR are '*Interest Rate VaR*' (IRVaR), '*Forex VaR*' (FXVaR), '*Equity VaR*' (EQVaR), and '*Credit VaR*' (CVaR) (Acerbi et al., 2008).

2.3.2. Definition and Calculation of Expected Shortfall

Expected shortfall (ES) has been proposed in various ways to address the limitations of VaR, which is generally not a consistent measure of risk. ES has previously been referred to as conditional value at risk or conditional tail expectation (Hull, 2023). This is because ES generally yields the same results when applied to continuous loss distributions. However, different results could be observed for discontinuous base loss distributions (Acerbi and Tasche, 2002).

As proposed by Artzner et al. (1999), ES is commonly defined as the expected loss when the loss is more significant than the corresponding VaR, and therefore, ES is informative on the extent of excess losses (Gao and Song, 2008). The below **Equation 3** and **Equation 4** apply to both continuous and discrete loss distribution for ES when it is the average of all VaR_α for confidence levels $\alpha \leq x \leq 1$ (Hull, 2012):

$$ES_\alpha = \frac{1}{1-\alpha}\int_{x=\alpha}^{x=1} VaR_x \, dx \tag{3}$$

Where:

- VaR_x is the Value at Risk at the alpha quantile α
- x=α is the threshold quantile, thus the integration is performed over the tail beyond this quantile

$$ES_\alpha = \frac{E\left[L \times I_{L>VaR_\alpha}\right] + VaR_\alpha \left(1-\alpha-\Pr(L>VaR_\alpha)\right)}{1-\alpha} \tag{4}$$

Below is the formula for the continuous loss distribution:

$$ES_\alpha = E[L/L > VaR_\alpha] \tag{5}$$

Where:

- ES is the expected value of losses conditional on the losses exceed the VaR at the α confidence level.

In other words, ES is the expected portfolio loss given that the portfolio loses more than VaR_α for the continuous loss distribution (Acharya et al., 2016). Acerbi and Nordio (2001) points out that the main difference between both risk measures is VaR's lack of subadditivity. To be more precise, Expected Shortfall is a coherent measure of risk, while VaR is not a coherent measure (Acerbi and Nordio, 2001). On the other hand, Ball and Fang, 2006, argue that VaR's lack of subadditivity does not seem to present a problem in practice.

2.4. Estimating VaR and ES

While the concept of VaR may seem straightforward, its calculation is sophisticated (Abad et al., 2014). The early approaches to calculating VaR and ES were based on models for the independent and identically distributed (IID) returns. Gradually, many advanced models have started to be used for the calculation of VaR and ES, such as the generalized autoregressive conditional heteroskedasticity (GARCH) model (McNeil and Frey, 2000), the extreme value theory (Embrechts, Kluppelberg, and Mikosch, 1997), and the kernel smoothing method (Chen and Tang, 2005; Scaillet, 2004). This chapter introduces popular approaches for calculating VaR and ES for market risk. The chapter covers non-parametric and parametric approaches to estimating both VaR and ES.

2.4.1. Non-parametric approaches

The non-parametric approach relies on empirical loss distribution or sample loss distribution. The most well-known non-parametric method for estimating VaR and ES is historical simulation (Jadhav and Ramanathan, 2009). Historical simulation involves using the daily changes in the values of market variables observed in the past directly to assess the likelihood of changes in the value of the present portfolio from today to tomorrow (Hull, 2023). The first step is to identify the market variables affecting the portfolio. These market variables are sometimes referred to as risk factors. According to Dow (2002), historical simulation has two main advantages:

1. The method is very easy to implement.
2. Due to the approach not being dependent on parametric assumptions on the distribution of the return portfolio, it can accommodate wide tails, skewness, and any other non-normal features in financial observations.

Using standard results of empirical distribution, the α^{th} quantile $F^{-1}(\alpha)$ of a return random variable X with distribution function F can be non-parametrically estimated by considering the following **Equation 6** (Jadhav and Ramanathan, 2009) :

$$VaR_{(\alpha)}(X) = F^{-1}(\alpha) = X_{n(i)},\ \ \alpha \in \left(\frac{i-1}{n}, \frac{i}{n}\right) \tag{6}$$

Where:
$X_{n(1)} \leq X_{n(2)} \ \dots \leq X_{n(n)}$ are the order statistics corresponding to the observations X_1 , X_2 , ..., X_n from F.

The basic historical simulation approach assumes that each day in the past is given equal weight (Hull, 2023). Basic historical simulation selects the VaR value associated with the confidence level from the empirical loss distribution (Hendricks, 1996). Consequently, BHS directly chooses the pertinent loss from the sample of losses as an estimation of VaR (Hull, 2023). In a set of T losses, the count of losses l that exceed VaR_α in basic historical simulation is defined as below:

$$(1-\alpha)T \tag{7}$$

Where:

T - stands for the total number of observations accounted for the simulation in the historical data set.

Therefore, the estimated value of ES_α is calculated as the average of the (1 - α) T largest losses. On the other hand, in case the losses are sorted, the one-day-ahead estimate of VaR is therefore taken as the (1-α)T+1 largest loss. This is given by the below **Equation 8**:

$$\Pr\left(L > l^{s}_{(1-\alpha)T+1}\right) = \frac{(1-\alpha)T}{T} = 1-\alpha \;\Rightarrow\; VaR_\alpha = l^{s}_{(1-\alpha)T+1} \tag{8}$$

Where:

The formula determines the number of observations that correspond to the tail end of the distribution beyond alpha quantile.

Boudoukh et al. (1998) propose that greater emphasis should be placed on recent observations as they better capture current volatilities and prevailing macroeconomic conditions. They advocate for employing a natural weighting scheme characterized by an exponential weight decline. Age-weighted historical simulation (AWHS) attaches weight to each loss observation. Dowd (2005) provides an overview of the enhancements offered by age-weighted historical simulation compared to basic historical simulation:

1. It offers a broader application of basic historical simulation models. Basic historical simulation can be seen as a specific instance with no decay ($\lambda = 1$).
2. An appropriate selection of λ can enhance the responsiveness of VaR estimates to significant loss observations. It also improves the ability of this approach to manage clusters of large losses, known as volatility clustering.
3. Average weighted historical simulation decreases the so-called ghost effects.

Another widely used non-parametric method is the volatility-weighted historical simulation (VWHS). Hull and White (1998) propose a method for integrating volatility estimates into the historical simulation approach. The rationale is that during turbulent market conditions, risk levels rise, and this should be reflected in VaR and ES estimates, which should adapt to current market conditions. This approach naturally incorporates changes in volatility and generates VaR estimates that reflect more recent information (Hendricks, 1996). Consequently, the VaR estimates may exceed any historical losses observed during the considered historical period for the current portfolio (Hull, 2023).

2.4.2. Parametric approaches

The other method used to estimate VaR and ES is called the parametric approach. In a parametric approach, the model presupposes that the data adheres to a particular probability distribution, which makes the approach highly dependent on these foundational assumptions. The method measures risk by fitting probability curves to the data and then inferring the VaR from the fitted curve (Abad et al., 2014). The first introduced parametric model for estimating Value at Risk is known as Riskmetrics (Morgan, 1996), where the author assumed that the return portfolios of Riskmetrics follow a normal distribution. The VaR of a portfolio at 1 - α alpha quantile is calculated as below:

$$VaR(\alpha) = \mu + \sigma_t G^{-1}(\sigma) \tag{9}$$

Where:

$G^{-1}(\sigma)$ - α quantile of the standard normal distribution,
σ_t - Conditional standard deviation of the standard normal distribution.

The student-t distribution, which is another parametric approach, can accommodate excess kurtosis besides the mean and the standard deviation, as opposed to the normal distribution. The method allows for a higher likelihood of tail events. This characteristic makes it particularly useful because it can account for fat tails and excess kurtosis observed in the data. Since financial data, such as bond and stock returns, frequently exhibit fat tails, employing a normal distribution might lead to an underestimation of risk (Li & Nadarajah, 2018). The drawback of the method is its instability, meaning that VaR estimates are not reliable over long periods.

The student's T-distribution is calculated as follows:

$$VaR = -\mu_r + \sqrt{\frac{v-2}{v}}\, t_{\alpha,v}\sigma_r \tag{10}$$

Where:
v - degrees of freedom.
μ - mean
σ - standard deviation.

The Stable Paretian approach estimates VaR by determining the parameters of the stable distribution through maximum likelihood estimation (Mittnik et al., 1999). As a next step, Monte Carlo simulation is employed to calculate observations from designated stable distribution (Rachev and Mittnik, 2000).

A parametric approach to estimate excess losses above a sufficiently high threshold u is called the generalized Pareto distribution (McNeil, 1997). This method is generally categorized under extreme value theory (EVT), which has gained popularity in financial applications (Danielsson and Vries, 2000). The rationale behind concentrating on substantial losses is to observe the severe losses rather than, for instance, average losses or significant gains (Jadhav and Ramanathan, 2009). As a result, the alpha quantile of the confidence level is high, such as α=0.999. The distribution function of generalized Pareto distribution in the case that ξ is not equal to zero as follows:

$$G_{\xi,\beta(u)}(y) = 1 - \left(1 + \frac{\xi y}{\beta(u)}\right)^{-\frac{1}{\xi}}, \xi \neq 0 \tag{11}$$

Where:
$\beta_u > 0$, and $y \geq 0$ when $\xi \geq 0$, and $0 \leq y \leq -\beta(u)/\xi$ when $\xi < 0$.
Parameters ξ and $\beta(u)$ can be obtained from $G_{\xi,\beta(u)}(y)$ by the method of maximum likelihood.

2.5. Estimating Systemic Risk

In the wake of the 2008 financial crisis, the spread of risk from individual financial institutions was recognized to harm the stability and security of the system (Acharya et al., 2010). However, VaR only considers the risk that an individual institution i encounters when the system has a median loss (Girardi and Ergun, 2013). This led to newly proposed monitoring indicators to overcome the VaR's shortcomings, especially its inability to account for the possibly systemic nature of an institution's risk and financial distress (Girardi and Ergun, 2013). Systemic risk means the possible collapse of the entire financial system rather than just the collapse of individual institutions (Zhou et al., 2020). Once an institution i is in distress, its individual risks will spread over the financial system through relationships of assets and liabilities (Borio, 2003). The most recognized proposed systemic risk measurements are Systemic Expected Shortfall (SES) and Marginal Expected Shortfall (MES) by Acharya et al. (2017), Systemic Risk Measure (SRISK) by Brownlees and Engle (2017) and Conditional Value-at-Risk (CoVaR) by Adrian and Brunnermeier (2016).

2.5.1 Marginal Expected Shortfall (MES)

The Marginal Expected Shortfall (MES) is characterized as the expected equity loss of a firm when the broader market experiences a decline over a given time horizon (Popescu and Turcu, 2014). Brownlees and Engle (2017) have defined MES as the partial derivative of the system's ES with respect to the weight of a firm i in the economy. Thus, the measurement is based on the expected shortfall and looks at the expected shortfall of an institution i when the financial system has a VaR violation:

$$MES_{\alpha}^{i} = E\left(L_i / I_{L_m > VaR_{\alpha}}\right) \tag{12}$$

Where:

- $I_{Lm>VaR}$ is the indicator function which takes the value one when the market has a VaR violation and otherwise zero.

2.5.2. Systemic Risk Measure (SRISK)

The SRISK index of an institution i quantifies the expected capital shortage that an institution i might encounter if there is a significant downturn in the market over a prespecified period. The SRISK is subject to the firm's leverage, size and the expected equity loss conditional on a market decline (Brownlees & Engle, 2017). These proposals of the risk measure argue that the index also computes the systemic risk contribution of the institution i as well as aggregate systemic risk of the whole financial system:

$$SRISK_t^i = E_t\left(CS_{t+q}^i / R_{t+1:t+1}^m < C\right) \quad (13)$$

Where:

$R^m_{t+1:t+q}$ is the multiperiod arithmetic market return between t+1 and t+q time periods

The SRISK is determined by the capital shortfall, focusing on estimating the approximate amount of capital that would need to be raised by the institution during the financial system's distress period. Therefore, the institutions with the largest capital shortfall are deemed the most significant contributors to the crisis (Zhou, 2020).

2.5.3. Conditional Value at Risk (CoVaR)

Adrian and Brunnermeier (2016) proposed Conditional Value at Risk (CoVaR) as a key tool in capturing systemic risk. The risk measurement CoVaR is defined as the VaR of the financial sector given that the institution i is in distress. The authors also denoted CoVaR as the VaR of the institution i (or the whole financial system), given that some even have C of institution i. This means that CoVaR is defined by the α quantile of the conditional probability distribution:

$$\Pr\left(X^j / C\left(X^i\right) \leq CoVaR_{\{\alpha}\}^{j/C\left(X^i\right)} = \alpha\% \quad (14)$$

3. Literature Review

Chapter 3 provides a comprehensive overview of the existing literature relevant to our research with three main sections. Firstly, it explores the relationship between ESG metrics and financial performance, delving into how environmental, social, and governance factors influence the financial outcomes of banks. Then, our study examines systemic risks in the European financial system, discussing the nature of these risks in the context of financial stability within the Eurozone. Consequently, the research suggests potential linkages between ESG metrics and systemic risks, highlighting how ESG practices may impact the broader financial system and contribute to or mitigate systemic vulnerabilities.

3.1. ESG Metrics and Financial Performance

Friede et al., (2015) conducted a comprehensive analysis, revealing a clear positive correlation between high ESG performance and better financial performance. Their findings suggest that companies prioritizing ESG considerations tend to outperform their counterparts financially. However, it is essential to recognize the contingent nature of this relationship. The research also highlighted the influence of industry-specific and geographical factors on the relationship between ESG performance and financial performance. This nuanced understanding underscores the need for tailored approaches in assessing the impact of ESG metrics on financial outcomes across different contexts.

Furthermore, Cai et al., (2016) contribute to this discourse by demonstrating the risk mitigation benefits associated with heightened Environmental engagement. Their research indicates that firms with strong environmental practices experience lower stock return volatility and downside risk. The finding suggests that environmental considerations contribute to sustainable practices and serve as effective risk management strategies, thereby positively influencing financial performance.

In addition to environmental factors, social initiatives also play a crucial role in driving financial performance. Flammer (2015) argues that robust Corporate Social Responsibility (CSR) initiatives contribute to long-term value creation with social trust, which, in turn, contribute to the overall financial health of organizations and enhance financial resilience during financial shocks. Simpson and Kohers (2002) affirm a positive correlation between corporate social performance and financial performance, specifically with a focus on the banking industry in Europe. Governance structures also play a pivotal role in shaping financial outcomes, as evidenced by Hartzell et al. (2008), who indicate that firms with stronger governance frameworks command higher IPO valuations and exhibit superior long-term operating performance compared to their counterparts.

Additionally, firms with high ESG commitment usually come with higher levels of social trust, thus, are better positioned to navigate challenging market environments and consequently enjoy improved access to capital funding (B Cheng, 2013). Specifically, firms engaging in ESG initiatives tend to enhance transparency through the public disclosure of their CSR strategies (Dhaliwal et al., 2011). This increased transparency serves to reduce information asymmetry, providing stakeholders with greater insight into the company's operations and practices. This transparency not only strengthens the relationship between a firm and its stakeholders and investors but also fosters trust in public investment, which has been proven to be a pivotal factor in financial performance especially in times of adverse shocks by Lins et al (2017).

3.2. Systemic Risks in the European Financial System

Systemic risks pose a critical concern for the stability of the European financial system, encompassing various forms such as credit, market, and contagion risks. Credit risk, defined as the potential for borrowers to default on their obligations, leading to losses for lenders and potentially triggering a chain reaction of financial distress across the system (Altman, 2004). Market risk refers to the risk of losses on financial investments caused by adverse price movements in the market (Hull, J. C., 2012). Contagion risk amplifies systemic vulnerabilities, as the distress of one institution or market can propagate throughout the financial system, triggering a cascade of failures and exacerbating systemic instability (Allen & Gale, 2000).

Empirical research on systemic risk among different regions by Ang and Longstaff's (2013) highlighted the significantly elevated systemic risk in Eurozone countries compared to US states, emphasizing its strong correlation with financial market conditions. This underscores the vulnerability of European economies to systemic shocks, specifically within the Eurozone. The Greek debt crisis, as examined by Reboredo and Ugolini (2015), offers a pertinent example of the level of systemic risk in this specific region. Before the crisis, systemic risk in European sovereign debt markets was relatively uniform across countries. However, during the crisis, systemic risk for distressed countries decreased while non-crisis countries increased.

Moreover, Georg's (2013) study on interbank network structures underscores the importance of institutional design in mitigating systemic risk. Money-center networks, characterized by centralized nodes, exhibit greater stability compared to random networks, proposing a dynamic multi-agent model with a central bank. Acemoglu et al. (2015) delve into the role of interconnected financial networks in amplifying systemic risk. While dense financial networks can enhance resilience to minor shocks, they can also serve as conduits for systemic risk during major disruptions. This highlights the delicate balance between network connectivity and systemic risk management in safeguarding financial stability.

3.3. Potential Linkages between ESG Metrics and Systemic Risks

Although an increasing amount of evidence highlights the beneficial influence of sustainable practices on banking profitability (Wu and Shen, 2013)., the exploration of whether and how Environmental, Social, and Governance (ESG) activities impact bank risk remains a pivotal and unresolved question. In the quest to understand systemic risks within the European financial system, it becomes imperative to delve into how these metrics might function as early indicators for predicting systemic risks. Theoretical frameworks and empirical evidence offer valuable avenues for investigating potential linkages between ESG metrics and systemic risks.

Researchers have sought to uncover the various channels through which ESG factors influence systemic risk dynamics, shedding light on the potential mechanisms and implications for financial stability. For instance, Eccles et al. (2014) suggested that firms with strong ESG performance exhibit *(1) greater long-term resilience* to systemic risks. By integrating sustainability considerations into their business models, these companies are better positioned to anticipate and adapt to changing market conditions, thereby reducing their susceptibility to systemic risk contagion. Similarly, Ararat et al. (2017) studied that firms with strong ESG performance are less susceptible to systemic risk shocks, as evidenced by their resilience during periods of market downturns. This implies that companies prioritizing ESG considerations may exhibit lower systemic risk profiles, potentially stemming from their enhanced risk management practices and stakeholder engagement strategies.

Giesecke et al. (2019) highlight the role of ESG factors in *(2) regulatory compliance and risk management practices*. Firms with robust ESG frameworks are more likely to comply with regulatory requirements and adopt proactive risk management strategies, which can mitigate the transmission of systemic risks throughout the financial system. This result is also aligned with evidence from research by Busch et al. (2016), indicating that firms with robust governance structures are better equipped to navigate turbulent market conditions, thereby reducing the likelihood of contributing to systemic risk contagion.

When examining the relationship between corporate social responsibility (CSR) activities and firms' access to finance, Cheng et al. (2013) suggest that firms with higher levels of CSR engagement can be perceived as *(3) less risky and more trustworthy* by external investors. This trust can act as a buffer against systemic risk contagion, as investors may be more confident in the company's ability to navigate turbulent market conditions. Similarly, Margolis (2017) emphasizes the importance of stakeholder engagement and trust-building in mitigating systemic risks. Companies that prioritize ESG initiatives not only enhance their relationships with stakeholders but also foster trust among investors and market participants. Additionally, good firms demonstrating stronger CSR performance tend to disclose their CSR information to the market

(Dhaliwal et al., 2011), aiming to underscore their commitment to long-term objectives and distinguish themselves from competitors (Spence, 1978). Consequently, the augmented availability of ESG data contributes to bolstering global financial transparency CFA Institute (2015), thereby mitigating systemic risks.

In conclusion, the existing literature consistently suggests a negative association between Environmental, Social, and Governance (ESG) metrics and contributed systemic risk. Building upon this foundation, our study hypothesizes that higher ESG and individual ESG pillar scores could potentially contribute to the mitigation of systemic risk within the financial system.

4. Methodology

This section covers the methodology of examining the relationship between ESG and systemic risk in the European financial banking sector. The methodology consists of three steps. The first step is estimating each bank's Value at Risk (VaR) using the Basic Historical Simulation method. The findings will allow for the computation of CoVaR (Conditional Value at Risk), ΔCoVaR (Delta Conditional Value at Risk), and €ΔCoVar (Euro Delta Conditional Value at Risk). The last step is to analyze the relationship between ESG and €ΔCoVaR and assess the findings.

4.1. Calculating Value at Risk

The methodology commenced with collecting data on stock prices, market capitalization, and ESG ratings, including separate pillars of the ESG ratings. The estimation of Value at Risk (VaR) commenced with the calculation of daily losses for each publicly traded bank's stock using the logarithmic return formula. The logarithmic return formula is stated in **Equation 15:**

$$L_t^i = -\ln\left(\frac{Stock\ returns_t^i}{Stock\ returns_{t-1}^i}\right) \tag{15}$$

This foundational step involved quantifying the day-to-day financial risk associated with each stock. We employed the BHS method for the VaR computation across a 200-day rolling window. The risk management practices focus predominantly on the characteristics of the left tail of the return distribution, where data is often scant, making it challenging to develop an appropriate model for this segment. The main advantage of non-parametric methods over parametric methods is their robustness to the model assumption. As a result, the method avoids the bias caused by the use of a misspecified return distribution (Jadhav and Ramanathan, 2009). This approach emphasizes allowing the data to dictate outcomes and rely on recent returns' empirical distribution rather than relying on assumed theoretical distributions to estimate VaR (Abad et al., 2014). Therefore, the BHS was chosen as a VaR estimator in this paper. The BHS method can provide a uniform weighting of all losses within the specified window, thereby delivering a reliable measure of annual risk. The rolling window approach ensures that the calculated VaR accurately reflects each bank's specific risk profile annually, enhancing the precision of our systemic risk analysis. The rolling-window approach will use 1282 company observations starting from January 2nd, 2019. The size of a 200-day rolling window is based on a few reasons. Firstly, the rolling window size cannot be too long and not too short either (Dowd, 2005). The ratio of the sample size to the rolling window should give the risk estimates of decent precision without the negative effects like the ghost effect. Such a phenomenon appears when old observations fall out of the sample and create 'jumps' in the data, which distort the VaR calculations (Dowd, 2005). The second reason is that the sample period partially lies in the pandemic era. A 200-day rolling window will ensure that our estimations are not affected by the pandemic shocks. By systematically applying these methodologies, our research rigorously analyzes the financial stability and risk factors affecting European financial banks, providing valuable insights into their risk management practices and resilience.

Subsequent to the computation of losses for our sample of 35 individual banks over a five-year period, the next step is to calculate the VaR for each institution in our sample annually. The VaR was estimated using alpha quantiles of 50%, 95%, and 99%. The rationale behind this selection includes specific methodological steps. Primarily, the VaR at the 95% confidence level was estimated to facilitate a comparative analysis with the results at the 99% confidence level. Furthermore, the choice to calculate the 50% and 99% VaR is grounded in our research methodology, which involves utilizing both estimates in further analyses, particularly in the computation of ΔCoVaR and €ΔCoVaR. This thoroughness in our research methodology ensures the accuracy and reliability of our results.

Referring to *Section 2.3.1*, VaR is calculated using **Equation 2**:

$$VaR_{\alpha} = \min\{l : \Pr(L > l) \leq 1 - \alpha\}$$

The VaR estimations at different confidence levels are illustrated in **Appendix 3**.

4.2. Calculating CoVaR

Among the described systemic risk estimation methods in *Section 5***,** this paper employs Conditional Value at Risk (CoVaR). CoVaR is introduced in the paper by Adrian and Brunnermeier, 2016 to measure conditional variance. In order to better illustrate the systemic nature of the risk measure, Adrian and Brunnermeier (2016) use the VaR method and add the prefix “Co,” which stands for conditional, contagion, or co-movement. CoVaR is a signal number estimating the maximal potential loss of the entire financial system conditional on institutions being under distress for a given probability (Xu et al., 2021). CoVaR was selected because it focuses on each institution's contribution to overall system risk, as opposed to traditional risk measures, whose main point lies with the risk of individual institutions (Zhou et al., 2020). CoVar’s properties of predicting the system value at risk conditional on the risk of an individual institution and time series make this paper consistent and unbiased (Zelenyuk and Faff, 2022). CoVaR is estimated by conditioning on an event C with the same likelihood to occur across institutions. Event C stands for the financial institution i’s loss being at or above its $VaR_{\alpha,i}$ level, which occurs with the likelihood (1-α)% (Adrian and Brunnermeier, 2016). CoVaR is calculated by **Equation 16**:

$$\Pr\left(L^s \geq CoVaR_\alpha^{s,i} \middle| L_i = VaR_\alpha^i\right) = \alpha \tag{16}$$

In order to estimate CoVaR, the losses across the entire financial system need to be calculated in addition to the individual bank losses. The first step is to calculate the weights for each bank for each year. The weights for each bank are estimated by dividing the market capitalization of each bank by the sum of the market capitalizations of all banks for that sample year. The calculation is illustrated in the **Equation 17**:

$$w_t^i = \frac{market\ cap_t^i}{\sum_{i=1}^n market\ cap_t^i} \tag{17}$$

The calculation of the weights ensures that the influence of each bank in the analysis is proportional to its size or market presence each year. These weighted factors are subsequently verified to ensure that they sum to one for each day.

The annually calculated weighted factors are then multiplied with the annual individual bank losses to provide financial system losses for each sample year. Once the system losses are estimated, the following step is to calculate the value at risk of the financial system. We sum up the multiplication results for all the companies to receive the daily financial system losses using **Equation 18**:

$$L_t^{system/L^i} = \sum_{i=1}^{n} w_t^i \ L_t^i \tag{18}$$

The VaR of the financial system is calculated at the same level as the VaR of the individual banks, which is 99% confidence level. The calculation of both individual bank losses and the financial system losses at the same confidence level is crucial due to few reasons:

1. Consistency in measurement
2. Accuracy in CoVaR calculation
3. Statistical perspective

The 99% confidence level effectively focuses on the extreme tail of the loss distribution or the unexpected values. Estimating individual banks and the financial system at the 99% confidence level will provide a much broader picture to analyze the companies' losses when the financial system is in distress. 99% confidence level allows us to look at the worst 1% of outcomes, which is crucial for understanding and preparing for severe stress scenarios. The subsequent step is to estimate the CoVaR. In CoVaR estimation, the commonly used methods are quantile regression (Adrian and Brunnermeier, 2016), multivariate GARCH (Girardi and Ergun, 2013), and copulas (Reboredo and Ugolini (2015). This paper follows Adrian and Brunnermeier, 2016 and adopts quantile regression to estimate the CoVaR. Quantile regression was developed by Koenker and Bassett (1978) and enhanced by Koenker (2005). Koenker (2005) argues that classical linear regression methods can be used for inference on the conditional mean functions. On the other hand, quantile regression was developed to estimate models for the conditional median function and the full range of all the other conditional quantile functions (Curcio et al., 2024). Quantile regression is consistent with the analysis of financial data under extreme conditions (Bernal et al., 2014). Previous papers that employ quantile regression have shown that this regression model can predict risk (De Mendonca and Da Silva, 2018). Therefore, quantile regression is chosen for CoVaR analysis due to its consistency with the tail ends of the distribution.

We start computing CoVaR for each sampled European financial bank by using system losses as a conditional on VaR. The estimated 99% VaR confidence level for both individual banks and financial systems is fit into a quantile regression model to estimate the tail beta and interpret for each financial bank for each sample year, which measures the sensitivity of the bank’s losses to the system's losses at the 99% confidence level. The tail beta is required to interpret how extreme movements in the system affect the individual banks. In addition to this, an OLS model is employed to calculate the CAPM beta. CAPM beta illustrates how banks' losses move during the median times. According to Adrian and Brunnermeier (2016), the computed tail beta and the interpretation subsequently used for the regression model to calculate annual CoVaR:

$$CoVaR_{\alpha}^{i} = c_{\alpha} + \beta_{\alpha}^{i} VaR_{\alpha}^{i} \tag{19}$$

Where:

$c\alpha$ and $\beta i\alpha$ are the estimated quantile regression coefficients **(Appendix 4).**

$CoVaRi\alpha$ is annual CoVaR estimate **(Appendix 5).**

4.3. Calculating ΔCoVaR and €ΔCoVaR

ΔCoVaR estimates the "tail-dependency" between two random return variables (Adrian and Brunnermeier, 2016). ΔCoVaR measures how much the VaR of the financial system increases when firm i is distressed as opposed to the VaR of the financial system when firm i has a loss equal to the median.

Once CoVaR is estimated for each sample year, ΔCoVaR is then computed through below **Equation 20**:

$$\Delta CoVaR_{\alpha}^{s,i} = \left(c_{\alpha} + \beta_{\alpha}^{i} VaR_{\alpha}^{i}\right) - \left(c_{\alpha} + \beta_{\alpha}^{i} VaR_{50}^{i}\right) = \beta_{\alpha}^{i}\left(VaR_{\alpha}^{i} - VaR_{50}^{i}\right) \tag{20}$$

Building on the initial computation of the VaR for each sampled financial bank at a 50% confidence level during the first step, the ΔCoVaR of the financial institutions is calculated by subtracting the CoVaR from the VaR of the financial institution at a 50% confidence level. Thus, **Equation 20** illustrates the difference between when the institution i is experiencing distress and when the firm has a median loss distribution, so a normal operating period. The result will reveal how much VaR of the financial system would be higher if the company is in distress.

As proposed by Adrien and Brunnermeier (2016), this paper employs €ΔCoVaR, a similar idea to $ΔCoVaR. €ΔCoVaR computation aims to look at the risk level conditioning at the risk of extreme losses given that a firm is in distress. Thus, through these steps, we will calculate an absolute € amount based on the risk a particular entity poses to the overall financial system or another specific entity under stress conditions.

€ΔCoVaR is calculated by taking the market cap of financial institution i and multiplying it with the estimated CoVaR for that firm **(Appendix 6)**, as seen in **Equation 21:**

$$€\Delta CoVaR = Size^{i,€} \times \Delta CoVaR_{\alpha}^{i} \tag{21}$$

4.4. Panel Regression

Based on the previous steps, where we calculated €ΔCoVaR to measure the contribution to systemic risk of each sampled institution for the 2019-2023 period, this study now turns its focus towards examining the impact of separate ESG pillars and ESG ratings on systemic risk. Since each financial institution in the sample has one observation for each sample year, resulting in a dataset that spans five-year periods, a panel regression approach is employed to analyze the relationship between the ESG pillars and systemic risk.

The panel regression model allows for the modeling of complex behaviors and enables the comparison of characteristics over time. The model effectively captures variations across both the cross-section and time series dimensions of our data. A pooled OLS model is a potential option to employ for our panel data analysis. However, it is less suitable due to its assumption of uniformity across entities and time-overlooking any entity-specific or time-specific heterogeneity. Additionally, the model ignores dependencies. Due to the mentioned facts, this paper instead employs a fixed-effects model. The model will allow the elimination of heterogeneity. As a result, the chosen model provides a more precise analysis of the influences impacting systemic risk. The commonly used fixed-effects model proposed by Allison (2009) stated in **Equation 22**:

$$y_{i,t} = \alpha + \beta X_{i,t} + \gamma z_i + v_t + \epsilon_{i,t} \tag{22}$$

Where:
- α stands for intercept
- β stands for coefficent
- $X_{i,t}$ stands for variables that change over time
- z_i stands for variables that don't change over time
- v_t stands for time-fixed effects
- $\varepsilon_{i,t}$ stands for error term over time

The dependent variable for the fixed-effects model is previously calculated €ΔCoVaR. This was in line with the similar ideology proposed by Zelenyuk and Faff (2022), who use $ΔCoVaR to estimate the relationship between the research topic and the systemic risk. The fixed effects model will employ the control variables to control the external effects into it. Previous studies such as Lopez-Espinosa et al. (2013) and Adrien and Brunnermeier (2016) have proposed to include bank-specific variables. The variables include Basel leverage, NPL ratio, total assets (log), risk sentiment variables, such as volatility, and macroeconomic variables, such as inflation, GDP growth rate, and unemployment rate. Unlike Adrien and Brunnermeier (2016), the sample data in this paper is collected from 12 different countries. As a result, macroeconomic control variables cannot be employed due to this. In order to tackle this, the panel regression model includes time-fixed effects to control time-specific heterogeneity. On the other hand, entity-specific effects control for cross-sectional variation. However, the sampled data includes only institutions from the European bank sector, and thus, the addition of entity-specific effects might result in multicollinearity. Multicollinearity occurs when two or more variables are highly correlated, thus violating the reliability and interpretability of the regression model. In order to tackle this, the fixed effects model will exclude entity-specific effects.

Building on this and considering the limited sample size we have due to constraints regarding the data availability, the model will employ the following control variables:

- Debt to Equity ratio
- Return on Equity (ROE)
- Default risk
- Firm-specific Beta

These bank-specific variables will account for external financial factors and address possible inconsistencies in the empirical results. The addition of the control variables aims to reduce the risk of omitted variable bias.

Lastly, apart from adopting the overall ESG, the model will account for environmental, social, and governance pillars separately to understand their impact on systemic risk. As a result, four different fixed-effects panel regression models will be employed in this paper to look at the ESG separate pillars' relationships with systemic risk. Therefore, this paper employs the below four regression models:

- *Model 1*: ESG
- *Model 2*: Environment
- *Model 3:* Social
- *Model 4:* Governance

However, to understand ESG pillars' impact, this paper will include ESG ratings and its pillars with a one-year lag. This is because firms tend to report their ESG data yearly. Therefore, regulatory changes or initiatives in response to ESG factors will be visible only over the next year and may not have an immediate effect. Considering the mentioned variables, the paper will employ the below illustrated **Equation 23** in which systemic risk plays a dependent variable role:

$$€\Delta CoVaR_{i,t} = \beta_1 ESG_{i,t-1} + \beta_2 DE_{i,t} + \beta_3 NPL_{i,t} + \beta_4 ROE_{i,t} + \beta_5 \beta_{i,t} + \delta_t + \epsilon_{i,t} \qquad (23)$$

5. Data

Chapter 5 introduces a detailed account of the data collection and filtering processes employed in this study. The first part covers the criteria used for selecting the data, including the standards that must be met for data to qualify for inclusion in our sample. In addition to this, the chapter describes the methodological approach taken to filter out and refine the dataset. Subsequently, the chapter delves into the rationale behind the selection of control variables for the panel regression analysis. A brief explanation will be provided for the chosen control variables. The chapter concludes with a presentation of the descriptive statistics for the sample data, accompanied by an interpretation of these statistics. The interpretation aims to provide insights into the observed characteristics within the dataset.

5.1. Sample Selection

We filtered our sample size by focusing on European Union countries that have adopted the Euro as their official currency. This initial step is critical as it sets the foundation for the subsequent use of €ΔCoVaR. Within the European Union, 20 countries meet this criterion.

To ensure our dataset impacts systemic risk analysis, we established a threshold for market capitalization at €800 million. Under this criterion, we identified 46 financial banks with publicly traded stocks. Our data collection spanned a period of five years, from January 2, 2019, to December 29, 2023, encompassing stock prices and market capitalization. Additionally, we gathered Environmental, Social, and Governance (ESG) ratings, including assessments for each ESG pillar. However, the ESG ratings were specifically collected for 2018-2022, explained in **Chapter 4.4**. The ESG data and its pillars are extracted from Thomson Reuters Eikon. The new methodology, developed in 2017, TR ESG Refinitiv, was used instead of Asset4 ESG. The ESG score ranges from 0 to 100. Each pillar is grouped into ten categories and calculated as an average of all the category weights:

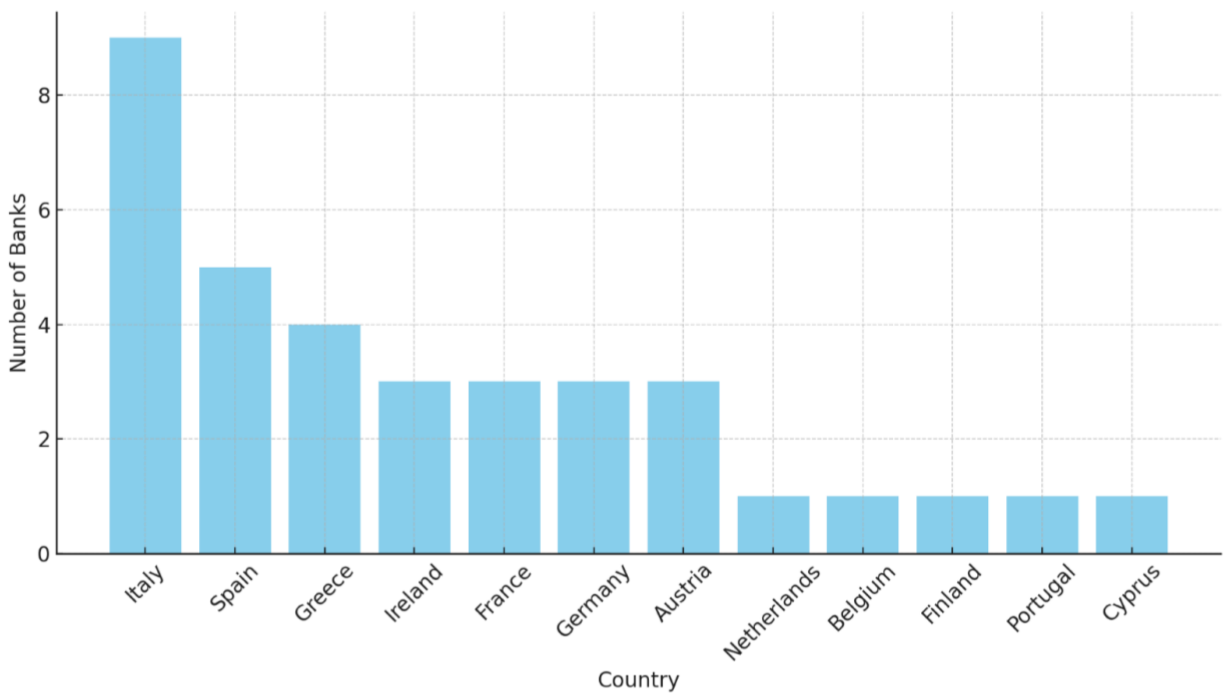
- The environmental pillar consists of emissions (emissions, waste reduction, biodiversity and environmental management systems), innovation (product innovation and green revenues, research and development and capital expenditure) and resources use (water, energy, sustainable packaging and environmental supply chain).
- Social pillar consists of community involvement, human rights, product responsibility (responsible marketing, product quality and data privacy) and workforce (diversity and inclusion, career development and training, working conditions and health and safety).
- Lastly, governance pillar consists of CSR strategy (CST strategy and ESG transparency), management (structure, diversity and compensation) and shareholders.

In order to collect further data, both Thomson Reuters Eikon and Bloomberg Terminal were examined for data consistency and robustness. Thomson Reuters Eikon has provided more consistent and accurate data for market cap, daily stock return and the ESG ratings. Furthermore, reliance on Thomson Reuters Eikon is consistent with the previous literature on the collection of the ESG data (Chiaramonte et al., 2022; Aevoae et al., 2022). Therefore, all data for the sampled companies were sourced exclusively from the Thomson Reuters Eikon database to maintain consistency.

After compiling the data, we embarked on a thorough refinement process. We applied filters to exclude companies missing any ESG pillars over the five-year span, given the paramount importance of ESG considerations in our study. We also removed companies with erratic ESG scores, such as an observed fluctuation where an ESG rating oddly fluctuated which we attributed to data inconsistencies or errors. This meticulous refinement process led us to focus our study on the remaining 35 European financial banks **(Appendix 1)**. The final dataset consists of financial banks from 12 European countries, equal to 60% of the countries that meet the Euro currency requirement, along with their ESG and separate pillar scores within 5 years **(Appendix 2)**.

Figure 1. Country of Headquarters for the 35 European sampling banks

Figure 1 provides the distribution of the headquarters of the 35 sampled European banks across different countries. Each country's count represents the number of banks headquartered there. The data highlights the concentration of banks in Italy, followed by Spain and Greece. The figure illustrates that 12 countries have been included in the sample.



Moreover, we adjusted the stock price data to only include exchange days, excluding weekends, during which no trading data is available. Given the variation in bank holidays across Europe, we standardized the data using the holiday system of the Netherlands, which had 1282 exchange days in the specified period. We estimated stock prices for non-trading days due to holidays by averaging the values from the closest preceding and following trading days. This normalization ensured that the dataset for each of the 35 banks was consistent and comprehensive.

5.2. Control Variables

In our panel regression, the control variables are incorporated to mitigate potential confounding factors or omitted variable bias, particularly within fixed effects models. These additional explanatory variables help capture unobserved heterogeneity across individual units, such as firms or countries, which could influence the dependent variable. The inclusion of control variables in fixed effects models is essential for enhancing the validity and reliability of estimated effects (BH Baltagi, 2008).

The analysis primarily focuses on firm-based characteristics for variable selection, drawing on data from Refinitiv Eikon. Specifically, the debt-to-equity (D/E) ratio, non-performing loan (NPL) ratio, return on equity (ROE), and firm-specific beta are included, as detailed in **Table 1.**

- The D/E ratio was computed by dividing a company's total debt by its total equity, providing insights into the proportion of financing provided by debt compared to equity.
- The NPL ratio was calculated by dividing the total non-performing loans by the total loans outstanding. This ratio quantifies the proportion of loans in a bank's portfolio that are non-performing or in default, serving as a key indicator of the bank's default risk.
- Return on equity (ROE) was calculated by dividing the net income of a company by its shareholder's equity, this measures the profitability of a company relative to its equity base, indicating the company's profitability and operational efficiency.
- Finally, a firm-specific beta, measuring the sensitivity of a company's stock returns to changes in the overall market returns, was included to capture the unique risk profile of each company and its potential impact on firm performance.

Table 1. Variables Description

Table 1 represents the types of variables and data sources, along with brief descriptions for each variable used in our model. The independent variables, ESG, E, S, and G, are all sourced from Thomson Reuters Eikon and represent the combined Environmental, Social, and Governance scores, as well as individual scores for each pillar. Control variables, also sourced from Thomson Reuters Eikon, include D/E (Debt to Equity ratio), NPL (Non-performing Loan ratio), ROE (Return on Equity), and firm-specific Beta. The dependent variable, €ΔCoVaR, measures systemic risk.

Variables	Types	Sources	Descriptions
ESG	Independent variable	Thomson Reuters Eikon	The combined score of ESG
E	Independent variable	Thomson Reuters Eikon	Environmental Pillar Score
S	Independent variable	Thomson Reuters Eikon	Social Pillar Score
G	Independent variable	Thomson Reuters Eikon	Governance Pillar Score
D/E	Control variable	Thomson Reuters Eikon	Debt to Equity = Total Debt / Total Equity
NPL	Control variable	Thomson Reuters Eikon	Non-performing Loan ratio = Total Non-performing Loans / Total Loans
ROE	Control variable	Thomson Reuters Eikon	Return on Equity = Net Income / Total Shareholder's Equity
Beta	Control variable	Thomson Reuters Eikon	Firm-specific Beta
€ΔCoVaR	**Dependent variable**		Measure of systemic risk

5.3. Descriptive Statistics

As outlined in the methodology, this study examines the daily closing stock prices of 35 listed banks in the Eurozone over the period from 2019 to 2023. Bank losses are quantified as the negative log returns of these stock prices. The table below presents a summary of the descriptive statistics for the computed bank losses of these 35 bank losses.

Table 2. Descriptive statistics of 35 sample bank losses

Table 2 provides descriptive statistics for 35 sample bank losses, calculated from daily stock close price from 2019 to 2023, for each company. One significant observation is the variability in mean losses across different banks, ranging from negative to positive values, suggesting varying degrees of profitability or loss among the sampled institutions. The varied standard deviation values further underscore losses' dispersion around each bank's means. Additionally, the minimum and maximum values offer insights into the range of losses experienced by each bank, highlighting the potential volatility or stability of their financial performance.

Identifier	Mean	Standard Error	Standard Deviation	Minimum	Maximum
ACBr.AT	0.0077%	0.0999%	3.4686%	-25.4279%	31.7598%
AIBG.I	-0.0068%	0.0919%	3.2692%	-22.0139%	27.3916%
ARLn.H	-0.0139%	0.0652%	2.3153%	-18.3169%	19.0044%
BAMI.MI	-0.0644%	0.0730%	2.5946%	-14.0255%	18.2699%
BAWG.VI	-0.0319%	0.0653%	2.3131%	-12.5305%	19.8120%
BBVA.MC	-0.0444%	0.0672%	2.4027%	-15.4058%	16.3396%
BCP.LS	-0.0143%	0.0720%	2.5759%	-17.3302%	16.4681%
BIRG.I	-0.0361%	0.0869%	3.0932%	-14.3737%	17.0958%
BKT.MC	-0.0092%	0.0643%	2.2985%	-18.1501%	17.1342%
BMPS.MI	0.1865%	0.1052%	3.7403%	-17.9765%	54.6630%
BNPP.PA	-0.0368%	0.0630%	2.2565%	-16.5351%	14.5261%
BOCH.CY	-0.0809%	0.0699%	2.4010%	-16.8990%	16.5514%
BOPr.AT	0.1271%	0.1356%	4.7066%	-35.5015%	35.6268%
BPSI.MI	-0.0589%	0.0665%	2.3631%	-12.7328%	20.9997%
CABK.MC	-0.0136%	0.0646%	2.3125%	-13.9573%	16.8633%
CAGR.PA	-0.0251%	0.0602%	2.1559%	-12.8102%	18.4690%
CBKG.DE	-0.0487%	0.0832%	2.9781%	-14.2984%	23.8435%

CRDI.MI	-0.0720%	0.0729%	2.6102%	-12.8597%	18.9466%
DBKGn.DE	-0.0428%	0.0733%	2.6244%	-12.1326%	20.3783%
EMBI.MI	-0.0320%	0.0481%	1.7097%	-7.9077%	8.8057%
EMII.MI	-0.0215%	0.0762%	2.7180%	-20.2181%	19.5456%
ERST.VI	-0.0211%	0.0650%	2.3265%	-12.8512%	13.2759%
EURBr.AT	-0.0915%	0.0851%	3.0427%	-23.2482%	19.0622%
FBK.MI	-0.0282%	0.0617%	2.1929%	-11.2123%	12.9693%
INGA.AS	-0.0289%	0.0684%	2.4466%	-18.6450%	21.5324%
ISP.MI	-0.0255%	0.0559%	1.9997%	-10.5173%	19.5811%
KBC.BR	-0.0033%	0.0640%	2.2903%	-13.1589%	21.2462%
MDBI.MI	-0.0334%	0.0553%	1.9796%	-13.0255%	20.6863%
NBGr.AT	-0.1383%	0.0945%	3.3816%	-25.6074%	23.5032%
NDAFI.HE	-0.0322%	0.0521%	1.8631%	-8.4980%	15.0000%
PTSB.I	0.0070%	0.0823%	2.9242%	-15.1806%	26.2364%
RBIV.VI	0.0143%	0.0675%	2.4150%	-15.9742%	26.3166%
SABE.MC	-0.0081%	0.0884%	3.1604%	-21.9867%	19.4543%
SAN.MC	0.0008%	0.0658%	2.3516%	-17.5841%	18.4606%
SOGN.PA	0.0103%	0.0756%	2.7049%	-16.8981%	19.4243%
System	**-0.0338%**	**0.0550%**	**1.9680%**	**-12.5690%**	**17.5824%**

The mean daily loss for the whole system is -0.0338%, with a standard deviation of 1.9680%. Among the companies, National Bank of Greece SA (NBGr.AT) emerges with the largest daily average loss, exhibiting an average loss of approximately -0.1383%, compared to its counterparts. Conversely, Banca Monte dei Paschi di Siena SpA (BMPS.MI) stands out with the smallest daily average loss, registering a mean return of about 0.1865%. In terms of volatility, Piraeus Financial Holdings SA (BOPr.AT) demonstrates the highest standard deviation of daily losses, indicating significant fluctuations in its day-to-day financial performance compared to other companies. Regarding maximum losses, Piraeus Financial Holdings SA (BOPr.AT) experiences the highest single-day loss, while Credito Emiliano SpA (EMBI.MI) has the lowest maximum loss.

Figure 2. Contribution of systemic risk by country

Figure 2 shows the geographical distribution of systemic risk, measured by the average €ΔCoVaR of all sampled companies within each country. As indicated by the visualization, France, the Netherlands, and Finland exhibit the highest impact on systemic risk.

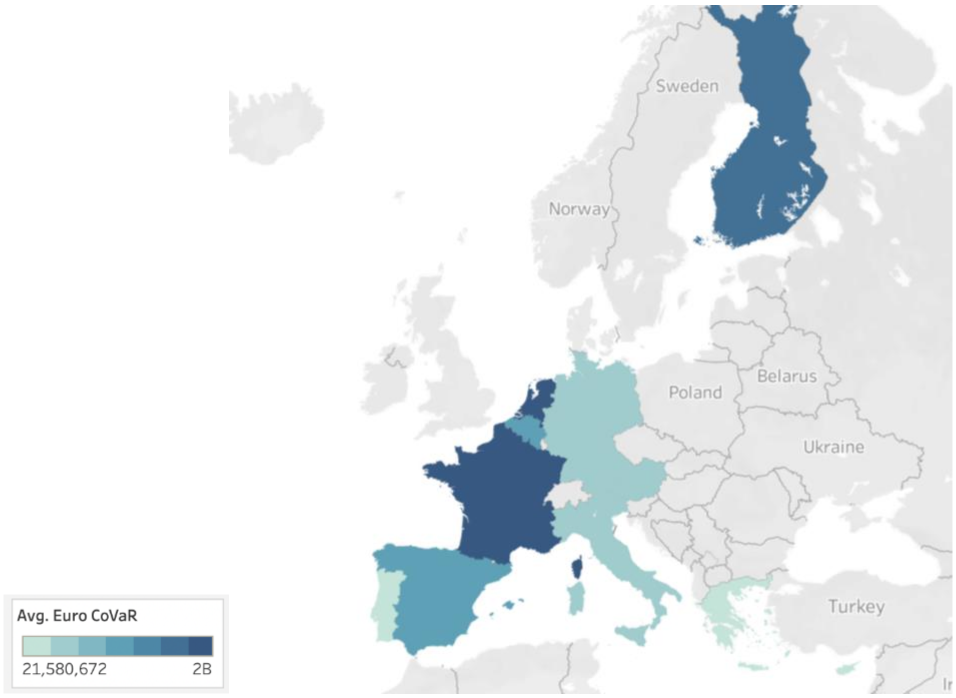


Table 3. Descriptive statistics of regression variables

Table 3 provides comprehensive descriptive statistics from the period from 2019 to 2023 for four independent variables - ESG, E, S, and G; four control variables reflecting bank-specific characteristics as mentioned previously – D/E, ROE, NPL, and Beta, all serving as regressors for the dependent variable, €ΔCoVaR. We categorized the 35 companies into three distinct groups - high, medium, and low - predicated on their ESG combined scores, assigning corresponding weight ratios of 10-15-10 companies, respectively.

		ESG Type		
Variables		**High**	**Medium**	**Low**
D/E	**Mean**	2.108	1.754	1.460
	Min	0.740	0.132	0.155
	Max	4.076	6.576	3.335
	Std. Dev	0.931	1.623	0.858
ROE	**Mean**	0.074	0.074	0.063
	Min	-0.040	-0.519	-0.266
	Max	0.160	0.278	0.218
	Std. Dev	0.041	0.090	0.078

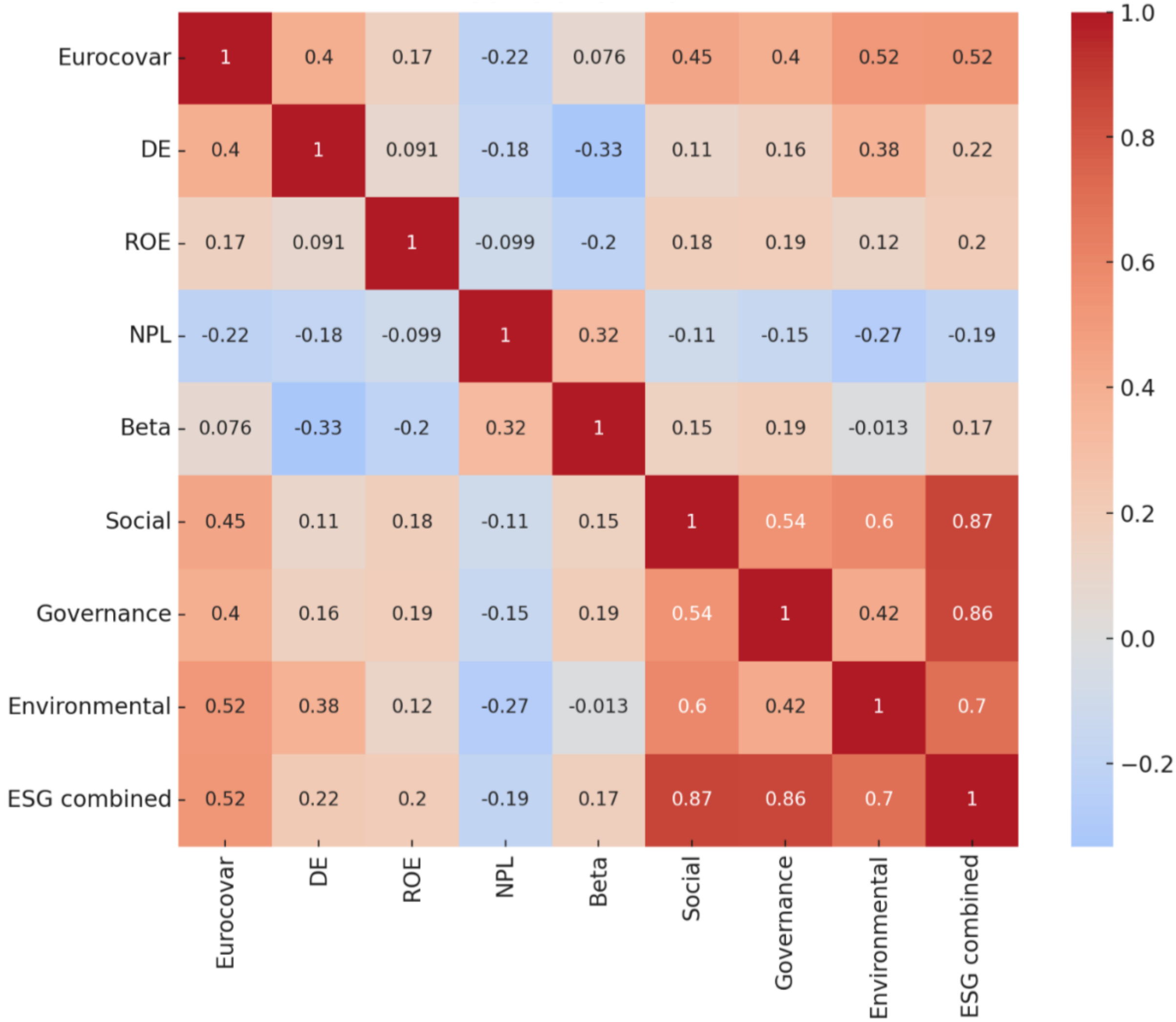
NPL	**Mean**	3.227	5.821	7.005
	Min	1.000	0.030	0.000
	Max	8.800	45.000	57.560
	Std. Dev	1.428	9.002	10.196
Beta	**Mean**	1.526	1.598	1.375
	Min	1.101	0.585	0.747
	Max	1.969	2.957	2.293
	Std. Dev	0.223	0.469	0.358
S	**Mean**	87.500	75.933	65.740
	Min	71.000	63.000	28.000
	Max	97.000	91.000	92.000
	Std. Dev	6.522	7.085	13.561
G	**Mean**	82.080	74.120	44.080
	Min	44.000	42.000	15.000
	Max	94.000	94.000	75.000
	Std. Dev	11.054	12.104	16.729
E	**Mean**	88.540	71.760	54.440
	Min	63.000	10.000	9.000
	Max	97.000	95.000	81.000
	Std. Dev	7.859	18.135	20.387
ESG	**Mean**	**85.680**	**74.653**	**56.380**
	Min	75.000	61.000	28.000
	Max	95.000	86.000	74.000
	Std. Dev	5.523	5.869	11.813
€ΔCoVaR	**Mean**	1,549,905,672	571,025,055	149,588,614
	Min	103,560,920	17,911,329	4,530,096
	Max	3,922,004,530	2,973,254,492	501,897,073
	Std. Dev	1,006,728,165	742,030,862	148,397,553

When looking into the mean and standard deviation values, it is evident that companies in the high ESG category, accordingly with high separate pillars' scores, exhibit the highest €ΔCoVaR. Additionally, the substantial disparity in mean €ΔCoVaR values between the high and low ESG categories aligns with our expectations. Descriptive statistics on the bank level are listed in **Appendix 7** and **Appendix 8.**

To identify the correlation among the dependent and independent variables, we then plotted a correlation matrix.

Figure 3. Correlation Matrix

Figure 3 illustrates the correlation matrix among dependent, independent and control variables. The variables are €ΔCoVaR, DE, ROE, NPL, Beta, Social, Governance, Environmental, and ESG. The figure illustrates that control variable that has the highest correlation with the €ΔCoVaR is debt-to-equity with 0.4, whereas NPL has a negative correlation with the dependent variable. In terms of dependent variables, the governance pillar has the lowest correlation with the dependent variable with 0.4, whereas the environmental pillar has the highest correlation with 0.52. All ESG pillars have high correlation with the ESG rating, with the highest correlation being with the social pillar.



As observed from the correlation matrix, all three separate ESG pillars have strong positive correlations with ESG rating (Environmental: 0.7, Social: 0.87, Governance: 0.86). This indicates that the overall ESG successfully reflects its individual components. On the other hand, the control variables have a noticeably low correlation with each other, meaning that there is no multicollinearity between the independent variables. The dependent variable has a significantly positive relationship with the overall ESG and environmental pillar. Such a positive relationship indicates that higher values in these independent variables are associated with higher €ΔCoVaR. The environmental pillar's relationship with the dependent variables also shows that out of all three ESG pillars, the environmental pillar stands out as the most significant pillar in relation to the systemic risk during the preliminary empirical results.

6. Empirical Result

The following chapter, **Chapter** 6, presents the empirical findings based on the methodology introduced in *Chapter 4*. It will provide and interpret four 5-year fixed-effects models examining the relationship between €ΔCoVaR and ESG, including its individual pillars. The interpretation aims to provide the findings necessary for drawing the study's conclusions. Moreover, the chapter will introduce the robustness analysis, which compares CoVaR estimates at the 95% and 99% confidence levels. Furthermore, it will provide a clear and comprehensive explanation of other measures employed to ensure unbiased estimators.

6.1. Regression Results

This section presents the results of the 5-year fixed-effects model examining the relationship between systemic risk and ESG, based on the **Equation 24**. We will interpret and explain four separate models: *ESG (Model 1), Environment (Model 2), Social (Model 3), and Governance (Model 4)*. Results of the regression models are illustrated in **Table 4** as follows:

Table 4. Regression results from 4 regression models

Table 4 presents the results of the four-regression model chosen to explain the relationship between the ESG, its pillars and the dependent variable €ΔCoVaR. The t-stat results are illustrated inside the bracket, followed by the p-value underneath. The models show that the consistently significant variables across all models are the intercept, debt-to-equity ratio, and beta. Regarding the ESG and its pillars, the models have shown a positive statistically significant relationship between the ESG, environmental, social and systemic risk. The model 2 has the highest R-squared value whereas the model 4 has the lowest R-squared value. The models are based on different independent variables: Model 1 focuses on ESG, Model 2 on the Environmental score, Model 3 on the social score, and Model 4 on the Governance score.

Dependent Variable: €ΔCoVaR	**Model 1: ESG**	**Model 2: Environmental**	**Model 3: Social**	**Model 4: Governance**
R-Squared	0.4052	0.4207	0.4018	0.3438
ESG	(3.8753) 0.0002			
E		(4.1740) 0.0001		
S			(3.7577) 0.0003	
G				(2.1509) 0.0340
DE	(4.6771) 0.0000	(3.8983) 0.0002	(5.3582) 0.0000	(5.0277) 0.0000
NPL	(-1.633) 0.1058	(-1.763) 0.0811	(-2.180) 0.0317	(-1.7166) 0.0892
ROE	(0.9253) 0.3571	(1.5823) 0.1168	(1.0758) 0.2847	(1.3098) 0.1934
Beta	(3.0283) 0.0032	(3.8106) 0.0002	(3.5713) 0.0006	(3.2914) 0.0014
F-statistic for Poolability	0.3325	0.4251	0.3713	0.3198
Time FE	Included	Included	Included	Included
Observations	145	145	145	145
Sampled banks	35	35	35	35

The baseline results in **Table 4** indicate a positive and statistically significant relationship in the model using the ESG as an independent variable. *Model 1* shows that the coefficient for ESG is positive and significant (p-value = 0.0002) at the 1% significance level, suggesting that a higher ESG is associated with increased systemic risk. Moreover, the control variable debt-to-equity ratio indicates a significant positive relationship with €ΔCoVaR. Similarly, beta shows a significant positive relationship with the dependent variable. Conversely, NPL has a negative but not statistically significant relationship with the dependent variable. ROE is positively related to the dependent variable, though this relationship is not statistically significant. The environmental variable exhibits a positive and statistically significant relationship with systemic risk, as indicated by a p-value of 0.0001. This suggests that higher environmental scores are associated with an increase in €ΔCoVaR, implying higher systemic risk.

Consistent with *Model 1*, the debt-to-equity ratio and beta in *Model 2* show positive and significant relationships with the dependent variable, with p-values of 0.0002 and 0.0002, respectively. ROE demonstrates a positive but not significant relationship with systemic risk in *Model 2*. Additionally, NPL has a non-significant negative relationship with systemic risk, indicated by a p-value of 0.0811, like the findings in *Model 1*.

Model 3 represents the relationship between the social pillar and the €ΔCoVaR. As shown in the table the social pillar has a positive and significant relationship with systemic risk, albeit only marginally significant. Debt-to-equity and beta variables have again indicated a positive and significant relationship with systemic risk. With a p-value of 0.0317, non-performing loans have a significant negative relationship. Similar to previous models, ROE shows a positive but not statistically significant relationship with the dependent variable.

Unlike the other pillars, the governance pillar and systemic risk relationship indicate a positive but not statistically significant relationship with €ΔCoVaR in the Eurozone market. The p-value of 0.0340 is not significant in 1% significance level where the extreme values are observed. The governance variable is only significant at 5% significance level. Debt-to-equity and beta have a positive and statistically significant relationship with the dependent variable. NPL in *Model 4* has a negative but not statistically significant relationship with systemic risk. ROE has a p-value of 0.1934, suggesting a positive relationship with the dependent variable, but it is not statistically significant.

To sum up, all models except Model 4 have a significant positive relationship with the dependent variable in the Eurozone. *Model 4* is the worst fit due to its lower R-squared values and F-statistic, suggesting it is the least effective in explaining systemic risk and explains the least variance in

€ΔCoVaR. The environment pillar has the highest R-squared value, meaning that the *Model 2* variable explains the most variance in systemic risk. Therefore, we can conclude that environmental factors have the strongest relationship with systemic risk, while governance factors have the weakest relationship.

Regarding the control variables, the analysis confirms our expectation that the debt-to-equity ratio is positively correlated with €ΔCoVaR. The NPLs exhibit a negative and not significant relationship with systemic risk across all models. The beta variable consistently demonstrates a significant positive relationship with systemic risk in all models. Thus, the debt-to-equity ratio and beta are strong predictors of higher systemic risk. Additionally, the ROE control variable shows a positive, non-significant relationship with €ΔCoVaR in all models.

6.2. Robustness Analysis

This section focuses on our model's robustness analysis, explaining the steps taken to ensure that our fixed-effects model remains unbiased and consistent.

In order to keep the model accurate, we excluded clustered errors. Clustering errors are used to adjust standard errors for within-cluster correlation, assuming errors are correlated within cross-sectional units over time (Abadie et al., 2022). However, our results for the panel regression models with the clustered errors has demonstrated that including clustered errors led to inflated standard errors, thus, we decided against their inclusion. Furthermore, we excluded the clustered standard errors in line with the Abadie et al. (2020) where it is stated that using conventional clustered standard errors can lead to inaccurate estimates in our specific setting.

Moreover, the entity-specific effects were also excluded. Taking into consideration that our sample is concentrated within the European financial banking system, which is only one sector, where companies do not change their sectors, incorporating entity-specific effects could introduce multicollinearity, leading to biased and inconsistent results. As the banks in our sample are relatively homogeneous, we have excluded the entity-specific effects. Additionally, our small sample size and the limited number of time periods in our panel regression model (2019-2023) further cement the fact that entity-specific effects should be excluded.

Despite previous literature recommending the inclusion of macroeconomic control variables in regression models, our sample comprises data from 12 different countries, making this approach impractical. In order to solve the problem, we include time-specific effects in our fixed-effects model. Not only would time-specific effects control changes over time, but their addition will solve the issue of dependencies in the pooled OLS; thus, the model will not have auto-correlation bias.

Further assessment of the robustness of our model was conducted by a robustness test using CoVaR data at both the 95% and 99% levels. By comparing CoVaR at these two confidence levels, we evaluated the model’s robustness and unbiasedness.

Table 5. Descriptive statistics of CoVaR at 95% and 99% confidence levels

The table 5 shows the descriptive statistics of CoVaR at 95% and 99% confidence levels. The table illustrates that both the mean and the standard deviation is higher for CoVaR at 99% confidence level, as expected. Aligning with these results, the media is higher at 99% confidence level than 95% confidence level

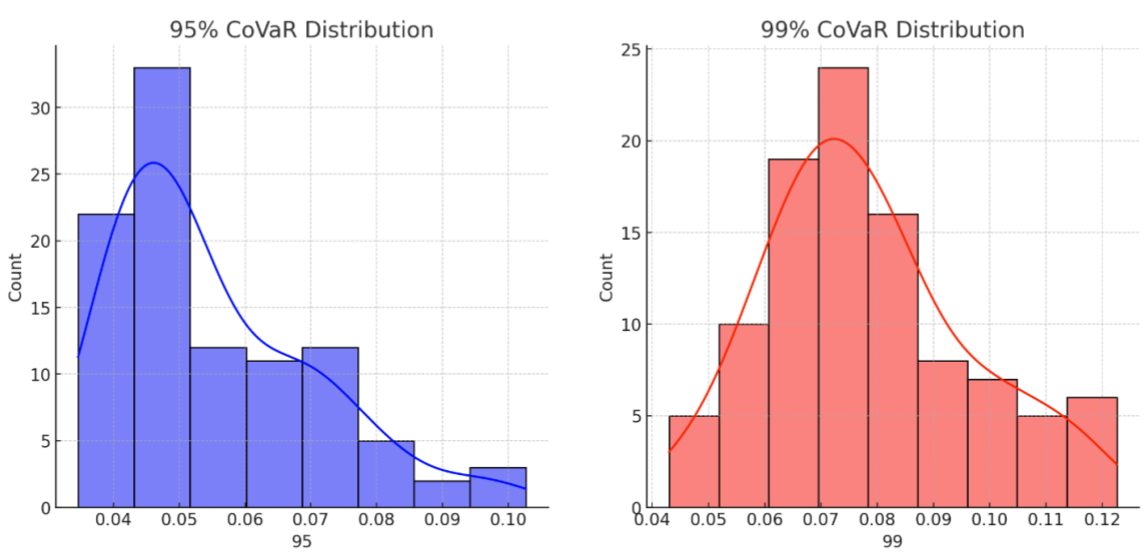
	CoVaR at 95% confidence	CoVaR at 99% confidence
Mean	0.055	0.078
Standard Deviation	0.016	0.035
Minimum	0.050	0.043
25th percentile	0.043	0.066
Median	0.050	0.075
75th percentile	0.065	0.088
Maximum	0.103	0.123

Table 5 presents descriptive statistics for both 95% and 99% CoVaR. The mean of the 99% CoVaR (0.078) is higher than that of the 95% CoVaR (0.0554), as expected, since the 99% CoVaR captures more extreme tail risks. The standard deviation of the 99% CoVaR (0.018) also exceeds that of the 95% CoVaR (0.0154), indicating greater variability in the 99% CoVaR values.

In addition to this, the paper conducts a robustness analysis to assess the correlation between the 95% and 99% CoVaR values across all companies and years. Paired t-tests were performed to compare the means of the two CoVaR measures, determining whether the differences were statistically significant.

Figure 4. Distribution table for 95% and 99% CoVaR

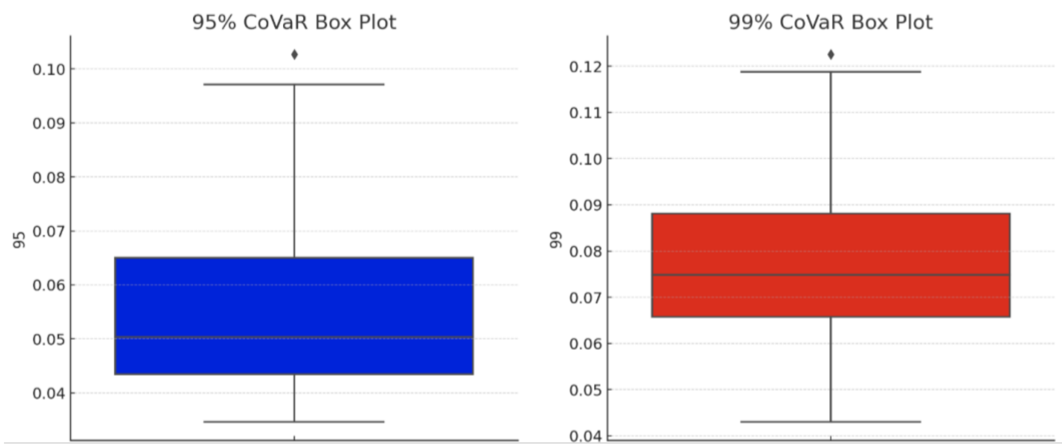
The histograms illustrate that both 95% and 99% CoVaR are normally distributed but with different means and spreads. As a result, the 99% CoVaR values are generally higher, as expected for a higher confidence level.



The Pearson correlation coefficient between both confidence levels is 0.925, indicating a very strong correlation and positive relationship. The positive relationship illustrates that the results for both 95% and 99% are able to reflect the relative risk of the companies. **Figure 4** shows that although both confidence levels are normally distributed, 99% CoVaR values are higher, as expected for a higher confidence level. The histogram illustrates that 99% CoVaR distribution leans more towards the right, meaning that 99% CoVaR can capture more extreme tail risks, as expected.

Figure 5. Box Plot for 95% and 99% CoVaR

The box plots show that the 99% CoVaR values have a higher median and interquartile range compared to the 95% CoVaR values. There are also more outliers in the 99% CoVaR, reflecting the more extreme risk measures captured.



The box plot demonstrates that 99% CoVaR has a higher median and interquartile range compared to the 95% confidence level. Additionally, more outliers attributed to 99% CoVaR prove that 99% CoVaR captures more extreme risk measures.

Based on the hypothesis testing between these two CoVaR confidence levels, the paired t-test results illustrate a t-statistic of –32.56 and a p-value of 1.06e-54. Low p-value results demonstrate that the difference between the two alpha quantiles is statistically significant. The statistically significant difference between 95% and 99% CoVaR confirms that 99% CoVaR is able to capture higher risk consistently, as expected. The visualizations and the statistical interpretation in the robustness analysis prove that the results are robust and unbiased for a given period and companies.

Furthermore, we test the F-test for poolability in all four regression models to assess whether the fixed effects approach is an appropriate model. **Table 4** illustrates that *Model 1* has an F-test for poolability equal to 1.1138 and a p-value of 0.3325, while for *Model 2* an F-test for poolability is 0.8631, and a p-value is 0.4251. Similar to both results, it also demonstrates that *Model 3* and *Model 4* have p-values exceeding 0.05, 0.3713, and 0.3198, respectively. The F-tests for poolability across all four models show p-values greater than 0.05, indicating no significant problem with pooling the data. However, using a fixed effects model is still advantageous in accounting for unobserved heterogeneity that might vary across entities or periods.

Lastly, the Variance Inflation Factor (VIF) test is used for robustness analysis. VIF is used to detect the presence and severity of multicollinearity in our fixed effects model. A VIF value greater than ten is often considered indicative of high multicollinearity, with VIF above still considered concerning. Below are the results of the VIF test for each model:

Table 6. VIF of 4 Models

Table 6 presents the Variance Inflation Factors (VIF) for four different models, which illustrates that all variables are below five thus no multicollinearity is observed.

Variables	**VIF**			
	Model 1: ESG	**Model 2: Environmental**	**Model 3: Social**	**Model 4: Governance**
DE	1.257373	1.372573	1.18655200	1.23057
NPL	1.070174	1.054879	1.03270100	1.095913
ROE	1.117265	1.046563	1.09974000	1.107678
Beta	1.326281	1.215487	1.24331500	1.359352
Dependent variable	1.255052	1.236152	1.11203900	1.269788

As we interpret the VIF test results, it is visible that all VIF values for the independent variables in each model are well below the threshold of five, indicating that multicollinearity is not a concern in these models. Therefore, the results suggest that the variables are not highly correlated with each other and do not inflate the standard errors of the coefficients excessively. Thus, we conclude that coefficient estimations are reliable and can be used to regress systemic risk with confidence.

Robustness analysis demonstrates that all four models are unbiased, efficient, and robust. Therefore, we conclude that the models can be effectively used for further testing.

7. Conclusion

Our thesis analyses the relationship between banks' environmental, social, and governance (ESG) scores and their contribution to systemic risk, specifically focusing on the banking industry within the Eurozone financial market. Using €ΔCoVaR as a measure of systemic risk and panel model for a sample of 35 publicly listed banks headquartered in 12 countries over the period 2019–2023, our study aimed to address two hypotheses. Firstly, we initially hypothesized *(H0) that banks with higher ESG would contribute relatively less to overall systemic risk*. However, our results revealed a positive relationship between ESG and systemic risk. These findings diverge from prior empirical studies conducted before the recent financial turmoil and global sequences of bank collapses, which generally indicated a negative link between ESG and systemic risk contribution. For instance, Aevoae's (2022) study, conducted on a global scale from 2007 to 2020, right before the pandemic, found that the positive link between ESG and financial stability applied only to large banks. Additionally, we explored further with another hypothesis (*H1) that individual ESG pillars have separate effects on systemic risk*. Our findings align with other previous studies (Monteiro et al., 2021; Chiaramonte et al., 2022), that show separate ESG pillars have different effects on systemic risk, though in a positive way. Specifically, the environmental pillar has the most substantial impact on systemic risk, followed closely by the social pillar. The governance pillar shows a comparatively weaker association with systemic risk in our analysis. We conclude that, in extreme conditions (at a 1% confidence level), the governance pillar is much less influential on systemic risk than the other two pillars.

These results can be rationalized by banks with higher ESG tend to be larger compared to ones with lower ESG, which typically fall into the small to medium-sized category. Specifically, the market size and systemic importance of larger banks inherently render them more influential in propagating systemic risk within the financial system. Even if these banks boast high ESG, their substantial scale and interconnectedness mean that any instances of financial distress or operational challenges can swiftly reverberate throughout the broader economy, amplifying systemic risk. Moreover, the complexity and interconnected nature of large banks, particularly those with elevated ESG, further compound this risk. These institutions often possess intricate organizational structures and expansive networks of subsidiaries and international operations, creating pathways for problems in one sector to cascade rapidly across the entire banking system. Additionally, market expectations and valuation dynamics play a pivotal role in exacerbating systemic risk among banks with high ESG. Perceived as safer and more stable investments, these banks often command higher valuations, making them susceptible to sharper corrections during periods of market stress. Finally, our study examined within the period spanning from 2019 to 2023. This timeframe coincided with a period of unprecedented global turmoil precipitated by the

COVID-19 pandemic, which significantly impacted financial markets worldwide. During times of economic uncertainty and volatility, larger banks, by virtue of their scale and interconnectedness, often play a more pronounced role in propagating systemic risk. In response to the challenges posed by the pandemic, larger banks may have extended their reach to maintain liquidity and stability, thereby amplifying their contribution to systemic risk. Moreover, the elevated scrutiny and pressure to navigate the complexities of the crisis may have diverted attention and resources away from ESG initiatives, potentially diminishing the effectiveness of higher ESG in mitigating systemic risk as these initiatives' benefits might take longer to be reflected on systemic risk. Consequently, the confluence of these factors underscores why rejecting our null hypothesis is substantiated, which confirms that banks with higher ESG contribute more significantly to systemic risk in the Eurozone market within the context of the period examined.

One limitation of our thesis is the need for a sample size encompassing only five years of data from 2019 to 2023. While this period captured the onset and aftermath of the COVID-19 pandemic, providing valuable insights into systemic risk dynamics during a period of significant market turbulence, a longer time frame would offer a more comprehensive view of the relationship between ESG and systemic risk. As we used basic historical simulation methods, extending the analysis to a 10-year period would allow for the identification of larger patterns of losses and a more robust assessment of the impact of ESG initiatives on systemic risk over time.

Our research contributes to understanding how environmental, social, and governance practices influence systemic risk within the Eurozone banking sector, particularly during global financial turmoil. By examining the impact of ESG pillars on systemic risk, we provide valuable insights for policymakers, regulators, and market participants navigating the complexities of one of the world's most interconnected financial markets. Our study underscores the critical importance of enhancing governance practices over environmental and social considerations, including corporate risk management, transparency, and compliance, as an utmost priority for financial institutions, particularly during the aftermath period of financial turmoil. From a policy perspective, our paper recommended that regulators impose standardized guidelines for non-financial requirements, such as mandatory ESG disclosures, to ensure greater transparency and accountability in the banking sector. For future research, it is essential to explore the relationship between ESG factors and systemic risk on a larger scale across Europe, including countries that use different currencies but significantly contribute to the continent's financial stability, and to extend the research period for a more comprehensive understanding of ESG's long-term impact on systemic risk.

References

Abad, P., Benito, S. and López, C. (2014) 'A comprehensive review of Value at Risk methodologies,' *the Spanish Review of Financial Economics*, 12(1), pp. 15–32. https://doi.org/10.1016/j.srfe.2013.06.001.

Abadie, A. *et al.* (2022) 'When should you adjust standard errors for clustering?' *the Quarterly Journal of Economics*, 138(1), pp. 1–35. https://doi.org/10.1093/qje/qjac038.

Abadie, A. and Spiess, J. (2021) 'Robust Post-Matching inference,' *Journal of the American Statistical Association*, 117(538), pp. 983–995. https://doi.org/10.1080/01621459.2020.1840383.

Abora, K. *et al.* (2013) 'Durability and testing – Chemical matrix degradation processes,' in *RILEM state-of-the-art reports*, pp. 177–221. https://doi.org/10.1007/978-94-007-7672-2_8.

Acemoglu, D., Ozdaglar, A. and Tahbaz-Salehi, A. (2015) 'Systemic risk and stability in financial networks,' *American Economic Review*, 105(2), pp. 564–608. https://doi.org/10.1257/aer.20130456.

Acerbi, C. and Scandolo, G. (2008) 'Liquidity risk theory and coherent measures of risk,' *Quantitative Finance*, 8(7), pp. 681–692. https://doi.org/10.1080/14697680802373975.

Acerbi, C. and Tasche, D. (2002) 'On the coherence of expected shortfall,' *Journal of Banking & Finance*, 26(7), pp. 1487–1503. https://doi.org/10.1016/s0378-4266(02)00283-2.

Acerbi, C., Nordio, C. and Sirtori, C. (2001) 'Expected shortfall as a tool for financial risk management,' arXiv (Cornell University). https://doi.org/10.48550/arxiv.cond-mat/0102304.

Acharya, V. et al. (2011) 'Dividends and Bank Capital in the Financial Crisis of 2007-2009,' National Bureau of Economic Research'. https://doi.org/10.3386/w16896.

Acharya, V.V. et al. (2016) 'Measuring systemic risk,' *Review of Financial Studies*, 30(1), pp. 2–47. https://doi.org/10.1093/rfs/hhw088.

Adrian, T. and Brunnermeier, M.K. (2016) 'COVAR,' *the American Economic Review*, 106(7), pp. 1705–1741. https://doi.org/10.1257/aer.20120555.

Aevoae, G.M. et al. (2022) 'ESG and systemic risk,' *Applied Economics*, 55(27), pp. 3085–3109. https://doi.org/10.1080/00036846.2022.2108752.

Alexandra Popescu, Camelia Turcu. Revue d'économie politique, Vol. 124, No. 6, Financial and Fiscal Aspects of the EMU Crisis (2014), pp. 899-925 (27 pages) https://www.jstor.org/stable/43860197

Allen, F. and Gale, D. (2000) 'Financial contagion,' *Journal of Political Economy*, 108(1), pp. 1–33. https://doi.org/10.1086/262109.

Allison, P.D., (2009). Fixed effects regression models. SAGE publications. https://books.google.se/books?hl=en&lr=&id=3UxaBQAAQBAJ&oi=fnd&pg=PT12&dq=allison+2009+fixed+effect&ots=PLWwcdQKPT&sig=f9h1xrJ1oYH27XGzbUxtgQN5dr0&redir_esc=y#v=onepage&q=allison%202009%20fixed%20effect&f=false

Altman, E., Resti, A. and Sironi, A. (2004) 'Default Recovery Rates in Credit Risk Modelling: A Review of the literature and Empirical evidence,' *Economic Notes - Monte Dei Paschi Di Siena/Economic Notes*, 33(2), pp. 183–208. https://doi.org/10.1111/j.0391-5026.2004.00129.x.

Amel-Zadeh, A. and Serafeim, G. (2018) 'Why and How Investors Use ESG Information: Evidence from a Global Survey,' *Financial Analysts Journal*, 74(3), pp. 87–103. https://doi.org/10.2469/faj.v74.n3.2.

Ang, A. and Longstaff, F.A. (2013) 'Systemic sovereign credit risk: Lessons from the U.S. and Europe,' *Journal of Monetary Economics*, 60(5), pp. 493–510. https://doi.org/10.1016/j.jmoneco.2013.04.009.

Ararat, M., Black, B.S. and Yurtoglu, B.B. (2017) 'The effect of corporate governance on firm value and profitability: Time-series evidence from Turkey,' *Emerging Markets Review*, 30, pp. 113–132. https://doi.org/10.1016/j.ememar.2016.10.001.

Artzner, P. et al. (1999) 'Coherent measures of risk,' *Mathematical Finance*, 9(3), pp. 203–228. https://doi.org/10.1111/1467-9965.00068.

Arvidsson, S. and Dumay, J. (2021) 'Corporate ESG reporting quantity, quality and performance: Where to now for environmental policy and practice?,' *Business Strategy and the Environment*, 31(3), pp. 1091–1110. https://doi.org/10.1002/bse.2937.

Ball, J. and Fang, V., 2006. A survey of value-at-risk and its role in the banking industry. *Journal of Financial Education*, pp.1-31. https://www.jstor.org/stable/41948541.

Baltagi, B.H. (2021b) Econometric analysis of panel data, Springer texts in business and economics. https://doi.org/10.1007/978-3-030-53953-5.

Boffo, R., and R. Patalano (2020), 'ESG Investing: Practices, Progress and Challenges', OECD Paris, https://www.oecd.org/finance/ESG-Investing-Practices-Progress-Challenges.pdf

Borio, C. (2003b) 'Towards a macroprudential framework for financial supervision and regulation?,' *CESifo Economic Studies*, 49(2), pp. 181–215. https://doi.org/10.1093/cesifo/49.2.181.

Boudoukh, J., Richardson, M. and Whitelaw, R., 1998. The best of both worlds. Risk, 11(5), pp.64-67. https://faculty.runi.ac.il/kobi/thebestrisk.pdf

Brownlees, C. and Engle, R.F. (2016) 'SRISK: A Conditional Capital Shortfall Measure of Systemic risk,' *Review of Financial Studies/the Review of Financial Studies*, 30(1), pp. 48–79. https://doi.org/10.1093/rfs/hhw060.

Busch, T., Bauer, R. and Orlitzky, M. (2015) 'Sustainable development and financial markets,' *Business & Society*, 55(3), pp. 303–329. https://doi.org/10.1177/0007650315570701.

Cai, L., Cui, J. and Jo, H. (2015) 'Corporate environmental responsibility and firm risk,' *Journal of Business Ethics*, 139(3), pp. 563–594. https://doi.org/10.1007/s10551-015-2630-4.

Chen, S.X. (2005) 'Nonparametric inference of Value-at-Risk for dependent financial returns,' *Journal of Financial Econometrics*, 3(2), pp. 227–255. https://doi.org/10.1093/jjfinec/nbi012.

Cheng, B., Ioannou, I. and Serafeim, G. (2013) 'Corporate social responsibility and access to finance,' *Strategic Management Journal*, 35(1), pp. 1–23. https://doi.org/10.1002/smj.2131.

Chiaramonte, L. et al. (2021) 'Do ESG strategies enhance bank stability during financial turmoil? Evidence from Europe,' *European Journal of Finance*, 28(12), pp. 1173–1211. https://doi.org/10.1080/1351847x.2021.1964556.

Curcio, D. *et al.* (2024) 'Do ESG scores affect financial systemic risk? Evidence from European banks and insurers,' *Research in International Business and Finance*, 69, p. 102251. https://doi.org/10.1016/j.ribaf.2024.102251.

Danielsson, N. and De Vries, N. (2000) 'Value-at-Risk and extreme returns,' Annales D'éConomie Et De Statistique/Annales D'économie Et De Statistique, (60), p. 239. https://doi.org/10.2307/20076262.

De Mendonça, H.F. and Da Silva, R.B. (2018) 'Effect of banking and macroeconomic variables on systemic risk: An application of ΔCOVAR for an emerging economy,' the North American Journal of Economics and Finance, 43, pp. 141–157. https://doi.org/10.1016/j.najef.2017.10.011.

Dhaliwal, D.S. et al. (2011) 'Voluntary nonfinancial disclosure and the cost of equity capital: the initiation of Corporate Social Responsibility reporting,' *Accounting Review*, 86(1), pp. 59–100. https://doi.org/10.2308/accr.00000005.

Dow, J. and Raposo, C.C., 2002. Active agents, passive principals: does high-powered CEO compensation really improve incentives?. Passive Principals: Does High-powered CEO Compensation Really Improve Incentives. https://ssrn.com/abstract=311439

Dowd, K., 2003. An introduction to market risk measurement. John Wiley & Sons. https://books.google.se/books?hl=en&lr=&id=4GhKQT3gjbIC&oi=fnd&pg=PR5&dq=dowd+2005+value+at+risk&ots=EWh3ga2oiA&sig=-hX8D4M8Bv5RSmH6jK4UB271MtQ&redir_esc=y#v=onepage&q=dowd%202005%20value%20at%20risk&f=false

Duffie, D. and Pan, J., 1997. An overview of value at risk. *Journal of derivatives*, 4(3), pp.7-49. https://web.mit.edu/people/junpan/ddjp.pdf

EBA publishes binding standards on Pillar 3 disclosures on ESG risks | European Banking Authority.https://www.eba.europa.eu/publications-and-media/press-releases/eba-publishes-binding-standards-pillar-3-disclosures-esg.

Eccles, R.G., Ioannou, I. and Serafeim, G. (2014) 'The impact of corporate sustainability on organizational processes and performance,' *Management Science*, 60(11), pp. 2835–2857. https://doi.org/10.1287/mnsc.2014.1984.

Elnahass, M., Trinh, V.Q. and Li, T. (2021) 'Global banking stability in the shadow of Covid-19 outbreak,' *Journal of International Financial Markets, Institutions & Money*, 72, p. 101322. https://doi.org/10.1016/j.intfin.2021.101322.

Emberchts, P., Klüppelberg, C. and Mikosch, T. (1997) 'Risk theory,' in Springer eBooks, pp. 21-57. https://doi.org/10.1007/978-3-642-33483-2_2.

Flammer, C. (2015) 'Does corporate social responsibility lead to superior financial performance? A regression discontinuity approach,' *Management Science*, 61(11), pp. 2549–2568. https://doi.org/10.1287/mnsc.2014.2038.

Friede, G., Busch, T. and Bassen, A. (2015) 'ESG and financial performance: aggregated evidence from more than 2000 empirical studies,' *Journal of Sustainable Finance & Investment*, 5(4), pp. 210–233. https://doi.org/10.1080/20430795.2015.1118917.

Galati, G. et al. (2010) How do inflation expectations form? Evidence from a high-frequency survey. https://www.newyorkfed.org/medialibrary/media/research/conference/2010/consumer/PaperGalati_Heemeijer_Moessner.pdf.

Gao, F. and Song, F. (2008) 'ESTIMATION RISK IN GARCH VaR AND ES ESTIMATES', *Econometric Theory*, 24(5), pp. 1404–1424. doi:10.1017/S0266466608080559.

Garzón-Jiménez, R. and Zorio-Grima, A. (2021) 'Effects of carbon emissions, environmental disclosures and CSR assurance on cost of equity in emerging markets,' *Sustainability*, 13(2), p. 696. https://doi.org/10.3390/su13020696.

Georg, C.-P. (2013) 'The effect of the interbank network structure on contagion and common shocks,' *Journal of Banking & Finance*, 37(7), pp. 2216–2228. https://doi.org/10.1016/j.jbankfin.2013.02.032.

Gillan, S.L., Koch, A. and Starks, L.T. (2021) 'Firms and social responsibility: A review of ESG and CSR research in corporate finance,' *Journal of Corporate Finance*, 66, p. 101889. https://doi.org/10.1016/j.jcorpfin.2021.101889.

Girardi, G. and Ergün, A.T. (2013) 'Systemic risk measurement: Multivariate GARCH estimation of CoVaR,' *Journal of Banking & Finance*, 37(8), pp. 3169–3180. https://doi.org/10.1016/j.jbankfin.2013.02.027.

Hartzell, J.C., Kallberg, J.G. and Liu, C.H. (2008b) 'The Role of Corporate Governance in Initial Public Offerings: Evidence from Real Estate Investment Trusts,' *Journal of Law & Economics*, 51(3), pp. 539–562. https://doi.org/10.1086/589701.

Hayat, U. and Orsagh, M. (2015) Environmental, social, and governance issues in investing: A Guide for Investment Professionals. https://www.cfainstitute.org/-/media/documents/article/position-paper/esg-issues-in-investing-a-guide-for-investment-professionals.ashx.

Hendricks, D. (1996) 'Evaluation of Value-at-Risk models using historical data,' *Social Science Research Network.* https://doi.org/10.2139/ssrn.1028807.

Ho, F.N., Wang, H.-M.D. and Vitell, S.J. (2011) 'A Global Analysis of Corporate Social Performance: the effects of cultural and Geographic environments,' *Journal of Business Ethics*, 107(4), pp. 423–433. https://doi.org/10.1007/s10551-011-1047-y.

Hull, J. and White, A. (1998) 'Incorporating volatility updating into the historical simulation method for value-at-risk,' *the Journal of Risk*, 1(1), pp. 5–19. https://doi.org/10.21314/jor.1998.001.

Hull, J., 2012. Risk management and financial institutions,(Vol. 733). John Wiley & Sons. https://books.google.se/books?hl=en&lr=&id=ixLD1gjPfoMC&oi=fnd&pg=PR19&ots=5bEnmzlMXx&sig=AeGI3-CZzSfVDBGW_umjpMOnHMU&redir_esc=y#v=onepage&q&f=false

Hull, J., 2023. Risk management and financial institutions,. John Wiley & Sons. https://books.google.se/books?hl=en&lr=&id=ixLD1gjPfoMC&oi=fnd&pg=PR19&dq=Risk+Management+and+financial+institutions+Hull+2023&ots=5bEqnAeLSz&sig=gl59KyYvvs6jJJoYhIXr9BGHkU&redir_esc=y#v=onepage&q=Risk%20Management%20and%20financial%20institutions%20Hull%202023&f=false

Jadhav, D. and Ramanathan, T.V. (2009) 'Parametric and non-parametric estimation of value-at-risk,' *Journal of Risk Model Validation*, 3(1), pp. 51–71. https://doi.org/10.21314/jrmv.2009.034.

James Dow (2000) 'What Is Systemic Risk? Moral Hazard, Initial Shocks, and Propagation,' *MONETARY AND ECONOMIC STUDIES*. https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=9d6cca24bb99daae03b172a426b553dd6b534688

Jorion, P. (2002) 'How informative are Value-at-Risk disclosures?,' *Accounting Review*, 77(4), pp. 911–931. https://doi.org/10.2308/accr.2002.77.4.911.

Koenker, R. and Bassett, G. (1978) 'Regression quantiles,' *Econometrica*, 46(1), p. 33. https://doi.org/10.2307/1913643.

Koenker, R., 2005. *Quantile regression* (Vol. 38). *Cambridge university press.* https://books.google.se/books?hl=en&lr=&id=WjOdAgAAQBAJ&oi=fnd&pg=PT12&dq=Koenker+2005&ots=CQGLOCam_V&sig=mw6yOT8j4zftsGnIB5ZPA5w2t9U&redir_esc=y#v=onepage&q=Koenker%202005&f=false

Laurențiu Paul Barangă, Elena-Ioana Țanea. "Introducerea raportării ESG - beneficii și provocări". Revista de Studii Financiare 13:174-181 https://www.ceeol.com/search/article-detail?id=1076224

Lins, K.V., Servaes, H. and Tamayo, A. (2017) 'Social Capital, Trust, and Firm Performance: The Value of Corporate Social Responsibility during the Financial Crisis,' *Journal of Finance*, 72(4), pp. 1785–1824. https://doi.org/10.1111/jofi.12505.

López-Espinosa, G. et al. (2013) 'Good for one, bad for all: Determinants of individual versus systemic risk,' Journal of Financial Stability, 9(3), pp. 287–299. https://doi.org/10.1016/j.jfs.2013.05.002.

Margolis, J.D., Elfenbein, H.A. and Walsh, J.P. (2009) 'Does it Pay to Be Good...And Does it Matter? A Meta-Analysis of the Relationship between Corporate Social and Financial Performance,' *Social Science Research Network*. https://doi.org/10.2139/ssrn.1866371.

Martins, A.M. (2023) 'Stock market effects of silicon valley bank and credit suisse failure: evidence for a sample of european listed banks,' *Finance Research Letters*, 58, p. 104296. https://doi.org/10.1016/j.frl.2023.104296.

McNeil, A.J. (1997) 'Estimating the tails of loss severity distributions using extreme value theory,' ASTIN Bulletin, 27(1), pp. 117–137. https://doi.org/10.2143/ast.27.1.563210.

McNeil, A.J. and Frey, R. (2000) 'Estimation of tail-related risk measures for heteroscedastic financial time series: an extreme value approach,' *Journal of Empirical Finance*, 7(3–4), pp. 271–300. https://doi.org/10.1016/s0927-5398(00)00012-8.

Mittnik, S. et al. (1999) 'Maximum likelihood estimation of stable Paretian models,' Mathematical and Computer Modelling, 29(10–12), pp. 275–293. https://doi.org/10.1016/s0895-7177(99)00110-7.

Mittnik, S., Paolella, M.S. and Rachev, S.T. (2000) 'Diagnosing and treating the fat tails in financial returns data,' *Journal of Empirical Finance*, 7(3–4), pp. 389–416. https://doi.org/10.1016/s0927-5398(00)00019-0.

Monteiro, G.F.A. et al. (2021) 'ESG: disentangling the governance pillar,' *RAUSP Management Journal*, 56(4), pp. 482–487. https://doi.org/10.1108/rausp-06-2021-0121.

Mrchkovska, N., Dolšak, N. and Prakash, A. (2023) 'Does ESG privilege climate action over social and governance issues? A content analysis of BlackRock CEO Larry Fink's annual letters,' *PLOS Sustainability and Transformation*, 2(12), p.e0000090. https://doi.org/10.1371/journal.pstr.0000090.

Nekhili, R., Foglia, M. and Bouri, E. (2023) 'European bank credit risk transmission during the credit Suisse collapse,' *Finance Research Letters*, 58, p. 104452. https://doi.org/10.1016/j.frl.2023.104452.

Ostalecka, A. and Swacha-Lech, M. (2013) 'Corporate social responsibility in the context of banks' competitiveness,' *Liberec Economic Forum*. https://dspace.tul.cz/handle/15240/6938.

Palhares, D. and Richardson, S.A. (2018) '(Il)liquidity Premium in Credit Markets: A Myth?,' *Social Science Research Network*. https://doi.org/10.2139/ssrn.3130213.

Phelan, M.J. Probability and Statistics Applied to the Practice of Financial Risk Management: The Case of J.P. Morgan's RiskMetrics™. *Journal of Financial Services Research 12*, 175–200 (1997). https://doi.org/10.1023/A:1007926803627

Porter, M.E. and Van Der Linde, C. (1995) 'Toward a new conception of the Environment-Competitiveness relationship,' *The Journal of Economic Perspectives*, 9(4), pp. 97–118. https://doi.org/10.1257/jep.9.4.97.

PricewaterhouseCoopers Global Annual Review 2023. https://www.pwc.com/gx/en/about/global-annual-review.html.

Reboredo, J.C. and Ugolini, A. (2015) 'Systemic risk in European sovereign debt markets: A CoVaR-copula approach,' *Journal of International Money and Finance*, 51, pp. 214–244. https://doi.org/10.1016/j.jimonfin.2014.12.002.

Richardson, M., Schoenholtz, K.L. and White, L.J. (2018) 'Deregulating Wall Street,' *Annual Review of Financial Economics*, 10(1), pp. 199–217. https://doi.org/10.1146/annurev-financial-110217-022513.

Risk, M.S. and Soundness, R.F., 2008. Global financial stability report. International Monetary Fund, *Washington 'Financial Stability Review'* (2009) ECB, pp. 134–135. https://www.ecb.europa.eu/pub/pdf/fsr/art/ecb.fsrart200912_02.en.pdf.

Rochet, J.-C. and Tirole, J. (1996) 'Interbank lending and systemic risk,' Journal of Money, Credit, and Banking/Journal of Money, *Credit and Banking*, 28(4), p. 733. https://doi.org/10.2307/2077918.

Saunders, A. and Allen, L., 2002. Credit risk measurement: New approaches to value at risk and other paradigms. John Wiley & Sons. https://books.google.se/books?hl=en&lr=&id=pGMLAd2WvasC&oi=fnd&pg=PR5&dq=Allen+and+Saunders,+2002&ots=4KcwoVVIfG&sig=Efo6lCRyBUnxWfH0TTqqB8MEsvE&redir_esc=y#v=onepage&q=Allen%20and%20Saunders%2C%202002&f=false

Scaillet, O. (2004) 'Density estimation using inverse and reciprocal inverse Gaussian kernels,' *Journal of Nonparametric Statistics*, 16(1–2), pp. 217–226. https://doi.org/10.1080/10485250310001624819.

Schultz, F., Castelló, I. and Morsing, M. (2013) 'The Construction of Corporate Social Responsibility in Network Societies: A Communication View,' *Journal of Business Ethics*, 115(4), pp. 681–692. https://doi.org/10.1007/s10551-013-1826-8.

Sedunov, J. (2016b) 'What is the systemic risk exposure of financial institutions?,' *Journal of Financial Stability*, 24, pp. 71–87. https://doi.org/10.1016/j.jfs.2016.04.005.

Simpson, W.G., Kohers, T. 'The Link Between Corporate Social and Financial Performance: Evidence from the Banking Industry'. *Journal of Business Ethics* 35, 97–109 (2002). https://doi.org/10.1023/A:1013082525900.

Smaga, Paweł, The Concept of Systemic Risk (August 8, 2014). Systemic Risk Centre Special Paper No 5, *The London School of Economics and Political Science*, August 2014, https://ssrn.com/abstract=2477928

Spence, M., 1978. Job market signaling. In Uncertainty in economics (pp. 281-306). *Academic Press*. https://doi.org/10.1016/B978-0-12-214850-7.50025-5.

Strategic risk failure is what unites Credit Suisse and SVB. https://www.ft.com/content/c0155638-bd0f-4e0f-9f68-d42f4834a301.

Walley, N. (2014) It's not easy being green. https://hbr.org/1994/05/its-not-easy-being-green.

Wu, M.-W. and Shen, C.-H. (2013) 'Corporate social responsibility in the banking industry: Motives and financial performance,' *Journal of Banking & Finance*, 37(9), pp. 3529–3547. https://doi.org/10.1016/j.jbankfin.2013.04.023.

Xu, Q., Jin, B. and Jiang, C. (2021) 'Measuring systemic risk of the Chinese banking industry: A wavelet-based quantile regression approach,' *the North American Journal of Economics and Finance*, 55, p. 101354. https://doi.org/10.1016/j.najef.2020.101354.

Zelenyuk, N. and Faff, R. (2022) 'Effects of incentive pay on systemic risk: evidence from CEO compensation and CoVar,' *Empirical Economics*, 63(6), pp. 3289–3311. https://doi.org/10.1007/s00181-022-02236-2.

Zhang, Y. and Nadarajah, S. (2017) 'A review of backtesting for value at risk,' Communications in Statistics. Theory and Methods/Communications in Statistics, Theory and Methods, 47(15), pp. 3616–3639. https://doi.org/10.1080/03610926.2017.1361984.

Zhou, H., Liu, W. and Wang, L. (2020) 'Systemic Risk of China's Financial System (2007–2018): A Comparison between ΔCoVaR, MES and SRISK across Banks, Insurance and Securities Firms,' *Chinese Economy*, 53(3), pp. 221–245. https://doi.org/10.1080/10971475.2020.1720962.

Appendix

Appendix 1: Descriptive list of companies

Identifier	Company Name	Country of Headquarters	Market Cap (EUR) (28/04/2024)
BNPP.PA	BNP Paribas SA	France	77,158,930,411
SAN.MC	Banco Santander SA	Spain	77,027,985,879
ISP.MI	Intesa Sanpaolo SpA	Italy	65,128,859,660
BBVA.MC	Banco Bilbao Vizcaya Argentaria SA	Spain	64,129,775,074
CRDI.MI	UniCredit SpA	Italy	59,878,320,059
INGA.AS	ING Groep NV	Netherlands	49,424,111,241
CAGR.PA	Credit Agricole SA	France	44,194,635,375
CABK.MC	CaixaBank SA	Spain	38,498,857,336
NDAFI.HE	Nordea Bank Abp	Finland	38,431,265,097
DBKGn.DE	Deutsche Bank AG	Germany	33,090,685,791
KBC.BR	Kbc Groep NV	Belgium	28,860,390,658
SOGN.PA	Societe Generale SA	France	20,413,996,798
ERST.VI	Erste Group Bank AG	Austria	18,571,678,064
CBKG.DE	Commerzbank AG	Germany	17,553,972,898
AIBG.I	AIB Group PLC	Ireland	12,823,542,247
MDBI.MI	Mediobanca Banca di Credito Finanziario SpA	Italy	11,433,048,146
BIRG.I	Bank of Ireland Group PLC	Ireland	10,512,786,244
BAMI.MI	Banco BPM SpA	Italy	9,451,011,269
SABE.MC	Banco de Sabadell SA	Spain	9,231,294,847
FBK.MI	FinecoBank Banca Fineco SpA	Italy	8,706,259,027
EURBr.ATc	Eurobank Ergasias Services and Holdings SA	Greece	7,533,305,505
NBGr.AT	National Bank of Greece SA	Greece	7,067,715,112
EMII.MI	Bper Banca SpA	Italy	6,796,902,056
BKT.MC	Bankinter SA	Spain	6,607,913,949

RBIV.VI	Raiffeisen Bank International AG	Austria	6,023,951,869
BMPS.MI	Banca Monte dei Paschi di Siena SpA	Italy	5,697,096,492
BOPr.AT	Piraeus Financial Holdings SA	Greece	4,993,707,372
BCP.LS	Banco Comercial Portugues SA	Portugal	4,916,936,237
BAWG.VI	BAWAG Group AG	Austria	4,535,162,234
ACBr.AT	Alpha Services and Holdings SA	Greece	3,890,917,147
BPSI.MI	Banca Popolare Di Sondrio SpA	Italy	3,484,970,436
EMBI.MI	Credito Emiliano SpA	Italy	3,329,128,214
ARLn.H	Aareal Bank AG	Germany	2,011,202,626
BOCH.CY	Bank of Cyprus Holdings PLC	Cyprus	1,638,751,200
PTSB.I	Permanent TSB Group Holdings PLC	Ireland	834,906,766

Appendix 2: ESG and Separate Pillar Scores

Identifier	ESG Score					Social Pillar Score					Governance Pillar Score					Environmental Pillar				
	2018	2019	2020	2021	2022	2018	2019	2020	2021	2022	2018	2019	2020	2021	2022	2018	2019	2020	2021	2022
BNPP.PA	95	95	95	95	92	97	96	97	96	95	91	94	93	93	87	95	95	94	95	95
SAN.MC	90	92	92	93	89	90	93	93	95	96	94	93	90	91	79	84	86	91	89	93
ISP.MI	77	75	90	93	92	94	93	93	93	94	49	44	82	90	88	89	89	97	97	96
BBVA.MC	86	80	78	85	88	84	78	78	82	89	91	81	71	87	85	84	83	93	94	94
CRDI.MI	88	87	86	82	84	89	87	84	78	77	90	88	87	85	94	83	84	91	88	87
INGA.AS	73	74	73	73	76	75	70	69	63	70	65	76	75	83	83	87	86	84	84	82
CAGR.PA	64	71	69	66	71	71	76	75	70	75	42	56	52	50	55	93	95	95	95	95
CABK.MC	75	88	86	83	85	91	89	88	86	88	57	90	85	79	83	63	83	83	83	80
NDAFI.HE	75	67	71	76	75	71	70	67	70	69	80	61	76	85	85	76	76	73	74	73
DBKGn.DE	80	86	84	80	86	82	86	87	85	89	71	81	75	67	77	97	96	96	96	95
KBC.BR	75	88	86	83	85	91	89	88	86	88	57	90	85	79	83	63	83	83	83	80
SOGN.PA	88	87	86	83	83	90	88	87	81	78	83	82	82	81	85	97	96	94	95	94
ERST.VI	84	85	81	76	73	80	83	79	75	74	89	90	83	78	70	81	81	79	77	77
CBKG.DE	70	71	77	76	76	72	70	74	72	72	63	65	74	74	76	80	89	91	92	90
AIBG.I	70	63	72	73	63	71	63	73	74	74	72	62	74	76	50	64	66	62	66	60
MDBI.MI	60	54	54	59	60	57	56	57	68	66	75	57	54	52	57	35	37	40	44	44
BIRG.I	60	65	60	66	59	67	73	69	73	65	55	60	49	60	53	45	49	54	56	54
BAMI.MI	64	68	76	71	75	64	74	78	75	78	61	58	73	63	64	69	71	77	82	92

SABE.MC	77	79	79	84	89	73	71	74	88	91	79	88	86	78	84	86	80	79	82	94
FBK.MI	69	82	86	86	81	70	80	86	87	78	66	85	89	90	88	77	82	81	77	74
EURBr.AT	69	71	77	79	79	70	72	84	91	91	69	73	73	68	68	62	64	64	65	64
NBGr.AT	64	82	81	78	84	63	88	86	85	84	86	94	94	88	91	10	27	30	33	62
EMII.MI	52	68	72	65	69	69	69	77	75	74	36	61	62	45	58	31	81	79	81	78
BKT.MC	78	80	81	77	81	65	72	77	76	79	93	91	88	78	79	84	83	79	81	93
RBIV.VI	63	66	71	63	74	91	92	87	87	86	24	33	52	31	61	61	63	61	63	62
BMPS.MI	50	63	74	74	68	71	79	77	74	69	18	41	70	73	65	57	57	76	75	74
BOPr.AT	79	80	82	83	78	84	84	83	84	80	78	81	80	80	74	64	64	83	84	81
BCP.LS	71	79	75	72	74	86	89	83	84	85	53	70	68	58	63	62	64	61	63	63
BAWG.VI	48	57	68	64	71	58	67	71	63	69	49	36	62	62	72	9	72	74	73	72
ACBr.AT	73	74	71	80	80	74	74	73	85	78	66	70	67	74	84	83	85	79	79	78
BPSI.MI	37	40	49	52	50	48	46	55	65	62	19	19	32	26	26	49	72	69	74	68
EMBI.MI	54	57	60	59	57	78	70	77	77	73	15	33	32	29	30	70	72	71	73	70
ARLn.H	70	73	73	68	61	71	73	71	69	65	82	89	91	77	64	36	32	35	40	40
BOCH.CY	39	42	56	45	53	46	48	60	56	57	39	38	59	36	47	18	31	33	35	57
PTSB.I	28	38	40	33	33	28	45	50	45	45	34	35	33	20	19	14	21	21	23	24

Appendix 3: VaR at 50%, 95% and 99% confidence levels

Identifier	5% VaR					1% VaR					50% VaR				
	2019	2020	2021	2022	2023	2019	2020	2021	2022	2023	2019	2020	2021	2022	2023
AIBG.I	-0.04239	-0.04245	-0.03569	-0.03518	-0.02725	-0.06093	-0.06393	-0.05692	-0.05651	-0.04170	0.00158	0.00796	0.00310	0.00099	-0.00103
BMPS.MI	-0.03896	-0.03969	-0.02542	-0.02495	-0.04206	-0.10991	-0.08093	-0.04732	-0.04838	-0.06273	0.00136	0.00239	0.00358	0.00914	0.00847
BBVA.MC	-0.02484	-0.02480	-0.02939	-0.02572	-0.02639	-0.03070	-0.03061	-0.03888	-0.04400	-0.03672	0.00125	0.00436	0.00000	0.00056	-0.00111
BAMI.MI	-0.03432	-0.03432	-0.02854	-0.02868	-0.02753	-0.04254	-0.04258	-0.05468	-0.05172	-0.04198	0.00052	0.00213	0.00000	0.00182	-0.00023
SABE.MC	-0.03696	-0.03219	-0.03960	-0.03851	-0.03072	-0.05959	-0.05959	-0.06911	-0.05819	-0.04351	-0.00044	0.00803	0.00455	0.00028	-0.00040
SAN.MC	-0.02586	-0.02808	-0.02725	-0.02746	-0.02914	-0.03586	-0.03586	-0.03838	-0.03846	-0.03984	0.00169	0.00647	0.00240	0.00207	0.00128
BKT.MC	-0.02709	-0.02709	-0.02598	-0.02599	-0.02563	-0.04184	-0.04442	-0.03078	-0.03081	-0.03719	0.00104	0.00270	0.00105	0.00159	-0.00010
BIRG.I	-0.03919	-0.03917	-0.03772	-0.03404	-0.02822	-0.06682	-0.06682	-0.05775	-0.04551	-0.03912	0.00363	0.00636	0.00000	-0.00038	0.00000
BNPP.PA	-0.02501	-0.02452	-0.02747	-0.02730	-0.02335	-0.03317	-0.02931	-0.03448	-0.03453	-0.03428	-0.00016	0.00378	0.00174	0.00160	0.00025
EMII.MI	-0.02619	-0.02593	-0.02875	-0.02882	-0.03245	-0.03843	-0.03856	-0.04122	-0.04266	-0.04326	-0.00051	0.00634	0.00324	0.00317	-0.00199
CABK.MC	-0.03168	-0.03233	-0.02445	-0.02443	-0.02368	-0.05130	-0.05130	-0.03641	-0.03641	-0.03454	0.00230	0.00432	0.00257	-0.00031	-0.00025
CBKG.DE	-0.03780	-0.03767	-0.03019	-0.03019	-0.02953	-0.05187	-0.05187	-0.03711	-0.03711	-0.05513	0.00196	0.00181	0.00046	-0.00151	-0.00139
CAGR.PA	-0.02516	-0.02251	-0.02372	-0.02312	-0.01459	-0.03385	-0.03317	-0.03456	-0.03218	-0.03003	-0.00093	0.00344	-0.00049	0.00194	0.00000
DBKGn.DE	-0.03497	-0.03411	-0.02873	-0.02873	-0.02440	-0.04605	-0.04605	-0.04182	-0.04182	-0.04483	0.00192	0.00211	0.00167	0.00146	-0.00056
ERST.VI	-0.02175	-0.02095	-0.02352	-0.02980	-0.02209	-0.03262	-0.02487	-0.03471	-0.04472	-0.03401	0.00000	0.00316	0.00082	0.00295	0.00091
EURBr.AT	-0.04384	-0.04338	-0.02727	-0.02466	-0.03458	-0.07415	-0.06186	-0.03973	-0.03506	-0.04593	0.00068	0.00331	0.00089	0.00041	0.00101
FBK.MI	-0.02745	-0.02755	-0.02119	-0.02250	-0.02725	-0.04425	-0.04428	-0.02787	-0.03054	-0.04428	0.00000	0.00102	0.00000	0.00035	0.00142
INGA.AS	-0.02515	-0.02477	-0.02693	-0.02677	-0.02082	-0.03844	-0.03318	-0.03366	-0.03312	-0.03696	0.00077	0.00224	0.00000	0.00033	-0.00016

ISP.MI	-0.02042	-0.02029	-0.02055	-0.02126	-0.02024	-0.02751	-0.02751	-0.02609	-0.02609	-0.03458	-0.00043	0.00165	0.00124	0.00020	-0.00027
KBC.BR	-0.02417	-0.02396	-0.02143	-0.02121	-0.02131	-0.03480	-0.03480	-0.03923	-0.03368	-0.03061	0.00031	0.00040	0.00059	0.00222	0.00092
MDBI.MI	-0.01993	-0.01963	-0.01649	-0.01604	-0.01990	-0.02542	-0.02542	-0.02698	-0.02681	-0.03067	-0.00032	0.00337	0.00015	0.00137	-0.00057
NBGr.AT	-0.04942	-0.04312	-0.03150	-0.03168	-0.03104	-0.08181	-0.06447	-0.04086	-0.04086	-0.04768	-0.00167	0.00187	-0.00022	-0.00148	-0.00069
NDAFI.HE	-0.02051	-0.02155	-0.02185	-0.02185	-0.02066	-0.02947	-0.02947	-0.03372	-0.03166	-0.02993	0.00117	0.00101	0.00044	0.00100	-0.00031
RBIV.VI	-0.02437	-0.02326	-0.02346	-0.02456	-0.02414	-0.03473	-0.03348	-0.03263	-0.03317	-0.04718	-0.00049	0.00219	0.00160	0.00276	-0.00035
SOGN.PA	-0.02968	-0.02885	-0.03233	-0.03125	-0.02232	-0.04029	-0.04029	-0.04257	-0.04251	-0.03826	-0.00042	0.00450	0.00225	0.00111	0.00064
CRDI.MI	-0.03164	-0.03015	-0.03096	-0.03411	-0.03214	-0.04840	-0.04843	-0.04877	-0.04484	-0.04631	0.00215	0.00373	0.00186	0.00144	-0.00067
BCP.LS	-0.02888	-0.03121	-0.03711	-0.03956	-0.02933	-0.04263	-0.04254	-0.05165	-0.05357	-0.04324	0.00088	0.00438	0.00393	0.00177	0.00137
BAWG.VI	-0.02364	-0.02369	-0.02413	-0.02525	-0.02481	-0.03368	-0.03382	-0.04167	-0.03845	-0.03842	0.00107	0.00155	-0.00118	-0.00041	0.00094
ACBr.AT	-0.04993	-0.04417	-0.03461	-0.03266	-0.03426	-0.07403	-0.06470	-0.06747	-0.05072	-0.05125	-0.00054	0.00580	0.00203	0.00242	0.00154
BPSI.MI	-0.02553	-0.02551	-0.03351	-0.03151	-0.02496	-0.04227	-0.04282	-0.03968	-0.04326	-0.03810	0.00321	0.00273	0.00055	0.00087	-0.00083
EMBI.MI	-0.01927	-0.01954	-0.01985	-0.01987	-0.02413	-0.03554	-0.03577	-0.02550	-0.02562	-0.03372	0.00000	0.00132	0.00119	0.00155	-0.00074
ARLn.H	-0.02950	-0.02854	-0.02510	-0.02212	-0.00675	-0.05271	-0.05301	-0.03796	-0.03472	-0.01070	0.00000	0.00167	0.00165	0.00070	0.00000
BOCH.CY	-0.03659	-0.02904	-0.03076	-0.02871	-0.02460	-0.05255	-0.04295	-0.04875	-0.04476	-0.04247	0.00210	0.00572	0.00078	0.00000	0.00000
PTSB.I	-0.04016	-0.04114	-0.04952	-0.03575	-0.03257	-0.05974	-0.06231	-0.07686	-0.05144	-0.04613	0.00174	0.00174	0.00000	0.00000	0.00147
BOPr.AT	-0.07279	-0.04792	-0.03550	-0.02946	-0.04426	-0.14134	-0.07404	-0.11207	-0.04265	-0.05647	-0.00246	0.00669	0.00685	0.00075	0.00000
System	**-0.02394**	**-0.04256**	**-0.02473**	**-0.02648**	**-0.01913**	**-0.03384**	**-0.06601**	**-0.03208**	**-0.04907**	**-0.02945**	**0.0002**	**0.0007**	**-0.0016**	**-0.0004**	**-0.0017**

Appendix 4: Estimated parameters of 5 years (2019-2023) quantile regression

Identifier	Intercept (α)	Tail Beta (β)
AIBG.I	0.0421	0.60
BMPS.MI	0.0508	0.41
BBVA.MC	0.0302	0.73
BAMI.MI	0.0381	0.61
SABE.MC	0.0336	0.50
SAN.MC	0.0247	0.82
BKT.MC	0.0367	0.72
BIRG.I	0.0372	0.63
BNPP.PA	0.0181	0.87
EMII.MI	0.0404	0.57
CABK.MC	0.0324	0.85
CBKG.DE	0.0292	0.60
CAGR.PA	0.0221	0.83
DBKGn.DE	0.0295	0.61
ERST.VI	0.0261	0.70
EURBr.AT	0.0497	0.39
FBK.MI	0.0457	0.68
INGA.AS	0.0246	0.69
ISP.MI	0.023	0.91
KBC.BR	0.0292	0.73
MDBI.MI	0.0308	0.78
NBGr.AT	0.0429	0.45
NDAFI.HE	0.0338	0.95
RBIV.VI	0.0357	0.79
SOGN.PA	0.0211	0.59
CRDI.MI	0.0274	0.63
BCP.LS	0.0337	0.61
BAWG.VI	0.038	0.70
ACBr.AT	0.0458	0.40
BPSI.MI	0.0443	0.60
EMBI.MI	0.041	0.72
ARLn.H	0.0601	0.56
BOCH.CY	0.0549	0.50
PTSB.I	0.0576	0.53
BOPr.AT	0.0513	0.29

Appendix 5: CoVaR and ΔCoVaR at 99% confidence level

Identifier	CoVaR					ΔCoVaR 99%				
	2019	2020	2021	2022	2023	2019	2020	2021	2022	2023
AIBG.I	0.06414	0.10045	0.07046	0.11421	0.10642	0.04023	0.05030	0.04880	0.07558	0.07704
BMPS.MI	0.04955	0.11881	0.05807	0.08891	0.07134	0.02310	0.03598	0.02410	0.03777	0.03522
BBVA.MC	0.06698	0.10487	0.06025	0.09372	0.06381	0.05523	0.05348	0.03575	0.05809	0.04464
BAMI.MI	0.05504	0.10084	0.07395	0.08159	0.06235	0.02835	0.05422	0.05043	0.03515	0.03332
SABE.MC	0.08428	0.09997	0.07131	0.09809	0.06825	0.06244	0.04096	0.04550	0.05602	0.04356
SAN.MC	0.06092	0.08096	0.05442	0.09032	0.07757	0.04883	0.05297	0.03777	0.06244	0.05158
BKT.MC	0.06106	0.09521	0.05724	0.07955	0.07759	0.04252	0.04554	0.02974	0.04200	0.04885
BIRG.I	0.04442	0.11008	0.06572	0.10969	0.08078	0.01570	0.05814	0.03885	0.06606	0.05150
BNPP.PA	0.06731	0.10499	0.07163	0.07933	0.06583	0.05672	0.06967	0.05691	0.06188	0.05027
EMII.MI	0.04314	0.11402	0.05691	0.08439	0.07786	0.01588	0.04011	0.03389	0.04378	0.04888
CABK.MC	0.05453	0.08637	0.06920	0.08573	0.07337	0.03698	0.04644	0.05050	0.04583	0.04874
CBKG.DE	0.06285	0.08783	0.05627	0.07113	0.06000	0.04240	0.04315	0.03358	0.04496	0.03509
CAGR.PA	0.06823	0.07809	0.07161	0.08260	0.09187	0.05454	0.05418	0.05666	0.06424	0.05396
DBKGn.DE	0.06344	0.09636	0.05607	0.07400	0.07298	0.04731	0.05079	0.03230	0.04960	0.04575
ERST.VI	0.07005	0.11595	0.08054	0.06933	0.07561	0.04614	0.07006	0.05816	0.03665	0.05268
EURBr.AT	0.04300	0.11499	0.07132	0.09832	0.08350	0.01531	0.04196	0.03928	0.05299	0.04616
FBK.MI	0.05047	0.12255	0.06720	0.08545	0.07153	0.02662	0.05515	0.04408	0.04978	0.04080
INGA.AS	0.06308	0.10521	0.06780	0.07793	0.08403	0.04661	0.06309	0.04932	0.05748	0.06546

ISP.MI	0.07322	0.09172	0.07319	0.07686	0.08384	0.05666	0.06116	0.05870	0.05868	0.06521
KBC.BR	0.06245	0.08217	0.07173	0.07732	0.08968	0.04592	0.04486	0.04933	0.04967	0.05860
MDBI.MI	0.07725	0.08063	0.07510	0.09056	0.08530	0.05579	0.04046	0.05306	0.05612	0.05273
NBGr.AT	0.05097	0.10327	0.08560	0.09590	0.05544	0.02253	0.04805	0.04971	0.06142	0.02307
NDAFI.HE	0.07301	0.10086	0.06357	0.10724	0.08178	0.05031	0.06089	0.03999	0.06574	0.06437
RBIV.VI	0.06563	0.11791	0.06654	0.07462	0.08701	0.04707	0.07308	0.03256	0.05016	0.05342
SOGN.PA	0.05265	0.10485	0.05812	0.08067	0.08323	0.03525	0.06575	0.04055	0.06128	0.06094
CRDI.MI	0.06124	0.08963	0.05449	0.06321	0.06376	0.04567	0.05625	0.03010	0.03787	0.04255
BCP.LS	0.04791	0.10840	0.06306	0.06904	0.06527	0.02754	0.04810	0.03647	0.03382	0.03850
BAWG.VI	0.05446	0.10597	0.08321	0.10163	0.07375	0.02681	0.04749	0.06101	0.05785	0.05247
ACBr.AT	0.03929	0.12900	0.06884	0.09904	0.08064	0.01196	0.05555	0.03300	0.06302	0.03573
BPSI.MI	0.04292	0.10823	0.06729	0.09948	0.08315	0.01639	0.04783	0.03737	0.06381	0.05297
EMBI.MI	0.04322	0.13122	0.05421	0.07971	0.06884	0.01596	0.05917	0.01962	0.04627	0.03877
ARLn.H	0.04765	0.10685	0.05927	0.10439	0.15398	0.01993	0.04215	0.02131	0.03874	0.10366
BOCH.CY	0.03839	0.12525	0.07135	0.09642	0.09397	0.00775	0.05581	0.03492	0.04426	0.03786
PTSB.I	0.03869	0.14463	0.05715	0.09965	0.09525	0.00781	0.05949	0.02274	0.04101	0.04863
BOPr.AT	0.04571	0.16257	0.06692	0.09451	0.09900	0.01829	0.09743	0.03511	0.02867	0.05629

Appendix 6: Market Cap and Euro ΔCoVaR at 99% confidence level

Identifier	Market Cap					€ΔCoVaR 99%				
	2019	2020	2021	2022	2023	2019	2020	2021	2022	2023
AIBG.I	9,278,670,506	3,800,255,667	5,935,532,286	6,615,786,621	10,466,225,824	373,243,800	191,137,659	289,653,976	500,001,305	806,286,639
BMPS.MI	1,543,995,745	1,547,041,036	1,118,677,530	1,027,806,408	3,074,692,009	35,660,126	55,667,178	26,962,366	38,818,192	108,293,727
BBVA.MC	32,928,743,384	21,967,923,130	33,897,100,031	32,211,195,128	42,468,043,686	1,818,654,497	1,174,778,625	1,211,719,635	1,871,083,903	1,895,815,938
BAMI.MI	2,874,086,013	2,330,703,652	3,851,897,776	4,358,764,669	6,451,787,835	81,491,835	126,361,429	194,235,797	153,201,861	214,973,571
SABE.MC	5,337,855,668	2,528,219,324	3,136,984,464	4,224,646,276	6,135,093,896	333,279,694	103,560,920	142,729,656	236,668,909	267,263,095
SAN.MC	64,761,369,939	39,669,278,717	52,978,368,653	47,602,638,177	56,512,211,259	3,162,427,217	2,101,281,694	2,000,728,092	2,972,261,125	2,914,786,832
BKT.MC	5,774,788,519	3,945,060,594	4,393,510,291	4,952,804,972	5,369,762,955	245,520,909	179,669,895	130,654,209	208,032,667	262,296,811
BIRG.I	5,084,267,970	2,601,463,360	4,933,528,915	6,914,363,383	9,745,006,572	79,843,344	151,238,674	191,677,465	456,749,016	501,897,073
BNPP.PA	55,534,039,377	46,804,275,285	66,427,485,153	63,385,931,801	71,199,221,972	3,149,724,111	3,260,853,859	3,780,653,890	3,922,004,530	3,578,828,892
EMII.MI	1,830,196,342	1,538,782,185	2,603,957,343	2,420,727,799	3,888,762,934	29,065,348	61,725,170	88,237,699	105,972,201	190,067,177
CABK.MC	16,050,262,420	12,134,964,594	19,208,491,074	25,517,279,805	28,271,625,349	593,506,604	563,584,161	970,009,591	1,169,507,968	1,377,845,933
CBKG.DE	7,759,171,321	5,653,531,873	7,297,738,405	9,254,318,665	12,802,403,861	328,950,068	243,972,514	245,021,567	416,046,404	449,185,142
CAGR.PA	31,880,190,280	25,855,824,755	36,279,389,420	31,065,162,312	34,250,131,623	1,738,618,057	1,400,791,018	2,055,481,366	1,995,750,288	1,848,000,102
DBKGn.DE	14,556,645,464	16,184,290,121	22,086,777,742	20,626,950,740	21,304,053,152	688,674,897	822,064,832	713,469,181	1,022,993,622	974,724,344
ERST.VI	13,816,756,722	9,827,750,739	14,180,320,331	12,690,510,769	14,288,708,304	637,463,705	688,522,389	824,784,152	465,056,458	752,657,710
EURBr.AT	2,464,057,534	1,757,245,965	2,918,749,889	3,588,508,885	5,396,895,131	37,722,257	73,741,070	114,639,739	190,162,263	249,099,092
FBK.MI	6,230,644,167	6,904,428,277	9,114,879,238	8,175,505,925	8,176,725,596	165,834,825	380,765,411	401,738,302	406,943,983	333,610,404
INGA.AS	39,845,790,770	27,499,966,100	42,800,561,786	39,367,814,761	45,422,324,118	1,857,212,308	1,735,055,361	2,110,838,106	2,262,940,728	2,973,254,492
ISP.MI	36,918,173,855	32,849,177,933	44,536,010,870	39,220,269,309	45,145,391,083	2,091,709,894	2,009,154,270	2,614,174,766	2,301,249,302	2,943,885,807

KBC.BR	25,317,215,172	21,958,741,568	28,496,936,031	24,531,605,135	25,798,906,069	1,162,515,886	985,135,023	1,405,753,854	1,218,362,169	1,511,893,292
MDBI.MI	8,139,321,765	6,237,468,347	8,480,494,698	7,776,733,099	9,142,008,064	454,052,065	252,392,919	449,932,646	436,430,261	482,012,375
NBGr.AT	1,991,303,410	1,405,114,886	2,260,215,224	3,077,817,318	4,985,924,948	44,858,092	67,512,960	112,350,778	189,027,228	115,045,232
NDAFI.HE	27,752,166,052	26,570,750,631	37,542,689,560	36,484,161,548	37,083,272,537	1,396,100,465	1,617,760,152	1,501,257,070	2,398,614,717	2,387,087,337
RBIV.VI	7,135,999,169	5,371,044,446	6,805,527,652	4,810,167,925	4,805,670,600	335,870,073	392,505,186	221,594,786	241,273,213	256,718,923
SOGN.PA	21,338,551,662	14,660,195,075	21,085,837,170	20,683,451,258	19,338,375,556	752,226,623	963,937,147	855,072,869	1,267,399,159	1,178,403,253
CRDI.MI	24,990,682,437	19,340,367,499	22,570,572,680	23,435,490,514	38,608,450,466	1,141,324,467	1,087,953,693	679,283,955	887,572,332	1,642,789,567
BCP.LS	3,449,454,474	1,768,719,085	2,047,307,102	2,341,580,471	3,596,074,593	95,008,325	85,082,463	74,671,432	79,182,885	138,459,660
BAWG.VI	3,760,035,926	2,936,965,407	4,211,444,268	4,199,251,594	3,810,415,665	100,802,803	139,464,739	256,923,369	242,935,103	199,943,941
ACBr.AT	2,318,211,484	1,278,035,537	2,104,874,864	2,362,104,153	3,224,357,814	27,728,128	70,996,152	69,456,661	148,859,804	115,199,856
BPSI.MI	957,996,950	825,386,140	1,524,329,029	1,624,502,491	2,043,148,754	15,705,402	39,479,870	56,956,554	103,666,002	108,219,460
EMBI.MI	1,639,214,099	1,443,311,704	1,823,950,393	2,052,346,885	2,551,526,225	26,161,857	85,406,527	35,787,731	94,962,090	98,930,326
ARLn.H	1,639,215,037	1,169,709,075	1,384,241,661	1,846,648,837	1,985,036,804	32,676,113	49,299,728	29,494,037	71,537,329	205,768,915
BOCH.CY	614,081,281	321,560,811	437,676,417	534,870,380	1,221,337,377	4,756,674	17,945,344	15,284,098	23,674,968	46,242,276
PTSB.I	579,815,210	277,065,856	590,638,745	744,384,248	1,162,771,634	4,530,096	16,483,202	13,432,897	30,527,942	56,550,236
BOPr.AT	979,135,693	659,036,875	1,388,978,350	1,534,071,008	3,346,326,665	17,911,329	64,209,304	48,768,419	43,984,884	188,347,996

Appendix 7 Descriptive Statistics of Control Variables of different ESG Groups

		D/E				ROE				NPL				Beta			
Identifier	**ESG**	**Mean**	**Min**	**Max**	**Std. Dev**	**Mean**	**Min**	**Max**	**Std. Dev**	**Mean**	**Min**	**Max**	**Std. Dev**	**Mean**	**Min**	**Max**	**Std. Dev**
BNPP.PA	High	1.332	0.740	1.839	0.381	0.078	0.063	0.094	0.010	2.050	1.700	2.600	0.339	1.658	1.260	1.969	0.277
SAN.MC	High	2.879	2.556	3.234	0.273	0.079	0.053	0.120	0.024	3.273	3.080	3.730	0.238	1.578	1.486	1.655	0.063
CRDI.MI	High	2.615	1.998	3.072	0.502	0.080	0.021	0.160	0.048	4.377	2.660	7.720	1.901	1.727	1.613	1.839	0.104
ISP.MI	High	3.691	3.253	4.076	0.315	0.086	0.060	0.152	0.033	4.767	2.300	8.800	2.795	1.497	1.381	1.562	0.072
SOGN.PA	High	1.245	0.765	2.516	0.637	0.038	-0.003	0.083	0.031	3.100	2.800	3.600	0.303	1.731	1.465	1.962	0.200
CABK.MC	High	1.443	1.218	1.565	0.137	0.081	0.055	0.126	0.026	3.433	2.700	4.700	0.742	1.330	1.119	1.494	0.136
BBVA.MC	High	1.588	1.409	1.914	0.180	0.102	0.052	0.141	0.031	3.767	3.400	4.100	0.301	1.734	1.521	1.881	0.142
KBC.BR	High	1.119	0.935	1.375	0.174	0.127	0.078	0.158	0.027	1.633	1.000	2.500	0.557	1.343	1.101	1.553	0.176
DBKGn.DE	High	3.179	2.778	3.417	0.249	0.022	-0.040	0.077	0.040	2.167	1.659	2.606	0.388	1.269	1.101	1.478	0.143
SABE.MC	High	1.986	1.757	2.251	0.205	0.047	0.000	0.095	0.033	3.702	3.410	4.200	0.281	1.397	1.352	1.445	0.037

		D/E				ROE				NPL				Beta			
Identifier	**ESG**	**Mean**	**Min**	**Max**	**Std. Dev**	**Mean**	**Min**	**Max**	**Std. Dev**	**Mean**	**Min**	**Max**	**Std. Dev**	**Mean**	**Min**	**Max**	**Std. Dev**
FBK.MI	Medium	0.521	0.132	1.076	0.360	0.226	0.192	0.278	0.033	0.077	0.030	0.180	0.053	0.963	0.858	1.146	0.110
BOPr.AT	Medium	0.369	0.230	0.459	0.085	0.061	0.004	0.152	0.069	22.633	3.500	45.000	17.144	2.367	2.116	2.957	0.321
ERST.VI	Medium	2.121	1.906	2.392	0.193	0.094	0.054	0.122	0.023	2.517	2.000	3.200	0.407	1.348	1.177	1.423	0.097
BKT.MC	Medium	4.362	3.206	6.202	1.092	0.108	0.064	0.155	0.031	2.372	2.100	2.900	0.303	1.116	0.908	1.316	0.178
NBGr.AT	Medium	0.551	0.388	1.113	0.279	0.090	-0.023	0.157	0.079	16.867	3.700	40.400	15.360	2.157	1.991	2.554	0.204
ACBr.AT	Medium	0.588	0.225	0.908	0.266	-0.070	-0.519	0.064	0.221	0.180	0.030	0.343	0.151	1.855	1.632	1.958	0.116
EURBr.AT	Medium	0.527	0.376	0.641	0.118	0.109	0.039	0.223	0.071	16.433	10.000	29.300	8.114	1.884	1.612	2.252	0.242
BCP.LS	Medium	0.540	0.454	0.646	0.070	0.057	0.023	0.149	0.047	3.000	1.300	6.100	1.867	1.929	1.734	2.230	0.182
CBKG.DE	Medium	1.560	1.457	1.680	0.085	0.037	-0.019	0.077	0.033	0.950	0.800	1.100	0.105	1.372	1.156	1.645	0.182
INGA.AS	Medium	2.338	1.816	2.756	0.365	0.091	0.046	0.142	0.032	1.500	1.400	1.700	0.110	1.777	1.306	2.235	0.367
NDAFI.HE	Medium	6.024	5.450	6.576	0.442	0.106	0.068	0.161	0.033	1.348	0.810	1.820	0.433	1.148	0.922	1.245	0.123
BAMI.MI	Medium	1.929	1.485	2.956	0.567	0.028	-0.006	0.069	0.036	6.788	3.480	10.800	2.855	1.630	1.130	2.200	0.412
ARLn.H	Medium	1.531	0.942	2.134	0.527	0.035	-0.026	0.071	0.034	4.131	2.849	6.053	1.201	1.213	0.942	1.534	0.259
AIBG.I	Medium	0.651	0.513	0.820	0.110	0.057	-0.057	0.148	0.066	5.767	3.000	10.000	2.582	1.532	0.585	2.239	0.630
CAGR.PA	Medium	2.693	2.300	2.931	0.240	0.078	0.059	0.095	0.012	2.750	2.100	3.200	0.423	1.680	1.417	1.900	0.190

Identifier	ESG	D/E Mean	D/E Min	D/E Max	D/E Std. Dev	ROE Mean	ROE Min	ROE Max	ROE Std. Dev	NPL Mean	NPL Min	NPL Max	NPL Std. Dev	Beta Mean	Beta Min	Beta Max	Beta Std. Dev
RBIV.VI	Low	0.982	0.883	1.188	0.113	0.087	0.005	0.120	0.045	2.200	1.600	3.800	0.837	1.353	1.174	1.656	0.200
BMPS.MI	Low	2.401	1.441	3.211	0.696	-0.012	-0.266	0.206	0.168	7.500	3.500	17.300	5.906	1.394	0.994	2.042	0.391
EMII.MI	Low	1.650	1.128	2.536	0.532	0.097	0.008	0.183	0.071	4.578	1.550	9.970	3.584	1.573	1.374	1.744	0.167
BIRG.I	Low	0.981	0.850	1.191	0.153	0.066	-0.048	0.137	0.062	4.767	3.100	6.300	1.268	1.561	1.260	1.867	0.244
BAWG.VI	Low	1.895	0.961	3.335	0.885	0.112	0.073	0.164	0.033	1.300	0.900	1.700	0.374	0.974	0.747	1.187	0.142
MDBI.MI	Low	2.295	1.967	2.619	0.284	0.081	0.062	0.091	0.011	2.978	1.670	4.100	0.930	1.372	1.161	1.508	0.144
EMBI.MI	Low	2.384	1.776	3.241	0.575	0.095	0.064	0.138	0.031	19.454	0.000	57.560	24.163	1.060	0.956	1.141	0.060
BOCH.CY	Low	0.272	0.155	0.409	0.093	0.053	-0.044	0.218	0.094	15.204	3.328	35.481	13.598	2.063	1.835	2.293	0.148
BPSI.MI	Low	1.228	0.955	1.778	0.290	0.046	0.000	0.121	0.048	5.796	0.000	13.137	5.518	1.372	1.135	1.555	0.149
PTSB.I	Low	0.510	0.395	0.746	0.127	0.007	-0.056	0.048	0.036	6.276	3.312	10.650	2.818	1.030	0.812	1.299	0.181

Appendix 8 Descriptive Statistics of Independent Variables and Dependent Variable of different ESG Groups

Identifier	ESG	S Mean	S Min	S Max	S Std. Dev	G Mean	G Min	G Max	G Std. Dev	E Mean	E Min	E Max	E Std. Dev
BNPP.PA	High	96.200	95.000	97.000	0.837	91.600	87.000	94.000	2.793	94.800	94.000	95.000	0.447
SAN.MC	High	93.400	90.000	96.000	2.302	89.400	79.000	94.000	6.025	88.600	84.000	93.000	3.647
CRDI.MI	High	83.000	77.000	89.000	5.339	88.800	85.000	94.000	3.421	86.600	83.000	91.000	3.209
ISP.MI	High	93.400	93.000	94.000	0.548	70.600	44.000	90.000	22.267	93.600	89.000	97.000	4.219
SOGN.PA	High	84.800	78.000	90.000	5.070	82.600	81.000	85.000	1.517	95.200	94.000	97.000	1.304
CABK.MC	High	88.400	86.000	91.000	1.817	78.800	57.000	90.000	12.814	78.400	63.000	83.000	8.706
BBVA.MC	High	82.200	78.000	89.000	4.604	83.000	71.000	91.000	7.616	89.600	83.000	94.000	5.595
KBC.BR	High	88.400	86.000	91.000	1.817	78.800	57.000	90.000	12.814	78.400	63.000	83.000	8.706
DBKGn.DE	High	85.800	82.000	89.000	2.588	74.200	67.000	81.000	5.404	96.000	95.000	97.000	0.707
SABE.MC	High	79.400	71.000	91.000	9.343	83.000	78.000	88.000	4.359	84.200	79.000	94.000	6.099

		S				G				E			
Identifier	**ESG**	**Mean**	**Min**	**Max**	**Std. Dev**	**Mean**	**Min**	**Max**	**Std. Dev**	**Mean**	**Min**	**Max**	**Std. Dev**
FBK.MI	Medium	80.200	70.000	87.000	6.870	83.600	66.000	90.000	10.015	78.200	74.000	82.000	3.271
BOPr.AT	Medium	83.000	80.000	84.000	1.732	78.600	74.000	81.000	2.793	75.200	64.000	84.000	10.281
ERST.VI	Medium	78.200	74.000	83.000	3.701	82.000	70.000	90.000	8.276	79.000	77.000	81.000	2.000
BKT.MC	Medium	73.800	65.000	79.000	5.541	85.800	78.000	93.000	6.907	84.000	79.000	93.000	5.385
NBGr.AT	Medium	81.200	63.000	88.000	10.281	90.600	86.000	94.000	3.578	32.400	10.000	62.000	18.796
ACBr.AT	Medium	76.800	73.000	85.000	4.970	72.200	66.000	84.000	7.294	80.800	78.000	85.000	3.033
EURBr.AT	Medium	81.600	70.000	91.000	10.114	70.200	68.000	73.000	2.588	63.800	62.000	65.000	1.095
BCP.LS	Medium	85.400	83.000	89.000	2.302	62.400	53.000	70.000	7.021	62.600	61.000	64.000	1.140
CBKG.DE	Medium	72.000	70.000	74.000	1.414	70.400	63.000	76.000	5.941	88.400	80.000	92.000	4.827
INGA.AS	Medium	69.400	63.000	75.000	4.278	76.400	65.000	83.000	7.403	84.600	82.000	87.000	1.949
NDAFI.HE	Medium	69.400	67.000	71.000	1.517	77.400	61.000	85.000	9.915	74.400	73.000	76.000	1.517
BAMI.MI	Medium	73.800	64.000	78.000	5.762	63.800	58.000	73.000	5.630	78.200	69.000	92.000	9.257
ARLn.H	Medium	69.800	65.000	73.000	3.033	80.600	64.000	91.000	10.831	36.600	32.000	40.000	3.435
AIBG.I	Medium	71.000	63.000	74.000	4.637	66.800	50.000	76.000	10.826	63.600	60.000	66.000	2.608
CAGR.PA	Medium	73.400	70.000	76.000	2.702	51.000	42.000	56.000	5.568	94.600	93.000	95.000	0.894

		S				G				E			
Identifier	**ESG**	**Mean**	**Min**	**Max**	**Std. Dev**	**Mean**	**Min**	**Max**	**Std. Dev**	**Mean**	**Min**	**Max**	**Std. Dev**
RBIV.VI	Low	88.600	86.000	92.000	2.702	40.200	24.000	61.000	15.579	62.000	61.000	63.000	1.000
BMPS.MI	Low	74.000	69.000	79.000	4.123	53.400	18.000	73.000	23.458	67.800	57.000	76.000	9.884
EMII.MI	Low	72.800	69.000	77.000	3.633	52.400	36.000	62.000	11.415	70.000	31.000	81.000	21.840
BIRG.I	Low	69.400	65.000	73.000	3.578	55.400	49.000	60.000	4.722	51.600	45.000	56.000	4.506
BAWG.VI	Low	65.600	58.000	71.000	5.177	56.200	36.000	72.000	13.936	60.000	9.000	74.000	28.522
MDBI.MI	Low	60.800	56.000	68.000	5.718	59.000	52.000	75.000	9.192	40.000	35.000	44.000	4.062
EMBI.MI	Low	75.000	70.000	78.000	3.391	27.800	15.000	33.000	7.328	71.200	70.000	73.000	1.304
BOCH.CY	Low	53.400	46.000	60.000	6.066	43.800	36.000	59.000	9.471	34.800	18.000	57.000	14.078
BPSI.MI	Low	55.200	46.000	65.000	8.349	24.400	19.000	32.000	5.505	66.400	49.000	74.000	10.015
PTSB.I	Low	42.600	28.000	50.000	8.444	28.200	19.000	35.000	7.981	20.600	14.000	24.000	3.912

Identifier	ESG	ESG Mean	Min	Max	Std. Dev	€ΔCoVaR Mean	Min	Max	Std. Dev
BNPP.PA	High	94.400	92.000	95.000	1.342	3,538,413,056.40	3,149,724,111.00	3,922,004,530.00	329,990,410.54
SAN.MC	High	91.200	89.000	93.000	1.643	2,630,296,992.00	2,000,728,092.00	3,162,427,217.00	537,877,936.67
CRDI.MI	High	85.400	82.000	88.000	2.408	1,087,784,802.80	679,283,955.00	1,642,789,567.00	359,810,640.67
ISP.MI	High	85.400	75.000	93.000	8.678	2,392,034,807.80	2,009,154,270.00	2,943,885,807.00	386,949,691.33
SOGN.PA	High	85.400	83.000	88.000	2.302	1,003,407,810.20	752,226,623.00	1,267,399,159.00	216,198,990.56
CABK.MC	High	83.400	75.000	88.000	5.030	934,890,851.40	563,584,161.00	1,377,845,933.00	355,984,404.26
BBVA.MC	High	83.400	78.000	88.000	4.219	1,594,410,519.60	1,174,778,625.00	1,895,815,938.00	367,498,975.80
KBC.BR	High	83.400	75.000	88.000	5.030	1,256,732,044.80	985,135,023.00	1,511,893,292.00	207,019,706.72
DBKGn.DE	High	83.200	80.000	86.000	3.033	844,385,375.20	688,674,897.00	1,022,993,622.00	150,642,094.21
SABE.MC	High	81.600	77.000	89.000	4.879	216,700,454.80	103,560,920.00	333,279,694.00	93,298,274.59

Identifier	ESG	ESG Mean	Min	Max	Std. Dev	Euro ΔCoVaR Mean	Min	Max	Std. Dev
FBK.MI	Medium	80.800	69.000	86.000	6.979	337,778,585.00	165,834,825.00	406,943,983.00	100,380,021.95
BOPr.AT	Medium	80.400	78.000	83.000	2.074	72,644,386.40	17,911,329.00	188,347,996.00	66,793,735.41
ERST.VI	Medium	79.800	73.000	85.000	5.167	673,696,882.80	465,056,458.00	824,784,152.00	136,130,122.32
BKT.MC	Medium	79.400	77.000	81.000	1.817	205,234,898.20	130,654,209.00	262,296,811.00	52,684,676.75
NBGr.AT	Medium	77.800	64.000	84.000	8.012	105,758,858.00	44,858,092.00	189,027,228.00	55,305,884.87
ACBr.AT	Medium	75.600	71.000	80.000	4.159	86,448,120.20	27,728,128.00	148,859,804.00	46,629,902.09
EURBr.AT	Medium	75.000	69.000	79.000	4.690	133,072,884.20	37,722,257.00	249,099,092.00	86,129,357.94
BCP.LS	Medium	74.200	71.000	79.000	3.114	94,480,953.00	74,671,432.00	138,459,660.00	25,735,114.20
CBKG.DE	Medium	74.000	70.000	77.000	3.240	336,635,139.00	243,972,514.00	449,185,142.00	94,884,299.47
INGA.AS	Medium	73.800	73.000	76.000	1.304	2,187,860,199.00	1,735,055,361.00	2,973,254,492.00	485,482,732.25
NDAFI.HE	Medium	72.800	67.000	76.000	3.768	1,860,163,948.20	1,396,100,465.00	2,398,614,717.00	492,571,353.25
BAMI.MI	Medium	70.800	64.000	76.000	4.970	154,052,898.60	81,491,835.00	214,973,571.00	53,288,468.16
ARLn.H	Medium	69.000	61.000	73.000	4.950	77,755,224.40	29,494,037.00	205,768,915.00	73,479,845.83
AIBG.I	Medium	68.200	63.000	73.000	4.868	432,064,675.80	191,137,659.00	806,286,639.00	237,930,658.81
CAGR.PA	Medium	68.200	64.000	71.000	3.114	1,807,728,166.20	1,400,791,018.00	2,055,481,366.00	259,195,797.08

		ESG				Euro ΔCoVaR			
Identifier	**ESG**	**Mean**	**Min**	**Max**	**Std. Dev**	**Mean**	**Min**	**Max**	**Std. Dev**
RBIV.VI	Low	67.400	63.000	74.000	4.930	289,592,436.20	221,594,786.00	392,505,186.00	72,062,038.16
BMPS.MI	Low	65.800	50.000	74.000	9.960	53,080,317.80	26,962,366.00	108,293,727.00	32,573,881.88
EMII.MI	Low	65.200	52.000	72.000	7.791	95,013,519.00	29,065,348.00	190,067,177.00	60,536,100.35
BIRG.I	Low	62.000	59.000	66.000	3.240	276,281,114.40	79,843,344.00	501,897,073.00	190,297,406.26
BAWG.VI	Low	61.600	48.000	71.000	9.236	188,013,991.00	100,802,803.00	256,923,369.00	66,839,314.42
MDBI.MI	Low	57.400	54.000	60.000	3.130	414,964,053.20	252,392,919.00	482,012,375.00	92,380,090.33
EMBI.MI	Low	57.400	54.000	60.000	2.302	68,249,706.20	26,161,857.00	98,930,326.00	34,548,427.11
BOCH.CY	Low	47.000	39.000	56.000	7.246	21,580,672.00	4,756,674.00	46,242,276.00	15,398,783.64
BPSI.MI	Low	45.600	37.000	52.000	6.656	64,805,457.60	15,705,402.00	108,219,460.00	40,338,330.56
PTSB.I	Low	34.400	28.000	40.000	4.722	24,304,874.60	4,530,096.00	56,550,236.00	20,303,387.82