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Essays in Sustainable Finance

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“Non si può mai attraversare l’oceano se non si ha il coraggio di perdere di vista la riva.”

Cristoforo Colombo

UNIVERSITY OF TRENTO

Abstract

Department of Economics and Management

Doctor of Philosophy

Essays in Sustainable Finance

by Karoline Bax, MS.c.

Sustainability is a top priority for now and in the future. In the last years, it has generated increasing interest from private investors, investment funds, academics, and regulatory bodies. As companies have progressively been characterized by non-financial information focusing on sustainability measures, including environmental, social, and governance (ESG) scores, this thesis explores different topics around sustainability in finance using econometric tools. In the different chapters, my co-authors and I explore questions concerning the ability of ESG scores to capture financial risks using high-dimensional vine copula models. Additionally, as the European Banking Authority has acknowledged that ESG risks can potentially impact the financial system and economy, we analyze the effects of ESG scores on systemic risk. Then, considering that the world has changed dramatically in the COVID-19 pandemic and topics of diversity and inclusion have gained traction, a closer look at whether investors can benefit from considering workplace contentment in their investment decision is taken.

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Dedicated to my parents
Brigitte and Wolfgang

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Chapter 1

Introduction

In recent years, sustainability has become a top priority. It is not just the large number of assets that are invested with explicit environmental, social, and governance (ESG) goals (see Global Sustainable Investment Alliance (GSIA), 2018) or the increased investment interest by international asset owners (see FTSE Russel, 2020), but even the executive branch of the European Union has stressed its importance. In 2018, the European Commission published its *Action plan on Financing Sustainable Growth* and with that provided the European Union (EU) with a roadmap on sustainable finance for future work across financial systems (European Banking Authority, 2018). By aiming to connect finance with sustainability further, they offer ten different recommendations, including incorporating sustainability in financial advice and better integrating sustainability in ratings and market research (European Banking Authority, 2018). Furthermore, their Green Deal Investment Plan intends to mobilize at least 1 trillion Euro to support sustainable investments over the following years. Hence, the European Banking Authority (EBA) also stressed the importance of including ESG information in the regulatory and supervisory framework of EU credit institutions (European Banking Authority, 2018). However, not just regulators and institutions are interested in sustainable investment; a part of the increase in demand for socially responsible investments stems from investors and asset managers pressured by stakeholders to push companies to behave responsibly and improve their ESG strategy (Henriksson et al., 2019).

While it might be more complicated to identify which company acts more sustainable than others, today, most companies are now characterized by some sort of non-financial information, including environmental, social, and governance (ESG) scores. These scores are published by different data providers and are based on a subset of underlying variables (Bhattacharya and Sharma, 2019). Using quantitative and qualitative methods to evaluate the public information, the data providers then assign an ESG score to a company (Berg and Lange, 2020). Furthermore, companies can also be linked to a rating class (i.e., A, B, C, or D) based on their ESG score value using thresholds or quartiles. Succinctly, companies are awarded high scores for ESG responsible behavior and low scores for ESG irresponsible behavior.

Limited by access and budget, investors are still given many choices for picking their favorite data provider as according to Li and Polychronopoulos (2020) in 2019, already 70 different firms were providing some sort of ESG rating. With an increase in rating providers comes an increase in ambiguity and divergence between the scores of these data providers, as pointed out by Berg, Fabisik, and Sautner (2021), Billio et al. (2021), Gibson, Krueger, and Schmidt (2021), Berg, Koelbel, and Rigobon (forthcoming), and Serafeim and Yoon (forthcoming). Nevertheless, investors are highly motivated to use such scores, as according to the biennial 2018 Global Sustainable Investment Review, over $30 trillion had already been invested with explicit ESG goals (Global Sustainable Investment Alliance (GSIA), 2018).

The wave of interest has also spread into the world of academia. In the recent years, academic scholars have tried to find a consensus on the effect of using ESG scores in investment decisions while mainly focusing on financial performance and not as much on financial risks (Friede, 2019; Shafer and Szado, 2020; Lööf, Sahamkhadam, and Stephan, 2021). Quantifying these risks is, however, of utmost importance as, according to the EBA, ESG risks are directly connected to financial risks as they can have a “negative financial impact to the institution stemming, from the current or prospective impacts of ESG factors on its counterparties" (European Banking Authority, 2020, p. 28). Moreover, these ESG risks can materialize in the form of "prudential risks (e.g., credit risk, market risk, operational risk)" (European Banking Authority, 2020, p. 139) and can “impact the financial system and economy as a whole, with potential systemic consequences" (European Banking Authority, 2021, p. 33). Thus, quantifying these risks is not only of importance for individual investors but also for the stability of the financial system.

While ESG scores have received an increasing amount of interest in the last years, the newly introduced Diversity & Inclusion (D&I) score by Refinitiv (formerly ASSET4), build using the underlying variables of the traditional ESG score, has only started to create traction. With the COVID-19 pandemic, the life of employees has changed dramatically. Employers have been faced with two main issues : cultural diversity and workplace transition (Refinitiv, 2022a). These topics have already been explored from a human resource and management perspective, but due to the measurement difficulty to investors, questions whether investors can benefit from considering workplace contentment in investment decisions were difficult to answer. The new D&I score can aid as a proxy and allows to shed light on the investor's view.

This thesis explores new approaches concerning financial risks in relation to ESG and D&I scores. The topics will be discussed from different angles in each of the three standalone chapters and aims to offer solutions to classify and quantify ESG risks as well as quantifying the benefits of investing into diverse and inclusive companies for investors.

Similar versions of all three chapters are published in peer-reviewed international journals. Further information is given in the relevant chapters. Additionally, to the three chapters presented here, in the time during my Ph.D. I have published a structured literature review on ESG from a management perspective.[1] Moreover, I have also largely contributed to three published papers on the topic of ESG in which I am second author.[2] However, due to the regulations of the Technical University of Munich I am not allowed to include them in my thesis. All other additional activities are listed in the report on additional activities.

Long-term investors and policymakers can benefit from this research as it continues the debate on how to best estimate and implement sustainable risks in a business and governmental setting and possibly offers practical tools.

In particular, Chapter 2 uses high-dimensional vine copula modeling to introduce a new risk modeling approach and three new risk measures. It analyzes companies' (tail) dependence structures with a range of ESG scores and aims to disentangle ESG, market,

[1] The paper is published as Bax, K. & Paterlini, S. (2022). Environmental Social Governance Information and Disclosure from a Company Perspective: a Structured Literature Review, *International Journal of Business Performance Management* 23(*3*), p. 304–322. DOI:0.1504/IJBPM.2022.123824

[2] The papers are published as: Czado, C., Bax, K., Sahin, Ö., Nagler, T., Min, A., & Paterlini, S. (2022) Vine copula based dependence modeling in sustainable finance. *Journal of Finance and Data Science (JFDS)* 8(*November 2022*), p. 309-330. DOI: 10.1016/j.jfds.2022.11.003 and Sahin, Ö., Bax, K., Paterlini, S., & Czado, C. (2022). ESGM: ESG scores and the Missing pillar - Why does missing information matter?, *Corporate Social Responsibility and Environmental Management.* DOI:10.1002/csr.2326 and Sahin, Ö., Bax, K., Paterlini, S., & Czado, C. (forthcoming). The pitfalls of (non-definitive) Environmental, Social, and Governance scoring methodology, *Global Finance Journal.* DOI: 10.1016/j.gfj.2022.100780.

and idiosyncratic risk. We show, using real-world data, that ESG risks are not negligible, especially during the 2008 crisis. Moreover, this chapter touches also on the question of causality, highlighting the need for further research. Then, Chapter 3 focuses on the relationship between ESG scores and systemic risk and tries to quantify the systemic risk impact. Using real-world data, we show that companies with higher ESG scores, so technically more sustainable companies, tend to exhibit lower systemic impact than lower rated companies indicating a positive effect of ESG scores to a certain degree. We also find some evidence of this behavior when clustering the companies into ESG portfolios and focusing on COVID-19. Finally, we find notable differences when considering the individual E-, S-, and G-pillar scores instead of the ESG score. In the final Chapter 4, a closer look at a D&I score is taken. As the COVID-19 pandemic slows down to an endemic stage and office workers tend to return to their offices slowly, the debate on an inclusive and diverse workplace has gained a lot of traction. While it has been discussed that workplace contentment can create positive outcomes for the employees and the company itself, this research questions the benefit of considering such characteristics in an investment decision. Using real-world data, I find evidence that investors might suffer from lower returns when investing in companies with a diverse and inclusive workplace.

Lastly, I would like to point out that each chapter studies short-term effects of ESG scores using data at a high frequency level. However, in the long run, non-financial information including ESG scores might be more stable, as the constant improvement of companies might level out. This would mean that companies might not be changing ESG rating classes so frequently or not at all anymore and the results could become more stable. Furthermore, another long term effect could be that the companies with mediocre ESG scores (not very high, nor very low) might show even more similar performance and large difference would only be found for companies with extreme ESG scores (very high and very low ESG scores). Additionally, the findings in this thesis are limited by being mostly descriptive with limited statistical evidence of differences in risk across the various ESG rating classes.

Chapter 2

ESG, Risk, and (Tail) Dependence

This research chapter, for which I am first author, is co-authored with Özge Sahin, Claudia Czado, and Sandra Paterlini. A similar version of this chapter is accepted for publication as

Bax, K., Sahin, Ö., Czado, C. & Paterlini, S. (in press). ESG, Risk, and (Tail) Dependence. *International Review of Financial Analysis.*

The work has been presented at different conferences including the 14th CFE 2020 in London, UK and the 31st EFMA Annual Conference 2021 in Rome, Italy. Additionally, this chapter has been featured on Global Association of Risk Professionals (GARP).[1]

Abstract

While environmental, social, and governance (ESG) trading activity has been a distinctive feature of financial markets, the debate if ESG scores can also convey information regarding a company's riskiness remains open. Regulatory authorities, such as the European Banking Authority (EBA), have acknowledged that ESG factors can contribute to risk. Therefore, it is important to model such risk dependencies and quantify what part of a company's riskiness can be attributed to the ESG scores. This chapter aims to question whether ESG scores can be used to provide information on (tail) riskiness. By analyzing the (tail) dependence structure of companies with a range of ESG scores, that is within an ESG rating class, using high-dimensional vine copula modelling, we are able to show that risk can also depend on and be directly associated with a specific ESG rating class. Empirical findings on real-world data show positive not negligible ESG risks determined by ESG scores, especially during the 2008 crisis.

[1] https://www.garp.org/white-paper/the-potential-impact-of-esg-on-tail-risk

2.1 Introduction

After the 2007-2009 financial crisis, many models which used to capture the dependence between a large number of financial assets were revealed as being inadequate during crisis. Moreover, research has shown that the dependence structure of global financial markets has grown in importance in areas of optimal asset allocation, multivariate asset pricing, and portfolio tail risk measures (Xu and Li, 2009). Consequently, the enormous losses and the increased volatility in the global financial market elicited calls for an even more diligent risk management.

Over the past decade, the interest in socially responsible investments has grown exponentially (Auer and Schuhmacher, 2016). The availability of non-financial data, including corporate social responsibility (CSR) or environmental, social, and governance (ESG) data, has skyrocketed and gained interest from investors for various reasons. According to Li and Polychronopoulos (2020), in 2019, 70 different firms were identified as providers of some sort of ESG rating. While some studies are pointing out ambiguity and divergence between these different ratings (see Berg, Fabisik, and Sautner (2021), Billio et al. (2021), Gibson, Krueger, and Schmidt (2021), Berg, Koelbel, and Rigobon (forthcoming), and Serafeim and Yoon (forthcoming)), the overall idea of ESG scores is to indicate a level of ESG performances. These scores are based on several criteria and measurements and are published by different rating institutions (Bhattacharya and Sharma, 2019). These rating institutions use quantitative and qualitative methods to assign an ESG score to a company (Berg and Lange, 2020). In brief, companies are awarded large scores for ESG responsible behavior but are awarded low scores for ESG irresponsible behavior. Typically a company is associated with a rating class (i.e., A, B, C, or D) based on its ESG score value using thresholds or quartiles. Then, companies with the same ESG score or ESG scores within the same threshold or quartile are allocated in the same ESG rating class. Acting as complementary non-financial information, ESG scores can have the potential to increase the accuracy in performance forecasts and risk assessments (Achim and Borlea, 2015).

In 2018, the European Commission published its *Action Plan on Financing Sustainable Growth* which provided the European Union (EU) with a roadmap on sustainable finance and for future work across financial systems (European Banking Authority, 2018).

Furthermore, the increase in demand in socially responsible investments stems from investors and asset managers pressured by stakeholders to push companies to behave responsibly and improve their ESG strategy (Henriksson et al., 2019). The biennial 2018 Global Sustainable Investment Review states that over $30 trillion had been invested with explicit ESG goals (Global Sustainable Investment Alliance (GSIA), 2018). According to a 2018 global survey, more than 50% of the international asset owners are currently considering or already implementing ESG scores in their investment strategy (Consolandi, Eccles, and Gabbi, 2020). Moreover, Eccles and Klimenko (2019) state that this interest in ESG assets is driven by the growing evidence of the positive impact of ESG materiality on financial performance. Also, the European Banking Authority (EBA) stressed the importance of including ESG information into the regulatory and supervisory framework of EU credit institutions (European Banking Authority, 2018). Furthermore, there is a need to improve the measurement and modeling of the impacts of climate change on financial stability in order to underpin a policy debate as highlighted by the European Central Bank (2021). Nevertheless, using ESG factors has made the investment process noticeably more complex (Berg and Lange, 2020). While more than 2000 empirical studies have been done analyzing ESG factors and financial performance, little is known about the dependence structure and associated risks (Friede, 2019; Shafer and Szado, 2020; Lööf, Sahamkhadam, and Stephan, 2021). Moreover, questions on causal relationships including direction and mechanisms have not received adequate attention (Ayton, Krasnikova, and Malki, 2022). This is especially important, as ESG scores are often linked to investment risk. The EBA defines ESG risks as “the risks of any negative financial impact to the institution stemming, from the current or prospective impacts of ESG factors on its counterparties" (European Banking Authority, 2020, p. 28). These ESG risks can materialize in form of "prudential risks (e.g. credit risk, market risk, operational risk)" (European Banking Authority, 2020, p. 139). While regulators finally acknowledge the role of ESG factors in determining part of a company’s risk, no guidelines are provided in how to best capture and quantify such risk and dependencies. Then, ESG scores should possibly deliver some information on a company’s ESG risk and its riskiness as a whole. This also means that companies that have the same ESG rating, as explained above, should share, to a degree, similar risk characteristics and properties. While the literature on divergence of ESG data providers has been growing (e.g. Berg, Koelbel, and Rigobon (forthcoming)), we contribute to the understanding of a single provider. When staying within the ESG information of one single provider, ESG scores should allow us to cluster assets that then exhibit some risk dependence as they have been built with the same methodology starting from the same set of variables when paying attention to sectors and countries. Understanding these components is especially important in times of increased volatility, as considering the (tail) dependence structure among similarly rated assets is essential in order to set in place effective risk management and diversification strategies (Ane and Kharoubi, 2003; Frahm, Junker, and Schmidt, 2005; Malevergne, Pisarenko, and Sornette, 2005; Berg and Lange, 2020).

The contribution of this research is manifold. We propose a R-vine copula ESG risk model to capture the dependence using vine copulas (Bedford and Cooke, 2001; Bedford and Cooke, 2002; Aas et al., 2009; Joe, 2014; Czado, 2019; Czado and Nagler, 2022) and to identify the systematic and the idiosyncratic risk component considering specific ESG classes of each asset. However, the work is not limited to ESG risk dependence and should serve as a methodical guide. It can easily be adapted to individual E-, S-, and G-pillar risk dependence. Inspiration for this model arise from Brechmann and Czado (2013) who considered sectorial dependencies. Following this approach allows us to show, to our knowledge for the first time, that risk dependence can also be linked to ESG rating classes. Furthermore, it contributes to the understanding of the (tail) dependence structure of various assets belonging to the same ESG rating class and introduces different risk dependence measures that try to capture specific ESG risk and the market risk conditionally on ESG classes. By quantifying the overall and lower tail ESG risk among assets that belong to the same ESG class, we show that these dependencies exist, can be quantified, and are not negligible, especially in times of crisis. Furthermore, we are able to disentangle the overall risk and attribute some risk dependence to different ESG classes. Furthermore, as a reviewer of this chapter pointed out the missing link to causality and as the question on causality has been debated increasingly, in the last section, we investigate this topic and give an empirical analysis.

The chapter is structured as follows: Section 2.2 summarizes the literature and creates an understanding of ESG scores and the occurrence of (tail) risk and dependence structures while Section 2.3 describes the S&P 500 data used and includes a preliminary risk analysis. Section 2.4 introduces dependence modeling and vine copulas and then proposes the R-vine copula ESG risk model. Section 2.5 reports the empirical results. Then, Section 2.6 analysis the question of causality. Lastly, Section 2.7 concludes and provides an outlook for future research.

2.2 ESG Scores, Dependence, and Risk

While ESG scores solely try to capture the amount of positive ESG disclosure of a company, the large influx into ESG investments have brought attention to the risk and return of such investments. It has been shown that ESG factors may impact financial performance by substantiating themselves in “financial or non-financial prudential risks, such as credit, market, operational, liquidity and funding risks" (European Banking Authority, 2020, p. 27). According to the EBA, ESG risks are defined to materialize when ESG factors have a negative impact on financial performance or solvency (European Banking Authority, 2020). Furthermore, it is argued that the materiality of ESG risks depends on the risks posed by ESG factors over different time frames (European Banking Authority, 2020). If this is accurate, the ESG scores and ratings should contain information about the company's risk. Even though ESG has mostly been defined in terms of risk by the regulator, and there is an ongoing debate on the effects of using ESG scores on the financial performance research, there is no consensus on the (tail) dependence structure of assets within and between each ESG rating class. Understanding the (tail) dependence and risk structure of several assets, however, is necessary to access inherent risks in the financial market.

Generally, market returns are assumed to follow a multivariate normal distribution; however, research has shown that this is found to be not accurate in reality, and left tails are often heavier than right tails (Cont, 2001; Jondeau and Rockinger, 2003). Therefore, modeling the possibly non-Gaussian dependence among assets and understanding the appearance of joint (tail) risk is especially important for asset pricing and risk management. Tail risk or tail dependence is characterized as the probability of an extremely large negative (positive) return of an asset given that the other asset yields an extremely large negative (positive) return and is commonly quantified by the so-called tail-dependence coefficient (Embrechts, Lindskog, and McNeil, 2001; Frahm, Junker, and Schmidt, 2005; Xu and Li, 2009). Tail risk arises when the likelihood of an extreme event that is more than three standard deviations away from the mean, is more likely to occur than shown by a normal distribution (Kelly and Jiang, 2014). Generally, it is accepted that tail dependence can be used as a proxy of systemic risk, and tail risk has been linked to negative consequences for corporate investment and risk-taking (Gormley and Matsa, 2011; Gormley, Matsa, and Milbourn, 2013; Shirvani and Volchenkov, 2019).

Some researchers argue, that responsible ESG practices might mitigate the market's perception of a company's tail risk and, therefore, reduce ex-ante expectations of a left-tail event (Shafer and Szado, 2020). In brief, they state that considering responsible business practices when creating an equity portfolio can act as insurance against left-tail risk (defined as stock price tail risk using the slope of implied volatility) and, with that, protect company value. This is also in line with De and Clayman (2015) as well as Wamba et al. (2020) who add that especially positive environmental performance can act as insurance for companies, reducing the probability of an adverse event occurring and with that, reducing the company's systematic risk. Kumar et al. (2016) add that positive ESG practices can make a company "less vulnerable to reputation, political and regulatory risk and thus leading to lower volatility of cash flows and profitability" (p. 292). Furthermore, positive ESG performance may generate more loyalty from customers and employees and, through that, protect companies from unforeseen harmful events, resulting in reduced tail risk (Shafer and Szado, 2020). Besides, better ESG performance allows companies to experience adverse events less often and lose less value if they do occur (Minor, 2011). On the other hand, Zhang, De Spiegeleer, and Schoutens (2021) extend the work by Shafer and Szado (2020) by considering implied skewness and find a higher negative tail risk for higher ESG rated companies.

Others recognize that improving ESG performance can also help with risk control and exposure (Giese et al., 2019). Maiti (2021) finds that overall portfolios developed using the overall ESG as well as the individual E (Environment), S (Social), and G (Governance) factors generally show better investment performance, implying policy modifications. In contrast, Breedt et al. (2019) show that ESG-tilted portfolios do not necessarily have higher risk-adjusted returns. These findings are in line with Lööf, Sahamkhadam, and Stephan (2021) who argue, focusing on the COVID-19 crisis, that higher ESG scores are associated with less downside tail risk but also lower upside potential on returns. Moreover, Sherwood and Pollard (2017) find that integrating ESG information into the emerging market equity investment of institutional investors can create higher returns and lower downside risks compared to non-ESG equity investments. Other scholars have observed a mitigating effect of ESG performance on stock price crash risk if a company has less effective governance (Kim, Li, and Li, 2014). Hoepner et al. (2016) found supporting evidence on one single institutional investor that ESG engagements can be associated with subsequent reductions in downside risk. Furthermore, it has been shown that higher CSR performance can be linked to larger firm value as it possibly reduces excessive risk taking as well as better financial performance at the firm level (Harjoto and Laksmana, 2018; Brooks and Oikonomou, 2018).

Looking at a country's creditworthiness, Capelle-Blancard et al. (2019) show that countries with above-average ESG scores are linked to reduced default risk and smaller sovereign bond yield spreads. Additionally, Breuer et al. (2018) state that the cost of equity is reduced when a company invests in CSR, given that it is located in a country with high investor protection. Moreover, Li, Wang, and Wang (2017) find that companies in regions of high social trust tend to have lower tail risk. A possible reason why environmental practices have the power to control tail risk could be that a company's good social records will be more valuable in the long run due to a lower frequency of litigation (Goldreyer and Diltz, 1999). Additionally, higher environmental standards are valuable to shareholders due to companies avoiding litigation costs, reputation losses, and environmental hazards (Chan and Walter, 2014). Furthermore, ESG can drive an asymmetric return pattern in which socially responsible investment (SRI) funds (using positive rather than negative screenings) outperform conventional funds in times of crisis but underperform in calm periods (Nofsinger and Varma, 2014). Moreover, Bae et al. (2019) find that CSR reduces the costs of high leverage and decreases losses in market share when firms are highly leveraged. Additionally, Bouslah, Kryzanowski, and M'Zali (2018) found that higher social performance within CSR investments can generate moral capital which reduces uncertainty of capital flow leading to a reduction in company risk.

While all scholars above have shown that there seems to be a link between ESG and risks and performance to a certain degree, less work has been done to pin down questions of causality. Different theories (e.g., the stakeholder theory (Freeman, 1984), the risk management theory (Godfrey, 2005)) should indicate a positive effect of ESG on firm value and risk, while others (e.g., managerial opportunism) indicate the opposite (Ayton, Krasnikova, and Malki, 2022).

Scholars have not yet found a consensus, and research results have also been inconclusive. More specifically, Sharfman and Fernando (2008) discussed the link between different levels of environmental performance and environmental risk management. They argue that high levels of environmental performance indicate a positive risk management strategy for the firm (Sharfman and Fernando, 2008). As also firstly discussed by King and Shaver (2001), Buallay (2018) argues that the main mechanism why ESG disclosure should be related to firm performance is due to cost of capital reduction. Other scholars have already shown that companies with higher ESG performance often experience lower cost of capital (see e.g., Sharfman and Fernando (2008), El Ghoul et al. (2011), and Hamrouni, Boussaada, and Toumi (2019)). According to Buallay (2018), the cost encountered by a firm to publish ESG information is then directly offset by the money saved from reduced cost of capital. Recently, Ayton, Krasnikova, and Malki (2022) showed on a sample of UK companies that for the majority of cases, no causality exists between CSR and different types of risks. However, they reference the works of Benlemlih and Girerd-Potin (2017) and Chollet and Sandwidi (2018) who find completely opposite results. Additionally, Chen and Xie (2022) show, using Chinese companies in a difference-in-differences (DID) analysis, that disclosing non-financial ESG information significantly improves a company's financial performance. Also, other scholars look at the causal relationship between ESG portfolios and conventional and ethical equity prices, exchange rates, and commodity prices but find mixed results depending on the time period and choice of instrument (Andersson et al., 2020). Furthermore, they conclude that ESG portfolio could be used as a separate asset class to increase diversification (Andersson et al., 2020). Lastly, using European bank data, Buallay (2018) finds different results depending on the choice of information and financial measure (ROA, ROE, Tobin's Q).

Despite these extensive efforts, the effect of ESG scores on (tail) dependence and (tail) risks has not yet been clearly understood, and literature studying the impact of ESG behavior on tail risk is still very limited (Zhang, De Spiegeleer, and Schoutens, 2021). While some question whether an ESG-related risk factor that can help to identify superior investments even exists (Cornell, 2021), others provide evidence that ESG ratings are subject to a non-diversifiable risk component as the development depends on the overall market (Dorfleitner, Halbritter, and Nguyen, 2016). Therefore, in order to estimate ESG risk, a closer look at the assets within the ESG class and possibly the complete market has to be taken. Investors have been aware of the need to use more sophisticated models to assess the dependence behavior of assets since the financial crisis, however, such models, which allow investors to quantify (tail) dependence and (tail) risk among ESG-based classes of assets, have yet to be introduced. In this chapter, we apply vine copulas to model the complex dependence structure and compute different risk measures, including ESG risk, market risk conditionally on ESG class, and an idiosyncratic risk component, which allow to explicitly capture (tail) dependence and possibly aid the investor in their decision-making process.

2.3 The Data

We consider daily logarithmic return and yearly environmental, social, and governance (ESG) data of 330 US companies j, constituents of the S&P 500 index, for which the yearly ESG scores ($ESG_{y,j}$) from Refinitiv[2], which are ranked based and have values between 0 and 100, are retrieved for the period from 4 January 2007 to 31 December 2021[3]. Similarly to many scholars, we use yearly ESG data (e.g., Reboredo and Ugolini (2022), Lioui and Tarelli (2022), Takahashi and Yamada (2021), and Dyck et al. (2019)), however, the model also works with other frequencies of data, for example weekly ESG data. Refinitiv (2021) allows to attribute the assets into four different rating classes based on their ESG score. Assets are given a D grade for an ESG score lower than 25, C for an ESG score between 25 and lower than 50, B for an ESG score between 50 and lower than 75, and finally A for an ESG score between 75 and 100. While ESG data is sporadically available prior to 2007, the period 4 January 2007 to 31 December 2021 is chosen in order to have the largest possible time period for the largest number of assets to get a comprehensive analysis of assets belonging to the S&P 500. The overall time frame is split into five equally sized time periods in order to be able to compare different economics states q: $q_1 = 2007-2009, q_2 = 2010-2012$, $q_3 = 2013-2015$, $q_4 = 2016-2018$ and , $q_5 = 2019-2021$. While the first and last interval capture the financial crisis and the beginning of the COVID-19 pandemic, the intervals inbetween allow us to understand what

[2]The ESG scores considered are the ones available from Refinitiv, the financial and risk business unit of Thomson Reuters. Refinitiv offers a comprehensive ESG database across more than 500 different ESG metrics (Refinitiv, 2021). These percentile-ranked ESG scores are designed to measure the company's relative ESG performance, commitment, and effectiveness across ten main topics, including emissions,resource use, and human rights, all of which are based on publicly reported data (Refinitiv, 2021).

[3]Date of retrieval was 28 April 2022

happens during non-crisis periods. Additionally, we point out that the ESG scores in period q_4 and q_5 are to be considered not definitive according to Refinitiv as they were not yet five years old when downloading the data (Refinitiv, 2021). This means that the ESG scores can be modified from the provider post-publication. It is, however, not an option for investors to wait until scores are definitive as investment decisions are made daily using all the data available at the time. In order to compute the weighted ESG class indices, which we later need in our R-vine copula ESG risk model, the latest available S&P 500 market capitalization weights (M_j) at the time of download as well as the information on the economic sector S for each asset j are retrieved from Refinitiv (2021).

95% VaR

To get a preliminary understanding if ESG scores can provide additional information on a company's riskiness, the empirical 95% Value at Risk (VaR), computed as the empirical quantile of the asset return distribution based on daily data for each asset j in the period q grouped according to their mean ESG scores across all sectors S is presented in Figure 2.1. The assets are attributed to the four different ESG classes A, B, C, and D following the thresholds (25, 50, 75) given by Refinitiv (2021) as explained above. The fact that ESG disclosure can be associated with lower idiosyncratic volatility, VaR, and conditional VaR has already been shown by Reber, Gold, and Gold (2021). We here now take a closer look at the assets belonging to different ESG rating classes.

In Figure 2.1, notice that the VaR values are smaller and exhibit larger variability during the time period 2007-2009, due to the 2008 financial crisis, while estimates become larger and, therefore, less extreme in the other time periods. It is also quite evident, especially for the time periods 2007-2009, 2010-2012, and 2013-2015, that ESG scores seem to be capable of providing information on the tail risk of an asset, as better-rated companies tend to have less negative median VaR values. This does not happen for the last two period, 2016-2018 and 2019-2021, where ESG scores are not yet definitive and might possibly be revised by Refinitiv in the future. Nevertheless, differences tend to diminish in the last two periods for classes A, B, and C as also companies tend to improve their ESG scores, as shown in Figure 2.2. Still, ESG class D, which typically contains companies that have not yet fully disclosed ESG information and are also lower-rated than other companies, exhibit the worst VaR levels also for the time intervals 2016-2018 and 2019-2021. This is in line with the findings of Sahin et al. (2022) who show that there is no clear relationship with risk measures in the most recent ESG scores.

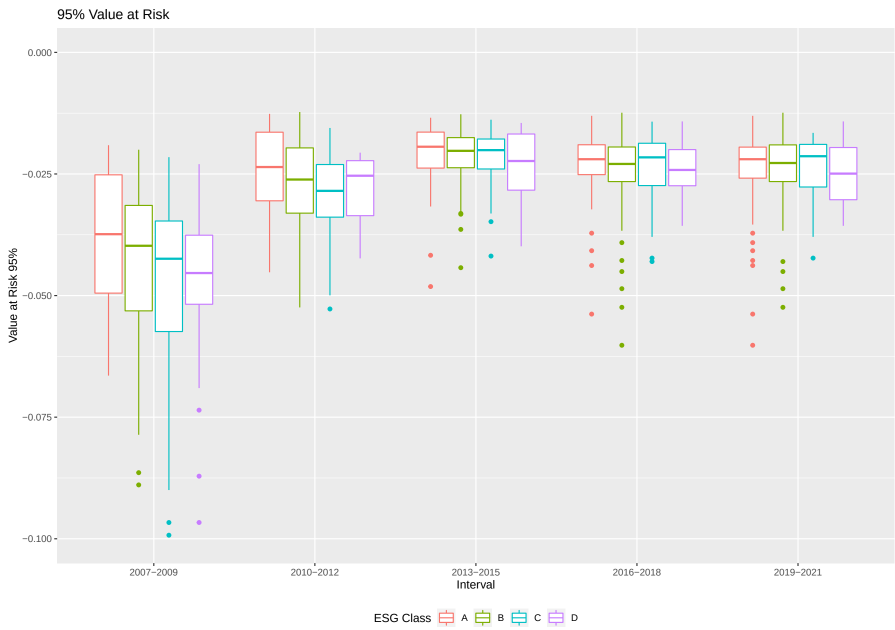

Figure 2.1: Empirical 95% Value at Risk (y- axis) classified by ESG class using Refinitiv thresholds and time period q (x- axis).

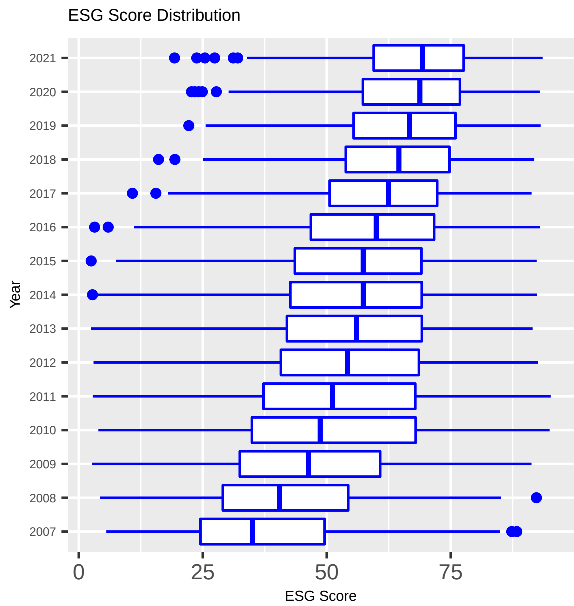

Figure 2.2: Development of ESG scores over the years.

Summing up, empirical data suggest that ESG scores can provide information on tail riskiness of companies and allow to group assets that might share similar tail-risk characteristics, at least in the first time periods. Plots for 99% VaR and 95% and 99% Expected Shortfall show similar behavior and are available upon request.

2.4 R-Vine Copula ESG Risk Model and Methodology

In general, a distribution rarely follows the strict spherical and elliptical assumptions as implied by correlation (Embrechts, McNeil, and Straumann, 2001). Therefore, according to Embrechts, McNeil, and Straumann (2001), this traditional dependence measure is often not suited to create a proper understanding of the dependence in financial markets or fully comprehend the risk in extreme events. While Pearson correlation has been used as a measure of pairwise dependence, modern risk management requires a thorough stochastic understanding beyond linear correlation. As ESG risk is possibly non-diversifiable (see Dorfleitner, Halbritter, and Nguyen (2016)), and the European Banking Authority (2020) argues that ESG risk is supposed to manifest also in market risk, it takes a more complex risk measure to estimate its magnitude. This is where copula modeling steps in.

A copula C is a cumulative distribution function (cdf) with univariate uniform marginal distributions on the unit interval.[4] The copula approach is especially popular due to Sklar's theorem (1959), which allows to model the marginal distribution and the dependence separately. Therefore, if F is a continuous d-dimensional distribution function of $\mathbf{X} = (X_1, \ldots, X_d)^\top$ with univariate cdf $F_p(x_p)$ of a continuous random variable X_p for $p = 1, \ldots, d$ with its realizations x_p, the joint distribution function F can be written as

$$F(x_1, \ldots, x_d) = C\Big(F_1(x_1), \ldots, F_d(x_d)\Big). \tag{2.1}$$

The corresponding density is

$$f(x_1, \ldots, x_d) = c\Big(F_1(x_1), \ldots, F_d(x_d)\Big) \cdot \prod_{p=1}^{d} f_p(x_p), \tag{2.2}$$

where c is the d-dimensional copula density of the random vector $\mathbf{F} = \big(F_1(X_1), \ldots, F_d(X_D)\big)^\top \in [0,1]^d$ and $f_p(x_p)$ is the associated univariate marginal density of $F_p(x_p)$ for $p = 1, \ldots, d$.

Different copula types with their reflections and rotations can accommodate flexible dependence patterns in the bivariate case ($d = 2$), as shown in the Appendix in Table A.3. Nevertheless, the existing parametric families of multivariate copulas are not as flexible as the bivariate copula families to represent complex dependence patterns. For instance, the multivariate Gaussian copula does not accommodate any tail dependence and has

[4] For completeness, more information about copulas and vine copulas can be found in Appendix A.1.

been strongly criticized after the 2008 financial crisis (Li, 2000; Salmon, 2012; Puccetti and Scherer, 2018; Czado, 2019). The multivariate Student's t copula allows for tail dependence but does not capture any asymmetry in the tails. Furthermore, multivariate exchangeable Archimedean copulas become inflexible as the dimension increases since they model the dependence between a large number of pairs of variables using not more than two parameters. If no dependence is found, and the random variables are independent, the independence copula best models their behavior.

In order to improve the copula method with regard to larger dimensions and to accommodate a great variety of dependence structures, vine copulas (so-called pair copula constructions) use conditioning and were made operational for data analysis by Aas et al. (2009). They are a class of copulas, which are based on the conditioning ideas first proposed by Joe (1996) and further developed by Bedford and Cooke (2001) and Bedford and Cooke (2002). The approach allows to construct any d-dimensional copula and its density by $\frac{d\cdot(d-1)}{2}$ bivariate copulas and their densities. Furthermore, the expression can be represented by an undirected graphical structure involving a set of linked trees, i.e., a *regular (R-)vine structure* (Bedford and Cooke, 2001). An example is given in Figure 2.3 and more details on R-vines and vine trees are given by Kurowicka and Cooke (2006), Kurowicka and Joe (2011), and Joe (2014); and Czado (2019).

In previous works, copulas and vine copulas have had various financial applications. Some examples include but are not limited to: Bhatti and Nguyen (2012) who applied time-varying copulas to capture the tail dependence between selected international stock, and Nguyen and Bhatti (2012) who used non-parametric and parametric copulas to capture the dependence between oil prices and stock markets. Furthermore, Naifar (2012) modeled the dependence structure between risk premium, equity return, and volatility in the presence of jump-risk, and Brechmann and Czado (2013) analyzed the sectorial dependence of Euro Stoxx 50. Morover, Fenech, Vosgha, and Shafik (2015) discussed loan default correlation using an Archimedean copula approach, and Pourkhanali et al. (2016) used vine copulas to estimate systemic risk by looking at the connection of financial institutions. Recently, Fink et al. (2017) and BenSaïda (2018) introduced the regime-switching vine copula approach, and Abakah et al. (2021) re-examined international bond market dependence.

2.4.1 Inputs for the R-Vine Copula ESG Risk Model

In this research, we apply a R-vine copula model to estimate different dependence structures among assets given their ESG classes in order to compute different risk measures. In order to be able to fit the R-vine copula ESG risk model with the five specified vine trees (see Section 2.4.2), the inputs have to be computed. We start by computing the mean ESG score ($\overline{ESG}_j^q$) for each asset j for each time period q. We then divide the assets into their ten different economic sectors and rank them according to their $\overline{ESG}_j^q$. This allows us to group the assets within each sector into four different quartiles according to their ESG performance. Within each sector, we categorize assets with the highest scores in the first quartile as ESG class A, assets with the second to highest scores in the second quartile as ESG class B, assets with the second to lowest scores in the third quartile, as ESG class C, and finally, assets with the lowest scores in the fourth quartile, as ESG class D (for details see A.2.2 and A.2.3). While we provide a method to measure the overall ESG risk dependence, if one is interested in the individual E-, S-, G-Pillar risk dependence, one could also use the individual pillar score to compute the mean and group the assets. We show an example of the overall individual E-, S-, G-Pillar risk dependence in A.7.

We define the ESG class quartiles as $k \in (A, B, C, D)$. We choose to rank the assets within their economic sector instead of overall as it has been shown by Kumar et al. (2016) that ESG scores affect various sectors to a different degree. Furthermore, we know that ESG score values are weighted differently within economic sectors (Refinitiv, 2021). Therefore, categorizing the assets within their sector allows us to take into account these differences. More importantly, it also allows us to later compute the ESG risk measures that are comparable across sectors. As it has been shown that investors cannot eliminate ESG risk fully through diversification (see Dorfleitner, Halbritter, and Nguyen (2016)), it is not sufficient to compute the risk on an individual level without taking a look at the surrounding assets. We choose to use quartiles instead of Refinitivs's thresholds to avoid low numerosity in some classes. We now combine all assets according to their ESG class quartile k. This means that each ESG rating class k includes assets from all ten different sectors. Overall, ESG class A includes $n_a = 86$ assets, ESG class B includes $n_b = 84$ assets, ESG class C includes $n_c = 84$ assets, and finally ESG Class D includes $n_d = 76$ assets.

Next, we compute the ESG class indices per ESG class k ($I_{t,k}^q$, i.e. the ESG class index

A in period q on trading day t is $I^q_{t,A}$) by linearly combining asset returns ($Y^q_{t,j,k}$ defined as the return of an asset j in period q on trading day t belonging to ESG class k) in the same mean ESG class ($K^{S,q}_j$) using the market capitalization weights. As shown in Figure 2.3 we use only the variable names such as M (Market), A (ESG class index), a_1 (asset) etc. to denote the nodes. The associated daily data is given by $I^q_{t,M}$, $I^q_{t,A}$, $Y^q_{t,1,A}$ and a full table of notation can be found in A.2.1.

Then, we use the two step inference for margins approach, proposed by Joe and Xu (1996), to compute our pseudo-copula data which serves as the input for our R-vine copula ESG risk model (for details see A.3) and allows us to estimate the copula parameters of the chosen bivariate copula family (for details see A.4).

Additionally, when fitting the R-vine copula ESG risk model, we can specify different bivariate copula families for the pairs of variables. In the first specification, we allow only for the bivariate *itau* copulas, for which the estimation by Kendall's τ inversion is available (Student's t, Frank, Gaussian, Clayton, Joe, Gumbel, and Independence copula). Using these, we also allow for asymmetry in the upper and lower tails, as shown in Table A.3 in the Appendix. These copula families have a one-to-one relationship between their copula parameter and Kendall's τ. In the second specification, we include additional copula families with two parameters such as BB1 (a combination between both extreme cases of Clayton copula and Gumbel copula), BB7 (a combination of Joe copula and Clayton copula), and the extreme-value copula BB8 (extended Joe) in order to see if this improves our model fit. Lastly, we fit a specification using only Gaussian copulas to see the change in model fit if we do not account for the dependence in the extremes. To choose our optimal bivariate copula family specification, we use the modified Bayesian Information Criteria (mBIC) for vines instead of the widely used Bayesian Information Criteria (BIC) by (Schwarz, 1978). The mBIC for vines has been proposed by Nagler, Bumann, and Czado (2019) and is tailored to sparse vine copula models in high-dimensions.[5] These scholars show that the mBIC can consistently distinguish between the true and alternative models. We then continue our analysis using the best fitting model only.

[5]More information in the mBIC is given in Appendix A.5.1.

2.4.2 R-Vine Copula ESG Risk Model

To be able to capture the ESG risk and market risk conditionally on the ESG class of an asset j, the proposed first five vine tree structures are defined as shown in Figure 2.3.

In the first vine tree T_1 in Figure 2.3, we connect the assets j (abbreviated by $a_1, \cdots, a_{n_a}, b_1, \cdots, b_{n_b}, c_1, \cdots, c_{n_c}, d_1, \cdots, d_{n_d}$, where n_k is defined as the number of assets within the ESG class k) to their belonging ESG class index ($I^q_{t,k}$ abbreviated by $k \in \{A, B, C, D\}$) and market index (M^q_t abbreviated by M) in period q. This allows us to compute the dependence of an asset j with its ESG class, later we use this to compute its ESG risk in Equation (2.3). In T_2, in Figure 2.3, we connect the nodes so that they allow us to compute the market risk conditionally on the ESG class (see Equation (2.4)) following the sequential ESG class order. We then continue to fix T_3 to T_5 to be able to compute our risk measures as a fraction of all dependence, positive and negative, an asset has with all ESG classes k. In T_3 in Figure 2.3 we choose to connect the nodes so that we separate the best and lowest ESG performance from the middle ESG performance, classes B and C. By defining T_4 and T_5 further, we guarantee that in our risk measures in Section 2.4.3, only dependencies with the different ESG class indices $I^q_{t,k}$ are included, which is not yet modeled in T_1, T_2, and T_3. This ensures that the ESG risk is not an individual measure and takes into account complex market movements and dependencies with other ESG classes k.

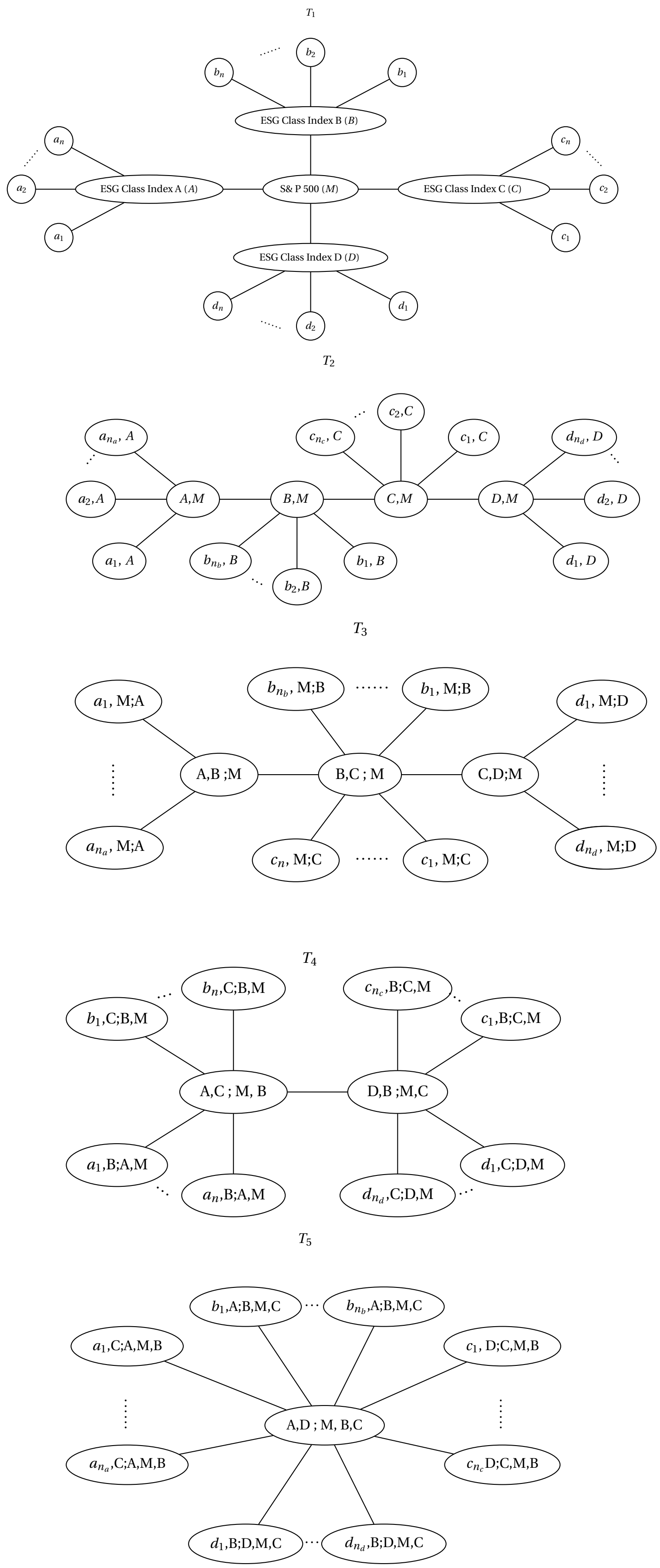

Figure 2.3: The first five vine trees of the regular vine used.

2.4.3 R-Vine Risk Measures

After computing the inputs for the R-vine copula ESG risk model, estimating the pseudo-copula data, and fitting it to our model with the specified five vine trees, we can compute three different risk measures using the overall dependence (τ) and lower (tail) dependence (λ). We introduce an overall ESG risk $R^{ESG}_{j^q_k}(\tau)$ and lower tail ESG risk $R^{ESG}_{j^q_k}(\lambda)$, which we can compute for each asset j with its ESG class k in period q. It accounts for the ESG risk of an asset j belonging to a specific ESG class k and gives the fraction of all dependence, positive and negative, explained by the asset's ESG class. Additionally, we estimate the market risk conditionally on the ESG class for each asset j as $R^{Market}_{j^q_k}(\tau)$ and $R^{Market}_{j^q_k}(\lambda)$ with all the (tail) dependence on the ESG class being removed. Lastly, by subtracting both indicators from 1, we can get the overall idiosyncratic risk $R^{idio}_{j^q_k}(\tau)$ and lower tail idiosyncratic risk as $R^{idio}_{j^q_k}(\lambda)$ for each asset j within each time period q. See Brechmann and Czado (2013) for sectorial estimation.

We choose the empirical Kendall's τ and its estimate $\hat{\tau}$, whose values range from $[-1,1]$ (Joe, 2014), as our dependence measure for the overall risk measures[6] : $R^{ESG}_{j^q_k}(\tau)$, $R^{Market}_{j^q_k}(\tau)$, and $R^{idio}_{j^q_k}(\tau)$. To exclude unrealistic assumptions, we assume that asset j is not independent of all other assets and include all Kendall's τ only in absolute value. Similarly, we can also define these risk measures using the lower tail dependence coefficient[7] as : $R^{ESG}_{j^q_k}(\lambda)$, $R^{Market}_{j^q_k}(\lambda)$, and $R^{idio}_{j^q_k}(\lambda)$. By using the lower tail dependence coefficient as the input value, these risk measures quantify the strength of the dependence within the lower-left-quadrant tail of an asset's return and its associated ESG class index in relation to all other assets within the fitted R-vine copula ESG risk model. The values for the risk measures are in the interval [0, 1]. As the equations are identical apart from dependence measure τ or λ, only the overall risk measures are presented below. For simplification, we drop the sector index S in the notation of the risk measures for each asset j.

[6]Kendall's τ is a ranked based dependence measure robust to outliers that fits the aim of our analysis and can be defined in terms of copulas for two continuous random variables (X_1, X_2) with copula C as $\tau = 4 \int_{[0,1]^2} C(u_1,u_2)dC(u_1,u_2) - 1$. An alternative overall weight measure could be Spearman's ρ.

[7]When Student's t and Clayton (and BB1 and BB7) copulas are chosen as best fit among the bivariate copula families given in Table A.3, we can use this information to also estimate the lower tail dependence coefficient λ which ranges from $[0,1]$ and is defined for a bivariate distribution with copula C as $\lambda^{lower} = \lim_{x\to 0^+} P(X_2 \le F_2^{-1}(t) \mid X_1 \le F_1^{-1}(t)) = \lim_{x\to 0^+} \frac{C(t,t)}{t}$. The lower tail dependence coefficient is also non-zero when the fitted bivariate copula class is Student's t, Clayton, 180° Joe, 180° Gumbel, BB1, BB7, or 180° BB8 in our model. For other bivariate copula families, we have zero lower tail dependence coefficient. Other methods could include estimating a specific distribution or a family of distributions; or working with a non-parametric model. We refer to Frahm, Junker, and Schmidt (2005) for further reading on estimation methods.

Overall ESG Risk

For each asset of ESG Class A in period q, i.e. $j_A^q \in \{j|K_j^{S,q} = A$ for $q = 1,2,3,4,5$ and $S = 1,\cdots,10\}$ and $q = 1,2,3,4,5$:

$$R_{j_A^q}^{ESG}(\tau) = \frac{|\hat{\tau}_{j_A^q,I_A^q}|}{|\hat{\tau}_{j_A^q,I_A^q}| + |\hat{\tau}_{j_A^q,I_M^q|I_A^q}| + |\hat{\tau}_{j_A^q,I_B^q|I_A^q,I_M^q}| + |\hat{\tau}_{j_A^q,I_C^q|I_A^q,I_M^q,I_B^q}| + |\hat{\tau}_{j_A^q,I_D^q|I_A^q,I_M^q,I_B^q,I_C^q}|}. \tag{2.3}$$

$R_{j_B^q}^{ESG}(\tau)$, $R_{j_C^q}^{ESG}(\tau)$, and $R_{j_D^q}^{ESG}(\tau)$ can be derived similarly.

Overall Market Risk conditionally on ESG Class

For each asset of ESG Class A in period q, i.e. $j_A^q \in \{j|K_j^{S,q} = A$ for $q = 1,2,3,4,5$ and $S = 1,\cdots,10\}$ and $q = 1,2,3,4,5$:

$$R_{j_A^q}^{Market}(\tau) = \frac{|\hat{\tau}_{j_A^q,I_M^q|I_A^q}|}{|\hat{\tau}_{j_A^q,I_A^q}| + |\hat{\tau}_{j_A^q,I_M^q|I_A^q}| + |\hat{\tau}_{j_A^q,I_B^q|I_A^q,I_M^q}| + |\hat{\tau}_{j_A^q,I_C^q|I_A^q,I_M^q,I_B^q}| + |\hat{\tau}_{j_A^q,I_D^q|I_A^q,I_M^q,I_B^q,I_C^q}|}. \tag{2.4}$$

$R_{j_B^q}^{Market}(\tau)$, $R_{j_C^q}^{Market}(\tau)$, and $R_{j_D^q}^{Market}(\tau)$ can be derived similarly.

Overall Idiosyncratic Risk

For each asset of ESG Class A in period q, i.e. $j_A^q \in \{j|K_j^{S,q} = A$ for $q = 1,2,3,4,5$ and $S = 1,\cdots,10\}$ and $q = 1,2,3,4,5$:

$$R_{j_A^q}^{idio}(\tau) = 1 - R_{j_A^q}^{ESG}(\tau) - R_{j_A^q}^{Market}(\tau). \tag{2.5}$$

$R_{j_B^q}^{idio}(\tau)$,$R_{j_C^q}^{idio}(\tau)$ and $R_{j_D^q}^{idio}(\tau)$ can be derived similarly.

Summing up, fitting the R-vine copula ESG risk model enables us to capture complex dependence structures as it allows us to account for asymmetric and tail dependence. Moreover, to get a more comprehensive understanding of the overall share of dependence an asset has with other assets within the same ESG class given all other assets, these (tail) risk measures are standardized as ratios instead of single dependence measures of an asset j with its ESG class index alone. This helps to understand if there are common behaviors - especially for tail dependence. Common dependencies could indicate that a time series (e.g., returns) exhibit co-movements and, therefore, could share some risk properties. As many investors tilt their portfolio towards comparable large ESG score, using an inclusion or exclusion approach, understanding the dependence between similarly ESG rated assets is necessary in order to be able to capture co-movements and promote diversification.

2.5 Empirical Results

After fitting the R-vine copula ESG risk model for three copula family specifications (*itau, parametric, Gaussian*), we find that according to the mBIC, the R-vine copula ESG risk model with the *itau* copula family specification best fits our model for three time period (2007-2009,2013-2015,2016-2018) while the *parametric* copula family specification best fits for two time period (2010-2012, 2019-2021). By choosing the best fitting model in each period, it allows us to most optimally estimate the dependencies between the assets for all five time periods q. We also notice that the *Gaussian* R-vine copula ESG risk model always performs worst. Also, when looking at which of the copula families are fitted most often within each specification, we find that not very often the Gaussian copula is chosen for the *itau* and *parametric* R-vine copula ESG risk model, especially in the first two periods. This is especially true for the first vine tree T_1 which models the dependence of an asset with its ESG class. As the Gaussian copula does not capture any tail dependence, and often the Student's t copula is chosen, these results indicate that the assets definitely share some tail dependence. Thus, the *Gaussian* R-vine copula ESG risk model does not fully comprehend the risk in extreme events. For more details, the information criteria for all three models in each time period q are given in the A.5.2 and the specific number of copula families fitted in the first vine tree T_1 *itau* and *parametric* copula family specifications are given in A.5.3, while all other vine trees are available upon request.

In Figure 2.4 and Table 2.1 focusing on overall ESG risk dependence we find that assets that belong to ESG class D perform worse compared to other ESG classes, as they experience the strongest overall ESG risk dependence in calm periods (2010-2012, 2013-2015, 2016-2018) and in the most recent period (2019-2021). This is in line with the literature, as Shafer and Szado (2020) argue that strong ESG practices can act as insurance against left-tail events as well as others who find that superior ESG performance reduces volatility (Bouslah, Kryzanowski, and M'Zali, 2018; Albuquerque et al., 2020). In contrast to other scholars who found that ESG performance mitigates financial risk during crisis using Chinese companies and the COVID-19 crisis (Broadstock et al., 2021), we find that in times of the financial crisis 2007-2009, especially assets belonging to a B and D ESG class tend to have comparably lower overall ESG risk dependence. We find this behavior for assets belonging to ESG class B also in time period 2013-2015. Assets belonging to ESG class A show unexpected strong overall ESG risk dependence, possibly because of a high investment volume and popularity from investors who might believe that ESG performance can make them resilient in times of crisis. These findings are in line with Demers et al. (2021) who argue that ESG scores did not immunize stocks during the COVID-19 crisis and did, therefore, not protect the investors from unexpected losses. Furthermore, Flori et al. (2021), who look at bipartite network representation of the relationships between mutual funds and portfolio holdings, find that the popularity of assets does not necessarily yield a beneficial outcome. This shows that portfolios which invest in less popular assets generally outperform those investing in more popular ones. Especially in the more recent time periods, we find a larger variability of overall ESG risk dependence belonging to the different classes. All standard deviation values can be found in Table A.6. Companies that are not best or worst performers, i.e., assets in ESG classes B and C, show weaker overall ESG risk dependence. Again, this could be due to the non-popularity of assets with mediocre ESG performance, as many investment strategies focus on inclusion or exclusion approaches. In the most recent period, we find that assets in ESG classes A and B show the weakest overall ESG risk dependence. We also have to keep in mind that the ESG scores are not yet definitive; therefore, they could still be changed and adapted to change the ESG risk behavior. When looking at the overall market risk conditionally on the ESG class, we find the dependence to be relatively weak for all assets. In times of the financial crisis, assets in ESG class B and D show strong risk dependence, while in the following periods assets in ESG class B and C show stronger risk dependence. The difference among ESG classes also diminishes in the most recent period. Nevertheless, assets in the ESG class A seem to carry weak market risk dependence, which is in line with the literature as ESG practices have been connected to better governance and possible reduction in risk exposure.

Finally, the overall idiosyncratic component of the assets varies again throughout the time periods. In times of crisis, companies with high ESG performance show stronger overall idiosyncratic risks dependence, while companies with a lower ESG score show weaker risk dependence. This is especially pronounced in the most recent period. However, it might be worth considering risk dependence measures together as Campbell et al. (2001) and Luo and Bhattacharya (2009) have shown that the overlapping effects of systematic and idiosyncratic risks affect the realized performance in portfolios.

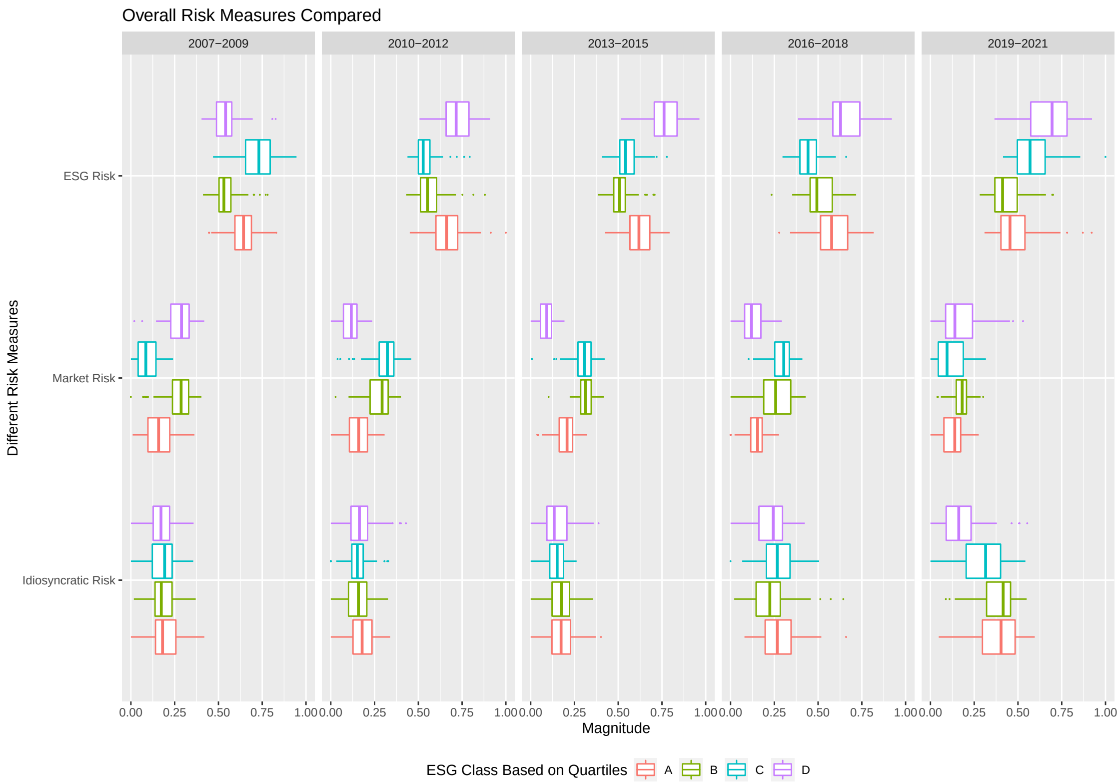

Figure 2.4: Overall ESG Risk measures for each time interval q using quartiles for ESG classes.

Time periods	ESG Risk				Market Risk				Idiosyncratic Risk			
	A	B	C	D	A	B	C	D	A	B	C	D
2007-2009	0.644	0.546	0.724	0.544	0.163	0.277	0.112	0.284	0.194	0.181	0.184	0.173
2010-2012	0.661	0.565	0.539	0.717	0.172	0.277	0.309	0.122	0.183	0.157	0.154	0.174
2013-2015	0.622	0.516	0.552	0.765	0.199	0.312	0.302	0.098	0.179	0.172	0.147	0.149
2016-2018	0.583	0.513	0.446	0.647	0.152	0.266	0.286	0.139	0.272	0.228	0.268	0.231
2019-2021	0.486	0.439	0.582	0.664	0.140	0.175	0.130	0.184	0.385	0.386	0.303	0.178

Table 2.1: Mean values for overall ESG Risk, Market Risk and Idiosyncratic Risk for each ESG Class k in time interval q.

When looking at the lower tail risk measures in Figure 2.5 and Table 2.2, using the estimated lower tail dependence coefficient (λ), we first notice that the magnitude is close to 1. This is due to the design of the indicator and the number of copula families with zero tail dependence coefficients. Nevertheless, we can still compare the risk dependence measures across ESG classes and time periods. The intuition why companies with high ESG scores could potentially encounter lower downside risk dependence is that it is common believe that socially responsible companies are less exposed to company-specific events that negatively impact the equity price (Diemont, Moore, and Soppe, 2016). Using questionnaires and annual assessments, some scholars already found a significant relationship between some parts of CSR and downside tail risk which differs when looking at region and time (Diemont, Moore, and Soppe, 2016).

We find that assets with ESG class B show weak lower tail ESG risk dependence throughout the first time period. Then in period 2010-2012, assets in ESG class C and in period 2013-2015, assets in ESG class B show weak lower tail ESG risk dependence. Also, we find large variability in the last two periods where ESG scores are not yet definite. While some scholars argue that ESG tail risk has become more pronounced in the most recent year using the COVID-19 crisis (Lööf, Sahamkhadam, and Stephan, 2021), our findings show that the risk dependence measures are very volatile in the most recent period (see also all standard deviation values in Table A.7). From our data provider, we know that these ESG scores are not yet definitive and can be updated as analyzed by Berg, Fabisik, and Sautner (2021), making the behavior in the last period subject to change.

Looking at the lower tail market risk conditionally on ESG classes, we find that the magnitude is much smaller. Assets in the ESG classes, B and D, show strong risk dependence in the first time period. Especially in the last period, the lower tail market risk conditionally on ESG class D is more variable and one can see larger dependence, which is possibly due to the non-definitive ESG scores. Lastly, the idiosyncratic component for lower tail risk events is very small but shows increasing variability in the most recent periods.

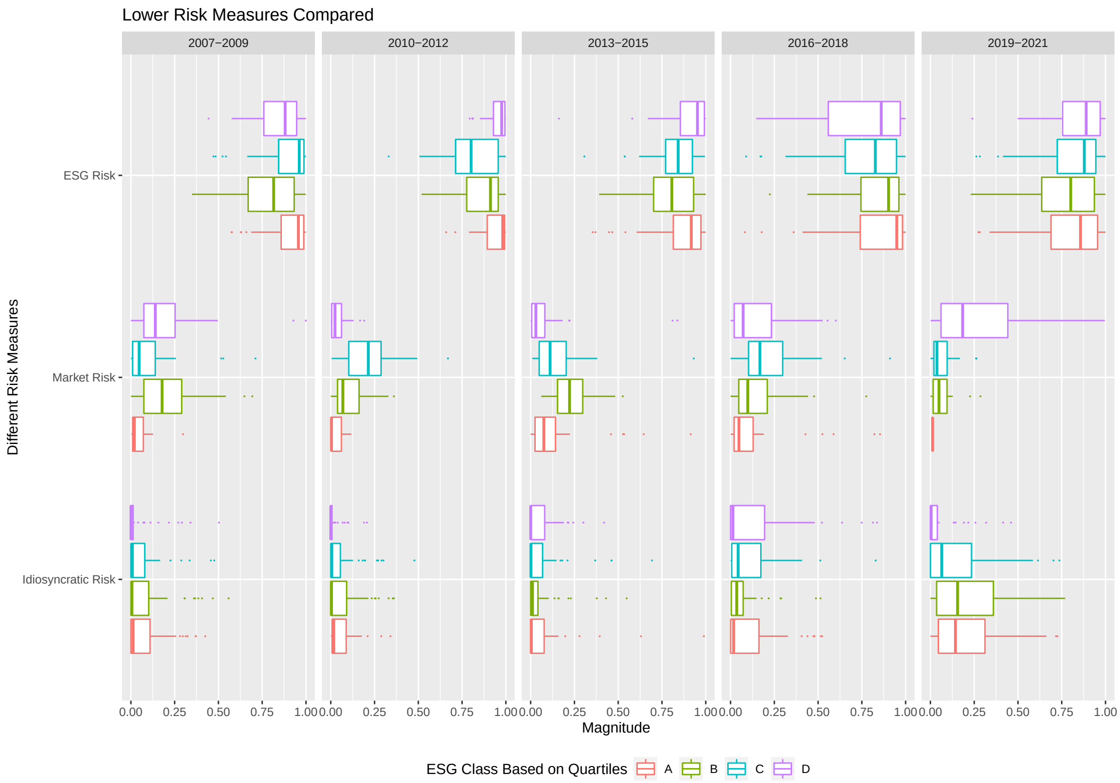

Figure 2.5: Lower tail ESG Risk measures (without 0s and 1s) for each time interval q using quartiles for ESG classes.

Time periods	Lower ESG Risk				Lower Market Risk				Lower Idiosyncratic Risk			
	A	B	C	D	A	B	C	D	A	B	C	D
2007-2009	0.902	0.789	0.894	0.843	0.046	0.213	0.127	0.198	0.071	0.078	0.063	0.043
2010-2012	0.940	0.865	0.807	0.953	0.041	0.111	0.213	0.043	0.057	0.067	0.054	0.016
2013-2015	0.853	0.794	0.828	0.894	0.156	0.238	0.152	0.107	0.078	0.061	0.070	0.055
2016-2018	0.821	0.827	0.776	0.769	0.149	0.169	0.224	0.144	0.102	0.076	0.115	0.140
2019-2021	0.804	0.756	0.805	0.827	0.012	0.072	0.063	0.278	0.196	0.218	0.159	0.067

Table 2.2: Mean values for lower tail ESG Risk, Market Risk and Idiosyncratic Risk for each ESG Class k in time interval q.

As previously mentioned, one could follow the same approach and compute the individual E-, S-, G-Pillar risk dependence by exchanging the ESG score with the individual E-, S-, G-Pillar score. We have computed the individual overall E-, S-, G-Pillar risk dependence by following Equation (2.3). We find that overall ESG and E-Pillar risk dependence are very similar in the first period, while they diverge in the following periods. Similarly, we find that companies in ESG class A show also strong S-Pillar risk dependence while showing weak G-Pillar risk dependence, especially in the first period, which is in line with the recent literature (e.g. Zhang, De Spiegeleer, and Schoutens (2021) and Diemont, Moore, and Soppe (2016)). A summary of the output is presented in A.7. More detailed information are available upon request.

2.6 Causality

While this model allows to disentangle and quantify different risk dependencies related to ESG, a journal reviewer of this chapter remarked the missing link to causality. In an attempt to touch on this topic we have analyzed whether an increase or decrease in the mean ESG score from one period to another period can give us any indication of any changes in the ESG risk. To do so, we have slightly modified the work of Giese et al. (2019) and used the one-sided Welch two sample t-test to test for significant differences in the means (Welch, 1938; Welch, 1947). We test the relationship between our ESG risk dependence measure and the ESG scores, as well as individual E-, S-, and G-Pillar scores. Our complete methodology and the thorough analysis can be found in the A.8.

While we thought about possible different approaches, we were limited in the number of data points per asset, as for each asset we only have either five risk measure data points and five mean ESG scores arising from the five considered periods. Therefore, many approaches, e.g., Granger causality, were not applicable. While we are aware of the limitations that a significance of differences across different groups is not a proof of causality in a traditional sense, the idea was to use a risk transmission channel in order to get a first understanding of the relationship. Thus, when we refer to the term causality in this section, we focus the transmission of risk and its relationship with shifts in ESG scores. According to the risk transmission channel, companies with high ESG scores tend to have high risk control measures in place and follow strict compliance standards, thus they suffer less often from severe risk events leading to less downturn and with that to lower overall and tail risk. The rational behind this risk transmission channel has been discussed by Godfrey, Merrill, and Hansen (2009), Oikonomou, Brooks, and Pavelin (2012), and Jo and Na (2012). Thus, we hypothesize if an increase/decrease in ESG scores leads to a lower/higher ESG risk dependence. Nevertheless, we want to stress that further research is needed to complete a causality analysis.

In our analysis, we find no indication that an increase in ESG or E-,S-, and G-Pillar score engagement leads to a decrease in ESG risk dependence apart from one period for the G- Pillar. Moreover, testing for reverse causality, we find that an increase in ESG risks dependence leads to lower ESG, E-, S-, and G-Pillar score engagement than a decrease in ESG risks in the most recent periods (see A.8.1 and A.8.2). However, we have to keep in mind that these findings are based on non-definite ESG scores.

Additionally, when looking at the individual pillar scores and the individual pillar risk dependence, we find only for the times of the financial crisis and the following years for the E-Pillar a significant difference in the means (see A.8.3). More specifically, we find that an increase in the E-Pillar score results in a decrease in the mean E-Pillar risk dependence. Additionally, we look at reverse causality and find that an increase in G-Pillar risk dependence leads to lower G-Pillar scores than a decrease in G-Pillar risk dependence for two time periods.

While the results from our R-vine copula ESG risk model indicate that financial risks can be attributed to ESG classes and ESG risk is not negligible, we cannot identify clear causal mechanisms and directions yet. Most of our statistical significant results indicating reverse causality are found in the time periods where our ESG data is defined as non-definite, indicating that the data can still be changed by our data provider. Furthermore, a potential type 1 error could also have affected the rejections (as further discussed in Appendix A.8). Thus, overall our analyses suggest the absence of causality and reverse causality defined as the transfer of risk using a transmission channel. Nevertheless, this additional analysis to our model shall not be seen as a full traditional causal analysis of the topic but should act as a motivation to explore the causality relationship even further.

2.7 Conclusion

The aim of this research is to try to disentangle which part of risk dependence can be attributed to belonging to a specific ESG class. Starting from a preliminary empirical analysis of real-world financial data, we notice that ESG rating classes can provide information on overall risk and tail risk. However, as companies tend to improve their rating throughout time, as seen in Figure 2.2, these differences tend to diminish, especially in the interval

2016-2018 and 2019-2021, in which, however, Refinitiv ESG scores cannot yet be considered definitive. Based on such observations, we propose the R-vine copula ESG risk model to capture (tail) dependence and compute three new risk measures both for overall and lower tail risk.

Using vine copula models allows us to capture financial times series characteristics including non-symmetry and dependence in the extremes, as it can rely on a pair copula construction. Especially the proposed R-vine copula ESG risk model is able to flexibly model the dependence structures using the ESG scores. Moreover, as for each level an arbitrary bivariate copula can be specified, every complex dependence structure can be captured effectively and optimally. After estimating the R-vine copula ESG risk model, we cannot only estimate all the conditional dependencies among assets as well as specify their interactions as modeled by different copulas families, but we can also introduce three ESG risk measures that capture ESG risk, market risk conditionally on the ESG class, as well as an idiosyncratic risk component. We notice that in times of calm, assets with a *D* score show strong individual ESG risk dependence and tail ESG risk dependence, however, we do not confirm this finding in times of crisis. Assets belonging to ESG class *A* show unexpected strong ESG risk dependence throughout the whole time period, possibly because of a high investment volume and popularity from investors who might believe that ESG performance can make them resilient in times of crisis. We also find a lot of variability in the risk dependence measures in the last years, when the ESG scores are not definitive and can still be changed. Companies that are not best or worst performers, leaving assets in ESG Class *B* and *C*, often show weaker ESG risk dependence. Again, this could be due to the non-popularity of assets with mediocre ESG performance. When looking at the individual pillar risk, we find that the overall E-Pillar risk dependence behaves similar to the overall ESG risk dependence in terms of crisis. Also we show that in the first period, companies with an *A* rating show strong S-Pillar risk dependence and weak G-Pillar risk dependence which is in line with the recent literature. The understanding and estimation of such dependencies and risks is of utmost importance for setting up adequate risk management and mitigation tools as well as building portfolios, ideally, also ESG diversified and resilient to crises. Current popular ESG inclusion approaches that focus on picking only assets in the highest ESG rating classes could have indeed possibly benefited in the past from better VaR values but such behavior is not clear for the most recent interval, where ESG classes are overlapping and differences are diminishing. In fact, picking assets with the highest ESG scores does not lead to better VaR values necessarily and could result in applying too much pressure on a specific set of assets without a clear benefit. The constant trend in improving ESG scores, as shown in Figure 2.2, might be a factor behind the lack of VaR differentiation between the classes *A*, *B*, and *C* as well as the large variability in the ESG risk in the last time interval, joint to the fact that such ESG scores are not yet definitive. Still, we notice that ESG class *D* assets tend to exhibit poorer VaR values than other ESG classes and, especially in times of calm, exhibit large overall and lower tail ESG risk, as such classes mostly include assets which have yet to disclose information needed for ESG score computation. This suggests that ESG disclosure might also have some indirect and positive effect on company risk management.

Our work is limited in the amount of statistical evidence presented and would be improved by including further statistical tests. While we find mixed results overall, we are able to show some trend for different time periods. As this is a start to disentangle the different risks, further research could focus on understanding the underlying mechanisms which drive ESG risk. Additionally, it could be interesting to get a deeper understanding of the link between risk and negative ESG events and disclosure practices. While we have touched on the topic of causality, there is more work to be done to get a comprehensive understanding of the direction of causality and its underlying mechanisms. Moreover, high on the agenda, the current model could be used to develop new ESG investment strategies and ESG based risk mitigation and management modeling tools.

Chapter 3

Do lower ESG rated companies have higher systemic impact? Empirical Evidence from Europe and the United States

This research chapter, for which I am first author, is co-authored with Giovanni Bonaccolto and Sandra Paterlini. A similar version of this chapter is published as

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The work has been presented at the A.M.A.S.E.S Special Session "ESG risk and portfolio management" and the 13th CEQURA Conference.

Abstract

In recent years, companies have increasingly been characterized by environmental, social, and governance (ESG) scores, and investors and academics have raised questions concerning financial performance and investment risks. Now, as the European Banking Authority has acknowledged that ESG risks can potentially impact the economic and financial system, the debate on systemic risk has gained traction. Understanding the relationship between ESG merit and systemic risk is of utmost importance for the stability of the economic and financial system, still, research is limited. Relying on real-world European and US data, we quantify systemic risk by means of QL-CoVaR. Empirical analyses of the entire period from 2007-2021 show that companies with high ESG scores tend to exhibit low QL-CoVaR values indicating a positive effect of ESG scores. Such evidence is confirmed by clustering the individual companies into ESG portfolios and focusing on the COVID-19 pandemic. Additional insights using the individual pillars are also provided.

3.1 Introduction

Company characteristics are the key driver in determining performance and risk profiles. Besides financial information, non-financial information has recently gained relevant attention as investors also look for sustainability in their investment decisions. Companies are increasingly characterized by their non-financial information, more specifically by environmental, social, and governance (ESG) scores and the debate about the impact of ESG information on company performance and risk is still open.

Generally, ESG scores are designed by different rating providers (e.g., Bloomberg and Reuters) and aim to assess the ESG performance of companies by considering several criteria, measurements, and quantitative and qualitative methods; see, among others, Bhattacharya and Sharma (2019), and Berg and Lange (2020). ESG scores typically range between 0 to 100. More specifically, assets with higher ESG scores indicate a more responsible ESG behavior. Moreover, ESG scores are typically associated with a rating class (i.e., A, B, C, D) using thresholds or quartiles of the ESG score values.

This complementary non-financial information can have the potential to increase the accuracy of performance forecasts and risk assessments (Achim and Borlea, 2015). Technically, quantifying these aspects should help to reach one of the main objectives of the European Commission's 2018 Action Plan, which is "managing financial risks stemming from climate change, resource depletion, environmental degradation, and social issues" (European Banking Authority, 2021, p. 15). To do so, it is crucial to understand how these factors translate into financial risks that may affect the whole financial system (European Banking Authority, 2021). In particular, the European Banking Authority (EBA) states that ESG risks can materialize when ESG factors have a negative impact on financial performance or solvency (European Banking Authority, 2020). Moreover, according to a recent report,"ESG risks can also impact the financial system and economy as a whole, with potential systemic consequences" (European Banking Authority, 2021, p. 33). This effect could be prominent in macroeconomic factors (i.e., economic growth, labor productivity, or sovereign debt) and hence impact different institutions through the whole economy (European Banking Authority, 2021). Thus, higher ESG scores could be connected to more prudent and sustainable actions leading to a reduction in the overall risk. Additionally, Cerqueti et al. (2021) argued that high ESG-ranked funds could comprise an intrinsic property of lowering systemic risk due to less overlap with other funds, lower contagion, and a long-term investment approach. Furthermore, companies with higher ESG scores are less exposed to the risk of future litigation (Cerqueti et al., 2021).

While this is an essential topic for the stability of the financial system and the economy as a whole, research is still limited and often provides ambiguous results. Boubaker et al. (2020) were among the first to find that better corporate, social, and responsibility (CSR) practices, measured by all qualitative dimensions (except corporate governance) of the MSCI ESG index, lead to lower financial distress and default risk, with positive effects on financial stability and more crisis-resilient economies. Later, Eratalay and Cortés Ángel (2022) proposed a VAR-MGARCH model, performing a principal component analysis (Billio et al., 2012) to obtain systemic risk indicators. They found that companies with higher ESG scores contribute 7.3% less to systemic risk. Focusing on the COVID-19 period and the individual pillars, Eratalay and Cortés Ángel (2022) found no significant effects for the E-Pillar. In contrast, the S- and G-Pillar had a statistically significant impact (positive and negative, respectively) on systemic risk. Similarly, building on network analysis, Cerqueti et al. (2021) showed that ESG funds, defined as interconnected components of a unified system, may be less vulnerable to systemic shocks and more resilient to contagion under lower-volatility regimes. Furthermore, active disclosure is a key factor in effectively reducing the systemic risk for Chinese listed companies (Waner, 2021).

When considering the banking sector, Murè et al. (2021) added that higher ESG scores are connected to a lower probability of sanctions for Italian banks. Ducassy (2013) argued that lowering environmental costs and risks can aid in promoting financial stability during crisis periods. Moreover, Chiaramonte et al. (2021) showed that higher ESG and individual pillar scores are associated with lower default risk for European banks during times of crisis. These findings are in line with Aevoae et al. (2022), who used the ΔCoVaR to show that higher ESG Combined Scores are connected to a reduction of system-wide distress using a sample of publicly listed banks. In addition, higher G-Pillar scores imply lower bank interconnectedness, lower systemic risk, and higher financial stability (Aevoae et al., 2022). Furthermore, the S-Pillar also seems to play an important role. Indeed Scholtens and Van't Klooster (2019) argued that higher sustainability scores could reduce the systemic risk contribution of banks. Similarly, Lupu, Hurduzeu, and Lupu (2022) found evidence that the overall ESG score, as well as the individual pillar score, has a notable impact on the financial stability of banks in Europe, stressing that this influence is non-linear. Additionally, the duration of ESG disclosure also plays a role, as Chiaramonte et al. (2021) showed that it can positively affect stability for European banks. On the other hand, the study of Anginer et al. (2018) highlighted that shareholder-friendly corporate governance is linked to higher systemic risk in the US banking sector.

Several approaches have been proposed to estimate systemic risk in the literature. Among them, the CoVaR and ΔCoVaR introduced by Adrian and Brunnermeier (2016) are some of the most widely used. Recently, Bonaccolto, Caporin, and Paterlini (2019) proposed the so-called QL-CoVaR, which extends the CoVaR by employing an estimation process that captures the state in which the response and the conditioning variables are jointly in distress. An accurate estimation of the magnitude of the distress degree in financial connections is of utmost importance during economic or financial crises when the correlation among companies increases and the risk of contagion can impact the stability of the whole system (Bonaccolto, Caporin, and Paterlini, 2019). This is achieved by linking the left tails of the company's return and systemic return distributions. Thus, the QL-CoVaR better captures the degree of distress a stressed company exerts on the market. In contrast, the CoVaR's coefficients reflect the stressed state of the response variable only. As shown by Bonaccolto, Caporin, and Paterlini (2019), the QL-CoVaR model provides improvements in terms of predictive accuracy and is more informative than the CoVaR during tail events.

In this chapter, relying on a large sample of European (EU) and American (US) companies, we estimate the systemic risk by adopting the ΔQL-CoVaR and analyze the relationship between ESG merit and systemic risk, with a particular focus on crisis periods. Empirical analyses on the entire period from 2007-2021 show that A-rated companies tend to exhibit more limited ΔQL-CoVaR values than lower-rated companies. We also confirm these findings with a portfolio analysis, in which we cluster the individual companies into four ESG indexes during the COVID-19 pandemic, which turns out to be the most relevant event, in terms of systemic impact, from 2007 to 2021.

The chapter is structured as follows. Section 3.2 introduces the QL-CoVaR. Section 3.3 describes the data and the empirical setup. Then, Section 3.4 reports the empirical results obtained from the ESG analysis, while Section 3.5 focuses on the individual E-, S-, and G-Pillar analyses. Finally, Section 3.6 concludes the chapter.

3.2 Quantile-Located Conditional Value-at-Risk

Let y_t and $x_{j,t}$ be, respectively, the returns of the economic system and of company j observed at time t, for $t = 1,\ldots,T$ and $j = 1,\ldots,N$. We also define $\mathbf{M}_t$ as the vector of a set of control variables observed at time t. Following Adrian and Brunnermeier (2016), we estimate the conditional τ-th and θ-th quantiles of $x_{j,t}$ and y_t, denoted as $Q_\tau(x_{j,t})$ and $Q_\theta^{(j)}(y_t)$, respectively, using the following quantile regression models (Koenker and Bassett, 1978):

$$Q_\tau(x_{j,t}) = \alpha_\tau^{(j)} + \boldsymbol{\beta}_\tau^{(j)}\mathbf{M}'_{t-1}, \tag{3.1}$$

$$Q_\theta^{(j)}(y_t) = \delta_\theta^{(j)} + \lambda_\theta^{(j)} x_{j,t} + \boldsymbol{\gamma}_\theta^{(j)}\mathbf{M}'_{t-1}, \tag{3.2}$$

where $\tau, \theta \in (0,1)$.

In the CoVaR framework, θ and τ take low values, typically within the interval $(0, 0.05]$, to focus on left-tail relationships between y_t and $x_{j,t}$. After estimating the parameters $\alpha_\tau^{(j)}$, $\boldsymbol{\beta}_\tau^{(j)}$, $\delta_\theta^{(j)}$, $\lambda_\theta^{(j)}$ and $\boldsymbol{\gamma}_\theta^{(j)}$ in Equations (3.1) and (3.2), as well as $\widehat{Q}_\tau(x_{j,\tau}) = \widehat{\alpha}_\tau^{(j)} + \widehat{\boldsymbol{\beta}}_\tau^{(j)}\mathbf{M}'_{t-1}$, Adrian and Brunnermeier (2016) computed the Conditional Value-at-Risk (CoVaR) of the economic system conditional on the VaR of company j as follows:

$$\text{CoVaR}_{t,\theta,\tau}^{(j)} = \widehat{\delta}_\theta^{(j)} + \widehat{\lambda}_\theta^{(j)} \widehat{Q}_\tau(x_{j,t}) + \widehat{\boldsymbol{\gamma}}_\theta^{(j)}\mathbf{M}'_{t-1}. \tag{3.3}$$

Setting $x_{j,t} = \widehat{Q}_\tau(x_{j,t})$ allows us to estimate the VaR of the financial system conditional on institution i being in distress as described by Adrian and Brunnermeier (2016). Likewise, the CoVaR of y_t conditional on the median of company j is obtained by replacing τ with $1/2$:

$$\text{CoVaR}_{t,\theta,1/2}^{(j)} = \widehat{\delta}_\theta^{(j)} + \widehat{\lambda}_\theta^{(j)} \widehat{Q}_{1/2}(x_{j,t}) + \widehat{\boldsymbol{\gamma}}_\theta^{(j)}\mathbf{M}'_{t-1}. \tag{3.4}$$

From the difference of the conditional quantiles defined in Equations (3.3) and (3.4), we then compute the ΔCoVaR introduced by Adrian and Brunnermeier (2016):

$$\begin{aligned} \Delta\text{CoVaR}_{t,\theta,\tau}^{(j)} &= \text{CoVaR}_{t,\theta,\tau}^{(j)} - \text{CoVaR}_{t,\theta,1/2}^{(j)} \\ &= \widehat{\lambda}_\theta^{(j)} \left[\widehat{Q}_\tau(x_{j,t}) - \widehat{Q}_{1/2}(x_{j,t})\right], \end{aligned} \tag{3.5}$$

which quantifies the marginal contribution of company j to the overall systemic risk. Note that the parameters and coefficients in Equations (3.2)—(3.5) are functions of θ only, neglecting then the role of τ, which reflects the stressed state of $x_{j,t}$. In our study, we employ a generalization of the CoVaR, which builds on the quantile-on-quantile approach introduced by Sim and Zhou (2015) to measure the effects that the quantiles of oil price shocks have on the quantiles of the US stock return. After that, the quantile-on-quantile method was adopted by Bonaccolto, Caporin, and Panzica (2019) to estimate financial networks and introduced into the CoVaR framework by Bonaccolto, Caporin, and Paterlini (2019), who proposed the so-called Quantile-Located CoVaR (QL-CoVaR) model. The QL-CoVaR model builds on an estimation process depending on both θ and τ, capturing then the state in which y_t and $x_{j,t}$ are jointly in distress.

Taking into account the effects of both θ and τ, the model defined in Equation (3.2) is rewritten as:

$$Q_{\theta,\tau}^{(j)}(y_t) = \delta_{\theta,\tau}^{(j)} + \lambda_{\theta,\tau}^{(j)} x_{j,t} + \boldsymbol{\gamma}_{\theta,\tau}^{(j)} \mathbf{M}_{t-1}'. \tag{3.6}$$

Note that the parameters in (3.6) have both θ and τ as subscripts, as they depend on the quantile levels of both y_t and $x_{j,t}$, being estimated from the following optimization problem:

$$\underset{\delta_{\theta,\tau}^{(j)},\lambda_{\theta,\tau}^{(j)},\boldsymbol{\gamma}_{\theta,\tau}^{(j)}}{\arg\min} \sum_{t=2}^{T} \rho_\theta \left[y_t - \delta_{\theta,\tau}^{(j)} - \lambda_{\theta,\tau}^{(j)} x_{j,t} - \boldsymbol{\gamma}_{\theta,\tau}^{(j)} \mathbf{M}_{t-1}' \right] K\left(\frac{\widehat{F}(x_{j,t}) - \tau}{h} \right), \tag{3.7}$$

where $\rho_\theta(e) = e(\theta - \mathbf{1}_{\{e<0\}})$ is the asymmetric loss function characterizing the quantile regression method introduced by Koenker and Bassett (1978), $\mathbf{1}_{\{\cdot\}}$ is an indicator function, which takes the value of one if the condition in $\{\cdot\}$ is true, and the value of zero otherwise, whereas $K(\cdot)$ is a kernel function, with bandwidth h, that captures the impact of $x_{j,t}$ in the neighborhood of its τ-th quantile.

Following Sim and Zhou (2015), we employ a Gaussian kernel $K(\cdot)$ to weight the impact of $x_{j,t}$ in the neighborhood of its τ-th quantile, and use the following specification of $\widehat{F}(x_{j,t})$:

$$\widehat{F}(x_{j,t}) = T^{-1} \sum_{p=1}^{T} \mathbf{1}_{\{x_{j,p} < x_{j,t}\}}. \tag{3.8}$$

We then compute the QL-CoVaR at the (θ,τ)-th level as follows:

$$\text{QL-CoVaR}^{(j)}_{t,\theta,\tau} = \widehat{\delta}^{(j)}_{\theta,\tau} + \widehat{\lambda}^{(j)}_{\theta,\tau}\widehat{Q}_{\tau}(x_{j,t}) + \widehat{\boldsymbol{\gamma}}^{(j)}_{\theta,\tau}\mathbf{M}'_{t-1}, \tag{3.9}$$

where $\widehat{Q}_{\tau}(x_{j,t}) = \widehat{\alpha}^{(j)}_{\tau} + \widehat{\boldsymbol{\beta}}^{(j)}_{\tau}\mathbf{M}'_{t-1}$ is obtained from Equation (3.1).

We also estimate the QL-CoVaR model with 1/2 in place of τ, and obtain the ΔQL-CoVaR: $\Delta\text{QL-CoVAR}^{(j)}_{t,\theta,\tau} = \text{QL-CoVaR}^{(j)}_{t,\theta,\tau} - \text{QL-CoVaR}^{(j)}_{t,\theta,1/2}$. Following Bonaccolto, Caporin, and Paterlini (2019), we decompose the ΔQL-CoVaR as follows:

$$\begin{aligned}
\Delta\text{QL-CoVAR}^{(j)}_{t,\theta,\tau} &= \widehat{\delta}^{(j)}_{\theta,\tau} - \widehat{\delta}^{(j)}_{\theta,1/2} + \widehat{\lambda}^{(j)}_{\theta,\tau}\left[\widehat{Q}_{\tau}(x_{j,t}) - \widehat{Q}_{1/2}(x_{j,t})\right] \\
&+ (\widehat{\lambda}^{(j)}_{\theta,\tau} - \widehat{\lambda}^{(j)}_{\theta,1/2})\widehat{Q}_{1/2}(x_{j,t}) \\
&+ (\widehat{\boldsymbol{\gamma}}^{(j)}_{\theta,\tau} - \widehat{\boldsymbol{\gamma}}^{(j)}_{\theta,1/2})\mathbf{M}'_{t-1}.
\end{aligned} \tag{3.10}$$

We stress here the role of $\widehat{\lambda}^{(j)}_{\theta,\tau}$, which quantifies the sensitivity of y_t to $x_{j,t}$ when both are in distress (see Equation (3.6)). As a result, when keeping the other components in Equation (3.10) constant, $\Delta\text{QL-CoVAR}^{(j)}_{t,\theta,\tau}$ would react more readily to the shocks of those companies with greater $\widehat{\lambda}^{(j)}_{\theta,\tau}$ values. However, $\widehat{\lambda}^{(j)}_{\theta,\tau}$ is multiplied by $\left[\widehat{Q}_{\tau}(x_{j,t}) - \widehat{Q}_{1/2}(x_{j,t})\right]$ in Equation (3.10), and these two components are estimated from two different models; the ones defined in Equation (3.6) and (3.7), respectively. More specifically, $\left[\widehat{Q}_{\tau}(x_{j,t}) - \widehat{Q}_{1/2}(x_{j,t})\right]$ quantifies the specific idiosyncratic risk of company j, when it moves from its own median to its own VaR and, therefore, does not depend on y_t. As a result, risky companies with greater values of $\left[\widehat{Q}_{\tau}(x_{j,t}) - \widehat{Q}_{1/2}(x_{j,t})\right]$ would have a moderate or non-relevant systemic impact if $\widehat{\lambda}^{(j)}_{\theta,\tau}$ approaches zero.

The component $\widehat{\lambda}^{(j)}_{\theta,\tau}\left[\widehat{Q}_{\tau}(x_{j,t}) - \widehat{Q}_{1/2}(x_{j,t})\right]$ given in Equation (3.10) resembles the ΔCoVaR specification defined in Equation (3.5). However, $\widehat{\lambda}^{(j)}_{\theta,\tau} \neq \widehat{\lambda}^{(j)}_{\theta}$ due to the quantile-located effects.[1] In our study, we estimate the standard errors of the coefficients given in Equation (3.10) by employing a bootstrap method (Efron, 1992): the xy–pair approach of Kocherginsky (2003), which provides accurate results without any distributional assumption.

[1]In our empirical analysis, we found that $\widehat{\lambda}^{(j)}_{\theta,\tau}$ estimated for the QL-CoVaR is typically greater than the CoVaR $\widehat{\lambda}^{(j)}_{\theta}$ coefficient, highlighting the fact that the co-movement between the overall system and the individual companies becomes more relevant when capturing their joint distress. These additional results are available upon request.

3.3 Data description and empirical set-up

Firstly, we consider the daily logarithmic return, daily market capitalization, yearly environmental, social, and governance (ESG) and individual E-, S-, and G-Pillar data of 294 EU companies which are the constituents of the EURO STOXX 600 index and 323 US companies which are the constituents of the Standard & Poor' (S&P) 500 index whose observations are continuously available from January 2, 2007 to May 3, 2022. The return of each of these companies represents the variable $x_{j,t}$ from Equation (3.1) to Equation (3.10).[2] We employ the daily return of the S&P 500 index as the response variable y_t when focusing on the US companies, and the daily return of the EURO STOXX 600 index when considering the EU companies, spanning the time interval from January 2, 2007 to May 3, 2022.

We extract the time series and ESG data from Refinitiv, the financial and risk business unit of Thomson Reuters. Their rank-based ESG scores are based on publicly reported data (Refinitiv, 2021). ESG data is only sparsely available in the early 2000s from our data provider, thus we chose to start in 2007, allowing us to take into account different states of the economy. More specifically, we are looking at the 2007-2009 sub-prime crisis, the EU sovereign debt crisis beginning in late 2009, and the more recent COVID-19 pandemic and endemic, which made fundamental changes to the work life of many employees and employers (Microsoft, 2022).

Both datasets are similar in size, however, the US data exhibits stronger average kurtosis as shown in Table (3.1). Additionally, we find that the ESG scores of both datasets improve over time as companies are under pressure to improve their ESG performance and continue to disclose more information (see Table (3.2) and Figure (3.1)) (Sahin et al., 2022).

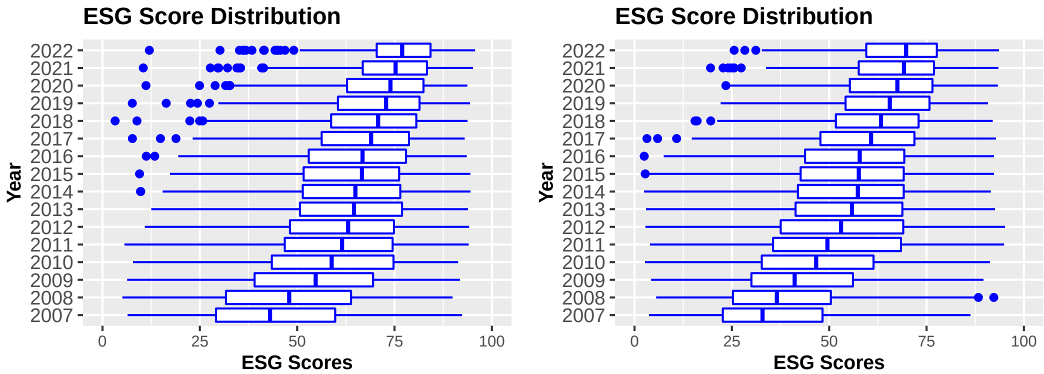
Dataset	j	T	$\hat{\mu}$	$\hat{\sigma}$	$\widehat{kurt}$	$\widehat{skew}$	freq.
EURO STOXX 600	294	4002	0.02	0.04	16.89	-0.37	daily
S&P 500	323	4001	0.06	0.05	19.48	-0.36	daily

Table 3.1: The table reports the descriptive statistics for the constituents of the Eurostoxx 600 and the S&P 500, respectively. Columns 1-8 report the dataset, the number of constituents (j), the number of observations (T), the average annualized mean ($\hat{\mu}$), the average annualized standard deviation ($\hat{\sigma}$), the average kurtosis ($\widehat{kurt}$), the average skewness ($\widehat{skew}$) of the company returns, and the sampling frequency ($freq.$).

[2] Date of retrieval of the ESG data were 28 April 2022 and 6 September 2022 of the E, S, and G Pillar data.

Dataset	j	T	$\hat{\mu}$	$\hat{\sigma}$	$\widehat{kurt}$	$\widehat{skew}$	$freq.$
EURO STOXX 600	294	16	62.35	76.53	3.09	-0.54	yearly
S&P 500	323	16	54.84	92.28	2.92	-0.42	yearly

Table 3.2: The table reports the descriptive statistics for the ESG data of the constituents of the Eurostoxx 600 and the S&P 500, respectively. Columns 1-8 report the dataset, the number of constituents (j), the number of observations (T), the average mean ($\hat{\mu}$), the average standard deviation ($\hat{\sigma}$), the average kurtosis ($\widehat{kurt}$), the average skewness ($\widehat{skew}$) of the company returns, and the sampling frequency ($freq.$).



(a) EU companies **(b)** US companies

Figure 3.1: Boxplots of ESG scores over time (y-axis. We report the boxplots for the individual pillar scores in B.1.

In this research, we aim to shed light on a possible relationship between the ESG profile of a given company and its systemic relevance considering the EU market and US market separately. For this purpose, we compute the average ESG score ($\overline{\text{ESG}}$) of each company in our dataset from 2007 to 2022. We then cluster these companies into four different classes, from A to D, using the thresholds defined by Refinitiv. Specifically, class A includes those companies with $\overline{\text{ESG}} > 75$. The companies of class B have $50 < \overline{\text{ESG}} \le 75$, whereas we require $25 < \overline{\text{ESG}} \le 50$ for class C. Finally, class D has the companies with the lowest average scores: $\overline{\text{ESG}} \le 25$. We provide the definition of these classes and the number of assets in Table (3.3).

ESG Class	Condition	EU Companies	US Companies
A	($\overline{\text{ESG}} > 75$)	71	33
B	($50 < \overline{\text{ESG}} \le 75$)	158	165
C	($25 < \overline{\text{ESG}} \le 50$)	59	117
D	$\overline{\text{ESG}} \le 25$)	6	8

Table 3.3: Composition of ESG classes A, B, C, and D. From left to right, this table reports the definition of classes A, B, C, and D, the condition required for each class, and the number of EU and US companies within each of them.

In addition to $x_{j,t}$ and y_t, that we defined above, ΔQL-CoVAR$^{(j)}_{t,\theta,\tau}$ depends on the vector of control variables $\mathbf{M}_{t-1}$, the composition of which is described below. Starting from the EU market, we considered the lagged observations of the following variables: i) the return of the EURO STOXX index (i.e., the lagged value of the response variable); ii) the return of the EURO STOXX 50 Volatility Index (VSTOXX);[3] iii) the return of the New Composite Indicator of Systemic Stress (CISS) Index provided by the European Central Bank.[4] The additional variables from iv) to ix) are the European Fama-French research factors: iv) the excess market return (MKT-RF); v) Small Minus Big, the average return on the small stock portfolios minus the average return on the big stock portfolios (SMB); vi) High Minus Low, the average return on the value portfolios minus the average return on the growth portfolios (HML); vii) Robust Minus Weak, the average return on the robust operating profitability portfolios minus the average return on the weak operating profitability portfolios (RMW); viii) Conservative Minus Aggressive, the average return on the conservative investment portfolios minus the average return on the aggressive investment portfolios (CMA); and ix) the risk-free rate (RF).[5] From the principal component analysis on the control variables described above, we find that the first two components explain 89.61% of their overall variability. We then use these two components as entries of the $\mathbf{M}_{t-1}$ vector. As highlighted by Bonaccolto, Caporin, and Paterlini (2019), this choice allows us to exploit the near totality of the information conveyed by these control variables, with advantages in terms of computational costs.

Likewise, when using the US data, we employ the first two components of the lagged values of the following variables: i) the return of the S&P 500 index (i.e., the lagged value of the response variable); ii) the return of the VIX index;[6] iii) the change in the Financial Stress Index (FSI) provided by the Office of Financial Research of the US Department of the Treasury.[7] The additional six variables are the same Fama-French research factors listed above for the EU data but are now obtained from the US market.[8]

In our empirical analysis, we set $\theta = \tau = 0.05$, so that we focus on the left tails of the

[3] This time series is available at https://www.stoxx.com.

[4] Further information about the CISS Index can be found online at https://sdw.ecb.europa.eu.

[5] The data on the variables from (iv) to (ix) were downloaded from the Kenneth R. French library at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[6] This time series has been downloaded from Thomson Reuters.

[7] Further information about the FSI can be found online at https:www.financialresearch.gov.

[8] These time series were downloaded from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

conditional distributions of y_t and $x_{j,t}$. Finally, we set the bandwidth value h equal to 0.15. As explained by Bonaccolto, Caporin, and Paterlini (2019), this is a good compromise between the bias and the variance of the estimates.

3.4 Empirical Results for ESG Indexes

In this section, we analyze the results obtained from the estimation of ΔQL-CoVAR$^{(j)}_{t,\theta,\tau}$ defined in Equation (3.10).[9] ΔQL-CoVAR$^{(j)}_{t,\theta,\tau}$ depends on different components. Among them, we highlight the central role of $\widehat{\lambda}^{(j)}_{\theta,\tau}$, which quantifies the sensitivity of y_t to the stressed state of $x_{j,t}$.

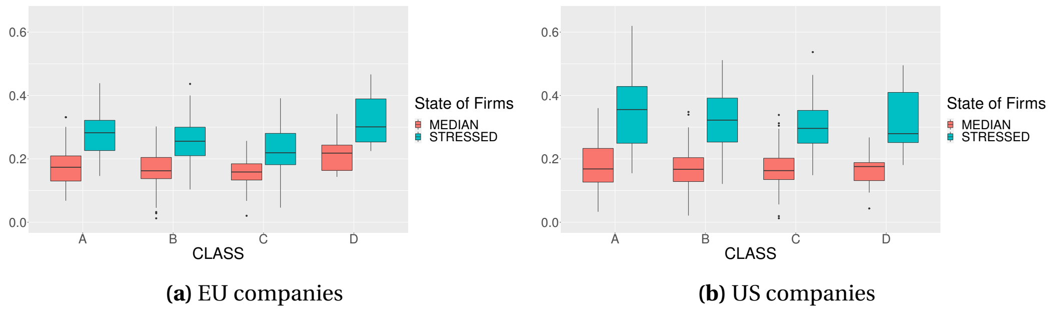


Figure 3.2: Boxplots of $\widehat{\lambda}^{(j)}_{\theta,\tau}$ (STRESSED, cyan color) and $\widehat{\lambda}^{(j)}_{\theta,1/2}$ (MEDIAN, red color) estimated for the EU and US companies clustered by $\overline{\text{ESG}}$ classes.

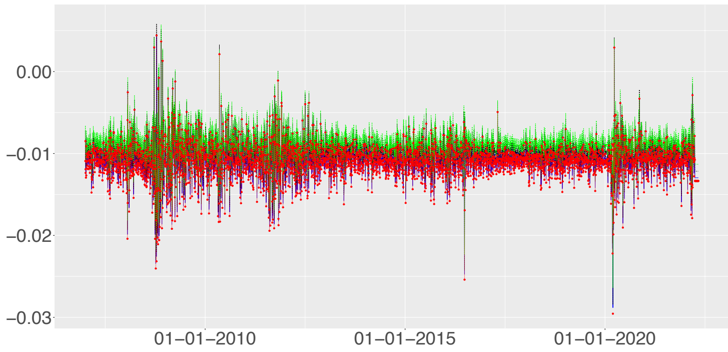
We first analyze in Figure (3.2) the boxplots of $\widehat{\lambda}^{(j)}_{\theta,\tau}$ estimated for each company included in our dataset. We cluster the EU (Figure (3.2a)) and US (Figure (3.2b)) companies into classes A, B, C and D, that we build according to their $\overline{\text{ESG}}$ values (see Table (3.3)). Moreover, for each boxplot, we contrast $\widehat{\lambda}^{(j)}_{\theta,\tau}$ with $\widehat{\lambda}^{(j)}_{\theta,1/2}$ to assess the quantile-located effects. In general, $\widehat{\lambda}^{(j)}_{\theta,\tau}$ and $\widehat{\lambda}^{(j)}_{\theta,1/2}$ take positive values (see Figure (3.2)), highlighting the fact that there is a positive relationship between the return of a given company and the quantile of the overall system. Moreover, the greater $\widehat{\lambda}^{(j)}_{\theta,\tau}$ and $\widehat{\lambda}^{(j)}_{\theta,1/2}$ are, the greater is the response of y_t in its θ-th quantile. Thus, we would observe a larger negative impact on systemic risk and financial stability. Additionally, it is notable that the $\widehat{\lambda}^{(j)}_{\theta,\tau}$ tend to be larger for the US sample compared to the EU sample indicating higher sensitivity.

[9]As a robustness check, we have also run the analysis using the traditional CoVaR measure by Adrian and Brunnermeier, 2016. The results are similar apart from Figure 3.3b were for the US market the A rated companies show on average the largest impact and for the trend analysis in Figure 3.5 shows less differences across different indexes for both the US and EU. Additionally, the impact is smaller in magnitude which is as expected as the CoVaR measure does not consider the joint distress between response and the conditioning variables. The results are available upon request.

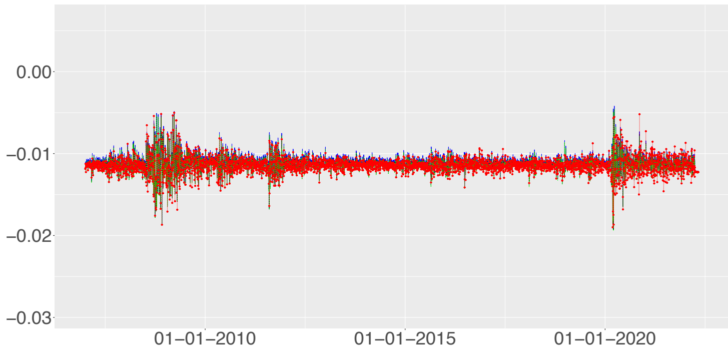
For each class, $\widehat{\lambda}^{(j)}_{\theta,\tau}$ is greater than $\widehat{\lambda}^{(j)}_{\theta,1/2}$, highlighting the fact that the relationships between the overall system and each company become more relevant when they are both in distress. Focusing on the EU companies (Figure (3.2a)), $\widehat{\lambda}^{(j)}_{\theta,\tau}$ takes, on average, greater values for class D, followed by classes A, B and C, with medians of 0.301, 0.282, 0.256 and 0.219, respectively. The third quartile of $\widehat{\lambda}^{(j)}_{\theta,\tau}$ follows the same order across the four classes: 0.389 for class D, 0.322 for class A, 0.299 for class B and 0.280 for class C. In contrast, the median of $\widehat{\lambda}^{(j)}_{\theta,\tau}$ decreases from class A to class D in Figure (3.2b), where we focus on the US market: 0.356 for class A, 0.322 for class B, 0.296 for class C and 0.279 for class D. However, we again find a U-shape behavior in the third quartile of $\widehat{\lambda}^{(j)}_{\theta,\tau}$, which takes higher values for the extreme A and D classes. Thus, as indicated by the greater $\widehat{\lambda}^{(j)}_{\theta,\tau}$, the economic and financial system is more sensitive to shocks of companies belonging to the extreme ESG classes A and D. Classes A and D might be attracting more attention from investors due to the positive and negative screening investment policies, respectively (Amel-Zadeh and Serafeim, 2018). In fact, best in class and worst in class are two investment criteria commonly used to decide which assets to focus on.

Thus, the boxplots in Figure (3.2) suggest substantial preliminary evidence: the VaR of both the EU and US markets tends to be more sensitive to the stressed state of companies that stand out from the crowd through more extreme ESG scores (such as the ones belonging to the A and D classes). This result is more notable for the D-rated companies in the EU market. Moreover, $\widehat{\lambda}^{(j)}_{\theta,\tau}$ is almost always statistically significant at a 5% level, with a p-value greater than 0.05 for only three EU companies belonging to class C.

We now focus on the overall $\Delta\text{QL-CoVAR}^{(j)}_{t,\theta,\tau}$ time series to analyze the systemic impact of the conditioning EU and US companies. We remind the reader that more negative values of $\Delta\text{QL-CoVAR}^{(j)}_{t,\theta,\tau}$ point out a greater systemic impact. Again, we evaluate the effects of the ESG classification. For this purpose, we compute, for each day t (with $t = 1,\dots,T$), the mean of $\Delta\text{QL-CoVAR}^{(j)}_{t,\theta,\tau}$ estimated for those companies belonging to class k, denoted as $\overline{\Delta\text{QL-CoVAR}}^{(k)}_{t,\theta,\tau}$, with $k \in \{A,B,C,\text{D}\}$. As a result, we obtain four time series displayed in Figure (3.3). First, we highlight the strong impact of important tail events, such as the 2007-2009 sub-prime crisis and the EU sovereign debt crisis beginning in late 2009. However, the greatest impact is caused by the outbreak of the more recent COVID-19 pandemic. Specifically, the most extreme (negative) peak in the EU market was observed on March 13, 2020. The day before, on March 12, 2020, the European Central Bank (ECB)



(a) EU companies



(b) US companies

Figure 3.3: Average of ΔQL-CoVAR$_{t,\theta,\tau}^{(j)}$ for the EU and US companies clustered by $\overline{\text{ESG}}$ classes: A (blue line), B (black line), C (green line) and D (red line and red points).

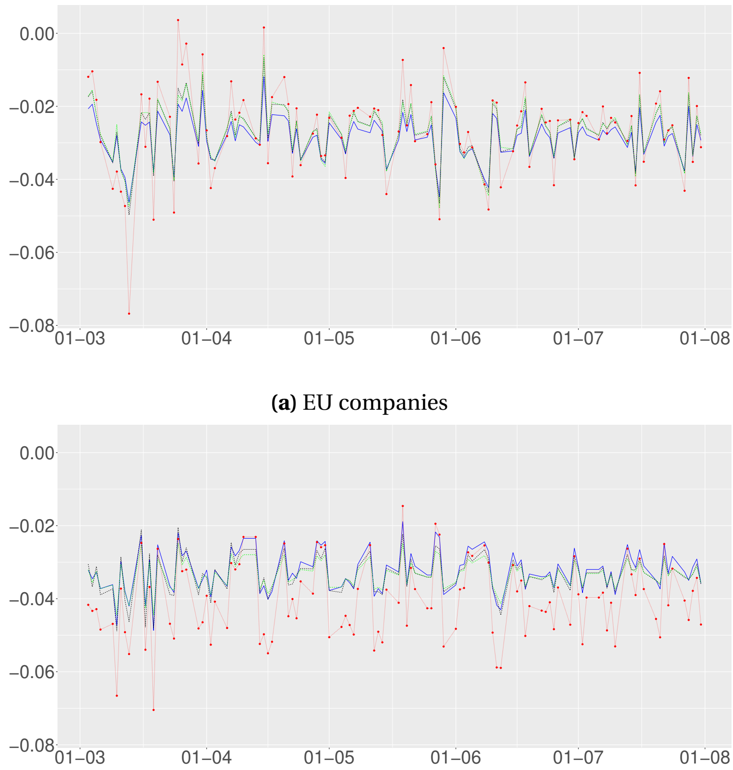
president Christine Lagarde had stated that "we are not here to close spreads, this is not the function or the mission of the ECB". This statement triggered the fears of investors, who interpreted it as refuting the "whatever it takes" policy advocated by the previous ECB president Mario Draghi (Moessner and de Haan, 2022). In contrast, the most extreme peak in the US market was detected on March 17, 2020, when Wall Street witnessed one of its worst days in history, given the threat of a possible global recession in the near term.

Second, we highlight (with the red points in Figure (3.3)) the impact of the D-rated companies for the EU and US markets. Starting from the EU market (see Figure (3.3a)), on average, the D-rated companies continuously have the greatest systemic impact from January 2, 2017, to May 3, 2022. Indeed, $\overline{\Delta\text{QL-CoVAR}}_{t,\theta,\tau}^{(\text{D})} < \overline{\Delta\text{QL-CoVAR}}_{t,\theta,\tau}^{(k)}$ for $t = 1, \dots, T$ and $k \neq D$. The A-rated companies continuously record, on average, the second greatest systemic impact for $t = 1, \dots, T$. Therefore, the companies with extreme ESG classes (i.e., classes D and A) turn out to be, on average, more systemically relevant, consistent with the U-shape behavior of the boxplots given in Figure (3.2a). As for the US market (see Figure (3.3b)), the D-rated companies record, on average, the greatest systemic impact on 2819 out of 4000 days. The C-rated companies have, on average, the greatest systemic impact on the remaining 1180 days. The latter result might appear quite surprising, given the moderate values of $\widehat{\lambda}^{(j)}_{\theta,\tau}$ for class C in Figure (3.2b). However, in addition to $\widehat{\lambda}^{(j)}_{\theta,\tau}$, ΔQL-CoVAR$^{(j)}_{t,\theta,\tau}$ depends on other relevant components. For instance, we refer to $\widehat{Q}_\tau(x_{j,t}) - \widehat{Q}_{1/2}(x_{j,t})$: the risk of a given company when it moves from its median to its extreme τ-th quantile, regardless of the dynamics of y_t. Similar to the previous exercise, for each day t, we compute the mean of $\widehat{Q}_\tau(x_{j,t}) - \widehat{Q}_{1/2}(x_{j,t})$ estimated for those companies belonging to class k, with $k = \{A, B, C, D\}$.[10]

The full-sample analysis discussed so far provides important findings. However, it relies on time-invariant coefficients estimated from a relatively long interval spanning 16 years, characterized by a continuous alternation of stable and turbulent phases of the financial markets. Therefore, the effects of an important tail event would be smoothed by other events (possibly different in nature) along this long time interval and would not be properly captured using these full-sample coefficients. For this reason, we enrich our study with an additional exercise based on a shorter time interval. Among the different and relevant events we can consider from 2007 to 2022, we focus on the COVID-19 pandemic, as it has the greatest impact in terms of ΔQL-CoVAR$^{(j)}_{t,\theta,\tau}$ on both the EU and US markets. Specifically, we re-estimate the QL-CoVaR model using the data from March 3, 2020, to July 31, 2020 and evaluate the contribution of each ESG class by computing the $\overline{\Delta\text{QL-CoVAR}}^{(k)}_{t,\theta,\tau}$ time series, that we display in Figure (3.4). In contrast to the previous full-sample analysis, where we clustered the EU and US companies of our dataset according to $\overline{\text{ESG}}$, we now directly use the ESG scores of the year 2020 to be consistent with the sub-sample from which we obtain the new estimates. The systemic impact of class D in Figure (3.4) is clearer compared to Figure (3.3). Interestingly, the D-rated companies have, on average, the greatest impact on only 32 out of 109 days in Figure (3.4a). In contrast, the A-rated companies provide the lowest ΔQL-CoVAR$^{(j)}_{t,\theta,\tau}$ on 71 days. As a result, it might seem that the latter have a greater systemic relevance during the time interval March 3, 2020—July 31, 2020. However, if we focus on the most relevant peaks, as well as

[10] Similar results are obtained using the median instead of the mean as we observe a change of ESG class for less than 12% of the companies.

on other bearish phases, class D has the greatest impact, with relevant values of the difference $\overline{\Delta\text{QL-CoVAR}}^{(\text{D})}_{t,\theta,\tau} - \overline{\Delta\text{QL-CoVAR}}^{(k)}_{t,\theta,\tau}$ (with $k \neq D$). Moving to the US data, the D-rated companies have, on average, the greatest systemic impact on 89 out of 109 days.



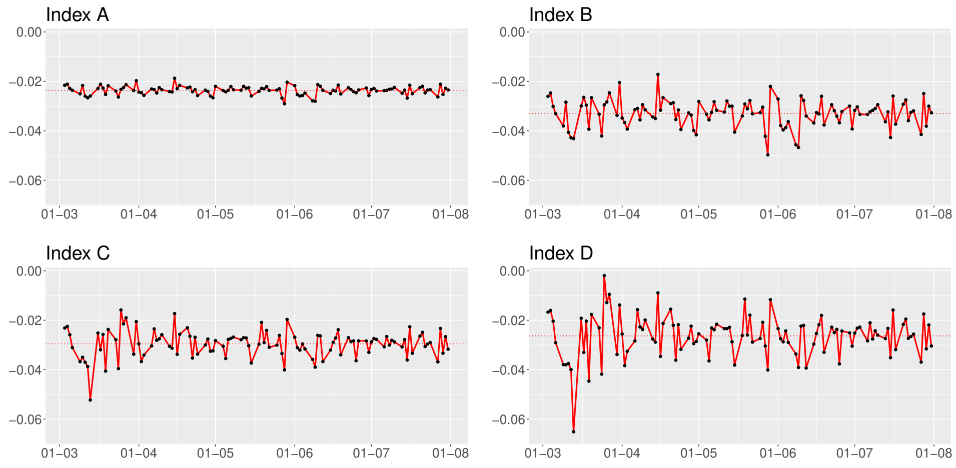
(a) EU companies

(b) US companies

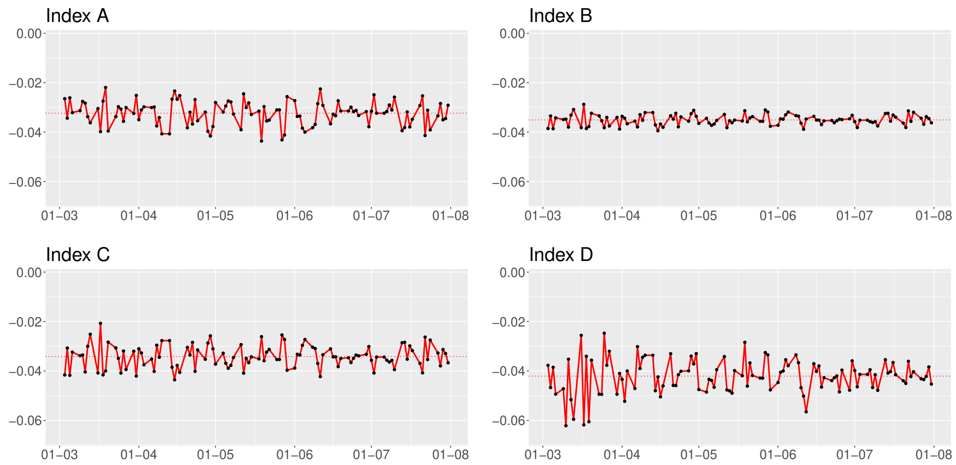
Figure 3.4: Average of $\Delta\text{QL-CoVAR}^{(j)}_{t,\theta,\tau}$ for the EU and US companies clustered by $\overline{\text{ESG}}$ classes: A (blue line), B (black line), C (green line) and D (red line and red points). The underlying QL-CoVaR model is estimated using the data observed from March 3, 2020, to July 31, 2020.

So far, we have evaluated the link between ESG and systemic relevance by estimating the QL-CoVaR model for each company in our dataset. In a second step, we aggregated the resulting estimates by ESG class. As a robustness analysis, we can also proceed differently, building on portfolio analysis. In a first step, we aggregate the individual companies into four indexes, according to their ESG scores observed in the year 2020, for both the EU and US markets. For instance, the constituents of Index A are the companies belonging to class A (i.e., the ones with ESG > 75). The return of Index A is computed as the weighted mean of the returns yielded by its constituents. The weight of each company is updated with a daily frequency and is calculated as its market capitalization observed on day t divided by the sum of the market capitalization of the other A-rated companies calculated on day t, for each day from March 3, 2020, to July 31, 2020. Likewise, we obtain the returns of

Indexes B, C, and D. In a second step, we then estimate ΔQL-CoVAR$^{(k)}_{t,\theta,\tau}$: the ΔQL-CoVaR that we obtain by replacing $x_{j,t}$ (i.e. the return of company j with the return of Index k, with $k \in \{A,B,C,D\}$. We display the results in Figure (3.5). We see that Index D has the greatest systemic impact during the outbreak of the COVID-19 pandemic in both the EU and US markets. It is interesting to see that the mean of ΔQL-CoVAR$^{(\mathrm{D})}_{t,\theta,\tau}$ in the bottom-right panel of Figure (3.5a) (depicted with the plotted-red line) is lower than the mean of ΔQL-CoVAR$^{(\mathrm{B})}_{t,\theta,\tau}$ and ΔQL-CoVAR$^{(\mathrm{C})}_{t,\theta,\tau}$ in the same figure. However, ΔQL-CoVAR$^{(\mathrm{D})}_{t,\theta,\tau}$ reaches the minimum value of -0.065 on March 13, 2020. ΔQL-CoVAR$^{(\mathrm{C})}_{t,\theta,\tau}$ also exhibits a relevant peak, but of a more moderate value of
-0.052 on the same day. In contrast, ΔQL-CoVAR$^{(\mathrm{B})}_{t,\theta,\tau}$ does not show any particular extreme value on March 13, 2020. ΔQL-CoVAR$^{(\mathrm{A})}_{t,\theta,\tau}$ continuously has a stable trend from March 3, 2020 to July 31, 2020 in the top-left panel of Figure (3.5a). Moving to the US market, ΔQL-CoVAR$^{(\mathrm{A})}_{t,\theta,\tau}$ and ΔQL-CoVAR$^{(\mathrm{C})}_{t,\theta,\tau}$ have a similar behaviour, whereas ΔQL-CoVAR$^{(\mathrm{B})}_{t,\theta,\tau}$ is more stable (see Figure (3.5b)).



(a) EU companies



(b) US companies

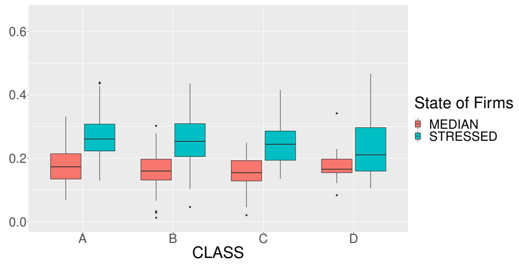
Figure 3.5: Trend of ΔQL-CoVAR$^{(k)}_{t,\theta,\tau}$, with $k \in \{A,B,C,D\}$ clustered by $\overline{\text{ESG score}}$. The underlying QL-CoVaR model is estimated using the data observed from March 3, 2020, to July 31, 2020.

3.5 Results for Individual E-, S-, and G-Pillars

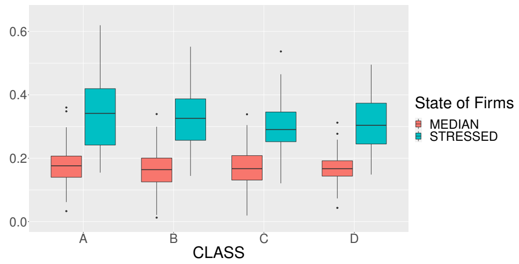
So far, we have analyzed the systemic impact of the EU and US companies in our dataset clustered by ESG scores. The ESG score of a given company is computed from three different components: the E-, S-, and G-Pillars. Hence, it is interesting to further develop our analysis by disentangling these three different pillars. Similar to Figure (3.1), we also find an increase in individual E-, S-, and G-Pillar scores throughout time as presented in Appendix B.1. Additionally, we point out that about a third to a half of the companies tend to change classes (A, B, C, or D) with a tendency towards higher levels (for instance, one company might be in ESG class C and equally in individual E-, S-, or G-Pillar class B), therefore, the results might differ when using the individual pillar scores.

Madison and Schiehll (2021) showed that the individual pillars might have a different sensitivity to materiality issues. Moreover, Lupu, Hurduzeu, and Lupu (2022) found that the impact of the individual pillars on systemic risk varies to a certain degree. Finally, according to the European Banking Authority (2021), especially the E-Pillar could significantly affect the overall financial system due to the scale and complexity of the environmental risks. It is worth taking a closer look at this additional analysis, the results of which are reported and discussed below.

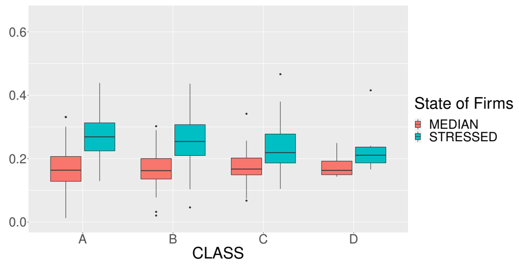
Following the same order adopted in Section 3.4, we start from the analysis of the $\widehat{\lambda}_{\theta,\tau}^{(j)}$ coefficients. Again, we cluster these coefficients according to the average scores of the individual EU and US companies, which are now computed for the three different pillars, denoted as $\overline{\text{E-Pillar}}$, $\overline{\text{S-Pillar}}$, and $\overline{\text{G-Pillar}}$, respectively. We display the results in Figure (3.6). Similar to the estimates depicted in Figure (3.2), $\widehat{\lambda}_{\theta,\tau}^{(j)}$ tends to be greater than $\widehat{\lambda}_{\theta,1/2}^{(j)}$. Therefore, we again have evidence that the relationships between the overall system and the conditioning companies become more relevant when both are in distress. The U-shaped behavior previously found in Figure (3.2) is again present when using the G-Pillar on the EU data in Figure (3.6e). In contrast, in the other cases, the median of $\widehat{\lambda}_{\theta,\tau}^{(j)}$ tends to decrease from higher to lower classes. Let's remember that the $\widehat{\lambda}_{\theta,\tau}^{(j)}$ coefficient quantifies the sensitivity of the ΔQL-CoVaR to $\widehat{Q}_{\tau}(x_{j,t}) - \widehat{Q}_{1/2}(x_{j,t})$; that is, the specific risk of company j when it moves from its median to its stressed state (see Equation (3.10)). As a result, on average, the systemic risk would react more readily to the idiosyncratic risks or shocks of higher E-, S-, and G-Pillar classes for a given value of $\widehat{Q}_{\tau}(x_{j,t}) - \widehat{Q}_{1/2}(x_{j,t})$. Nevertheless, as discussed in Section 3.4, moderate values of $\widehat{\lambda}_{\theta,\tau}^{(j)}$ could be offset by large values of $\widehat{Q}_{\tau}(x_{j,t}) - \widehat{Q}_{1/2}(x_{j,t})$ in determining the magnitude of the overall ΔQL-CoVaR measure. Focusing on the E-Pillar, we find larger variability in the $\widehat{\lambda}_{\theta,\tau}^{(j)}$ values of D-rated EU companies and A-rated US companies. Moving to the S-Pillar, D-rated companies show the lowest variability. It is also interesting to observe that the variability in the $\widehat{\lambda}_{\theta,\tau}^{(j)}$ values of both the EU and US companies is similar across the G-Pillar classes; see Figures (3.6e) and (3.6f).



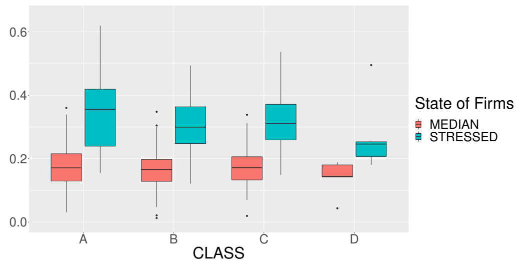
(a) EU companies - clustered by $\overline{\text{E-Pillar}}$ classes



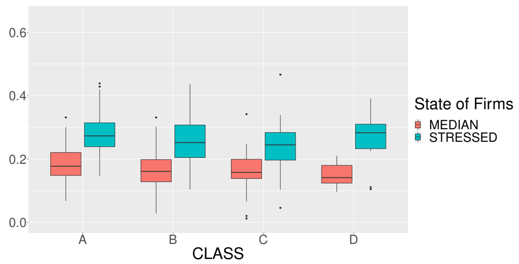
(b) US companies - clustered by $\overline{\text{E-Pillar}}$ classes



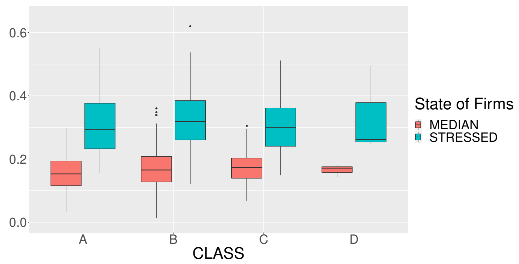
(c) EU companies clustered by $\overline{\text{S-Pillar}}$ classes



(d) US companies clustered by $\overline{\text{S-Pillar}}$ classes



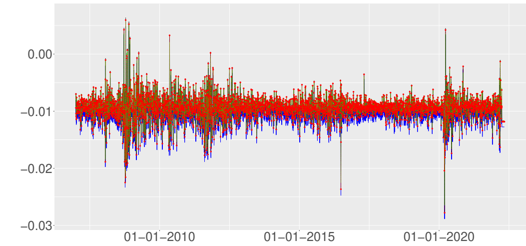
(e) EU companies clustered by $\overline{\text{G-Pillar}}$ classes



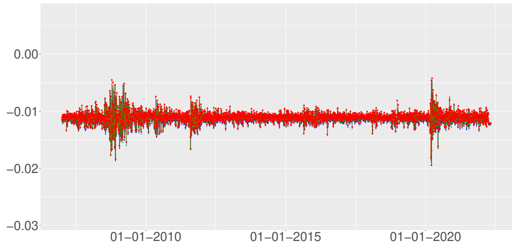
(f) US companies clustered by $\overline{\text{G-Pillar}}$ classes

Figure 3.6: Boxplots of $\widehat{\lambda}^{(j)}_{\theta,\tau}$ (STRESSED, cyan color) and $\widehat{\lambda}^{(j)}_{\theta,1/2}$ (MEDIAN, red color) estimated for the EU and US companies clustered by the individual pillar classes.

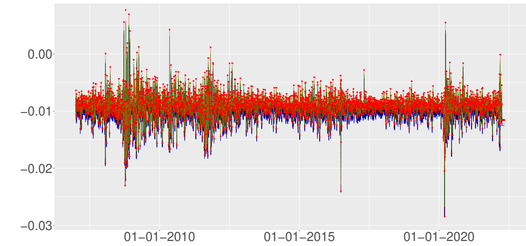
Similar to Figure (3.3), Figure (3.7) shows the time series of the cross-sectional mean of ΔQL-CoVAR$^{(j)}_{t,\theta,\tau}$ estimated for the EU and US companies. Using the individual E-, S–, and G-Pillars still allows us to identify the impact of important tail events, such as the sub-prime crisis, the EU sovereign debt crisis, and the COVID-19 outbreak. In Section 3.4, we saw that, on average, the D-rated companies have the greatest impact, followed by the A-rated companies (see Figure (3.3)). Now, the D-rated companies are the most critical contributors to systemic risk in the US market when employing the S- and G-Pillars (Figures (3.7d) and (3.7f)). However, the A-rated companies have a lower relevance in Figures (3.7d) and (3.7f). As for the EU market, the systemic relevance of the A- and D-rated companies is evident when adopting the E- and S-Pillars, mainly during the tail events mentioned above (Figures (3.7a) and (3.7c)).



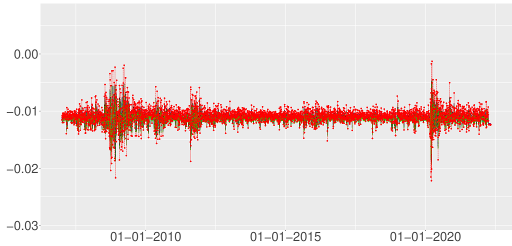
(a) EU companies - clustered by $\overline{\text{E-Pillar}}$ classes



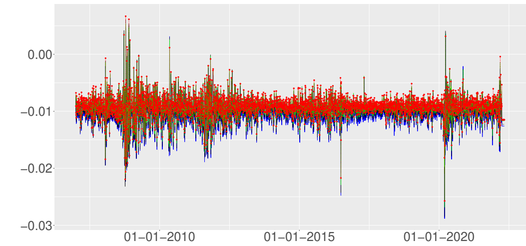
(b) US companies - clustered by $\overline{\text{E-Pillar}}$ classes



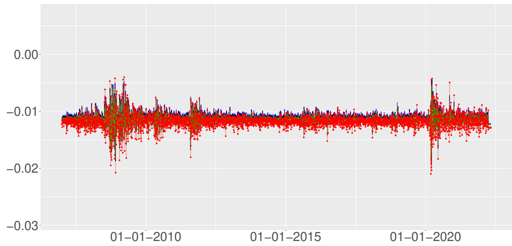
(c) EU companies clustered by $\overline{\text{S-Pillar}}$ classes



(d) US companies clustered by $\overline{\text{S-Pillar}}$ classes



(e) EU companies clustered by $\overline{\text{G-Pillar}}$ classes

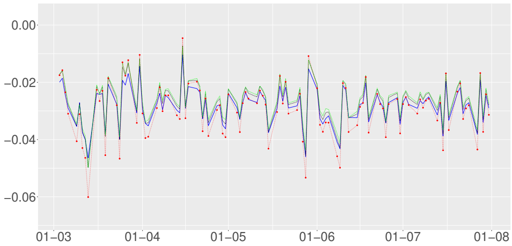


(f) US companies clustered by $\overline{\text{G-Pillar}}$ classes

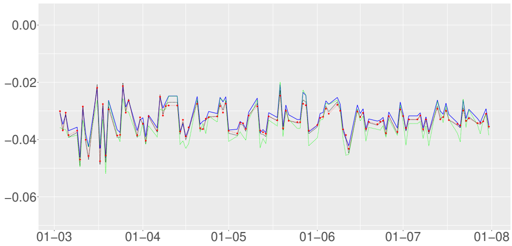
Figure 3.7: Average of ΔQL-CoVAR$^{(j)}_{t,\theta,\tau}$ for the EU and US companies clustered by individual pillar classes: *A* (blue line), *B* (black line), *C* (green line) and *D* (red line and red points).

The results discussed above build on the estimates obtained from the full-sample data. Now, we present the results based on the estimates derived from the COVID-19 period. We find that, during the COVID-19 pandemic, the results obtained from the overall ESG scores are similar to those using the E-, S-, and G-Pillar scores on the EU data, and for the S-Pillar score on the US data as presented in Figure (3.4). However, we find notable differences in the US data when clustering the companies according to the E- and G-Pillar scores (Figure (3.8b and 3.8f)). In Figure (3.8b), in which we focus on the E-Pillar score, *C*-rated companies show the highest systemic impact during the COVID-19 pandemic. In contrast, when considering the G-Pillar (Figure (3.8f)), companies in the highest (*A*) rating class show the highest systemic impact. We highlight the fact that this class includes the companies that are generally top performers on the topics of Management, Shareholders, and CSR.[11] Thus, better governance does not necessarily imply less systemic risk.

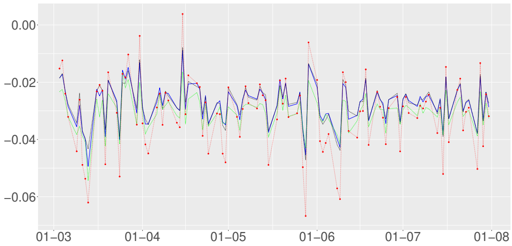
[11]The G-Pillar score includes these three main categories (Refinitiv, 2021).



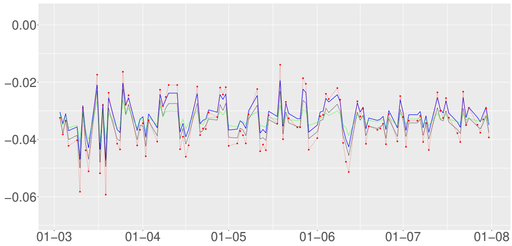
(a) EU companies - clustered by $\overline{\text{E-Pillar}}$ classes



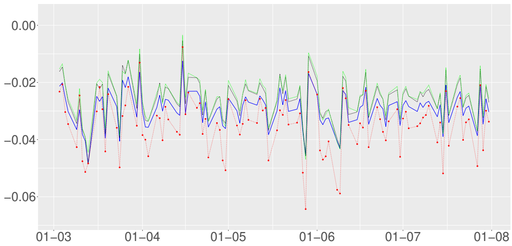
(b) US companies - clustered by $\overline{\text{E-Pillar}}$ classes



(c) EU companies clustered by $\overline{\text{S-Pillar}}$ classes



(d) US companies clustered by $\overline{\text{S-Pillar}}$ classes



(e) EU companies clustered by $\overline{\text{G-Pillar}}$ classes

(f) US companies clustered by $\overline{\text{G-Pillar}}$ classes

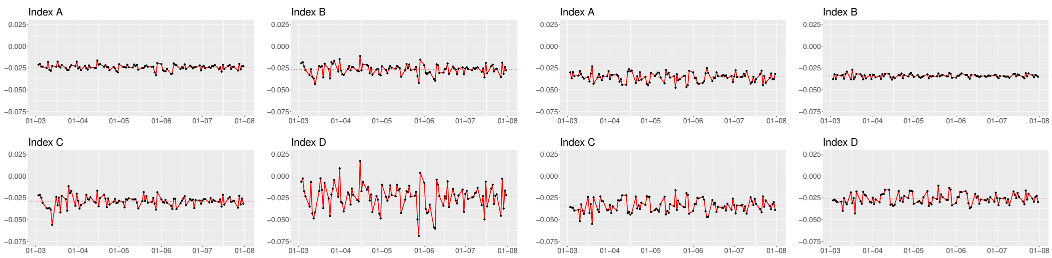
Figure 3.8: Average of ΔQL-CoVaR$^{(j)}_{t,\theta,\tau}$ for the EU and US companies clustered by the individual pillar classes: A (blue line), B (black line), C (green line) and D (red line and red points). The underlying QL-CoVaR model is estimated using the data observed from March 3, 2020, to July 31, 2020.

It is evident that the COVID-19 pandemic has impacted employees and employers and thus affected Management and CSR. Employees have reconsidered how they define the role of work in their lives and have raised their expectations towards their employer (Microsoft, 2022). These include the request for more flexibility and well-being. Additionally, 43% of the employees, especially Gen Z and millennials, are significantly more likely to change employers this year (Microsoft, 2022). As companies are already competing in the war for talent, possibly the threat of top performers leaving to work at a different company is more prominent in already responsible (i.e., high G-Pillar score) companies. Companies in lower categories might not be as severely affected as they are not competing for top performers in the first place.[12]

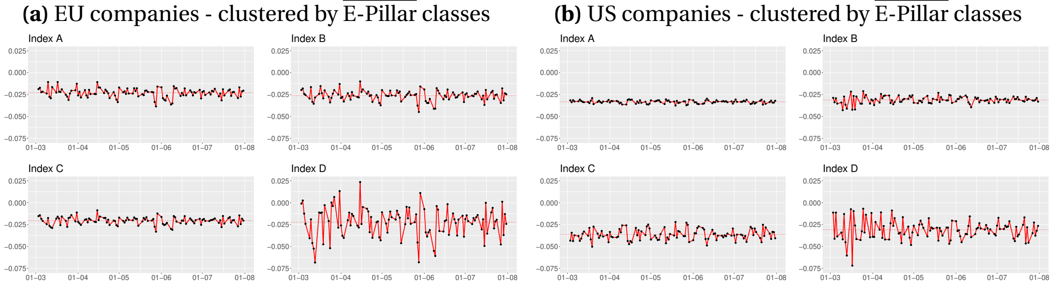
As a last analysis, we replace company j with the return of Index k, with $k \in \{A,B,C,D\}$.

[12]While aspects of employee relations are attributed to the S-Pillar (i.e., working conditions or career development), the G-Pillar also covers some aspects related to employees (i.e., compensation, committee structures, takeover defense).

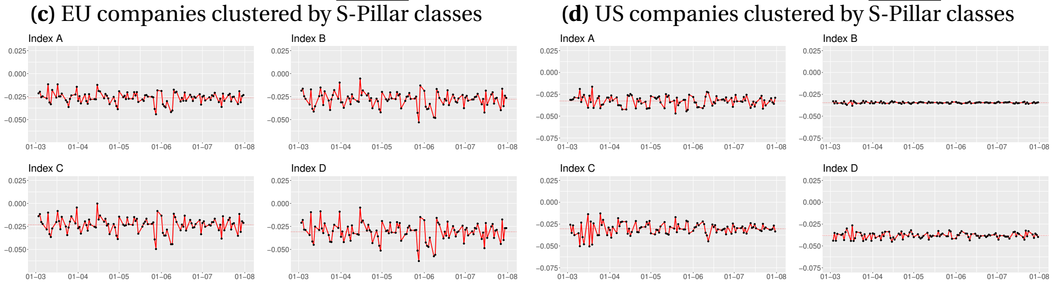
Now, in place of the mean ESG score, we use the mean of the individual pillar scores. Thus, for each pillar analysis, we have four indexes. Index A has low variability and impact in Figure (3.5). Now, for the E-Pillar (Figure (3.9b), top-left) on US data and the G-Pillar (Figure (3.9e) and (3.9f), top-left) on EU and US data, we find larger variability for higher-rated indexes. It is also notable that the US Index B shows negligible variability and systemic impact when adopting the G-Pillar scores (Figure (3.9f), top-right). The fact that Index A shows a high impact could result from the increased attention and possibly the increased expectations and change in the workforce, as discussed previously. Similar to the analysis based on the overall ESG scores, we find, for all individual pillars in the EU market and the E- and S-Pillars in the US market, large variability and systemic impact for the Index D. Finally, we highlight the relevant peak observed for Index D built from the S-Pillar scores in March 2020. This highlights the social effects of the lockdown due to the outbreak of the COVID-19 pandemic, which were more severe for those companies characterized by low S-Pillar scores.



(a) EU companies - clustered by $\overline{\text{E-Pillar}}$ classes **(b)** US companies - clustered by $\overline{\text{E-Pillar}}$ classes



(c) EU companies clustered by $\overline{\text{S-Pillar}}$ classes **(d)** US companies clustered by $\overline{\text{S-Pillar}}$ classes



(e) EU companies clustered by $\overline{\text{G-Pillar}}$ classes **(f)** US companies clustered by $\overline{\text{G-Pillar}}$ classes

Figure 3.9: Trend of ΔQL-CoVAR$^{(k)}_{t,\theta,\tau}$, with $k \in \{A,B,C,D\}$ clustered by individual pillar. The underlying QL-CoVaR model is estimated using the data observed from March 3, 2020, to July 31, 2020.

Overall, when looking at the individual pillars and the ESG score, we find a notable difference in the full sample as well as during the COVID-19 pandemic. Additionally, we find evidence of differences between the EU and US markets. In the EU market, especially the S- and G-Pillar show higher volatility compared to the ESG score for Index A during the COVID-19 pandemic. In contrast, we find some notable differences between the pillar and overall ESG scores in the US, especially when looking at the E- and G-Pillars during the COVID-19 pandemic.

3.6 Conclusion

The aim of this research is to analyze the relationship between ESG scores and systemic risk. We do so by estimating the QL-CoVaR proposed by Bonaccolto, Caporin, and Paterlini (2019). We contribute by enriching the discussion on systemic risk and ESG scores using a single data provider.

By relying on a large sample of EU and US companies over a long time period, we are able to compare different economic states within two different markets. We conclude by highlighting the main results. First, by contrasting $\widehat{\lambda}_{\theta,\tau}^{(j)}$ with $\widehat{\lambda}_{\theta,1/2}^{(j)}$, we found that the relationships between the overall system and the conditioning companies become more relevant when focusing on a state in which they both are in distress. This evidence is also supported by the comparison of $\widehat{\lambda}_{\theta,\tau}^{(j)}$ with $\widehat{\lambda}_{\theta}^{(j)}$ defined in Equation (3.5) for the CoVaR model (Adrian and Brunnermeier, 2016), with $\widehat{\lambda}_{\theta,\tau}^{(j)} > \widehat{\lambda}_{\theta}^{(j)}$.[13] On the one hand, $\widehat{\lambda}_{\theta,\tau}^{(j)}$ tends to follow a U-shape behavior across the ESG classes, suggesting greater sensitivity of the VaR of the system to the stressed state of those companies belonging to the extreme A and D classes. Nevertheless, the analysis of the overall ΔQL-CoVaR measure points out a greater systemic impact of the D-rated companies, whereas the A-rated companies have less relevant effects. This evidence is clearer when focusing on the sub-sample characterized by the outbreak of the COVID-19 pandemic. This result is also evident to a certain degree when clustering the individual companies into ESG indexes and estimating the systemic impact of the resulting portfolios. Additionally, we find opposite evidence when considering the G-Pillar score for the US data. While we are able to show various trends for the

[13] For the sake of space, we do not report here the estimates obtained from the estimation of the CoVaR model (Adrian and Brunnermeier, 2016). However, these estimates are available upon request.

EU and US companies, our results are mixed and could be improved by adding further statistical evidence.

These findings are relevant for investors, regulators, and policymakers when making investment decisions and setting regulations. High on the agenda is investigating possible spillovers and interactions of the different pillars that could "simultaneously disrupt multiple parts of the financial system" as stressed by the European Banking Authority (2021, p.33).

Further analysis could include considering other sustainability measures and industry-focused analysis. Additionally, it could be interesting to consider the effect of different regulations set in place, i.e., the Paris Agreement in 2015. Furthermore, additional analysis on causality and endogeneity effects including risk factors that may affect both ESG risk and systemic risk is high on the agenda.

Chapter 4

Do diverse and inclusive workplaces benefit investors?

An Empirical Analysis on Europe and the United States

This chapter is a single author chapter and a similar version of this chapter is published as
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Abstract

As the COVID-19 pandemic restrictions slow down, employees returning to their offices, bring reshaped wants and needs. Hence, the discussions on optimal workplaces and issues of diversity and inclusion have peaked. Previous research has shown that employees and companies benefit from positive workplace changes. This research questions whether allowing for diversity and inclusion criteria in portfolio construction is beneficial to investors. By considering the new Diversity & Inclusion (D&I) score by Refinitiv, I find evidence that investors might suffer lower returns and pay for investing in *responsible* (i.e., more diverse and inclusive) employers in both the US and European market.

4.1 Introduction

As infection rates are mostly static now, and the COVID-19 pandemic reaches an endemic stage[1], one can notice the fundamental changes made to how employees define the role of work in their lives (Microsoft, 2022). Since 2020, employees have increasingly re-evaluated their self-worth, prioritized health and well being over work, and re-considered time spend commuting to the offices (Microsoft, 2022). As the pandemic slows down, employers are starting to cautiously fill their offices again and focus on designing a productive workspace, creating incentives for employees to return, and trying to match the reshaped expectations of their employees (Refinitiv, 2022c). According to the EY 2021 Work Reimagined Employee Survey, most prominent is the request for extra flexibility in terms of when and where employees work (Ernst & Young, 2021). Trying to match these expectations is highly important as employees are more willing to change jobs and follow new opportunities (Ernst & Young, 2021).[2] By creating a diverse and inclusive workplace, companies are able to secure their competitive position in the war for talents.

While companies realized that diverse and inclusive environments create financial benefits, increase employee satisfaction, and build a productive working environment already prior to the COVID-19 pandemic[3], the discussion has now gained further traction.

More specifically, the discussion is subject on the newly introduced Diversity & Inclusion (D&I) score by Refinitiv (Refinitiv, 2022a). The score is built using 24 metrics defined on four main pillars linked to workplace well-being (Refinitiv, 2022a). These are: diversity (e.g., gender diversity and diversity process), inclusion (e.g., flexible working hours and daycare services), people development (e.g., internal promotion, employee satisfaction, and career development process), and news and controversies (e.g., diversity and opportunity and wages and working conditions) (Refinitiv, 2022a). The input data is gathered from publicly available sources, and an overall D&I score is computed. The D&I score ranges from 0 to 100, 0 indicating poor D&I performance. According to Refinitiv (2022a),

[1] See e.g., https://www.mckinsey.com/industries/healthcare-systems-and-services/our-insights/when-will-the-covid-19-pandemic-end

[2] In order to full-fill these expectations, companies try to offer on-site flexibility, new adaptable working schedules, and reward program and policy changes. To motivate employees to go back into the office, they have to feel welcome and comfortable at their workplace.

[3] These beneficial effects can take place either directly (Krapivin, 2018; Refinitiv, 2022c), indirectly through customer satisfaction (Chi and Gursoy, 2009), or in an investment setting (Mishra, 2018), and also help the organization to grow (Spreitzer and Porath, 2012).

this score shall provide insights into two main issues employers face: cultural diversity and workplace transition.

Different scholars have already shown that diversity can positively affect economic performance and firm value.[4] Others find mixed effects using a sample of Bangladesh companies (Dutta and Bose, 2006) and Italian companies (Gordini and Rancati, 2017). Additionally, diversity and inclusion have been linked to workplace happiness, productivity, and better performance in challenging situations (Frey and Stutzer, 2010; Warr, 2011; Arenas, 2017; Vasa and Thatta, 2018).

While this topic has been explored from a company management and human resource perspective, happiness and satisfaction can technically translate into higher financial performance measures through different channels (Kessler et al., 2020; Refinitiv, 2022c), including increased productivity (Utami, Suhartanto, Triyuni, et al., 2018) or employee well-being (Krekel, Ward, and De Neve, 2019). However, measuring and predicting workplace happiness can be complex and different measures and dimensions have been proposed.[5] For investors to whom the company might be a black box, gathering this kind of information is even more challenging. This is where the new D&I score could aid as a proxy for workplace happiness and diversity and become a first step in solving the measuring issue for investors (Refinitiv, 2022a).

While it is clear that a diverse and inclusive workplace setting benefits the employees and helps the company to grow, I question whether this setting can also directly benefit investors. More specifically, as the differences in the welfare social systems in Europe (EU) and in American (US) are so prominent (see e.g., Alber (2010), Vaughan-Whitehead (2003), and Wickham (2002)), I am focusing on comparing these two markets. Using different portfolio strategies including Minimum-Variance portfolio, Equally Weighted, and Market portfolio, I compare the out-of-sample performance and identify little to no difference between these markets but consistent difference between companies with high versus low D&I scores for both markets. More specifically, I find evidence that investors might have to suffer from lower returns when investing into companies with *responsible* employers

[4]See for diversity in general in the US (Erhardt, Werbel, and Shrader, 2003), diversity on boards in Spain (Campbell and Mínguez-Vera, 2008; Reguera-Alvarado, Fuentes, and Laffarga, 2017) and in Malaysia (Lee-Kuen, Sok-Gee, and Zainudin, 2017)), on top management teams in Denmark (Opstrup and Villadsen, 2015)).

[5]See Fisher (2010), Sirota and Klein (2013), Wesarat, Sharif, and Abdul Majid (2014), Mousa (2021), Arslan and Polat (2021), and Barak and Levin (2002).

(i.e., companies with high D&I scores) but might be rewarded for taking higher D&I risks (invest into companies with low D&I scores). This is evident in the US and in the European market.

The chapter proceeds as follows: Section 4.2 describes the methodology and the data. Section 4.3 elaborates results, and Section 4.4 concludes the study.

4.2 Methodology and data

I consider the most recent D&I scores, return data, and market capitalization weight data of 363 EU companies which are the constituents of the EURO STOXX 600 (STOXX) index, and 365 US companies which are the constituents of the Standard & Poor' (S&P) 500 index (SPX), whose observations are continuously available from January 3, 2020 to August, 31 2022. The return data, market capitalization, and the D&I scores were retrieved on September 16, 2022 from Refinitiv. The time period was chosen so that it includes the COVID-19 outbreak, the pandemic, and now the endemic stage. The reason for not including all constituents of these indices is that the D&I score is not available for every single company. While I include companies that have a zero score, I exclude companies that have no associated D&I score.[6] The datasets are similar in their descriptive statistics; nevertheless, the D&I scores of the constituents of the SPX show larger kurtosis and skewness as reported in the Appendix Tables C.1 and C.2. In both datasets, there are companies (48 companies for SPX and 74 companies for STOXX) that have a score equal to zero; the remaining companies have a score in the higher quartiles. According to Refinitiv (2022b), companies are only given a non-zero D&I score if they have non-zero scores on all four pillars. This means that companies with a zero score might, on some level, contribute to diversity and inclusion; however, not on all dimensions leading to a zero score. Furthermore, D&I scores are benchmarked against the country.[7] Therefore, employee benefits and diversity and inclusion efforts are not directly comparable across countries. However, the scores allow for an in-country comparison. More specifically, a high D&I score of a US company indicates that this company is performing better than most others in the USA in terms of diversity and inclusion. The same line of argumentation can be made for

[6] Indicated by Refinitiv as *NA*.
[7] Examples here are the sub metrics of the diversity pillar: *Percentage of females on the board* and the inclusion pillar: *Percentage of employees with disabilities or special needs* Refinitiv (2022b).

a company in Europe. However, if one directly compares both scores of the US and EU companies, it is problematic as the score indicates the relative performance within the respective origin. Due to the limitation of the scores as well as the differences in the welfare social systems in the EU versus the US, individual portfolios for the EU and US are created and their performance is compared.

I use the most recent D&I score to categorize the companies into different portfolios for each dataset, as also suggested recently for ESG scores by Cerqueti et al. (2021).[8] More specifically, to compare the effect of D&I scores on investors, four portfolios (from now on referred to as PT) are formed using evenly spaced cumulative probabilities to divide the companies into quartiles using the D&I score. This approach is similar to ESG portfolios, as companies can be attributed to a rating class (i.e., A, B, C, or D) based on its ESG score value using thresholds or quartiles. Using quartiles instead of thresholds allows to create similarly sized portfolios, making performance comparison more accurate. PT 1 contains the companies with the lowest D&I score while PT 4 contains the companies with the highest D&I score.[9]

The process of dividing the companies into different portfolios based on their D&I score is similar to the most prominent approach in ESG investing. According to Amel-Zadeh and Serafeim (2018), most investors use the ESG score to follow a negative screening approach. More specifically, companies with a low ESG score are excluded from the investment portfolio. The rational is that investors tend to believe that additional non-financial information is an indicator for different company risks, including reputational, legal, and regulatory risk (Amel-Zadeh and Serafeim, 2018). Also, Verheyden, Eccles, and Feiner (2016) showed that there is a positive effect of ESG screening resulting in improved risk-adjusted returns. As D&I scores also provide additional non-financial information to the investor, a similar approach is used here.

4.2.1 Alternative Portfolio Strategies

To examine the effect of different D&I scores for investors, I use the previously defined portfolios created by grouping the companies in quartiles according to their D&I score

[8] One reviewer pointed out that it would be more accurate to re-balance the portfolio periodically according to the corresponding D&I score. This is true and can be applied in future research, however, the data is right now not available from Refinitiv.

[9] The number of companies within the portfolios is equal to PT 1-4 = 91, 92, 93, 89 companies for the US portfolios and PT 1-4 = 91, 96, 86, 90 companies for the EU portfolios.

(PT 1-PT 4 US and PT 1-PT 4 EU) in combination with different portfolio construction methods to ensure the robustness of the results.

I consider a minimum variance (MV), an Equally Weighted (EW), and a Market Capitalization Weighted (MC) portfolio approach and analyze the out-of-sample returns. While the EW portfolio employs equal capital allocation between each company and the MC uses the market capitalization as weights, in the MV portfolio, the weights of the optimal minimum-variance portfolio are computed as a result of the minimization of the variance. The optimization problem can be stated as $min\ w^{\top}\hat{\Sigma}w$ subject to $1^{\top}w = 1$ and $w \geq 0$ with w being the $n \times 1$ vector of company weights, 1 a $n \times 1$ unit vector, and $\hat{\Sigma}$ the $n \times n$ covariance matrix.

4.2.2 Empirical Set-up and Performance Measures

For each portfolio set-up, a rolling window approach with different window sizes (ws) and a no short-selling constraint is implemented. The first number of returns specified in the ws are used to compute the estimates for the inverse covariance matrix. These are then used as inputs to compute the optimal weights w for the MV portfolios. For the EW and the MC portfolios, the weights are already predefined by the chosen strategy. The resulting portfolios for each strategy are assumed to be held for one day. Then, I roll the look-back window forward by one day. By doing so, I discard the oldest observation and include one new observation. This process is repeated until the end of the time series is reached. Using M out-of-sample returns, where r_{t+1} is defined as the vector of returns at time $t+1$, I evaluate the resulting portfolios in terms of risk and return profile and portfolio composition. Following this process, I generate for window size $ws = 50$, $M = 635$ out-of-sample returns for the EU portfolios and $M = 621$ out-of-sample returns for the US portfolios.[10]

To test the performance of the different portfolios, I use five different factor models to calculate the risk-adjusted abnormal performance of the EW, MV, and MC portfolio. This set up is inspired by Pavlova and Boyrie (2022). More specifically, I am using the following models: 1) CAPM, 2) Fama and French (1993) 3-factor model, 3) Carhart (1997)

[10]The analysis has been run additionally on $ws = 25, 84, 170$ and results are similar and available upon request from the author.

model 4) Fama and French (2015) 5-factor model, and 5) Fama-French 5-factor model plus momentum factor as by Pavlova and Boyrie (2022).[11] Thus, I get

$$
\begin{aligned}
&1) R_t - R_{ft} = \alpha + \beta_1 \left(R_{mt} - R_{ft}\right) + \varepsilon_t \\
&2) R_t - R_{ft} = \alpha + \beta_1 \left(R_{mt} - R_{ft}\right) + \beta_2 \left(SMB_t\right) + \beta_3 \left(HML_t\right) + \varepsilon_t \\
&3) R_t - R_{ft} = \alpha + \beta_1 \left(R_{mt} - R_{ft}\right) + \beta_2 \left(SMB_t\right) + \beta_3 \left(HML_t\right) + \beta_4 \left(MOM_t\right) + \varepsilon_t \\
&4) R_t - R_{ft} = \alpha + \beta_1 \left(R_{mt} - R_{ft}\right) + \beta_2 \left(SMB_t\right) + \beta_3 \left(HML_t\right) + \beta_4 \left(RMW_t\right) + \beta_5 \left(CMA_t\right) + \varepsilon_t \\
&5) R_t - R_{ft} = \alpha + \beta_1 \left(R_{mt} - R_{ft}\right) + \beta_2 \left(SMB_t\right) + \beta_3 \left(HML_t\right) \varepsilon_t + \beta_4 \left(RMW_t\right) + \beta_5 \left(CMA_t\right) + \beta_6 \left(MOM_t\right) + \varepsilon_t
\end{aligned}
\tag{4.1}
$$

where R_t is defined as the portfolio return at time t for the four different portfolios of either the EW, MC, or MV portfolio construction.

Then, $R_{mt} - R_{ft}$ is defined as the the excess return on the market, R_{ft} is the risk-free rate, SMB_t and HML_t are the size and value factors, respectively of 3-factor model by Fama and French (1993), while RMW_t and CMA_t are the profitability and investment factors of the Fama and French (2015) 5-factor model. Finally, MOM_t denotes the momentum factor and ε_t an error term.

4.3 Empirical Results

In order to ensure robustness of my results, I run the analysis on all three different portfolios strategies for each of the four portfolios. The out-of-sample return performance using the five factor models for the MC portfolios is reported in Tables 4.1 and 4.2, for the EW portfolios in Tables 4.3 and 4.4, and for the MV portfolios in Tables 4.5 and 4.6.

Starting with the PT 1 and PT 2 which include the companies with the lowest D&I scores, the significant alphas are found to positive with variation across the factor models. Also there is some variation in magnitude across portfolio strategy but the significant alphas remain positive. The results look quite different to the portfolios with higher D&I scores, namely PT 3 and PT 4. The significant alphas for these groups are negative with very little variation across factor models and across portfolio strategies. Also comparing US versus EU, I find little difference in the magnitude of the alphas for PT 3 and PT 4.

Moreover, for each portfolio strategy I find the largest absolute alpha for PT 1 for the CAPM, FF3, and FF5, while for the Cahart and FF5+Mom model the largest absolute alphas is always found for PT 2. This is evident in the US and EU market. It is also notable that

[11] Data used to estimate these models was retrieved on 21. September 2022 from https://mba.tuck.dartmouth.edu/.

for the MV portfolios, I find no significant alphas for PT 3, in the US and also in the EU market.

For both, the US and EU portfolios, these results suggest that investor who take higher D&I risk (invest into companies with lower D&I scores) may be rewarded with higher returns. Portfolios with higher D&I scores (PT 3 and PT 4) seem to underperform, i.e., alphas where mostly significant and negative.

Market Capitalization Portfolios

Portfolio	CAPM α	FF3 α	Cahart α	FF5 α	FF5 + MOM α
Portfolio 1	0.0633	0.0499	0.0005***	-0.0017***	0.0005***
Portfolio 2	0.0005***	0.0004***	-0.0287	0.0005***	-0.0197
Portfolio 3	-0.0008*	-0.0006	-0.0006	-0.0002	-0.0006
Portfolio 4	-0.0005***	-0.0004***	-0.0005***	-0.0006	-0.0005***

Table 4.1: Market Weighted Portfolio using the SPX data with $ws = 50$. Other ws are similar and available upon request from the author. *,**, *** p-values indicate significance at the 10%, 5%, and 1% level, respectively.

Portfolio	CAPM α	FF3 α	Cahart α	FF5 α	FF5 + MOM α
Portfolio 1	0.0309	0.0586	0.0005***	0.0225***	0.0005***
Portfolio 2	0.0005***	0.0005	-0.0162***	0.0005***	-0.0419
Portfolio 3	-0.0003	-0.0005**	-0.0005***	-0.0001***	-0.0005**
Portfolio 4	-0.0005***	-0.0005***	-0.0005***	-0.0005***	-0.0005***

Table 4.2: Market Weighted Portfolio using the STOXX data with $ws = 50$. Other ws are similar and available upon request from the author. *,**, *** p-values indicate significance at the 10%, 5%, and 1% level, respectively.

Equally Weighted Portfolios

Portfolio	CAPM α	FF3 α	Cahart α	FF5 α	FF5 + MOM α
Portfolio 1	0.0112	0.0290	0.0005***	0.0184***	0.0005***
Portfolio 2	0.0005***	0.0005***	-0.0181	0.0005***	-0.0373
Portfolio 3	-0.0004***	-0.0004***	-0.0004***	-0.0003***	-0.0004***
Portfolio 4	-0.0005***	-0.0005***	-0.0005***	-0.0004***	-0.0005***

Table 4.3: Equally Weighted Portfolio using the SPX data with $ws = 50$. Other ws are similar and available upon request from the author. *,**, *** p-values indicate significance at the 10%, 5%, and 1% level, respectively.

Portfolio	CAPM α	FF3 α	Cahart α	FF5 α	FF5 + MOM α
Portfolio 1	0.0274	0.0445	0.0005***	0.0238***	0.0005***
Portfolio 2	0.0005***	0.0005***	-0.0083	0.0005 ***	-0.0360
Portfolio 3	-0.0005***	-0.0005***	-0.0005***	-0.0002***	-0.0005 ***
Portfolio 4	-0.0005***	-0.0005***	-0.0005***	-0.0005***	-0.0005***

Table 4.4: Equally Weighted Portfolio using the STOXX data with $ws = 50$. Other ws are similar and available upon request from the author. *,**, *** p-values indicate significance at the 10%, 5%, and 1% level, respectively.

Mean Variance Portfolios

Portfolio	CAPM α	FF3 α	Cahart α	FF5 α	FF5 + MOM α
Portfolio 1	0.0380	0.0853	0.0004***	0.0228***	0.0005***
Portfolio 2	0.0005***	0.0004***	-0.0069	0.0004***	-0.0361
Portfolio 3	-0.0004	-0.0003	-0.0002	-0.0000	-0.0003
Portfolio 4	-0.0005***	-0.0004***	-0.0004***	-0.0002	-0.0005***

Table 4.5: Mean Variance Portfolio using the SPX data with $ws = 50$. Other ws are similar and available upon request from the author. *,**, *** p-values indicate significance at the 10%, 5%, and 1% level, respectively.

Portfolio	CAPM α	FF3 α	Cahart α	FF5 α	FF5 + MOM α
Portfolio 1	0.0417	0.0462	0.0005***	0.0225***	0.0005***
Portfolio 2	0.0005***	0.0005***	-0.0151	0.0005***	-0.0414
Portfolio 3	-0.0001	-0.0002	-0.0002	-0.0001	-0.0002
Portfolio 4	-0.0005***	-0.0005***	-0.0005***	-0.0002	-0.0005***

Table 4.6: Mean Variance Portfolio using the STOXX data with $ws = 50$. Other ws are similar and available upon request from the author. *,**, *** p-values indicate significance at the 10%, 5%, and 1% level, respectively.

From the empirical results, one can argue that investors have to pay more in order to invest into more diverse and inclusive companies. This is similar to the idea that investors have to pay to be green and higher ESG risks can be rewarded with higher returns (see i.e., Pavlova and Boyrie, 2022; Pástor and Vorsatz, 2020; Pyles, 2020), this concept could also apply for the D&I scores. One possible reason for these findings is the extensive effort companies have to take in order to fall into the high D&I score category. These include for example offering Day Care services and a large number of skill and career development trainings (Refinitiv, 2022a). Additionally, wages and working conditions are also also critically assessed when the D&I scores are computed (Refinitiv, 2022a). All of these variables mentioned, result in additional costs for the companies. Thus, they possibly negatively impact the overall financial performance of the companies. Nevertheless, the request for changes and flexibility have only recently gained momentum, and possibly in the future investors might be able to benefit from investing into companies with *responsible* employers. Technically, these companies should attract higher quality employees which in the end might be more productive and lead to a more qualified workforce.

Additionally, the need for periodic D&I scores is prominent and could also improve the analysis further.

4.4 Conclusion

In this new COVID-influenced world, diverse and inclusive work environments and employee satisfaction have gained importance. While research has already shown great benefits for employees and companies in general when adopting more diverse and inclusive strategies, in this chapter, I question whether a diverse and inclusive workplace can be taken into account by investors. Acting on this information became now significantly easier as Refinitiv's new D&I scores allow investors to easily gather information on the workplace culture of many different companies.

By creating portfolios with different mean D&I scores and using different portfolio strategies and window sizes, I find some evidence that abnormal returns are generally only notable for portfolios of lower-scoring (i.e., low D&I score) companies, while companies with high D&I scores tend to show no abnormal returns for investors. At this point, I conclude that investors cannot benefit from investing into companies with *responsible* employers. In order to improve the statistical evidence of the results, further statistical tests could be implemented in the future. Regulators should take these findings as incentives to foster change in order to steer investments into *responsible* employment which then hopefully benefits the investors as well as the employees.

Furthermore, these findings are, however, limited by the data availability of the D&I scores. There is a pressing need for periodic D&I scores which would make the analysis more accurate. Moreover, the chapter could be updated in the future when more data providers have published D&I scores.

Future research could look into differences within Europe and consider different periods to distinguish the effect in times of crisis. Additionally, it could be interesting to consider the time period prior to, during, and after COVID-19, when this chapter is finally closed. Furthermore, building a time series for D&I indicators is high up on the agenda.

Appendix A

ESG, Risk and Tail Dependence

A.1 Background on Copulas and Vine Copulas

In an effort to make Chapter 2 more easily to understand for the reader, I try to give a brief overview of the background of copulas and vine copulas. I refer to Czado (2019) for further information as the book is written for researchers novel to this area.

In order to fully understand what copulas and vine copulas are, one has to start by reviewing multivariate distributions. These distributions allow to describe the random behavior of several random variables. One can then differentiate between marginal, joint, and conditional distributions.[1]

Within this, there are different classes of distributions. For example, elliptical distributions is a well-known class of multivariate distributions which includes the multivariate normal and the multivariate multivariate Student's t-distribution.

While for univariate data, the shape can be easily explored using for example histograms, for multivariate data this is more complex. A starting point are pairwise plots, however, then the dependence structure between the variables is mixed with the marginal behavior of the variables (Czado, 2019). By normalizing the variables, one can extract the marginal effects on the dependence structure (Czado, 2019). Real data as also indicated in the example 1.9 in Czado (2019), can be characterized by different marginal distributions and non-symmetric dependencies between some variable pairs. In these cases, standard parametric distributions fail to accommodate different marginal distribution types since the marginal distributions belong to the same distributional class (e.g. Anderson et al. (1958)). Additionally, they do not account for asymmetry.

[1] Following the notation in Czado (2019) and in the main chapter, the marginal distribution functions and densities have a subscript j , while conditional distributions of X_j given X_k are indicated by subscripts $j|k$.

A more sensible and flexible approach for modeling multivariate data includes copulas, as they allow to model the margins individually. Concerning the different scales of variables, we can use the probability integral transform to standardize the variables (Czado, 2019). As we aim to represent the dependence between random variables with the common marginal distribution given by the uniform distribution, we separate the dependence between the components from the marginal distributions (Czado, 2019). To do so, the dependence between random variables with uniform margins has to be modeled by a corresponding joint distribution function, namely a copula (Czado, 2019).

Following from above and according to Czado (2019), we can define a copula C as a d-dimensional multivariate distribution function on the d-dimensional hypercube $[0,1]^d$ with uniformly distributed marginals. The corresponding copula density c can be obtained by partial differentiation $c(u_1,\ldots,u_d) := \frac{\partial^d}{\partial u_1 \ldots \partial u_d} C(u_1,\ldots,u_d)$ for all $\boldsymbol{u}$ in $[0,1]^d$.

As discussed in main Section 2.4, the copula approach has gained popularity due to Sklar's theorem (1959), which allows to model the marginal distribution and the dependence separately. Therefore, if F is a continuous d-dimensional distribution function of $\mathbf{X} = (X_1,\ldots,X_d)^\top$ with univariate cdf $F_p(x_p)$ of a continuous random variable X_p for $p = 1,\ldots,d$ with its realizations x_p, the joint distribution function F can be written as

$$F(x_1,\ldots,x_d) = C\Big(F_1(x_1),\ldots,F_d(x_d)\Big). \tag{A.1}$$

The corresponding density is

$$f(x_1,\ldots,x_d) = c\Big(F_1(x_1),\ldots,F_d(x_d)\Big) \cdot \prod_{p=1}^{d} f_p(x_p), \tag{A.2}$$

where c is the d-dimensional copula density of the random vector $\mathbf{F} = \big(F_1(X_1),\ldots,F_d(X_D)\big)^\top \in [0,1]^d$ and $f_p(x_p)$ is the associated univariate marginal density of $F_p(x_p)$ for $p = 1,\ldots,d$.

Taken from 1.9 in Czado (2019), the inverse also holds as the copula corresponding to a multivariate distribution function F with marginal distribution functions F_p for $p = 1,\ldots,d$ can be expressed as

$$C(u_1,\ldots,u_d) = F\left(F_1^{-1}(u_1),\ldots,F_d^{-1}(u_d)\right) \tag{A.3}$$

and its copula density or probability mass function is determined by

$$c(u_1,\ldots,u_d) = \frac{f\left(F_1^{-1}(u_1),\ldots,F_d^{-1}(u_d)\right)}{f_1\left(F_1^{-1}(u_1)\right)\cdots f_d\left(F_d^{-1}(u_d)\right)} \tag{A.4}$$

As different distribution functions exist, also different copula types exist. The different types include reflections and rotations, which allows them to accommodate flexible dependence patterns in the bivariate case ($d = 2$), as shown in the Appendix in Table A.3. More information is given in the main Section 2.4. For even more detailed information, I suggest to check Czado (2019).

From a traditional copula model, one can move seamlessly to a vine copula model (so-called pair copula constructions). The vines copula models allow for larger dimensions and to accommodate a great variety of dependence structures by using conditioning. They are a class of copulas, which are based on the conditioning ideas first proposed by Joe (1996) and further developed by Bedford and Cooke (2001) and Bedford and Cooke (2002). The approach allows the construction of any d-dimensional copula and its density by $\frac{d\cdot(d-1)}{2}$ bivariate copulas and their densities. Furthermore, this can be illustrated by an undirected graphical structure involving a set of linked trees, i.e., a *regular (R-)vine structure* (Bedford and Cooke, 2001). An example is given in Figure 2.3, and more details on R-vines and vine trees are given by Kurowicka and Cooke (2006), Kurowicka and Joe (2011), and Joe (2014); and Czado (2019). We define the inputs for the vine copula model further in the main text Section 2.4.2. Further information on how the model is fitted the choice of the bivariate copula families and the estimation of the copula parameters can be found in A.3 and A.4.

A.2 Notation and Computation

A.2.1 Data

We introduce the mathematical indices, data sets and their notations used in the paper.

Type of Data	Notation
Economics Sector	S= $1, \cdots, 10$
Trading day	$t = 1, ..., 3376$
Year	$y = 2007, \ldots, 2021$
Period	$q = 1, 2, 3, 4, 5$
ESG class Quartiles	$k \in \{A, B, C, D\}$
ESG score of asset j in year y	$ESG_{y,j}$
Log return of asset j on trading day t	$Y_{t,j}$
Log return of asset j in period q on trading day t belonging to ESG class k	$Y^q_{t,j,k}$
S&P 500 log return on trading day t in period q	$I^q_{t,M}$
Market capitalization weight of asset j (by 1.01.2015)	M_j
Mean ESG score of asset $j$and period q	$\overline{ESG}^q_j$
ESG class of asset j and period q per sector S	$K^{S,q}_j$
ESG class weight of asset j in period q	α^q_j
Values of ESG class k and period q at trading day t	$I^q_{t,k}$

Table A.1: Mathematical Indices, datasets, and their notation used in the paper.

As mentioned in Section 2.3, we worked with the mean ESG score and the corresponding ESG class of an asset j for period q. Accordingly, we calculated the assets' ESG class weights, which were then used to calculate their corresponding ESG class values, as defined in Table A.1. Their computations are given as follows.

A.2.2 Mean ESG score of asset j and period q ($\overline{ESG}^q_j$) :

$$\overline{ESG}^q_j = \frac{1}{|P_q|} \sum_{y \in P_q} ESG_{y,j} \quad \text{for} \quad \forall_{j,q}, \tag{A.5}$$

where $P_1 = [2007, 2009]$, $P_2 = [2010, 2012]$, $P_3 = [2013, 2015]$, $P_4 = [2016, 2018]$,$P_5 = [2019, 2021]$, and $|P_q|$ denotes the number of years in P_q.

A.2.3 Define ESG classes for each asset j within sector S and period q using quartiles ($K_j^{S,q}$) :

Assume $j^{S,q}$ contains asset j in sector S and period q based on their mean ESG scores $\overline{ESG}_j^q$, so that the assets are ordered non-decreasingly. To simplify notation we remove the indices S and q from the asset e.g., $l_1 = l_1^{S,q}$. n_s is defined as the total number of assets with in each sector S. Then, we define the ESG quartiles for Sector S in period q as follows:

We have $\forall_{j,S,q}$:

$$\begin{aligned} j^{S,q} &= \{l_1, \cdots, l_{n_s}\} \\ D^{S,q} &= \{l_1, \cdots, l_{n_{D_s}}\}, \quad \text{where} \quad n_{D_s} = \text{int}\left(\frac{n_s}{4}\right) \end{aligned} \tag{A.6}$$

$$C^{S,q} = \{l_{n_{D_s+1}}, \cdots, l_{n_{C_s}}\}, \quad \text{where} \begin{cases} n_{C_s} = 2 \cdot n_{D_s} + 1 & \text{if} \quad \text{mod}(n_s, 4) = 3 \\ n_{C_s} = 2 \cdot n_{D_s} & \text{else} \end{cases} \tag{A.7}$$

$$B^{S,q} = \{l_{n_{C_s+1}}, \cdots, l_{n_{B_s}}\}, \quad \text{where} \begin{cases} n_{B_s} = 3 \cdot n_{D_s} + 1 & \text{if} \quad \text{mod}(n_s, 4) = 2, 3 \\ n_{B_s} = 3 \cdot n_{D_s} & \text{else} \end{cases} \tag{A.8}$$

$$A^{S,q} = \{l_{n_{B_s+1}}, \cdots, l_{n_s}\} \tag{A.9}$$

$$K_j^{S,q} = \begin{cases} A, & \text{if } j \in A^{S,q}, \\ B, & \text{if } j \in B^{S,q}, \\ C, & \text{if } j \in C^{S,q}, \\ D, & j \in D^{S,q}. \end{cases} \tag{A.10}$$

ESG class weight of asset j in period q :

$$\alpha_j^q = \frac{M_j}{\sum\limits_{\substack{j' \in [1,n] \\ j' : K_{j'}^{S,q} = K_j^{S,q}}} M_{j'}} \quad \text{for} \quad \forall_{j,S,q}. \tag{A.11}$$

A.2.4 Values of ESG class k in period q at trading day t :

$$\boldsymbol{I}^q_{t,k} = \sum_{\substack{j' \in [1,n] \\ j' : K^{S,q}_{j'} = k}} \alpha^q_{j'} \cdot Y^q_{t,j',k} \quad \text{for} \quad \forall_{q,k} \quad \text{and} \quad t \in T_q, \tag{A.12}$$

where $T_1 = [1,755]$, $T_2 = [756,1510]$, $T_3 = [1511,2265]$, $T_4 = [2266,3019]$, $T_5 = [3020,3776]$.

A.3 Two-Step Inference for Margins

As financial data are strongly dependent on past values and not uniformly distributed on $[0,1]^d$, which is the necessary input for a copula, a two-step inference for margins (IFM) approach is followed. This approach as been investigated by Joe (2005). We follow a parametric marginal model and estimate the margins first, we then use the estimated marginal distributions to transform the data on the copula scale by defining the pseudo-copula data. This allows us to remove the marginal time dependence by utilizing standard univariate time series models and then proceed with standardized residuals obtained from these models. We fit a generalized autoregressive conditional heteroskedasticity (GARCH) model with Student t innovations to our data, allowing for time-varying volatility and volatility clustering.

Parameters	Notation
The set of trading days in period q	p_q with $p_0 = \emptyset$, $p_1 = \{1,\dots,1260\}$, $p_2 = \{1261,\dots,2517\}$, $p_3 = \{2518,\dots,3271\}$
S&P 500 log returns in period q	$\boldsymbol{I}^{M,q} = (I^M_{1+\lvert p_{q-1}\rvert},\dots,I^M_{\lvert p_{q-1}\rvert+\lvert p_q\rvert})^\top \in \mathbb{R}^{\lvert p_q\rvert}$
Matrix of log returns $Y_{t,j}$ in sector and period q for $T \in t_q$	$Y^q = [\boldsymbol{Y}_1,\dots,\boldsymbol{Y}_n] \in \mathbb{R}^{\lvert p_q\rvert \times n}$, where $\boldsymbol{Y}_{j'} = (Y_{1+\lvert p_{q-1}\rvert,j'},\dots,Y_{\lvert p_{q-1}\rvert+\lvert p_q\rvert,j'})^\top$, $j' \in [1,n]$
Data matrix for in period q	$X^q = [Y^q, \boldsymbol{I}^q, \boldsymbol{I}^q_A, \boldsymbol{I}^q_B, \boldsymbol{I}^q_C, \boldsymbol{I}^q_D] \in \mathbb{R}^{\lvert p_q\rvert \times P}$
Columns of the data matrix X^q	$d = 1,\dots,P$
Rows of the data matrix X^q	$i = 1,\dots,\lvert p_q\rvert$
Column d of the data matrix X^q	$\boldsymbol{X}^q_d = (X^q_{1,d},\dots,X^q_{\lvert p_q\rvert,d})^\top \in \mathbb{R}^{\lvert p_q\rvert}$
Conditional variance vector of $\boldsymbol{X}^q_{t,d}$ on trading day t	$(\sigma^q_{d,t})^2$
Estimated degree of freedom for $\boldsymbol{X}^q_{t,d}$	$\hat{\nu}_d$
Estimated covariance for $\boldsymbol{X}^q_d$ on trading day t	$\hat{\sigma}^2_{d,t}$
Estimated distribution function of the innovation distribution for time series $\boldsymbol{X}^q_{t,d}$	$\hat{F}^q_d(\cdot\,;\hat{\nu}_d)$
Estimated u-data for an observation $X^q_{t,d}$ in period q	$\hat{u}^q_{t,d}$ where $t \in T_q$

Table A.2: Notation of the GARCH and Copula model.

As an input of a R-vine model in period q, we have a data matrix X^q defined in Table A.2.

In period q, we fit a GARCH(1,1) model with appropriate error distribution for a marginal time series, $\boldsymbol{X}_d^q$, and estimate the parameters of the following model:

$$\varepsilon_{d,t}^q = \sigma_{t,d}^q \cdot z_t \qquad (\sigma_{d,t}^q)^2 = \gamma_0 + \gamma_1 \cdot (\varepsilon_{t-1,d}^q)^2 + \beta_1 \cdot (\sigma_{t-1,d}^q)^2 \tag{A.13}$$

where $(z_t)_{t>1}$ is a sequence of normal random independent and identically distributed random variables satisfying the standard assumptions $E[z_t] = 0$ and $var[z_t] = 1$ and follows a Student's t distribution. Then, using the cumulative distribution function of the standardized Student's t distribution, we determine the *pseudo-copula data* with the probability integral transformation (PIT), i.e.

$$\hat{u}_{t,d}^q := \hat{F}_d\left(\frac{X_{t,d}^q}{\hat{\sigma}_{t,d}}; \hat{\nu}_d\right). \tag{A.14}$$

Following this two-step approach allows us to convert data to the copula scale, which serves as the input for our R-vine copula ESG risk model.

A.4 Choosing the Bivariate Copula Families and Estimating the Copula Parameters

Then, from the set of bivariate copula families in Table A.3, the optimal pair copula families for the variable pairs are selected using the Akaike Information Criterion (AIC) (Akaike, 1998), which has been shown to have good copula family selection properties and high accuracy (Brechmann, 2010). Since each pair copula family can be specified sequentially and independently at the same tree level, an alternative selection criteria like the BIC would not be needed to induce sparsity at this step. In the next step, we compute the pseudo copula data as defined in A.3 and also more detailed in Czado (2019) for the second tree level T_2, using the estimated pair copulas in the first tree level T_1. This input data is similarly used to select the second tree level T_2 of the vine and corresponding pair copula families with their parameters. The approach continues sequentially up to the last tree level. Following this method, we select the pair copula families, fit the five vine trees, and estimate the parameter values. As we choose a pair copula family corresponding to each edge separately, the parameter estimation step is at most a two-dimensional optimization, which is computationally efficient. Moreover, the performance of this method is satisfactory compared to the full log likelihood method, which could be computationally intractable in high dimensions (Haff, 2012). More details about R-vines and vine trees are given by Kurowicka and Cooke (2006), Kurowicka and Joe (2011), and Joe (2014); and Czado (2019).

	Itau[1] Copulas							BB Copulas		
Properties	*t*	*F*	*N*	*C*	*J*	*G*	***I***	*BB1*	*BB7*	*BB8*
Positive Dependence	✓	✓	✓	✓	✓	✓	-	✓	✓	✓
Negative Dependence	✓	✓	✓	-	-	-	-	-	-	-
Tail Asymmetry	-	-	-	✓	✓	✓	-	✓	✓	✓
Lower Tail Dependence	✓	-	-	✓	-	-	-	✓	✓	-
Upper Tail Dependence	✓	-	-	-	✓	✓	-	✓	✓	✓

Table A.3: Parametric copula families and their properties without rotations and reflections. Notation of copula families:t = Student's t, F = Frank, N = Gaussian, C = Clayton, J = Joe, G = Gumbel, ***I*** = Independence, BB1 = Clayton- Gumbel, BB7 = Joe-Clayton, BB8= Extended Joe.
[1]Copula families for which the parameter estimation by Kendall's τ inversion is available without rotations.

To extend the range of dependence, counterclockwise rotations and reflections of the copula density are included. This allows the Gumbel, Clayton, Joe, BB1, BB7 and BB8 to also accommodate negative dependence ($\tau < 0$). For more details, we refer to Chapter 3 of Czado (2019).

A.5 Model Fit

A.5.1 mBIC for vines as defined by Nagler, Bumann, and Czado (2019)

As the number of estimation parameters in vine copula models increase quadratically with the dimension, Nagler, Bumann, and Czado (2019) propose a modified Bayesian information criterion (mBIC). This reduces the computational burden and risk of overfitting. In the following, I am going to give a brief overview of its definition as defined by Nagler, Bumann, and Czado (2019), for further information I refer to their published paper.

The scholars consider a vine copula model with density c^η that is characterized by a finite-dimensional parameter η and denote the number of parameters in the model by ν.

The maximal model contains $q_{\max} = d(d-1)/2$ non-independence copulas. A sparse vine copula model contains many independence copulas and, thus, only few non-zero parameters. Let $q = \#\{\eta_e : \eta_e \neq 0, e \in \{E_1, \ldots, E_{d-1}\}\}$ be the number of non-independence copulas in the model. The authors define a sparse model if $q \ll q_{\max}$ or, asymptotically, $q/q_{\max} \to 0$ as $d \to \infty$.

Then letting $\boldsymbol{u}_1, \dots, \boldsymbol{u}_n \in [0,1]^d$ be a random sample and $\hat{\eta}$ be the estimated parameter. The Bayesian information criterion (BIC) is defined as

$$\mathrm{BIC}(\widehat{\eta}) = -2\ell(\widehat{\eta}) + \widehat{\nu} \ln n \tag{A.15}$$

where $\ell(\widehat{\eta}) = \ln c^{\widehat{\eta}}(\boldsymbol{u}_1) + \cdots + \ln c^{\widehat{\eta}}(\boldsymbol{u}_n)$ denotes the log likelihood and $\widehat{\nu}$ is the number of non-zero parameters in $\widehat{\eta}$ as in Nagler, Bumann, and Czado (2019). The more favorable model is characterized by the lowest BIC. The BIC is derived from a Bayesian argument stating that the posterior log probability of a model is proportional to

$$-2\ell(\widehat{\boldsymbol{\eta}}) + \widehat{\nu} \ln n - 2 \ln \psi(\widehat{\boldsymbol{\eta}}) + O_p(n), \tag{A.16}$$

where $\psi(\widehat{\eta})$ is the prior probability of the model $c^{\widehat{\eta}}$ and the $O_p(n)$ term is independent of the model choice (Nagler, Bumann, and Czado, 2019).

Now, the authors define the mBIC by assigning each pair-copula a prior probability ψ_e of not being independence.

Furthermore, they assume that the indicators $I_e = \mathbf{1}\left(\eta_e \neq 0\right)$ are independent Bernoulli variables with mean ψ_e and propose to choose $\psi_e = \psi_0^m$ for any edge in tree T_m. The resulting prior probability of a vine copula model c^{η} is

$$\psi(\eta) = \prod_{m=1}^{d-1} \psi_0^{m q_m} \left(1 - \psi_0^m\right)^{d-m-q_m}, \tag{A.17}$$

where q_m is the number of non-independence copulas in tree m. Now following the process of adjusting the prior probabilities in Equation (A.16) such that sparse models are more likely than dense models, the following criterion is suggested by the authors

$$\mathrm{mBIC}(\widehat{\eta}) = -2\ell(\widehat{\eta}) + \widehat{\nu} \ln n - 2 \sum_{m=1}^{d-1} \left\{ \widehat{q}_m \ln \psi_0^m + \left(d - m - \widehat{q}_m\right) \ln\left(1 - \psi_0^m\right) \right\}, \tag{A.18}$$

where $\ell(\widehat{\boldsymbol{\eta}}) = c^{\widehat{\eta}}(\boldsymbol{u}_1) + \cdots + c^{\widehat{\eta}}(\boldsymbol{u}_n)$ is the log-likelihood and $\widehat{q}_m$ is the number of non-independence copulas in tree m of the fitted model $\widehat{\eta}$.

In their work, they show that the mBIC can consistently distinguish between the true and alternative models. For more details, we refer to Nagler, Bumann, and Czado (2019).

A.5.2 mBIC of the R-vine copula ESG risk model with three specifications

Comparison of the *itau* and *parametric* and *Gaussian* R-vine models.

YEAR	FAMILIES	NOBS	NPAR	LOGLIK	MBIC
2007-2009	par	757	2070	69 233.38	−116 287.26
	itau	757	2028	69 266.01	**-116588.55**
	gaus	757	1660	64 502.14	−109 127.56
2010-2012	par	754	1962	56 833.03	**-92192.43**
	itau	754	1900	55 888.45	−90 686.61
	gaus	754	1660	51 592.32	−83 314.53
2013-2015	par	756	1928	74 742.43	−128 328.19
	itau	756	1799	74 441.97	**-128575.81**
	gaus	756	1660	69 693.29	−119 512.07
2016-2018	par	754	2095	93 963.51	−165 526.41
	itau	754	2028	94 026.62	**-166065.44**
	gaus	754	1660	86 758.32	−153 646.53
2019-2021	par	755	1917	89 252.28	**-157394.91**
	itau	755	1969	86 613.67	−151 639.51
	gaus	755	1660	81 267.43	−142 662.54

Table A.4: Model fit for each model at different time interval q- decision measure mBIC (Nagler, Bumann, and Czado, 2019). Additional information are available upon author request.

A.5.3 Copula Families Estimated from 7 different copula families and their rotations

	Itau Copula Families					Parametric Copula Families				
Year	2007-2009	2010-2012	2013-2015	2016-2018	2019-2021	2007-2009	2010-2012	2013-2015	2016-2018	2019-2021
Students t	288	316	265	290	311	235	265	234	252	243
Clayton	0	0	0	1	0	0	0	0	0	0
Frank	21	5	35	21	8	8	3	13	12	3
Gaussian	2	0	10	10	9	1	0	9	7	7
Gumbel	1	2	12	4	3	1	1	6	2	1
Independence	0	0	0	0	0	0	0	0	0	0
Joe	0	0	0	0	0	0	0	0	0	0
Clayton 90°	0	0	0	0	0	0	0	0	0	0
Gumbel 90°	0	0	0	0	0	0	0	0	0	0
Joe 90°	0	0	0	0	0	0	0	0	0	0
Clayton 180°	0	0	0	0	0	0	0	0	0	0
Gumbel 180°	21	11	12	8	3	10	4	2	4	0
Joe 180°	0	0	0	0	0	0	0	0	0	0
Clayton 270°	0	0	0	0	0	0	0	0	0	0
Gumbel 270°	0	0	0	0	0	0	0	0	0	0
Joe 270°	0	0	0	0	0	0	0	0	0	0
BB1	0	0	0	0	0	31	16	16	32	41
BB6	0	0	0	0	0	0	0	0	0	0
BB7	0	0	0	0	0	2	3	1	2	13
BB8	0	0	0	0	0	0	0	0	0	0
BB1 90°	0	0	0	0	0	0	0	0	0	0
BB6 90°	0	0	0	0	0	0	0	0	0	0
BB7 90°	0	0	0	0	0	0	0	0	0	0
BB8 90°	0	0	0	0	0	0	0	0	0	0
BB1 180°	0	0	0	0	0	11	29	5	6	12
BB6 180°	0	0	0	0	0	0	0	0	0	0
BB7 180°	0	0	0	0	0	2	5	0	2	3
BB8 180°	0	0	0	0	0	33	8	48	15	11
BB1 270°	0	0	0	0	0	0	0	0	0	0
BB6 270°	0	0	0	0	0	0	0	0	0	0
BB7 270°	0	0	0	0	0	0	0	0	0	0
BB8 270°	0	0	0	0	0	0	0	0	0	0

Table A.5: Bivariate copula families and independence copula fitted for Tree 1 (T_1). Only copula families which are chosen at least once are presented. In case of only Gaussian copula families, 334 copulas are fitted in each period. Additional vine trees are available upon author request.

A.6 Additional Information on Risk Measures

A.6.1 Standard Deviation of Risk Measures

Time periods	ESG Risk				Market Risk				Idiosyncratic Risk			
	A	B	C	D	A	B	C	D	A	B	C	D
2007-2009	0.084	0.073	0.100	0.074	0.083	0.078	0.058	0.080	0.083	0.074	0.079	0.073
2010-2012	0.095	0.076	0.065	0.095	0.062	0.073	0.078	0.051	0.077	0.077	0.067	0.088
2013-2015	0.077	0.065	0.070	0.100	0.060	0.050	0.069	0.040	0.082	0.069	0.058	0.092
2016-2018	0.105	0.096	0.073	0.121	0.054	0.102	0.067	0.065	0.101	0.112	0.092	0.091
2019-2021	0.127	0.099	0.108	0.148	0.056	0.052	0.085	0.114	0.133	0.110	0.130	0.117

Table A.6: Standard deviation values for ESG risk, Market Risk and Idiosyncratic Risk for each ESG Class k in time interval q using the best fitting model.

Time periods	Lower ESG Risk				Lower Market Risk				Lower Idiosyncratic Risk			
	A	B	C	D	A	B	C	D	A	B	C	D
2007-2009	0.116	0.162	0.139	0.136	0.057	0.164	0.188	0.204	0.113	0.135	0.115	0.103
2010-2012	0.079	0.124	0.157	0.056	0.066	0.099	0.149	0.049	0.079	0.105	0.099	0.041
2013-2015	0.175	0.155	0.139	0.159	0.218	0.114	0.158	0.213	0.184	0.119	0.150	0.099
2016-2018	0.224	0.186	0.223	0.249	0.236	0.183	0.213	0.170	0.159	0.120	0.161	0.228
2019-2021	0.191	0.206	0.192	0.192	0.0123	0.072	0.067	0.275	0.191	0.214	0.207	0.122

Table A.7: Standard Deviation values for lower tail ESG risk, Market Risk and Idiosyncratic Risk for each ESG Class k in time interval q using the best fitting model.

A.7 Individual Pillar Risk

As in this work we provide a method on how to model different ESG risk dependence, we use this section to given an example of the individual E-, S-, G-Pillar risk. The computational steps to compute the individual E-, S-, G-Pillar risk are the same as the ESG risk in Equation (2.3) apart from using the E-, S-, G-Pillar scores instead of the ESG score to categorize the assets into different groups. It is important to note that the class membership changes with ESG, E-, S-, G-Pillar, and time. In order to be able to better compare the different ESG, E-, S-, G-Pillar risks we have presented them below. One can see that the overall ESG risk and E-Pillar risk are very similar when looking at the magnitude as well as the distribution among ESG or E-Pillar classes. The S-Pillar and G-Pillar risk is higher in magnitude and the ordering within S-Pillar and G-Pillar according to the different quartiles is different compared the overall ESG risk and E-Pillar risk .

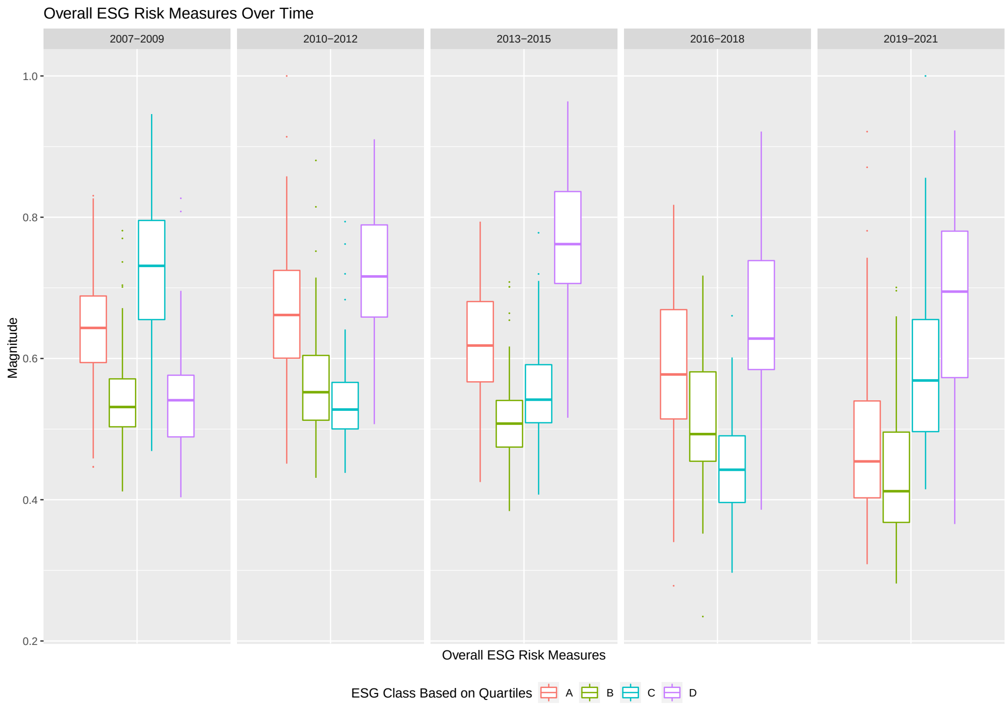

Figure A.1: Overall ESG risk measures for each time interval q using quartiles for ESG classes as presented already in Figure (2.4).

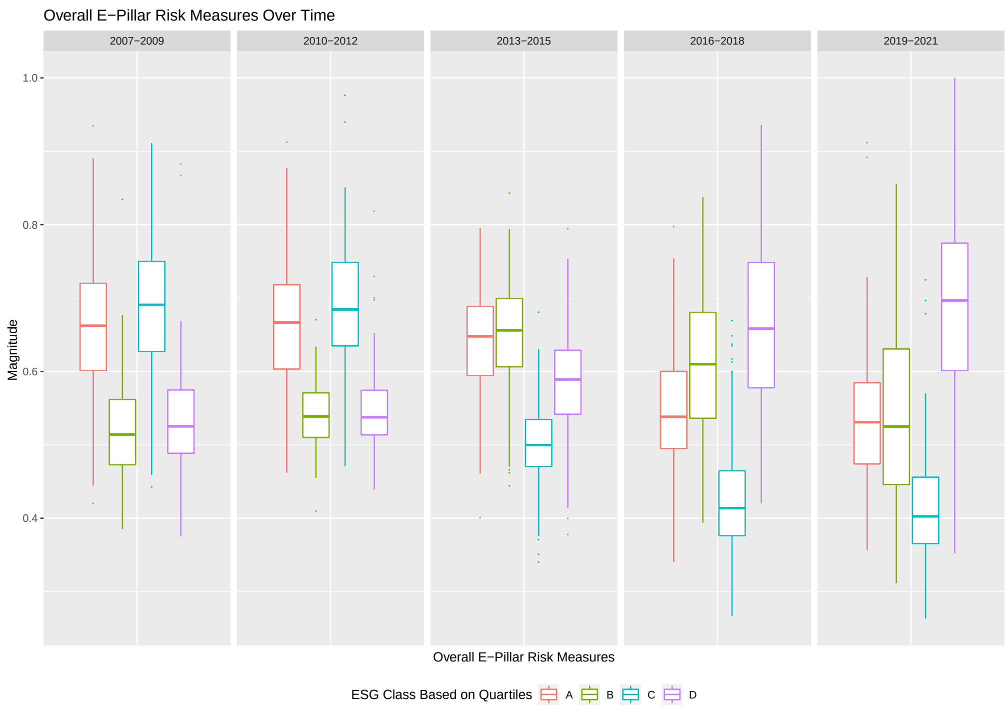

Figure A.2: Overall E-Pillar risk measures for each time interval q using quartiles for ESG classes as presented already in Figure (2.4).

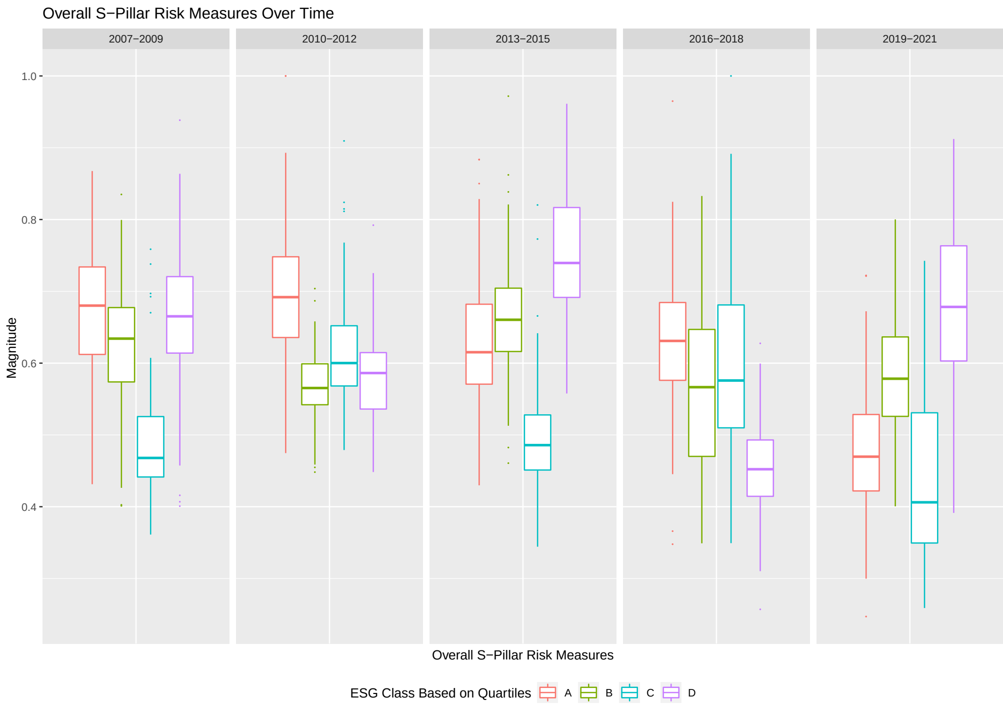

Figure A.3: Overall S-Pillar risk measures for each time interval q using quartiles for ESG classes as presented already in Figure (2.4).

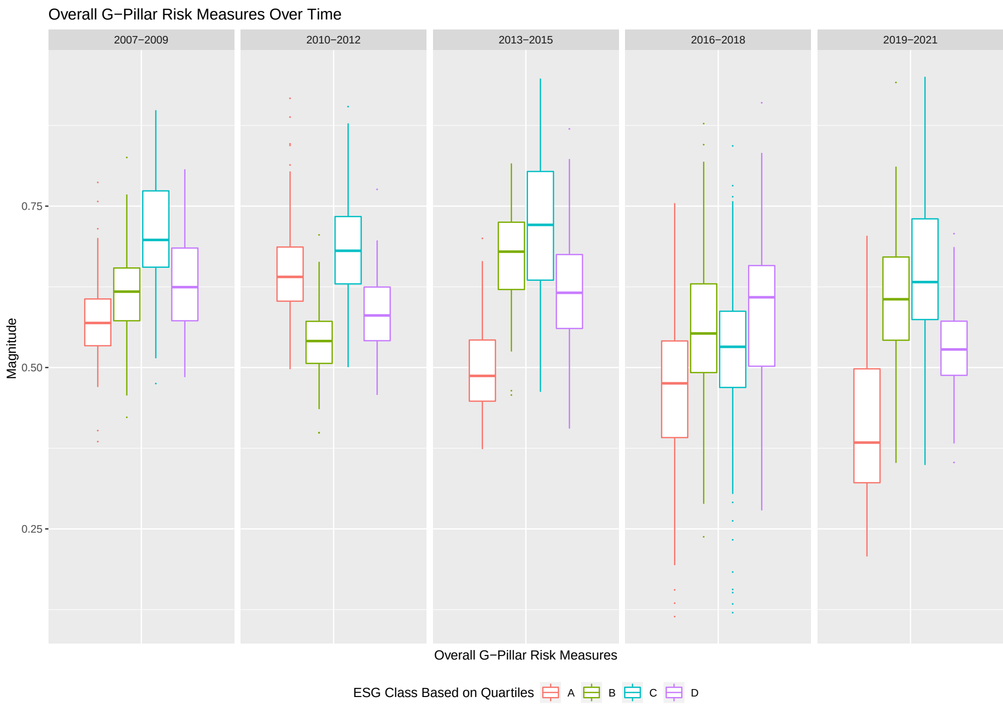

Figure A.4: Overall G-Pillar risk measures for each time interval q using quartiles for ESG classes as presented already in Figure (2.4).

A.8 Causality Analysis

Methodology

From the theory and literature we can see that possibly there could be a causal relationship between ESG and risk. In the following, we provide the additional steps for the causal analysis in Section 2.6

Causality - Compare the means

We have followed the approach of comparing the means suggested by Giese et al. (2019) to get an indication of the relationship of our new ESG risk dependence measure from our model and the ESG scores (and later using the individual E-, S-,G-Pillar scores). Thus, we hypothesize if an increase/decrease in ESG scores leads to a lower/higher ESG risk dependence. To do so, we have chosen to group the assets according to the difference in their mean ESG score over one period to another. The mean per period is computed using each ESG score per year within that period. The periods are defined as $q_1 = 2007-2009$, $q_2 = 2010-2012$, $q_3 = 2013-2015$, $q_4 = 2016-2018$, and $q_5 = 2019-2021$.

$$\Delta\overline{ESG}_J^{q,q-1} = \overline{ESG}_J^{q} - \overline{ESG}_J^{q-1} \quad \text{for} \quad q = 2,\cdots,5 \quad \text{and} \quad J = 1,\cdots,330. \tag{A.19}$$

Therefore, for each asset J and time period q we compute $\Delta\overline{ESG}_J^{2,1}, \Delta\overline{ESG}_J^{3,2} \Delta\overline{ESG}_J^{4,3} \Delta\overline{ESG}_J^{5,4}$.

For example, here if we look here at the imaginary asset 1. The mean ESG score in time period q is equal to 50, while the mean ESG score in time $q-1$ has been equal to 40.

$$\begin{aligned} \overline{ESG}_1^{q} &= 50 \\ \overline{ESG}_1^{q-1} &= 40 \\ \Delta\overline{ESG}_1^{q,q-1} &= 10 \end{aligned} \tag{A.20}$$

The difference in their mean ESG score over these two periods is then 10, as there was an increase from period $q-1$ to period q. Asset 1 is then categorized in the *increase* category

- *Group 0*. We divide all 330 assets into these two groups (the detailed number of assets per group can be found in Table A.11).

$$\begin{aligned} G_0^{q,q-1} &= \{J : \Delta\overline{ESG}_J^{q,q-1} > 0\} \quad \text{for} \quad q = 2, \cdots, 5, \\ G_1^{q,q-1} &= \{J : \Delta\overline{ESG}_J^{q,q-1} < 0\} \quad \text{for} \quad q = 2, \cdots, 5. \end{aligned} \tag{A.21}$$

We then get two groups $G_0^2, G_0^3, G_0^4, G_0^5$ and $G_1^2, G_1^3, G_1^4, G_1^5$ for each time period q.

Next, we compute the difference in the ESG risk dependence measure, which we have introduced in the paper Equation (2.3), of consecutive time periods as

$$\Delta DR_J^{ESG,q,q-1} = R_J^{ESG,q} - R_J^{ESG,q-1} \quad \text{for} \quad q = 2, \cdots, 5 \quad \text{and} \quad J = 1, \cdots, 330. \tag{A.22}$$

We then group the assets according to the difference in their mean ESG scores (see Equation A.15). More specifically, DR_0^q includes all the $\Delta DR_J^{ESG,q,q-1}$ values (differences in our risk dependence measure R_J^{ESG}) of all assets that have been categorized into the *increase* group $G_0^{q,q-1}$, for which the mean ESG score has improved from one period to another. DR_1^q includes all the values of differences in the risk measure $\Delta DR_J^{ESG,q,q-1}$ for assets for which the ESG scores has decrease from one period to another and, therefore, have been categorized in to the *decrease* group, $G_1^{q,q-1}$.

By testing whether the difference between the means is statistically significantly different from another, we are able to capture any causal effects.

$$\begin{aligned} \widehat{DR}_0^q &= \{\Delta DR_J^{ESG,q,q-1} : J \in G_0^{q,q-1} \quad \text{for} \quad J = 1, \cdots, 330\} \quad \text{for} \quad q = 2, \cdots, 5, \\ \widehat{DR}_1^q &= \{\Delta DR_J^{ESG,q,q-1} : J \in G_1^{q,q-1} \quad \text{for} \quad J = 1, \cdots, 330\} \quad \text{for} \quad q = 2, \cdots, 5. \end{aligned} \tag{A.23}$$

We then define the following hypothesis which we will test using the one-sided Welch two sample t-test (Welch, 1938; Welch, 1947).

$$\begin{aligned} H_0 &= DR_0^q - DR_1^q = 0 \\ H_1 &= DR_0^q - DR_1^q < 0 \end{aligned} \tag{A.24}$$

Here DR_0^q and DR_1^q denote the corresponding theoretical means to $\widehat{DR_0^q}$ and $\widehat{DR_1^q}$.
Null Hypothesis: The difference between the ESG risk dependence of assets which experience an increase in ESG score engagement (Group DR_0^q) and assets which experience a decrease in ESG score engagement (Group DR_1^q) is equal to 0.
Alternative Hypothesis : An increase in ESG score engagement (Group DR_0^q) leads to lower ESG risk dependence than a decrease in ESG score engagement (Group DR_1^q) in two consecutive periods. A reviewer of the thesis noted that by failing to adjusting the significance level when performing a number of statistical tests, one should be aware of the type 1 error which could lead to some rejections.

Reversed Causality - Compare the means

In order to ensure that we do not fail to account for reverse causality, we have re-run the analysis in the reverse direction of the cause-and-effect relationship.

Similarly to before, we divide the 330 assets again into two groups (the detailed number of assets per group can be found in Table A.12). However, as we are aiming to pin point reverse causality, we divide the assets depending on whether their ESG risk dependence has increased or decreased in the consecutive period.

$$\begin{aligned} N_0^{q,q-1} &= \{J : \Delta DR_J^{ESG,q,q-1} > 0\} \quad \text{for} \quad q = 2, \cdots, 5, \\ N_1^{q,q-1} &= \{J : \Delta DR_J^{ESG,q,q-1} < 0\} \quad \text{for} \quad q = 2, \cdots, 5. \end{aligned} \tag{A.25}$$

Therefore, we get for each period q two groups: $N_0^2, N_0^3, N_0^4, N_0^5$ and $N_1^2, N_1^3, N_1^4, N_1^5$. As you can see in Equation (A.17), $N_0^{q,q-1}$ ($N_1^{q,q-1}$) are the assets that have experienced an increase (decrease) in ESG risk dependence over two consecutive periods.

As we already have computed the difference in the mean ESG scores over the time periods, we go ahead and group the assets.

$$\begin{aligned} \widehat{DE_0^q} &= \{\Delta \overline{ESG}_J^{q,q-1} : J \in N_0^{q,q-1} \quad \text{for} \quad J = 1, \cdots, 330\} \quad \text{for} \quad q = 2, \cdots, 5, \\ \widehat{DE_1^q} &= \{\Delta \overline{ESG}_J^{q,q-1} : J \in N_1^{q,q-1} \quad \text{for} \quad J = 1, \cdots, 330\} \quad \text{for} \quad q = 2, \cdots, 5. \end{aligned} \tag{A.26}$$

Group DE_0^q contains all the differences in the mean ESG score of two consecutive time periods of all assets that have been categorized in group $N_0^{q,q-1}$, so the *increase* category. Group DE_1^q contains all the differences in the mean ESG score of two consecutive time periods of all assets that have been categorized in the *decrease* category, group $N_1^{q,q-1}$.

We state our hypothesis as follows

$$
\begin{aligned}
H_0 &= DE_0^q - DE_1^q = 0 \\
H_1 &= DE_0^q - DE_1^q < 0
\end{aligned}
\tag{A.27}
$$

So we define our hypotheses as :

Null Hypothesis: The difference between the mean ESG score of the assets which experienced an increase in ESG risk dependence (Group DE_0^q) and assets which experienced a decrease in ESG risk dependence (Group DE_1^q) is equal to 0.
Alternative Hypothesis : An increase in ESG risk dependence (Group DE_0^q) leads to lower mean ESG scores than a decrease in ESG risk dependence (Group DE_1^q) in two consecutive periods.

Again, we follow the one-sided Welch two sample t-test to test for statistical significance.

A.8.1 ESG Risk Dependence and ESG scores

In the following, we are using the ESG risk dependence measures computed in the paper Equation (2.3) and the ESG scores. We fail to reject the Null Hypothesis for all four cases in terms of causality. When looking at reverse causality, we reject the Null Hypothesis for two cases, in time periods q_4 and q_5. Thus, we conclude for these time periods that an increase in ESG risk dependence (Group DE_0^q) leads to lower ESG scores than a decrease in ESG risk dependence (Group DE_1^q) in two consecutive period. However, periods q_4 and q_5 include scores that can still be changed by our data provider, as they are defined as non-definitive.

Grouping	Differences in	Alternative H1	q_2	q_3	q_4	q_5
ESG Score	ESG Risk Dep.	True difference in means is smaller than 0	0.92	0.60	0.99	0.45
ESG Risk Dep.	ESG Score	True difference in means is smaller than 0	0.20	0.87	**0.00**	**0.02**

Table A.8: p-Values of Welch t-test one sided for row 1: causality DR^q and row 2: reverse causality DE^q

A.8.2 ESG Risk Dependence and E-, S-,G-Pillar Scores

In the following, we ran the same analysis, but instead of using the ESG scores, we used the individual pillar scores. Our results are very similar to those generated using the ESG score and ESG risk dependence. Using the ESG risk dependence measure and either the E- or S-Pillar score, we find no statistically significant difference in the means of the ESG risk dependence (DR_0^q, DR_1^q) for any time period. However, for the G-Pillar score in time period q_3, we reject the Null Hypothesis and conclude that an increase in G-Pillar score engagement (Group DR_0^q) leads to lower ESG risk dependence than a decrease in G-Pillar score engagement (Group DR_1^q) in two consecutive periods.
When looking at the reverse causality, we find some statistically significant outcomes for the last time periods using each E- ,S-, G-Pillar score. Using the E- and S-Pillar score for time period q_4 and q_5 and the G-Pillar score for the time period q_4, we reject the Null Hypothesis of no difference and conclude that an increase in ESG risk dependence (Group DE_0^q) leads to lower E-, S-and G-Pillar scores, respectively, than a decrease in ESG risk dependence (Group DE_1^q) in two consecutive periods. Again, most statistical significance is found for the periods q_4 and q_5, for which the data can still be changed by our data provider.

Grouping	Differences in	Alternative H1	q_2	q_3	q_4	q_5
E-Pillar	ESG Risk Dep.	True difference in means is smaller than 0	0.99	0.31	0.90	0.92
S-Pillar			0.91	0.88	0.97	0.90
G-Pillar			0.65	**0.02**	0.98	0.61
ESG Risk Dep.	E-Pillar	True difference in means is smaller than 0	0.28	0.68	**0.01**	**0.02**
	S-Pillar		0.11	0.75	**0.01**	**0.01**
	G-Pillar		0.36	0.87	**0.03**	0.46

Table A.9: p-Values of Welch t-test one sided for row 1-3: causality DR^q and row 4-6: reverse causality DE^q

A.8.3 E-, S-G-Pillar Risks and E-, S-, G-Pillar Scores

In the following, instead of using the ESG scores, we we use the individual the E-, S-, G-Pillar scores and also use the respective E-, S-, G-Pillar risk dependence measures that we computed and discussed in the paper at the end of discussion Section 2.5.

We only reject the Null Hypothesis for one time period, q_2, for the E-Pillar data (using the E-Pillar score and E-Pillar risk dependence measure) and conclude that an increase in E-Pillar score engagement (Group DR_0^q) leads to lower E-Pillar risk dependence than a decrease in E-Pillar score engagement (Group DR_1^q) in two consecutive periods. For all other cases, we fail to reject the Null Hypothesis of no difference. When looking at reverse causality, similar to the analysis of the ESG risk dependence and G-Pillar score, we find some statistically significant results using the G-Pillar risk dependence and G-Pillar scores, this time for two time periods, q_3 and q_4. Thus, in these two cases, we reject the Null Hypothesis and conclude that an increase in G-Pillar risk dependence (Group DE_0^q) leads to lower G-Pillar scores than a decrease in G-Pillar risk dependence (Group DE_1^q).

Grouping	Differences in	Alternative H1	q_2	q_3	q_4	q_5
E-Pillar	E-Pillar Risk Dep.	True difference in means is smaller than 0	**0.03**	0.05	0.031	0.94
S-Pillar	S-Pillar Risk Dep.	True difference in means is smaller than 0	0.35	0.73	0.46	0.66
G-Pillar	G-Pillar Risk Dep.	True difference in means is smaller than 0	0.84	0.99	0.89	0.96
E-Pillar Risk Dep.	E-Pillar	True difference in means is smaller than 0	0.89	0.99	0.68	0.54
S-Pillar Risk Dep.	S-Pillar	True difference in means is smaller than 0	0.94	0.74	0.71	0.99
G-Pillar Risk Dep.	G-Pillar	True difference in means is smaller than 0	0.90	**0.01**	**0.00**	0.1

Table A.10: p-Values of Welch t-test one sided for row 1-3: causality DR^q and row 4-6: reverse causality DE^q

A.8.4 Number of Assets in Decrease/Increase Group

		q_2	q_3	q_4	q_5
ESG	Decrease	279	191	253	248
	Increase	49	139	77	82
E-Pillar	Decrease	294	209	223	217
	Increase	35	121	106	113
S-Pillar	Decrease	264	188	249	248
	Increase	65	142	81	80
G-Pillar	Decrease	228	177	224	192
	Increase	100	152	106	138

Table A.11: The different number of assets after splitting the assets according to their mean ESG score

		q_2	q_3	q_4	q_5
ESG risk	Decrease	172	146	97	143
	Increase	158	184	233	187
E-Pillar risk	Decrease	190	152	127	143
	Increase	140	178	203	187
S-Pillar risk	Decrease	156	179	122	149
	Increase	174	151	208	181
G-Pillar risk	Decrease	228	177	224	192
	Increase	100	152	106	138

Table A.12: The different number of assets after splitting the assets according to their mean ESG risk dependence

Appendix B

Do lower ESG rated companies have higher systemic impact?

Empirical Evidence from Europe and the United States

B.1 Distribution of the Individual Pillar Scores

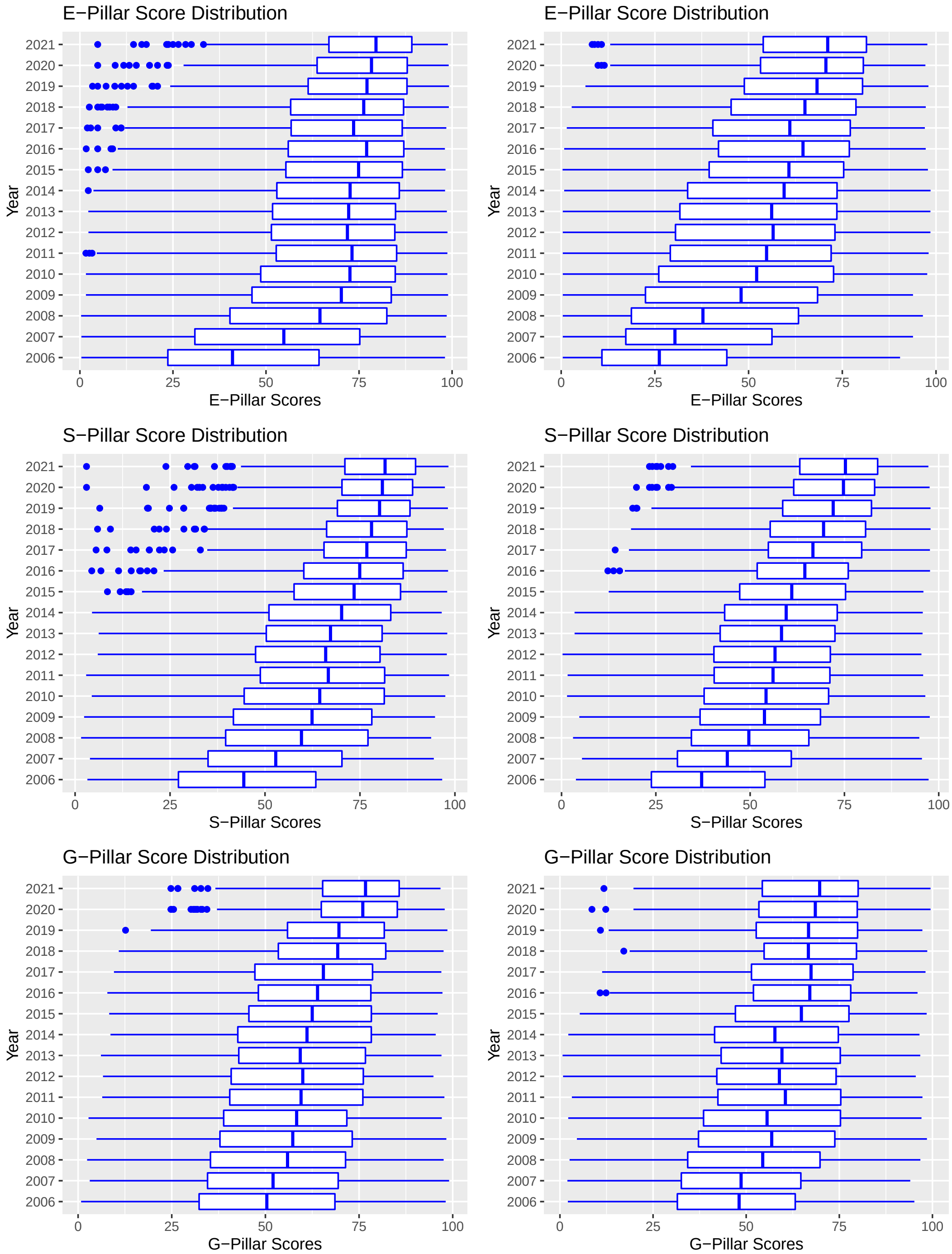

Figure B.1: Distribution of individual pillar scores.

Appendix C

Do diverse and inclusive workplaces benefit investors?

An Empirical Analysis on Europe and the United States

C.1 Descriptive Statistics

DATASET	T	N	$\hat{\mu}$	$\hat{\sigma}$	$\widehat{skew}$	$\widehat{kurt}$	$period$	$freq.$
SPX	672	363	0.13	0.17	-0.07	13.81	03/01/2020 - 31/08/2022	DAILY
STOXX	686	365	0.04	0.14	-0.25	15.58	03/01/2020 - 31/08/2022	DAILY

Table C.1: The table reports the descriptive statistics for the constituents of the Eurostoxx 600 and the S&P 100 (SP100), respectively. Columns 1-9 report the number of observations (T), the number of constituents (k), the average annualized mean ($\hat{\mu}$), the average annualized standard deviation ($\hat{\sigma}$), the average skewness ($\widehat{skew}$), the average kurtosis ($\widehat{kurt}$) of the asset returns, the time period ($period$) and the sampling frequency ($freq.$).

Dataset	$\hat{\mu}$	$\hat{\sigma}$	$\widehat{skew}$	$\widehat{kurt}$
SPX	50.24	450.13	-1.56	4.36
STOXX	48.46	652.03	-1.19	2.84

Table C.2: The table reports the descriptive statistics for the D&I score of the constituents of the Eurostoxx 600 and the S&P 100 (SPX), respectively. Columns 1-4 report the the average mean ($\hat{\mu}$), the average standard deviation ($\hat{\sigma}$), the average skewness ($\widehat{skew}$), the average kurtosis ($\widehat{kurt}$) of the D&I scores.

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