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Equity Investor ESG Preferences in Times of Crises

Master Thesis

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Abstract

There is an increasing trend among investors to invest sustainably. Previous research has shown inconsistent findings about the ESG factor's contribution to abnormal returns of ESG stocks and their similarity with conventional stocks. This paper analyzes the properties of ESG stocks in normal times and during crises in terms of volatility. Moreover, tests are conducted to determine the diversifier, hedging, and safe haven properties. I constructed a dataset that contained information on stock prices and ESG scores of 1,549 unique companies. Subsequently, I then ranked the companies to create best-in-class ESG portfolios and their non-ESG counterparts. I use Fama-French regressions, DCC-GARCH, the principal component regressions, and the wavelet coherence analysis. Although the paper concludes that the ESG factor contributes positively to abnormal returns of ESG stocks, the difference in volatilities between ESG stocks and conventional stocks is negligible. Furthermore, there is no difference in volatility between individual ESG dimensions. Finally, support is found for diversifier, hedging, and safe haven properties of ESG stocks. However, the validity of the results depends on geographic scope and the method used.

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1. Introduction

Can investors stay committed to investing sustainably during times of market stress or do they prefer to seek out other assets that have been proven to withstand the turmoil? Sustainable investments are investment strategies that evaluate an asset's financial and non-financial performance through environmental, social, and governance (ESG) factors and select assets that rank high on the factors mentioned above (Sharma et al., 2021; Sherwood & Pollard, 2018). They have been gaining on significance over the past decades and comprised over 35% of all assets under management in 2020 (Avramov et al., in press; GSIA, 2021).

Much of the existing literature has shown the present benefits of investing sustainably, as assets that rank high on the ESG factors yield at least equal or higher returns while being equally or less risky than their conventional counterparts (Derwall et al., 2005; Halbritter & Dorfleitner, 2015; Kempf & Osthoff, 2007; Kumar et al., 2016; Sadorsky, 2014; Sharma et al., 2021; Sherwood & Pollard, 2018; Verheyden et al., 2016). Past studies have also established support for the persistence of this benefit in times of market stress. Sustainable investments outperformed conventional assets during the Great Financial Crisis (GFC) of 2008 (Lins et al., 2017; Nofsinger & Varma, 2014) and the first wave of the Covid pandemic in 2020 (Díaz et al., 2021; Engelhardt et al., 2021; Ferriani & Natoli, 2021; Omura et al., 2021; Pavlova & Boyrie, 2021).

However, the invasion of Russian troops on Ukrainian territory has caused a seeming shift in investor behavior. As a response to the shock in the markets, high ESG risk (and thereby low ESG-ranking) companies and sectors have experienced soaring investor interest as the prices of oil rose substantially. The increase was in parallel with the increase of the stock prices of companies in the energy, industrials, and materials sectors (Macintosh, 2022; Olde Riekerink, 2022; Temple-West, 2022). Simultaneously, the demand for ESG stocks experienced a decrease (Haslett, 2022; Murugaboopathy & Jessop, 2022). Provided the existing research and recent economic developments, the objective of this paper is to answer the following research question:

"What are investor preferences in times of crises, and what role does an equity's ESG factor play in current economic conditions?"

Prior to the invasion, the results of past studies suggested the possibility of considering ESG stocks among assets, such as gold, bonds, currencies, and commodities, which have proven to possess safe haven properties in previous crises (Baur & Lucey, 2010; Bouri et al., 2020; Grisse & Nitschka, 2015; Flavin et al., 2014; Rubbaniy, 2021). However, have the developments around the market shock caused by the invasion of Russian troops into Ukraine changed investors' perception of ESG stocks? How does the performance of ESG stocks in the first half of 2022 compared to the Covid-19 shock? Do investors value the ESG factor of a stock despite increased volatility and shortages of energies and fuels? Could ESG stocks still be considered safe-haven assets, and do they have other risk-mitigating properties?

In summary, this research paper aims to determine investor preferences for ESG stocks during the last five years. This goal can be achieved in four steps. The first step is to test for (abnormal) returns stemming from market shocks and analyze the degree of contribution of the ESG factor using multi-factor models. This allows us to infer whether investors place significance on a stock's ESG factor or whether there are other more salient considerations. Second, this paper analyzes the volatilities of high-ranked ESG stocks compared to low-ranked or unranked stocks as means of contrast to the results of Sadorsky (2014). Third, it expands the research of Rubbaniy et al. (2021), who use the novel wavelet coherence method to test the hedging and safe haven properties of ESG stocks during the first wave of the Covid pandemic by comparing the results of the novel method on the retrieved data sample to the results of classical regression, as defined by Baur & Lucey (2010), Baur & McDermott (2010), and Shahzad et al. (2020), adjusted for the ESG factors. Finally, I conduct robustness checks of each of method to ensure the results' validity. The methods mentioned above help determine whether the primacy of ESG stocks holds throughout recent economic developments and shed light on the strength of the investors' commitment to sustainability.

Compared with existing research, this paper uses a more diverse set of data, as it includes the standard indices such as the S&P 500, as well as companies in sectors that were positively affected by the Russian invasion of Ukraine, such as the oil & gas industry. The dataset comprises 1,549 companies, of which more than three-fourths come from developed economies. Due to the index selection method, the two most represented countries are the United States and China, which make up almost half of the dataset. The three most represented sectors are industrials, materials, and financials. The universe of retrieved companies is used to create portfolios based on a company’s origin, sector, and ESG score. I constructed the portfolios using the “best-in-class” approach, which guarantees each sector a balanced representation.

The results indicate that the ESG factor contributes to abnormal returns based on the Fama-French models. ESG stocks are also found to perform differently from conventional stocks in times of high market volatility. Yet, their volatility is not different from conventional stocks in normal times. The analysis has found no difference in performance in terms of volatility differences between individual dimensions. The principal components regression and the wavelet coherence model both found existing hedging properties of ESG stocks. The results of both the wavelet coherence model and DCC-GARCH indicate that ESG stocks have diversifying properties (when matched with conventional stocks). However, the principal components regression and the wavelet coherence model retrieved differing conclusions on the safe haven properties of ESG stocks. While the principal components regression found safe haven properties of ESG stocks in times of crises, the same could not be concluded based on the wavelet coherence results. This discrepancy could stem from the different approaches used in the two methods and the fact that the results of wavelet coherence included multiple investment horizons, which contributed to a more intricate result.

I subjected the Fama-French regressions, DCC-GARCH, and principal components regressions to robustness tests to determine the validity of the results. Wavelet coherence does not have any non-causality-related robustness methods available due to the nature of the model, which attempts to fit itself onto the data rather than fitting the data onto itself. The methods for which robustness could be tested are robust on a global scale. Once the data is split into developed and emerging markets, both Fama-French and DCC-GARCH results are not robust anymore. Nevertheless, the results of the robustness test, as well as that of wavelet coherence, do indicate that the differences between ESG and conventional stocks could stem not from the ESG factor but rather from the geographical scope, as the variation was observed only in the global market but not in the regional ones. For the principal components regression, the results remained robust for all portfolios tested. Nonetheless, the model’s main assumption, namely that the conventional (non-ESG) stocks are the only asset that affects the returns of ESG stocks, did not hold after adding other assets to the base equation.

In conclusion, the results show that on a global scale, investors treat ESG stocks differently from conventional stocks, as the volatilities of these two assets differ in crises. As the correlation and the co-movement of the returns is very high, investors may use ESG stocks to diversify their portfolio of conventional stocks. In some cases, there are opportunities for ESG stocks to act as a hedge. The results also show that the preferences of investors do not clearly steer for one of the three dimensions (Environmental, Social, and Governance). As investors perceive ESG stocks differently in times of high volatility, there are opportunities for resorting to ESG stocks as a safe haven asset. The limitations include data selection and processing techniques, the definition of crisis periods, and assumptions of the methods used for analysis. Future research should include a broader sample of companies from other countries and regions and consider companies with a smaller market capitalization. Moreover, it could also map the interactions of ESG stocks with other financial asset types available in the market.

2. Theoretical Framework

This chapter is structured into three sections. The first section defines sustainable investing and briefly discusses its history and relevance. Next, the chapter discusses previous sustainable investing research, specifically research on risk and returns. Finally, the last section connects existing findings on safe haven, hedging, and diversifying properties with ESG equities.

2.1 The historical and contemporary relevance of sustainable investing

Sustainable investing can be defined as investing in assets that fulfill predefined environmental, social, and governance (ESG) criteria, which serve as trackers of the companies' non-financial objectives next to the traditional financial performance indicators (Busch et al., 2016; Pástor et al., 2021; Roca et al., 2010). While sustainable investing takes financial and non-financial performance into account, it originated from purely values-driven ethical investing strategies. These ethical strategies are either based on religious (e.g., Quaker[1] and Islamic investing[2]) or political beliefs (e.g., anti-alcohol, anti-war, anti-tobacco). On a corporate level, investing using values-driven principles has become known as socially responsible investing (SRI) (Fulton et al., 2012).

There are three different types of SRI strategies, namely negative (exclusionary) screening, positive screening, and the "best-in-class" approach (Roca et al., 2010). First, negative SRI

[1] Only businesses that "serve a beneficial purpose to society" should be funded (Friends Fiduciary, n.d.), one should invest in products embracing peace and non-violence (Schueth, 2003).
[2] The receival of interest is not permitted. Instead, it is encouraged to adopt profit-sharing and partnership schemes (Walkhäusl & Lobe, 2012).

strategies exclude companies whose actions are against a particular set of beliefs, policies, or criteria, commonly known as *sin stocks* (Roca et al., 2010). These include companies that capitalize on human vices and are typically active in sectors such as gambling, weapons, or the adult entertainment industry (Robeco, n.d.). Second, the positive screening approach selects companies committed to benefiting society. Companies are typically selected from the renewable energy, sustainable agriculture, healthcare, and education sectors (Roca et al., 2010). Negative screening is favored in the United States, while positive screening is more common in Europe (Reveli & Viviani, 2015). Third, the "best-in-class" approach builds around the notion that sustainable leaders in their sectors are better managed than others and therefore have a better investment potential (Roca et al., 2010).

In the modern context, early SRI gained attention in the 1960s because of the civil rights movement and the Vietnam War (Schueth, 2003). The first modern example of institutionalized values-driven investing was the establishment of the *Pax World Fund* in 1971, which offered to invest in companies that were against weapons production and nuclear arms races. While the early SRI (prior to the 1990s) considered only values-based factors and engaged in negative screening techniques, modern SRI (from the late 1990s onwards) also uses risk- and return-driven criteria to maximize financial return while maintaining a socially responsible investment strategy. In order to achieve this strategy, investors employ both negative and positive-screening techniques (Fulton et al., 2012).

The relative lack of concrete definitions and the relative fragmentation of SRI, as well as the investors' and governments' growing focus on good corporate governance[3], led to the introduction of formalized ESG factors in the early 2000s. Known as ESG investing, this approach considers the three (Environmental, Social, and Governance) pillars (Fulton et al., 2012). Examples of these criteria include environment, diversity, human rights, community involvement, employee relations (Sadorsky, 2014), executive compensation, worker safety standards, and the company's board structure (Clark & Viehs, 2014). In this paper uses "sustainable investing" as a catch-all term to describe SRI and ESG investing unless specified otherwise.

[3] An example is the Sarbanes-Oxley Act of 2002, which was introduced to tackle corporate fraud, conflict of interest, and to improve the reporting transparency and corporate governance following the scandals of Enron and WorldCom (Romano, 2004).

The interest in sustainable investing has increased over time. Political and popular support for sustainable investing first accelerated following the UN's Rio Declaration in 1992 (Fulton et al., 2012), declaring the importance of international cooperation in tackling environmental issues (UNCED, 1992). The United Nations recognized the link between finance and ESG factors in 2003, concluding that *"economic, social, and governance issues affect long-term shareholder value […] and in some cases, these effects can be profound"* (Fulton et al., 2012). Simultaneously, there is a notion of urgency concerning climate change and the reshaping of markets to tackle the impact of such by allocating capital to sustainable projects in private sector as well (Avramov et al., in press).

Sustainable investing has gained further importance in recent years. It is considered a key to further development and global economic growth (El Alfy et al., 2020; Sharma et al., 2021) and reaching the 2030 Sustainable Development Goals (United Nations, 2015; United Nations General Assembly, 2015). Since the launch of the United Nations Principles for Responsible Investing (PRI), an international network of investors promoting sustainable investments, the total amount of assets under management of its signatories grew from 6.5 trillion USD in 2006 (Atkins, 2020) to 103 trillion USD in 2020 (Avramov et al., in press). Albeit the growth has been considerable, there are commitment differences between first movers and late signatories, with the latter reporting a lower ESG performance than the former (Baukloh et al., 2021). Second, the majority of sustainable investing is conducted in developed countries, most notably in the United States and Europe (de Souza Cunha & Samanez, 2013); GSIA, 2020). Meanwhile developing countries have been slow in integrating sustainability into their investment strategies (Odell & Ali., 2016).

In order to invest sustainably, investors need companies with a set of policies and principles that satisfy investor criteria. This set of policies and principles is known as Corporate Social Responsibility (CSR), which determines a company's non-financial performance. A company's CSR decisions affect the overall shareholder value and contribute to the degree of fulfillment of investors' ESG criteria (Renneboog et al., 2008). While early CSR (1950-1960) focused on philanthropy and community relations, it expanded in the following two decades as the concept of utility maximization and stakeholder theory was formed. The rise of shareholder activism, corporate disclosure, and proxy voting embedded sustainability further into CSR. Contemporary CSR encompasses all three ESG factors and is integral to a company's strategy (Fulton et al., 2012). Integrating CSR into a company's strategy ensures long-term success and survival (El Alfy et al., 2020). It can be viewed both as a means of maintaining or creating its competitive advantage (Hart, 1995), a gateway to facilitate innovation, and better financial performance (Bocquet et al., 2017).

In conclusion, sustainable investing has gained significant attention in past decades. Its ESG pillars have become a crucial part of non-financial performance evaluation as the demand for future sustainable growth and development increases. The following section will discuss whether a company's non-financial performance has also been found to affect its financial performance.

2.2 Sustainable investing and financial performance

This section is split into two parts. The first part discusses the findings of previous academic research on returns while the second discusses risk and the role of market cycles. Moreover, this section presents the derived hypotheses of this research.

2.2.1 Returns and access to finance

The discussion of whether companies that are more socially responsible outperform the market commenced in the 1970s when Moskowitz (1972) and Vance (1975) found contradicting results on the relation of the EGS factor to stock returns, with the former author finding a positive relationship and the latter finding a negative one. Yet, the results regarding the benefit of sustainable investing have remained unclear for an extended period, with some papers finding negative returns (Cordeiro & Sarkis, 1997; Rudd, 1981), positive returns (Derwall et al., 2005; Kumar et al., 2016; Sherwood & Pollard, 2018; Verheyden et al., 2016), and no difference in returns (Baur et al., 2007; Beccheretti & Ciciretti, 2009; Chetty et al., 2015; Jain, Sharma & Srivastava, 2019; Landi & Sciarelli, 2018; Statman, 2000; Van de Velde et al., 2005), compared to the control sample. Nevertheless, most academic literature finds a positive relationship between sustainability and financial performance (Alshehhi et al., 2018; Friede et al., 2015; Verheyden et al., 2016).

Multiple research design considerations may cause discrepancies in findings. Shank et al. (2005) and Brammer & Millington (2008) concluded that the time horizon plays a significant role, as sustainable stocks outperform the control sample on the medium- and long-term horizon but not on the short-term. However, to counter this finding, out of the papers mentioned in the previous paragraph, those finding a positive result had a shorter data range on average compared to those papers that found no difference. The only outlier is Van de Velde et al. (2005), whose research period focused on the times of the Dotcom crisis (2000-2003) and found no performance differences (albeit they found a positive, yet insignificant result). Research examining sustainable funds has found the opposite relationship between the time horizon and returns (Climent & Soriano, 2011). However, this could be due to the very long period examined (1987-2009), during which sustainable investing developed considerably.

Further research specified that abnormal returns are more achievable using the best-in-class approach (Kempf & Osthoff, 2007; Shank & Shockey, 2016). However, it is essential to note that, as a result, abnormal returns may be caused by the economic and sector exposures augmented by the screening approaches rather than by the ESG factors (Barnett & Salomon, 2006; DiBartolomeo & Kurtz, 1999).

The region of interest is also an explanatory factor, as de Souza Cunha et al. (2019) show. ESG indices underperformed conventional indices in the past decade everywhere except in Europe. However, the choice of indices matters, as for the same period, Sharma et al. (2021) found a high correlation and close co-movement between sustainable and conventional indices. The difference could stem from the use of different indices and empirical methods. Research of Managi et al. (2012) established identical results to those of Sharma et al. (2021). Bauer et al. (2005) found that while US sustainable funds do not outperform conventional funds, the opposite is true in the UK.

In addition, returns are also affected by market uncertainty. Lean & Nguyen (2014) show that increasing uncertainty leads to lower ESG returns in Western markets, while the opposite is true for Asian markets. Takahashi & Yamada (2021) note that the differences in Asian markets could stem from the investors' degree of awareness and commitment to ESG, which varies by country. Sherwood & Pollard (2018) find that integrating ESG emerging market equities into investor portfolios leads to higher risk-adjusted returns.

In summary, studies have shown that the effect of sustainable performance varies, although the consensus is that sustainable investments perform better than their conventional counterparts. However, additional factors play a role as well, namely the research period, index selection and its constituents, funds, and the geographical region of interest. In addition to returns, sustainable investing affects the company in several other ways, as explained in the paragraphs below.

Besides returns and risk, existing academic literature discusses several ways in which sustainable investing affects the company, namely the short-term announcement effects, the characteristics and behavior of companies concerning sustainability, and the cost of capital.

Previous research discovered that news relating to the company's sustainability efforts may lead to abnormal returns. This includes short-term positive announcement effects from their inclusion in sustainability indices (Consolandi et al., 2009) or ethical rating lists (Karim et al., 2016), philanthropic gifts to environmental causes, ISO certifications (Jacobs et al., 2010), awards (Klassen & McLaughin, 1996). Therefore, there are short-term effects on a company's performance, which is affected by the company's CSR.

Announcement effects are not the sole cause of a positive effect of ESG performance on financial performance measures. In addition, metrics such as profitability, return on assets (ROA), cash flows, Tobin's Q, and market value are also positively impacted by good ESG performance (Ameer & Othman, 2012; Amber & Lanoie, 2008; Faleye & Trahan, 2006; Guenster et al., 2011; Konar & Cohen, 2001; Russo & Fouts, 1997; Semenova & Hassel, 2008).

Incorporating ESG factors also leads to a positive effect on access to finance (Cheng et al., 2014), as the ESG-related risks are lowered (Chen et al., 2009; Renneboog et al., 2006) and environmental performance increases (Ambec & Lanoie, 2008). More specifically, both the cost of debt (Bauer et al., 2009; Bauer & Hann, 2010; Chava et al., 2009; Jung et al., 2018; Klock et al., 2005) and equity (Dhaliwal et al., 2011; El Ghoul et al., 2011; Pae & Choi, 2011) decreases with increasing ESG performance and disclosure. Therefore, companies have incentives to incorporate sustainability into their strategy to improve their performance and obtain better access to finance.

In conclusion, ESG performance affects a company's financial performance through stock returns, profitability metrics, and cash flows, and it can also improve or worsen a company's access to finance. As a result, the (null) hypothesis below defines the role of the ESG factor in relation to financial performance, more precisely, (abnormal) returns. The rationale for choosing to analyze returns instead of other variables is for comparison purposes with existing literature, which considers stock returns as the primary performance metric.

Hypothesis 1: The ESG factor does not contribute to (abnormal) returns.

2.2.2 Risk, exposure, and market cycles

Earlier studies show that the comparable volatility of ESG stocks relative to conventional stocks has evolved as ESG stocks, funds, and indices have displayed lower riskiness than their conventional peers, on average (Beccheretti & Ciciretti, 2009; Feldman et al., 1997; Lean & Nguyen, 2014; Lee et al., 2010; Kumar et al., 2016; Verheyden et al., 2016). More recent research found ESG stock volatility corresponds to conventional stocks' volatility (Jain et al., 2019; Managi et al., 2012; Sadorsky, 2014; Sharma et al., 2021), except for de Souza Cunha et al. (2019), whose results suggest higher volatility for ESG investments.

Existing literature shows two different regimes for the bull and bear markets (Managi et al., 2012). ESG investments fared better than or equal to the benchmark during the Great Financial Crisis of 2008 (Lins et al., 2017; Nofsinger & Varma, 2014) as well as during the initial shock of the 2020 pandemic (Díaz et al., 2021; Engelhardt et al., 2021; Ferriani & Natoli, 2021; Omura et al., 2021; Pavlova & Boyrie, 2021). In both cases, while market uncertainty was high, investors preferred low-ESG risk investments (therefore, high ESG score) to conventional equities (Ferriani & Natoli, 2021). Nofsinger & Varma (2014) have also found that while the ESG outperformance holds during crises, there is a risk of underperformance in normal times. The authors argue that the difference between investor behavior during crises and normal periods stems from greater attention to the behavior of companies during economic downturns.

The geographical aspect plays an essential factor, as Takahashi & Yamada (2021) analyze the pandemic's impact on ESG performance in Japan, concluding that there is no superior performance of ESG equities during the crisis. It is important to note that there are differences in results between individual companies and ESG funds. The latter is found to be more likely to overperform conventional funds than companies with a high ESG score to outperform non-ESG companies.

Moreover, further findings can be derived from segmenting the ESG scores into individual pillars. The results of Engelhardt et al. (2021) show that during the Covid crisis, the Social pillar of ESG was the main driver for European companies. On a global scale, Ferriani & Natoli (2021) identified Environmental and Governance pillars as the primary performance drivers, while Díaz et al. (2021) found Environmental and Social dimensions to drive performance. This discrepancy could stem from the former analyzing performance at the fund level while the latter used data from individual companies.

In summary, with the sustainable market growing over time, there is a trend of lowering the volatility differences with its conventional peers. Many past papers found an outperformance of ESG investments during the past two crises. Therefore, the null hypotheses defining the relationship between ESG equities' performance during high market volatilities, relative to conventional equities are defined as:

Hypothesis 2a: ESG equities do not perform differently from conventional stocks in times of high market volatility.

Hypothesis 2b: There is no difference in performance between the Environmental, Social, and Governance pillars of ESG.

Hypothesis 2c: The volatility of ESG equities is not different from the volatility of conventional stocks.

2.3 Safe havens, hedges, and diversifiers

Historically, many assets have been deemed to have unique characteristics that would allow for risk mitigation in a portfolio depending on the stage of the market cycle. The three main types of such properties are: safe havens, hedges, and diversifiers.

An asset is a safe haven if it is *"uncorrelated or negatively correlated with another asset or portfolio in times of market stress or turmoil"* (Baur & Lucey, 2010). Historically, gold and other precious metals (Baur & McDermott, 2010; Baur & Lucey, 2010; Hood & Malik, 2013; Reboredo, 2013; Shahzad et al., 2020), commodities (Bouri et al., 2020; Elie et al., 2019), bonds (Flavin et al., 2014), and foreign currencies (Grisse & Nitschka, 2015; Kaul & Sapp, 2006; Ranaldo & Söderlind, 2010) have been considered safe havens for periods of market stresses. Nevertheless, there is a potential for expanding the asset types that function as safe havens during crises. For instance, Ferriani & Natoli (2021) analyzed funds' behavior, finding a strong preference for low-ESG risk assets during the first wave of the pandemic. In addition, Rubbaniy et al. (2021) performed a wavelet analysis of ESG stocks during the first wave of the Covid pandemic. They found support for ESG stocks functioning as a safe haven in a longer frequency band, although with mixed results in shorter frequencies. Therefore, the findings open the discussion on the possibility of ESG stocks possessing one of the aforementioned properties. As a result, the null hypothesis for ESG equities concerning their safe haven properties is:

Hypothesis 3: ESG equities do not possess safe haven properties.

Moreover, provided the assets discussed function as safe havens during times of stress, there is a question of whether they have the same properties in normal times too, functioning as hedges. Hedges are *"uncorrelated or negatively correlated with another asset or portfolio on average"* (Baur & Lucey, 2010; Shahzad et al., 2020). In times of no market turmoil, traditional safe-haven assets have been found to possess hedging properties (Bouri et al., 2020; Campbell et al., 2010; Kroner & Sultan, 1993; Mensi et al., 2013; Nguyen et al., 2020; Shahzad et al., 2020). Although, past research shows that some asset types, such as commodities, are less effective as hedges (Olson et al., 2017). Alternative assets (Le et al., 2021), such as ESG equities, may also have a hedging potential (Kuang, 2021). Jain et al. (2019) compared the performance of conventional and sustainable indices, finding no significant performance differences, concluding that one may reap hedging benefits from either equally. As a result, provided the previous findings, the null hypothesis describing ESG equities and hedging properties is specified as:

Hypothesis 4: ESG equities do not possess hedging properties.

The conclusions of Jain et al. (2019) and Kuang (2021) may also be extended to the diversifying properties. A diversifying asset is *"positively (but not perfectly) correlated with another asset or portfolio on average"* (Baur & Lucey, 2010). Depending on the portfolio, it can be gold (Emmrich & McGroarty, 2013; Lucey et al., 2006; Selmi et al., 2018), bonds (Bouri et al., 2020), commodities (Bouri et al., 2021; Irwin & Landa, 1987), or real estate (Hoesli et al., 2004; Irwin & Landa, 1987). Research on alternative asset types, namely ESG equities, has found that ESG-only portfolios cannot diversify more than all-universe portfolios. As the former is a subset of the latter, they are diversifying due to a high positive correlation with conventional portfolios (Verheyden et al., 2016). Therefore, there is potential for ESG equities to possess diversifying properties, hence the respective null hypothesis is:

Hypothesis 5: ESG equities do not possess diversifying properties.

3. Data

This chapter is divided into five sections. First, I discuss the retrieval process of equities and the definition of crisis periods. The second section provides information on the differences between ESG score providers and the methodologies to derive the ESG scores used in this paper. The third section explains the equity portfolio creation process and the descriptive statistics. The fourth section reviews the data retrieval of all other asset types and their descriptive statistics. Finally, the last section discusses correlations between asset types during crisis and non-crisis periods.

3.1 Equities data retrieval and crisis period definition

The data is collected from *Bloomberg* and *Refinitiv Eikon* databases. The dataset consists of equities, bond indices, gold, oil, the US Dollar, and the Swiss Franc (see Table 17 in the Appendix for a complete overview of indices and price lists used). I retrieved data on constituents of several indices and lists between January 1, 2017, and June 30, 2022. The indices include equities from both developed and emerging global markets. The preliminary equity dataset consisted of 2,111 observations. However, as some companies appear in multiple indices, stock exchanges, or may also include multiple share classes, I removed their duplicates. I also eliminated all companies that did not have their financials available from 2017 onward. In the end, 1,549 unique companies remained in the sample. I used the MSCI classification of developed and emerging[4] markets. In this sample, 76.8% of companies come from developed markets, while the rest is classified as emerging. I used the GICS classification for industries and sectors. The top five most represented sectors in the dataset are Industrials (16.9%), Materials (14.5%), Financials (14%), Information Technology (10.7%), and Consumer Discretionary (9.7%). The portfolio factors come from the *Kenneth R. French Data Library*.

In addition, I acquired ESG scores from *Refinitiv Eikon* and *Bloomberg*. Using different ESG scores allows for further examination of the ESG score's impact on the stock's performance and its validity. This paper defines ESG stocks as equities whose ESG score is in the top 20% of the respective sector.

Previous research has yet to agree on the official start of the Covid shock. Some papers consider January 30, 2020 (declaration of a public health emergency by the World Health

[4] For convenience purposes, I combined emerging markets and frontier markets (as defined by MSCI) together.

Organization) or February 27, 2020, when the number of cases outside of China exceeded the number of cases in China (Corbet et al., 2020), while others take the first day (January 1, 2020) the virus was reported (Díaz et al., 2021). In addition, Omura et al. (2020) use February 1, 2020, as the number of cases exceeded 10,000 globally. I chose to use the same starting date as Omura et al. (2020) and the ending date of April 30, 2020. I selected the ending date based on the recovery of the S&P 500 index, as it reached 10% below the pre-shock level (from sinking to 68.8% of the pre-shock level at its lowest point). The index did not reach complete recovery until August 2020. However, the initial shock in the markets did not last until then.

In the case of the second crisis, Russia's invasion of Ukraine, the definition of the start is more straightforward, as the Russian troops entered Ukrainian territory on February 24, 2022 (Reuters, 2022). As this event is more regional (compared to a pandemic), I used the performance of two European indices to determine the end date of the shock. Both Euronext100 (a European index composed of predominantly French companies), and FTSE 100 (companies listed on the London Stock Exchange) have recovered (the index value was at least equal to the pre-shock index value for at least a day) from the invasion by March 30, 2022 (Euronext, n.d.; London Stock Exchange, n.d.). Therefore, this date is also the end date of this crisis.

3.2 ESG scores

The analysis uses six equity ESG scores: the *S&P ESG Rank*, *Sustainalytics ESG Risk Rating*, and *Refinitiv ESG Score* (ESG, E, S, G). Each of the ESG scores has a slightly different methodology and evaluation.

First, the S&P ESG Rank looks at a company's the current to near-term effectiveness in managing its risk exposure relative to its peers. The company that wishes to receive a score initiates the evaluation process. It fills out S&P's Corporate Sustainability Assessment and then holds conversations with the rating agency's analysts. Finally, S&P compares the company to its peers. The companies are evaluated on 12 sub-dimensions, weighted depending on the industry and profile. The risks must be material to be taken into consideration by the ESG score. The overall ESG score is weighted towards the Governance dimension (40%), while the remainder is equally distributed between the Environmental and Social dimensions. The score awarded is between 0 (worst) and 100 (best) (S&P Global, 2021).

Second, the Sustainalytics ESG Risk Rating measures a company's ESG-driven at-risk economic value. The risk rating has two parts: Unmanaged Risk and Risk Category. The scale of Unmanaged Risk is open-ended, but 95% of the rated companies do not exceed 50. The lower the score, the lower the ESG risk, so the better the ESG performance. The Risk Category has five segmentations, which are absolute, and can be used to compare the risk of companies across all industries. In comparison to the S&P ESG Rank, this ESG score considers both material and idiosyncratic risks in the evaluation. Next to clients' self-reported assessments, Sustainalytics conducts independent research to validate ESG issues on industry and company levels. The evaluation is conducted annually (Sustainalytics, 2021). As this ESG score is available only for the year 2021 onwards, it will not be used in the analysis. However, I will use it for robustness tests of some of the hypotheses in the results section. Hence, five ESG equity scores will be used.

Third, the Refinitiv ESG score uses a standardized framework that creates a score based on a company's publicly available data and focuses solely on material risks. The framework comprises ten different categories spread across the three ESG dimensions. The weights of each category are industry specific. The score awarded can take a value between 0 (worst) and 100 (best). In addition to the score, companies also receive a letter grade. The companies are reviewed weekly at most and annually at least. Compared to S&P ESG Rank, Refinitiv's database does not include any self-assessments, as it is expanded systematically by constituents of a specific index. This ESG score provider has the score available for all three dimensions (Environmental, Social, and Governance) and the overall ESG dimention (Refinitiv, 2022).

3.3 Equities portfolio creation and descriptive statistics

This section discusses the creation of the ESG and non-ESG equity portfolios used later for analysis. It also discusses key financial ratios related to the Fama-French model. Finally, this section also includes descriptive statistics of the equity portfolios. The threshold for statistical significance is set at 5% ($p \leq 0.05$).

The ESG scores of S&P are generally available from February 6, 2017, onwards, with some companies being added later. However, only companies with available ESG ratings for the Covid pandemic crisis and the Ukraine invasion are considered in the portfolio creation. Out of the total in the sample, 1,345 companies had their ESG scores available for both periods. I averaged the ESG scores during the two crises to retrieve one value, based on which I selected companies for the S&P ESG portfolio (top 20%). Another consideration in the portfolio is a company's sector, as I used the best-of-class approach, whereby I chose the best performers out of each sector. The portfolio includes 276 companies (20.5% of all ranked companies), with the ESG score ranging from 81 to 100. The number of companies used in the portfolio slightly exceeds 20% due to multiple companies having identical scores. Therefore, I included all companies that meet the threshold to qualify to be a part of the portfolio. In addition, I created two different portfolios by market type (developed and emerging). The developed ESG portfolio comprises 228 companies, while the emerging markets ESG portfolio includes 40 companies. On average, the developed markets ESG score is higher than that of emerging markets.

I applied the same sample selection method to the ESG scores from Refinitiv. I made an adjustment to the ESG scores between January 1, 2022, and March 30, 2022, as these scores were unavailable for any of the companies at the time I acquired the data. Therefore, I took the ESG score from December 31, 2021, and assumed no significant change occurred in the two months between the end of official reporting and the beginning of the invasion. Derwall et al. (2005) applied the same assumption in their research, as they pointed out the relatively low variability of ESG scores in the short term. This assumption finds support in most of the current sample, as the ESG score has changed by more than 25% for less than 13% of the companies between December and March of the year prior to the Ukraine conflict. Therefore, although the variability is higher than in the period Derwall et al. (2005) analyzed, and outliers are present, I assume no change between December 2021 and February 2022 rankings, as the variability is low for the remainder of the sample. Out of the total number in the sample, 497 companies had complete data for both crises. I applied the best-of-class approach to construct the Refinitiv ESG portfolio, which consists of 98 companies (top 20%). The lowest score in the portfolio is 76.9, and the highest is 95.3.

The three other portfolios (E, S, and G) constructed using Refinitiv each include 126 companies that ranked highly (top 20%) on each of the dimensions in their sector. Overall, at least 63% of the companies have scored in the top 20% in at least two dimensions, and 27 companies appear in all three portfolios. Most duplicates are in the financial, materials, or industrial sectors, while the largest share of companies appearing in all three portfolios comes from the financial sector.

Although the S&P ESG and Refinitiv ESG scores share many similarities, they are not identical. For once, comparing the distribution of scores among the companies which have ESG scores available for both periods, Refinitiv awards approximately 10% of the companies with a score of 85 or higher, while almost 20% of all companies in the S&P sample are in the same score range. Although it is not the point of this research to seek bias in scoring methodologies, provided S&P uses data obtained from a company's self-assessment. At the same time, Refinitiv relies uniquely on publicly available data. This discrepancy may indicate a potential variation in results between ESG scores. This finding is also in line with recent news questioning the general reliability of ESG scores as a measure of sustainable investing (Klasa, 2022; Nauta, 2022; Quinson, 2022). On the other hand, 58 out of the total of 98 companies included in the Refinitiv ESG portfolio also appear in the S&P ESG portfolio, which is not perfect, yet a partial overlap. The reason for only a medium degree of overlap could be that the Refinitiv portfolio has fewer observations than the S&P portfolio due to a lack of data. Thus, it is possible that some companies, which would theoretically rank high in both lists based on the evaluating methodologies, were not matched, as the observations were missing in the Refinitiv Eikon database.

The descriptive statistics for ESG portfolios can be found in Tables 18 and 19 in the Appendix. Table 18 shows the average daily returns, standard deviation, and Sharpe ratio of portfolios constructed based on all three dimensions. Although the average daily returns of all portfolios are positive for the entire period, they experience some heterogeneity during crises. In addition, there are significant differences between crisis and non-crisis volatilities. During the first Covid shock, the portfolios experienced negative returns, apart from the emerging ESG and the low-ESG Refinitiv portfolios. However, the volatilities of all portfolios are comparable. On the other hand, all portfolios, except for emerging ESG, did not experience average negative daily returns during the Ukraine war. The volatilities of the portfolios are comparable, with a slightly higher standard deviation of the emerging ESG portfolio. The opposite effect on portfolio returns occurred during the recovery period after the first shock caused by the Ukraine war was over, as all portfolios, except for emerging ESG, had negative returns. When looking at the combined performance of the portfolios during both crises, the average daily returns are positive for all portfolios, apart from emerging ESG and Refinitiv ESG.

There are also differences in the movements of the S&P ESG and Refinitiv ESG portfolios, and the returns of the two portfolios are significantly different for the pre-Covid period. During both crises, the Refinitiv ESG portfolio underperformed the S&P ESG portfolio. At the same time, the former was less volatile during the Covid period and similarly volatile as the latter during the

Ukraine war. However, the mean average daily returns between the two portfolios are not significantly different from one another. Similarly, there are no significant differences between the average daily returns of developed and emerging ESG portfolios during the entire period, crises, and recovery periods. Figures 8 to 11 (see Appendix) show the squared daily returns of the four main ESG portfolios. The figures indicate that the global and developed markets experienced the most volatility during the Covid crisis. On the global level, the Refinitiv portfolio was relatively less volatile over time than the S&P portfolio. However, the former experienced a higher volatility during the Covid period. At the same time, the emerging markets portfolio was more volatile, but its peak was below the peak of other main portfolios.

Table 19 displays the descriptive statistics of ESG portfolios constructed based on each of the three ESG dimensions. All one-dimension portfolios follow the same trend during pre-crisis, crisis, and recovery periods, with minor differences in magnitudes. The average daily returns are positive for all three portfolios for the analyzed period, with the Environmental dimension portfolio having the highest returns and the Governance portfolio having the lowest returns. During the Covid period, all portfolios have average negative returns, while during post-Covid recovery and the Ukraine war, their average daily returns are positive. The returns turned negative again only during the war recovery period. The t-test revealed no significant differences among the returns of the three portfolios for any of the periods. The only difference found was the difference in returns between the war recovery period and prior periods for the Social and Governance portfolios. The volatilities of returns of the three portfolios are comparable over time (see Figures 12 to 14 in the Appendix), as all three have increased squared returns during the Covid period and the Ukraine war crisis. In addition, the Environmental portfolio has also increased volatility during the second wave of Covid lockdowns in Europe (fall 2020).

The interpretations of the data are two-fold. First, although S&P and Refinitiv have different methodologies and do not award one company with the same score, the company overlap between the two portfolios is 30.6%, the differences between the respective portfolios during crisis and recovery periods are not statistically significant. Second, as there are no considerable differences in daily average returns among the one-dimension portfolios, it supports the hypothesis that there should not be differences in portfolio performance.

The last step is to compare the returns of the main ESG and non-ESG portfolios. Table 20 (see Appendix) shows the descriptive statistics of non-ESG portfolios. A t-test that compared mean returns between the ESG and non-ESG portfolios of the same provider has found no significant difference in returns between S&P ESG and non-ESG portfolios for any of the periods examined. Conversely, the average daily returns have differed between the Refinitiv ESG and non-ESG portfolios for the pre-Covid and Covid recovery periods and the whole period. In the pre-Covid period, the average returns of both portfolios are positive, while all but the emerging markets non-ESG portfolio experienced negative returns during the Covid period. This trend reversed during the Ukraine war, where emerging markets non-ESG portfolio was the only one with negative average daily returns. There are no significant differences in average returns between the S&P ESG and non-ESG portfolios that include only companies from developed markets. On the other hand, there are significant differences in returns between the S&P ESG and non-ESG emerging markets portfolios during the Covid and war recovery periods.

3.4 Bonds, gold, commodities, and currencies

I use three different indices to measure bond returns. First, I used a random selection of constituents of the Bloomberg Global Aggregate Index. I obtained the constituent list from the Rabobank database, with the permission of prof. dr. Pieterse-Bloem. The index is a global composite of investment-grade government and corporate bonds (Bloomberg, n.d.) and has 28,254 members. Given the size of the index, I chose to apply random selection to extract the returns of the representative bonds. I applied the random selection only on bonds, having excluded mortgage, commercial mortgage, and asset-backed securities, as not all securities had valid identifiers. The random selection process consists of assigning random numbers between 0 and 1 to all the remaining constituents and choosing to select values in an arbitrary interval between 0 and 0.05, or 568 bond index constituents. I then retrieved their daily returns from Refinitiv and followed a filtration process similar to the one I applied for the equities. For an equity to be considered in the analysis, it had to have returns available from January 2017. I relaxed this requirement for the bonds, as I will not be ranking any bond-specific information. Therefore, I included all bonds issued prior to the start of the Covid pandemic. As a result, the final number of bond constituents in the reduced Bloomberg Global Aggregate Index is 326. For simplicity, I also assumed equal representation of each bond in the portfolio.

Second, I retrieved information on returns of the S&P500 Bond Index, iBoxx Euro Corporates Index, and iBoxx Euro Liquid High Yield Index from Refinitiv Eikon. The S&P 500

Bond Index is the counterpart of the S&P 500 equity index and measures the performance of the debt issued by the S&P 500 constituents (S&P, n.d.). The iBoxx Euro Corporates Index comprises 40 investment-grade corporate bonds denominated in Euros. The minimum issue requirement for inclusion in this index is EUR 750 million (VanEck, n.d.). The iBoxx Euro Liquid High Yield Index comprises 250 high-yield Euro-denominated corporate bonds (Markit, n.d.).

I chose two commodities, gold and oil, to be part of the analysis. I included gold as it has been previously researched for its safe haven properties, while oil was the commodity most linked to the Ukraine war. I retrieved the daily returns for gold and oil from Bloomberg. In addition, I also collected the daily exchange rates for the Euro-US Dollar and Euro-Swiss Franc currency pairs from the same database. Descriptive statistics for bonds, commodities, and currency pairs can be found in Table 21 (see Appendix).

Over the entire period analyzed, only the randomized global bond index (Bloomberg Aggregate) and corporate bonds (iBoxx Euro Corporate) recorded negative average daily returns. On average, the most volatile asset was oil, while bonds were the least volatile. During the pre-Covid period, the S&P 500 Bond index and gold recorded the highest average daily returns. For the same period, the US Dollar was losing its position against the Euro, and the Swiss Franc was slightly gaining in value relative to the Euro. All bond indices as well as oil had negative returns during the Covid period, with oil experiencing the highest volatility out of all assets. At the same time, both US Dollar and the Swiss Franc were strengthening their position against the Euro. Oil had the highest average daily returns during the post-Covid recovery period. The bond indices were gaining in value again, apart from the global bond index. US Dollar was weakening against the Euro during this period.

The Ukraine war impacted the bond indices negatively, but the volatility of the bonds did not change significantly relative to previous periods. On the other hand, both currencies (US Dollar and Swiss Franc) and gold experienced positive average daily returns. Oil was the most volatile asset during the Ukraine war crisis and had the highest daily returns. During the recovery period, the average daily returns of all bond indices remained negative and increased in magnitude without changing volatility. The average daily returns of gold also became negative. Simultaneously, the returns of oil and the two currencies remained positive. Oil maintained its primacy in being the most volatile asset. On average, bonds and oil experienced negative returns during the two crises, while gold and currencies experienced positive returns. However, it is important to note that the average is skewed towards the first crisis, as it has lasted longer than the second crisis, which kept returns from oil negative. The volatilities of the bonds follow a trend similar to that of the equity portfolios, except the magnitude of the squared returns of bonds, is smaller (see Figures 15 to 22 in the Appendix).

As opposed to equities, the returns of the bond indices are significantly different from each other during some periods. For instance, the returns of Bloomberg Aggregate, Euro-denominated corporate bonds, and S&P 500 bonds are significantly different in the pre-Covid period, however, the differences become insignificant during crisis periods. The only period where the returns of the bond indices diverge from one another is during the post-Covid recovery.

3.5 Correlations

This section discusses the correlations between asset pairs used in the analysis. Due to multiple events that occurred during the period of interest, I choose to report on correlations by each sub-period, identical to those in the two previous sections.

Tables 22 and 23 (see Appendix) show the return correlations between financial assets in the pre-Covid period. The ESG and non-ESG portfolios are strongly correlated (0.93 for S&P and 0.83 for Refinitiv portfolios). Both developed and emerging markets ESG and non-ESG portfolios are perfectly correlated with one another. In addition, the correlation between the ESG portfolios is strong (0.83). ESG portfolios have a weak negative correlation with the S&P 500 bond index and Bloomberg Global Aggregate (between -0.1 and -0.2), they are not correlated with Euro-denominated corporate bonds (-0.04 to -0.01), and their correlation with high-yield bonds is moderate (0.38 to 0.4). Furthermore, the ESG portfolios are very weakly correlated with gold (-0.04 to -0.05), but they have a moderate positive correlation with oil and weak negative correlations with the currencies (-0.13 to -0.28).

The return correlations during the Covid period can be found in Tables 24 and 25 (see Appendix). The correlation between ESG and non-ESG portfolios increased during the Covid period (0.99 for S&P and 0.96 for Refinitiv portfolios). Moreover, the ESG portfolios became more correlated with one another (0.94). Developed and emerging ESG and non-ESG portfolios remained perfectly correlated. While the correlation between ESG portfolios and the Bloomberg Global Aggregate is zero (between -0.04 to 0.04), the remainder of the bond indices increased their correlation with ESG portfolios to moderately and strongly positive levels (between 0.22 to 0.65). The correlation between ESG portfolios and currencies stayed the same (-0.10 to -0.27).

The post-Covid period return correlations are displayed in Tables 26 and 27 in the Appendix. The decrease in market volatility during this period led to a decrease in correlations between ESG and non-ESG portfolios. However, they remain above pre-Covid levels. ESG portfolios also stay strongly correlated with one another (0.81). The correlation between ESG portfolios, global and high-yield bonds did not change, while it decreased for the other bond indices. The correlation reduced with gold but not with oil. The correlation with US Dollar is more negative (-0.17 to -0.33), as the opposite trend is true for that with the Swiss Franc (-0.06 to -0.15).

Tables 28 and 29 (see Appendix) show the correlations of returns during the Ukraine war period. The correlations between ESG and non-ESG portfolios, and individual ESG portfolios did not change. The ESG portfolios are weakly to moderately negatively correlated with Bloomberg Global Aggregate and Euro-denominated corporate bonds (-0.06 to -0.25). At the same time, they are weakly correlated with S&P 500 Bonds (zero to 0.14) and moderately correlated with high-yield bonds (0.4 to 0.49). The shock caused the correlations of ESG portfolios with commodities and currencies to become moderately to strongly negative (-0.63 to -0.65 for gold, -0.37 to -0.45 for oil, and -0.52 to -0.85 for currencies).

The post-war correlations can be found in Tables 30 to 32 (see Appendix). In general, no significant correlation change can be observed for the equities compared to the previous period. On the other hand, the ESG portfolios are moderately correlated with all bond indices (0.19 to 0.45). The correlation with commodities is weakly to moderately positive (0.09 to 0.21). ESG portfolios have become moderately negatively correlated with the US Dollar (-0.41 to -0.56), and the negative correlation with the Swiss Franc is lower (-0.07 to -0.14) than in the previous period.

On average, the correlations between ESG and non-ESG portfolios increase during crises, compared to non-crisis periods. Overall, with the Covid and Ukraine war periods combined into one ("Crisis"), ESG portfolios very weakly correlate with the Bloomberg Global Aggregate bond portfolio (-0.04 to -0.01), moderately with S&P 500 Bonds and Euro-denominated corporate bonds (0.21 to 0.3), and a strongly with high-yield bonds (0.61 to 0.63). Furthermore, ESG portfolios are moderately correlated with commodities (0.17 to 0.3) and currencies (-0.17 to -0.35).

In summary, ESG and non-ESG portfolios are always strongly correlated, with the magnitude increasing during crises. The correlations of ESG portfolios with bonds are weaker, yet there is more variation, which is determined by the bond index composition. For once, ESG portfolios are more correlated with the high-yield bond index than with indices that include sovereign and corporate investment-grade bonds. The variation is higher for correlations with commodities, as the correlation increases during crises, but the direction of the correlation differs by each crisis. The correlations with currencies are always negative. The change in magnitude of the correlation between ESG portfolios and currencies is smaller in the first three periods, while it becomes more extreme during the second crisis and post-war recovery.

4. Methodology

This chapter formalizes the statistical methods applied to test the hypotheses defined in the theoretical framework and subsequently answer the research question regarding investor preferences in crises. This chapter is structured in four parts, with each part discussing a different statistical model. There are four models used, namely the multi-factor models with ESG extensions, the DCC-GARCH model employed by Sadorsky (2014), the Baur & McDermott (2010) principal component regression models and its derivatives, and the wavelet coherence model. Moreover, each part also discusses the rationale for the selection of each model, including model extensions and adjustments.

4.1 Multi-Factor Models

I use the portfolios created to test Hypotheses 1, 2a, and 2b. Each portfolio is subjected to four different factor models. The base model is a Fama-French three-factor model, as defined by Fama & French (1996) and employed by Landi & Sciarelli (2019) in the ESG setting. The specification of the base model is:

$$R_i - R_f = \alpha_i + \beta_1 MRP_t + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_i \tag{1}$$

where $R_i - R_f$ is the daily portfolio *i* return minus the risk-free rate, α_i is the abnormal return of portfolio *i*, MRP_t is the market premium, SMB_t is the return difference between a small- and large-cap portfolios at time *t*, HML_t is the difference between value and growth portfolios at time *t* (Derwall et al., 2005; Fama & French, 1996).

To estimate the effect of the ESG factor, it is necessary to include the parameter in the equation. This can be done by computing the spread between the top and bottom quarters of firms, using ESG rankings (Díaz et al., 2021). The following model includes the said ESG factor:

$$R_i - R_f = \alpha_i + \beta_1 MRP_i + \beta_2 SMB_i + \beta_3 HML_i + \beta_4 ESG_i + \varepsilon_i \tag{2}$$

The fourth model combines the models of Nofsinger & Varma (2014) and Díaz et al. (2021) by including both the distress and ESG factor:

$$R_i - R_f = \alpha_{NC} D_i + \alpha_C D_i + \beta_1 MRP_i + \beta_2 SMB_i + \beta_3 HML_i + \beta_4 ESG_i + \varepsilon_i \tag{3}$$

where *D* is the dummy variable that takes a value of 1 in crises and 0 otherwise. The notation is the opposite in Nofsinger & Varma (2014), where 1 stands for non-crisis periods. The term *NC* stands for non-crisis, while *C* stands for a crisis. The crisis period can be either the shock caused by the COVID-19 pandemic, the Ukraine war or both.

4.2 Volatility

I use the DCC-GARCH methodology to test for correlations in volatility between ESG and non-ESG stocks (Hypothesis 2c) and the diversifying abilities of the ESG stocks (Hypothesis 5). The model assumes the correlations to vary over time, which gives the model its dynamic aspect (Sharma et al., 2021), as it allows to monitor investor behavior and their response to the news. Moreover, it directly accounts for heteroskedasticity by estimating the correlation coefficients of residuals. The time-varying correlation is also free of volatility bias, as the model adjusts for volatility (Celık, 2013). Engle (2002) discovered that the DCC mean-revering model has the smallest mean-absolute error (MAE) and, therefore, the highest accuracy compared to other multivariate specifications and moving average methods. Sadorsky (2014) evaluated the performances of multiple multivariate models (including DCC-GARCH) to assess volatility and conditional correlations between SRI investments, gold, and oil. He concluded that DCC-GARCH was the best model for this setting. I follow the methodology of Engle (2002), Sadorsky (2014), and Sharma et al. (2021 and estimate DCC-GARCH, which is defined as:

$$r_t = \mu_t + \alpha_t \tag{4a}$$

$$\alpha_t = H_t^{\frac{1}{2}} + z_t \tag{4b}$$

$$H_t = D_t R_t D_t, \tag{4c}$$

where r_t is a n x 1 vector of returns, μ_t is the vector of the expected value (constant), α_t is the returns vector, H_t is the matrix of time-varying conditional variances, D_t is the diagonal matrix of conditional standard deviations, and R_t the conditional correlation matrix. In addition, z_t is the vector of id errors (Sharma et al., 2021).

4.3 Regression Models

I use the principal components regression models as defined by Baur & McDermott (2010) and Shahzad et al. (2020) with modifications to test Hypotheses 3, 4, and 5. The standard principal component regression model combines linear regression and principal component analysis. This method is used for data that suffers from multicollinearity. The principal component analysis creates a principal component, where it gathers the highly correlated independent variables. As each component is independent of the other, the variables become uncorrelated. To build the linear regression, regression equations of individual components are constructed. Finally, the "best" equation of the components is transformed into linear regression, maximizing the R^2 and minimizing standard errors (Liu et al., 2003; NCSS, n.d.).

There are two assumptions of this regression model. First, it is assumed that the prices of ESG stocks are solely dependent on changes in prices of non-ESG stocks, as investors can choose to allocate their capital to alternative return-generating assets depending on their underlying preferences. Second, the relationship is not constant as extreme market conditions extrapolate the dependence (Baur & McDermott, 2010). In summary, investors may want to compare ESG stocks to non-ESG stocks (or other assets) and decide to invest a given ratio between the two assets, depending on the assets' (expected) future performance and market volatility at the time of investing.

In the case of the Baur & McDermott (2010) principal components model, certain aspects deviate from the standard model. Namely, the principal components are directly loaded onto the variables in the equation. Therefore, the procedure is done in a 'reverse' order.

The principal components regression model (based on Baur & McDermott (2010)) that analyzes the safe haven and hedging properties of ESG stocks is defined as:

$$r_{ESG\ stocks,t} = \alpha + \beta_t r_{non-ESG\ stock,t} + \varepsilon_t \tag{5}$$

where r is the return of ESG and non-ESG stocks, α and β_t are the estimation parameters, and ε_t is the error term. The equation above defines investors' decision in the equity market, namely whether to invest while considering financial and non-financial performance or to optimize for financial performance only. The main assumption of the main equation is that the returns of ESG stocks are to a large extent determined by the returns of non-ESG stocks, as it does not include any additional variables. The predicted value from Equation 7 is then used in Equations 8a and 8b Furthermore, $\hat{\beta}_t$ is specified in two distinct ways. The first specification method uses the volatility peak of the entire period of interest, whereas the second method employs the standard crisis periods as seen in previous equations. The $\hat{\beta}_t$ specifications are:

$$\begin{aligned}\hat{\beta}_t = c_0 + c_1 D(r_{non-ESG\ stocks} q_{10}) + c_2 D(r_{non-ESG\ stocks} q_5) \\ + c_3 D(r_{nonESG-stocks} q_1)\end{aligned} \tag{6a}$$

$$\hat{\beta}_t = c_0 + c_1 D(Covid\ Crisis, 2020) + c_2 D(Ukraine\ War, 2022) \tag{6b}$$

where α and $\hat{\beta}_t$ are the estimation parameters, ε_t is the error term, c_{0-3} are the components of $\hat{\beta}_t$, and D is the dummy variable that captures the market crisis periods. It is equal to zero when there is no crisis and to one in times of crisis. The $q_{10,5,1}$ stands for the quantiles of the returns distribution.

ESG stocks may be considered a general safe haven under two conditions. If all the c components are negative and statistically different from zero, ESG stocks function as a strong safe haven. If the components are negative but not statistically different from zero, ESG stocks are a weak safe haven. If the first component is zero or negative, and the sum of the remaining components is not larger than the value of the first component, ESG stocks can be classified as a hedge (Baur & McDermott, 2010).

Furthermore, to account for asymmetries caused by the lags between the markets, following Baur & McDermott (2010), I apply the asymmetric GARCH(1,1) process for the errors in the equation and to account for the heteroskedasticity in the data:

$$h_t = \pi + \alpha e_{t-1}^2 + \beta h_{t-1} \tag{7}$$

4.4 Wavelet Coherence

In addition, following the research of Bouri et al. (2021), Rubbaniy et al. (2022), as well as the recommendation of Sharma et al. (2021), the wavelet coherence analysis is employed. This analysis provides additional insight into the safe haven and hedging properties of ESG stocks. The wavelet coherence analysis follows the specifications defined by Torrence & Compo (1998). While originally used in geophysics, this method has been recently used to evaluate the hedge and safe haven properties of financial assets. The benefit of this method is that it can uncover co-movement between assets in focus and the control group at various frequencies (Bouri et al., 2020) by decomposing time into time-frequency space (Torrence & Compo, 1998). Through the decomposition, it is possible to separate the horizons of various market participants (e.g., traders, who have a relatively short-term investment horizon, and institutional investors, who tend to invest in the longer-term) and capture underlying persistent co-movements (Bouri et al., 2020). The decomposition takes effect through a value function (specified below), which is the result of a "mother wavelet" $\psi(t)$. This wavelet must fulfill several conditions (zero mean, square integration to unity, limited interval of time, and it must satisfy the admissibility condition which allows reconstructing the time series) (Rua & Nunes, 2009). The wavelets are specified as:

$$\psi_{\tau,s}(t) = \frac{1}{\sqrt{s}}\,\psi\left(\frac{t-\tau}{s}\right) \tag{8}$$

where τ is the time position, s is the scale (frequency), and the normalization factor is represented as a fraction of a square root of s. The normalization factor ensures comparability between the wavelet and the time series (Rua & Nunes, 2009).

Following previous literature, I use the continuous wavelet transform rather than the discrete wavelet transform as it allows for selecting wavelets based on data length and a more straightforward interpretation. Moreover, the method also enables an easier discovery of underlying patterns. The continuous wavelet transform spectrum of time series *x(t)* can be specified as:

$$W_x(\tau, s) = \int_{-\infty}^{+\infty} x(t)\psi_{\tau,s}^{*}(t)dt = \frac{1}{\sqrt{s}} \int_{-\infty}^{+\infty} x(t)\,\psi^{*}\left(\frac{t-\tau}{s}\right)dt \tag{9}$$

where $W_x(\tau, s)$ is the wavelet transform of time series x(t) and the asterisk (*) denotes a complex conjugate (Bouri et al., 2020).

Continuous wavelet transforms of two time series form a cross-wavelet transform:

$$W_{x,y}(\tau, s) = W_x(\tau, s)W_y^{*}(\tau, s) \tag{10}$$

where $W_x(\tau,s)$ and $W_y(\tau,s)$ represent the continuous wavelet transform of their respective time series and * stands for a complex conjugate (Bouri et al., 2020; Rua & Nunes, 2009). The cross-wavelet transform further allows to define the cross-wavelet power $\left|W_{x,y}(\tau, s)\right|$, which identifies high common power areas between two time series (Bouri et al., 2020).

The absolute values of the cross-wavelet spectrum are normalized (smoothened) by the wavelet squared coherence (Rua & Nunes, 2009):

$$R^2(\tau, s) = \frac{|S(s^{-1}W_{x,y}(\tau, s)|^2}{S(s^{-1}|W_x(\tau, s)|^2)S\left(s^{-1}\left|W_y(\tau, s)\right|^2\right)} \tag{11}$$

where R^2 stands for the squared coherency and *S()* stands for the smoothing operator (Bouri et al., 2020). The squared coherence takes values between 0 and 1, where increasing the squared coherence value signifies a stronger correlation between two time series (Rubbaniy et al., 2021).

The squared coherence only takes positive values and does not distinguish between positive and negative correlations. In order to solve this issue, it is possible to apply a phase difference specified as:

$$\phi_{x,y}(\tau, s) = tan^{-1}\left(\frac{\Im\left\{S\left(s^{-1}W_{x,y}(\tau, s)\right)\right\}}{\Re\left\{S(s^{-1}W_{x,y}(\tau, s))\right\}}\right) \tag{12}$$

where $\Im$ and $\Re$ are the imaginary and real components of the smooth power spectrum. The phase difference is graphically represented through directional arrows, which denote either a positive (arrow pointing to the right) or a negative correlation (arrow pointing to the left). Moreover, arrows pointing upwards (downwards) show the leading impact of the first (second) series. In case the phase difference is zero, the series are moving simultaneously. In addition, the graphical representation also shows the wavelet coherence signified through a color scale. Hotter (colder) colors represent a higher (lower) relationship between the series. (Bouri et al., 2020; Rubbaniy, 2021). In the case of this paper, ESG stocks would be considered a safe-haven or a hedge if a cold color represented the relationship between them and conventional stocks.

5. Results

This chapter discusses the tests conducted to evaluate the validity of the hypothesis defined in the second chapter. There are five sections in this chapter, where the first four analyze the results of each of the methods used, while the last section is dedicated to the robustness tests.

5.1 Multi-factor models

The difference between daily portfolio returns and the risk-free rate is the independent variable, which is continuous. I initially ran the tests with normal, unadjusted values of the independent variable and then with the natural logarithm adjustment. As the results retrieved were identical, I chose to use normal unadjusted values of daily portfolio returns for the rest of the analysis, as there was no need to transform the data into logarithms. Moreover, I corrected the standard errors for autocorrelation using the Newey-West standard errors.

The first hypothesis states that "*the ESG factor does not contribute to (abnormal) returns*" and is tested using Equations 1, 2, and 3. I look at abnormal returns during the whole period, the pre-Covid period, and the two crises (Covid and Ukraine war), using the global top 20% ESG portfolios based on the S&P and Refinitiv ESG rankings. As can be seen in Tables 1 to 4, the abnormal returns of both portfolios relative to the market are significantly negative during all periods, except for the Ukraine war crisis, during which they are positive but insignificant. On the other hand, the ESG factor is shown to have a significantly positive effect for all periods analyzed. Therefore, the larger the spread between returns of top and bottom of ESG-ranked equities, the higher the return of ESG portfolios. As a result, since the ESG factor significantly contributes to the portfolio's returns in all periods, the null hypothesis is not supported. It is also worth noting that the Fama-French three-factor model (with or without the ESG spread included) explains more variation in the S&P ESG portfolio than in the Refinitiv ESG portfolio, and the goodness of fit increases substantially during crisis periods.

Table 1: Fama-French Three-Factor Model with and without ESG spread by portfolio during the whole period

A = S&P ESG portfolio, B = Refinitiv ESG portfolio

Dependent variable: daily ESG portfolio returns				
		Whole period		
Variable	A	B	A	B
α	-0.0037***	-0.0040***	-0.0037***	-0.0039***
	(0.0001)	(0.0002)	(0.0001)	(0.0001)
MRP	0.0100***	0.0085	0.0099***	0.0088***
	(0.0001)	(0.0005)	(0.0001)	(0.0004)
SMB	-0.0025***	0.0007	-0.0021***	-0.0003
	(0.0004)	(0.0005)	(0.0003)	(0.0005)
HML	-0.0022***	0.0009	-0.0021***	0.0002
	(0.0001)	(0.0001)	(0.0002)	(0.0003)
ESG	-	-	0.2989***	0.3081***
			(0.0262)	(0.0220)
N	1,434	1,434	1,434	1,434
F	1265.91***	230.84***	1036.87***	372.34***
R^2	77.62	61.55	79.65	68.18

***p<0.01; **p<0.05; *p<0.10
Robust standard errors in parentheses.

Table 2: Fama-French Three-Factor Model with and without ESG spread by portfolio in the pre-Covid period

A = S&P ESG portfolio, B = Refinitiv ESG portfolio

Dependent variable: daily ESG portfolio returns				
		pre-Covid		
Variable	A	B	A	B
α	-0.0063***	-0.0064 ***	-0.0063***	-0.0063***
	(0.0002)	(0.0002)	(0.0003)	(0.0002)
MRP	0.0103***	0.0090***	0.0105***	0.0098***
	(0.0003)	(0.0004)	(0.0003)	(0.0003)
SMB	-0.0020***	-0.0009	-0.0019***	-0.0014**
	(0.0006)	(0.0009)	(0.0006)	(0.0007)
HML	-0.0033***	0.0004	-0.0033***	-0.0004
	(0.0005)	(0.0006)	(0.0005)	(0.0006)
ESG	-	-	0.2637***	0.2626***
			(0.0424)	(0.0274)
N	805	805	805	805
F	624.25***	213.93***	516.96***	247.80***
R^2	63.76	46.11	65.30	52.34

***p<0.01; **p<0.05; *p<0.10
Robust standard errors in parentheses.

Table 3: Fama-French Three-Factor Model with and without ESG spread by portfolio during the Covid crisis

A = S&P ESG portfolio, B = Refinitiv ESG portfolio

Dependent variable: daily ESG portfolio returns				
		Covid		
Variable	A	B	A	B
α	- 0.0062***	-0.0065***	-0.0061***	-0.0061***
	(0.0006)	(0.0012)	(0.0006)	(0.0009)
MRP	0.0107***	0.0092***	0.0108***	0.0096***
	(0.0003)	(0.0009)	(0.0003)	(0.0010)
SMB	- 0.003	0.0025*	-0.0001	0.0017*
	(0.0008)	(0.0014)	(0.0006)	(0.0010)
HML	-0.0043***	-0.0003	-0.0040***	-0.0023**
	(0.0011)	(0.0015)	(0.0010)	(0.0011)
ESG	-	-	0.2265***	0.4863***
			(0.0798)	(0.0771)
N	64	64	64	64
F	1089.38***	65.53***	828.12***	204.88***
R^2	97.26	88.47	97.57	93.17

***p<0.01; **p<0.05; *p<0.10
Robust standard errors in parentheses.

Table 4: Fama-French Three-Factor Model with and without ESG spread by portfolio during the Ukraine war crisis

A = S&P ESG portfolio, B = Refinitiv ESG portfolio

Dependent variable: daily portfolio returns (ESG – non-ESG)				
		Ukraine war		
Variable	A	B	A	B
α	0.0002	0.0000	0.0007	-0.0002
	(0.0007)	(0.0018)	(0.0006)	(0.0010)
MRP	0.0086***	0.0115***	0.0081	0.0093***
	(0.0007)	(0.0018)	(0.0005)	(0.0010)
SMB	-0.0029**	0.0043	-0.0029***	0.0034**
	(0.0011)	(0.0030)	(0.0009)	(0.0013)
HML	-0.0021***	0.0049**	-0.0031***	0.0007
	(0.0007)	(0.0023)	(0.0007)	(0.0012)
ESG	-	-	0.3614***	0.6223***
			(0.0722)	(0.0658)
N	26	26	26	26
F	75.24	15.12	172.18	57.14
R^2	94.57	76.21	97.03	94.21

***p<0.01; **p<0.05; *p<0.10
Robust standard errors in parentheses.

Hypothesis 2a is formalized as *"ESG equities do not perform differently from conventional stocks in times of high market volatility"*. I used Equation 3 to test the hypothesis, as previous tests revealed that the goodness of fit increases with the inclusion of the ESG factor. Tables 5 and 6 show that the constant (α), which is the abnormal return of the difference between ESG and non-ESG portfolio differences, is insignificant for the Covid period. However, the constant is significant for the Ukraine war period for both portfolios and for the S&P portfolio difference during pre-Covid. As a result, there is a difference in (abnormal) performance during the Covid and the Ukraine war period. The ESG factor is significant for both portfolios in all periods. Therefore, the ESG factor significantly contributes to the portfolio difference performance but does not generate abnormal returns relative to the market. Nevertheless, provided the hypothesis aims to compare the ESG and non-ESG portfolios and not the entire market, the null hypothesis cannot be supported, as the ESG factor still has a significant positive effect in both periods of high volatility.

Table 5: Fama-French Three-Factor Model by portfolio during the whole and pre-Covid period

A = S&P ESG-S&P non-ESG, B = Refinitiv ESG-Refinitiv non-ESG

Dependent variable: daily portfolio returns (ESG – non-ESG)				
	Whole period		**pre-Covid**	
Variable	A	B	A	B
α	0.0001** (0.0000)	-0.0002* (0.0001)	0.0001** (0.0000)	0.0000 (0.0001)
MRP	-0.0002*** (0.0001)	-0.0016*** (0.0002)	0.0000 (0.0001)	-0.0010*** (0.0002)
SMB	0.0011*** (0.0002)	-0.0005 (0.0003)	0.0011*** (0.0002)	0.0000 (0.0003)
HML	-0.0007*** (0.0001)	0.0017*** (0.0002)	-0.0003 (0.0002)	0.0023 (0.0003)
ESG	0.4324*** (0.0145)	0.3032*** (0.0134)	0.4566*** (0.0162)	0.3153*** (0.0147)
N	1,434	1,434	805	805
F	241.26***	230.90***	201.95***	184.07***
R^2	57.16	52.65	54.77	54.62

***p<0.01; **p<0.05; *p<0.10

Robust standard errors in parentheses.

Table 6: Fama-French Three-Factor Model by portfolio during the Covid and Ukraine war crises

A = S&P ESG-S&P non-ESG, B = Refinitiv ESG-Refinitiv non-ESG

Dependent variable: daily portfolio returns (ESG – non-ESG)				
	Covid		**Ukraine War**	
Variable	A	B	A	B
α	0.0003 (0.0004)	-0.0006 (0.0007)	-0.0061*** (0.0006)	-0.0061*** (0.0009)
MRP	0.0002 (0.0002)	-0.0008** (0.0003)	0.0108*** (0.0003)	0.0096*** (0.0010)
SMB	0.0023*** (0.0004)	0.0000 (0.0010)	-0.0001 (0.0006)	0.0017* (0.0010)
HML	-0.0008 (0.0006)	-0.0000 (0.0007)	-0.0040*** (0.0010)	-0.0023** (0.0011)
ESG	0.4851*** (0.0643)	0.3916*** (0.0620)	0.2265*** (0.0798)	0.4863*** (0.0771)
N	64	64	26	26
F	32.27***	22.35***	828.12***	204.88***
R^2	68.85	55.85	97.57	93.17

***p<0.01; **p<0.05; *p<0.10

Robust standard errors in parentheses.

I used Equations 2 and 3 to test Hypothesis 2b, which states that "*there is no difference in performance between the Environmental, Social, and Governance pillars of ESG"*. Regarding returns, all portfolios significantly underperform the market in all periods. An exception is the Ukraine war crisis, where they are on par with the market. Nevertheless, this underperformance is comparable during all periods, except the Covid crisis, during which the Social dimension portfolio performed slightly better than the other two, as seen in Tables 7-10. The goodness of fit of the Fama-French model of all three portfolios is comparable to the general Refinitiv ESG portfolio.

Moreover, Tables 7-10 show differences between portfolios in terms of the contribution of the ESG factor to portfolio return. For instance, the coefficient of the ESG factor is the highest in the Social dimension portfolio. At the same time, it is the lowest in the Governance dimension portfolio. The ESG factor is always significantly positive for the Environmental and Social dimension portfolios, while it is positively significant for the Governance portfolio during all periods, except for the Covid crisis. Therefore, as the performance of the portfolios is comparable, there are no significant differences in the factors which affect the returns and the magnitudes of said factors. As the results of both the t-test and the regressions find no performance differences, the null hypothesis is not rejected. Finally, this finding is in line with the results of Díaz et al. (2021), who also identified the Environmental and Social dimensions as largest performance drivers.

Table 7: Fama-French Three-Factor Model with the ESG spread by portfolio during the whole period

E = Refinitiv ESG - Environmental, S = Refinitiv ESG - Social, G = Refinitiv ESG - Governance

Dependent variable: daily portfolio returns			
		Whole period	
Variable	E	S	G
α	-0.0038***	-0.0038 ***	-0.0039***
	(0.0001)	(0.0002)	(0.0002)
MRP	0.0102***	0.0095***	0.0098***
	(0.0002)	(0.0003)	(0.0002)
SMB	0.0004	0.0021***	0.0004
	(0.0004)	(0.0005)	(0.0006)
HML	0.0013***	-0.0003	0.0009***
	(0.0003)	(0.0003)	(0.0002)
ESG	0.4064***	0.4559***	0.1326***
	(0.0360)	(0.0378)	(0.0363)
N	1,434	1,434	1,434
F	531.57***	358.37***	475.18***
R^2	70.75	66.07	70.72

***p<0.01; **p<0.05; *p<0.10
Robust standard errors in parentheses.

Table 8: Fama-French Three-Factor Model with the ESG spread by portfolio during the pre-Covid period

E = Refinitiv ESG - Environmental, S = Refinitiv ESG - Social, G = Refinitiv ESG - Governance

Dependent variable: daily portfolio returns			
		pre-Covid	
Variable	E	S	G
α	-0.0063***	-0.0063**	-0.0064***
	(0.0002)	(0.0002)	(0.0002)
MRP	0.0103***	0.0099***	0.0097***
	(0.0004)	(0.0004)	(0.0004)
SMB	-0.0014*	-0.0002	-0.0009
	(0.0007)	(0.0008)	(0.0007)
HML	-0.0009	-0.0008	-0.0002
	(0.0006)	(0.0006)	(0.0006)
ESG	0.3784***	0.3965***	0.1227**
	(0.0539)	(0.0546)	(0.0531)
N	805	805	805
F	277.61***	229.74***	244.43***
R^2	57.20	53.36	51.83

***p<0.01; **p<0.05; *p<0.10
Robust standard errors in parentheses.

Table 9: Fama-French Three-Factor Model with the ESG spread by portfolio during the Covid crisis

E = Refinitiv ESG - Environmental, S = Refinitiv ESG - Social, G = Refinitiv ESG - Governance

Dependent variable: daily portfolio returns			
		Covid	
Variable	E	S	G
α	-0.0058***	-0.0055***	-0.0061***
	(0.0010)	(0.0011)	(0.0013)
MRP	0.0101***	0.0096***	0.0106***
	(0.0006)	(0.0006)	(0.0006)
SMB	0.0011	0.0040***	0.0031**
	(0.0011)	(0.0013)	(0.0014)
HML	0.0012	-0.0004	0.0000
	(0.0013)	(0.0014)	(0.0014)
ESG	0.3205**	0.5148***	-0.1895
	(0.1427)	(0.1793)	(0.2484)
N	64	64	64
F	172.99***	108.04***	116.14***
R^2	96.24	90.05	90.82

***p<0.01; **p<0.05; *p<0.10
Robust standard errors in parentheses.

Table 10: Fama-French Three-Factor Model with the ESG spread by portfolio during the Ukraine war crisis

E = Refinitiv ESG - Environmental, S = Refinitiv ESG - Social, G = Refinitiv ESG - Governance

Dependent variable: daily portfolio returns			
		Ukraine war	
Variable	E	S	G
α	-0.0002	0.0015	0.0001
	(0.0012)	(0.0013)	(0.0008)
MRP	0.0136***	0.0119***	0.0102***
	(0.0010)	(0.0015)	(0.0008)
SMB	0.0049	0.0046	0.0009
	(0.0031)	(0.0028)	(0.0014)
HML	0.0027	0.0019	0.0009
	(0.0018)	(0.0018)	(0.0011)
ESG	1.0817***	1.1828***	0.5266***
	(0.1433)	(0.1865)	(0.1296)
N	26	26	26
F	126.63***	90.22***	70.34***
R^2	92.50	91.12	93.69

***p<0.01; **p<0.05; *p<0.10
Robust standard errors in parentheses.

5.2 Volatility

Hypothesis 2c states that "*the volatility of ESG equities is not different from the volatility of conventional stocks*". The DCC-GARCH method evaluates the (auto)correlations and volatilities of the ESG and non-ESG portfolios. I used the same model as Sadorsky (2014) and chose to analyze the volatility and autocorrelation in three periods: the whole period, the pre-Covid period, and the post-Covid period. The model does not fare well with extremely short periods, which is why the periods used are different from those described in the data section. I split the data into the period before and after the Covid-19 pandemic. I chose to only compare the volatility and autocorrelation between individual ESG and non-ESG portfolio pairs, which are based on the same ESG score, as it does not cause additional complexity in interpreting the results.

The results in Table 11 show the output of the DCC-GARCH model for the whole period and the two sub-periods. Furthermore, the Table variable lags, dependencies on the conventional stock portfolios, and autocorrelations. The autocorrelations are very high for both the S&P and Refinitiv ESG portfolios. However, Figures 23 to 27 (see Appendix) indicate that in the period before the pandemic, the autocorrelation between ESG and conventional portfolios was higher than in the period after. Overall, a slight decrease in autocorrelation during the Covid and Ukraine crises can be observed when looking at the entire period. When looking at the sub-periods separately, it becomes more apparent that the autocorrelation has become more volatile in the post-Covid period and that there is a substantial drop in the correlation between the ESG and non-ESG portfolios during the Ukraine war crisis. Table 11 shows the same findings, where the adjustment factor λ_1 increases in the post-Covid period compared to the pre-Covid period. Thus, the shock-dependent correlation increases in the post-Covid period. Nevertheless, λ_2, which explains how much correlation depends on the variable's lag remains higher than the adjustment factor. Therefore, albeit the shocks impact the correlations, it is mainly caused by its lag.

The answer to Hypothesis 2c is two-fold. When looking at the entire period, or the individual sub-periods, the volatility of the ESG and conventional stock portfolios is close to identical, meaning the hypothesis cannot be rejected. However, when comparing the correlations of the portfolios during the shock, the correlation between the portfolios drops significantly, suggesting different levels of volatility. In that case, the hypothesis should be rejected. In conclusion, provided Hypothesis 2c aims to compare the volatility between the ESG and conventional stock portfolios over the entire period, without specifying times of crises, the hypothesis cannot be rejected.

Table 11: DCC-GARCH

	S&P ESG			Refinitiv ESG		
Variable	Before	After	Total	Before	After	Total
L.1	- 0.0796	- 0.2683***	- 0.1586**	- 0.1706***	- 0.1458*	- 0.1411***
S&P non-ESG	0.1820**	0.3296***	0.2384***	-	-	-
Refinitiv non-ESG	-	-	-	0.2309***	0.1989***	0.2053***
ARCH	0.0783***	0.1464***	0.0964***	0.0783***	0.1274***	0.1025***
GARCH	0.8566***	0.7798***	0.8724***	0.8604***	0.8074***	0.8572***
Constant	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***
λ_1	0.0330**	0.1777***	0.0474*	0.0531**	0.0788***	0.0332**
λ_2	0.9171***	0.5934***	0.9262***	0.7720***	0.8376***	0.9480***
Corr. ESG-non-ESG	0.9122***	0.9298***	0.9172***	0.8128***	0.8646***	0.8307***
N	804	628	1,433	804	628	1,433
Log-Likelihood	6643.80	4554.16	11170.21	6257.81	4366.92	10611.6
χ^2	27.90***	22.87***	49.96***	21.94***	15.03***	34.22***

***p<0.01; **p<0.05; *p<0.10

Robust standard errors in parentheses.

The results displayed in the autocorrelation graphs (Figure 15 – 19, see Appendix) also answer Hypothesis 5 ("*ESG equities do not possess diversifying properties*"). According to the definition of a diversifying asset, as described in Baur & Lucey (2010), that type of asset is "*positively (but not perfectly) correlated with another asset or portfolio on average*". As the figures mentioned above show, S&P ESG, Refinitiv ESG, and S&P ESG Emerging have a positive but not a perfect correlation with their non-ESG pair. Therefore, they can be used as a diversifier. On the other hand, the S&P ESG Developed portfolio is close to being perfectly correlated with its non-ESG pair. Consequently, it cannot be used as a diversifier. Given the evidence provided, the null hypothesis can be rejected as the results indicate that it does not hold for most of the ESG portfolios.

5.3 Regression models – principal components

This section will test Hypotheses 3 and 4, namely whether "*ESG equities do not possess hedge/safe-haven properties*". Tables 12 and 13 show the results of Equations 6a and 6b respectively. As shown in the table below, in normal times (c_0), the ESG portfolios all take statistically significant values close to zero. Hence, they serve as weak hedges in normal times. However, when it comes to periods of slightly increased volatility (c_1), the values of S&P ESG, S&P ESG Developed, and Refinitiv ESG – E become negative and statistically significant. Thus, the portfolio can serve as a strong safe haven, as the values are negative. If the volatility is increased further (c_2), the other portfolios become strong safe havens instead. However, in times of extreme volatility (c_3), the initial three portfolios become strong safe havens again, while Refinitiv ESG (Global, S, and G) portfolios become weak safe havens. In addition, the value for the S&P ESG Emerging shows that this portfolio serves as a strong safe haven under extreme shocks. It is also the only portfolio of stocks that shows increasing safe haven properties as volatility increases, while other portfolios do not follow any trend.

Table 12: Hedge and safe haven portfolio pairs by volatility quantiles

Portfolio	**Volatility quantiles**			
	c_0 (Hedge)	c_1 (0.10)	c_2 (0.05)	c_3 (0.01)
S&P ESG	0.0010***	- 0.0045 ***	0.0026	- 0.0072***
Refinitiv ESG	0.0005**	- 0.0002	- 0.0036***	- 0.0009
S&P ESG Developed	0.0010***	- 0.0034**	0.0005	- 0.0069***
S&P ESG Emerging	0.0009**	0.0021	0.0044*	- 0.0222***
Refinitiv ESG - E	0.0009***	- 0.0038***	0.0023	- 0.0083***
Refinitiv ESG - S	0.0007***	- 0.0001	- 0.0044***	- 0.0006
Refinitiv ESG - G	0.0006**	- 0.0004	- 0.0042***	- 0.0004

***p<0.01; **p<0.05; *p<0.10

The table below shows an alternative way of looking at the hedge and safe haven properties of the ESG portfolios, namely through the predefined crisis periods. As the values in the table show, some of the ESG portfolios are still weak hedges in normal times. These portfolios are S&P ESG Global, Developed, Emerging, as well as Refinitiv ESG – E. During the Covid period, all portfolios have negative, statistically insignificant values. Therefore, they serve as weak safe havens in that period, while during the Ukraine crisis, all portfolios except for S&P ESG Emerging have positive values. It could be due to the limited impact of the Ukraine war on non-Western markets, as the regional character of the conflict. Baur & McDermott (2010) recognize that the method of measuring the crisis times by a predefined period instead of by the levels of volatilities of individual observations tends to be somewhat arbitrary and less statistical, which could explain the difference in results between the two methods.

Table 13: Hedge and safe haven portfolio pairs by crises

Portfolio	Crisis		
	c_0 (Hedge)	c_1 (Covid)	c_2 (Ukraine)
S&P ESG	0.0006**	- 0.0011	0.0014
Refinitiv ESG	0.0002	- 0.0008	0.0011
S&P ESG Developed	0.0006*	- 0.0012	0.0017
S&P ESG Emerging	0.0010***	- 0.0002	- 0.0030
Refinitiv ESG – E	0.0004*	- 0.0009	0.0017
Refinitiv ESG – S	0.0004*	- 0.0011	0.0010
Refinitiv ESG – G	0.0003	- 0.0010	0.0011

***p<0.01; **p<0.05; *p<0.10

As a result, Hypothesis 3, which states that "*ESG equities do not possess safe haven properties*", can be rejected as there are portfolios for each level of volatility where ESG portfolios do possess safe haven properties in times of increased volatility. Furthermore, Hypothesis 4, which states that "*ESG equities do not possess hedging properties*", can be rejected as the results show that some of the ESG can serve as hedges in normal times.

5.4 Wavelet coherence

The wavelet coherence method also tests Hypotheses 3 and 4. As mentioned in the methodology section, heatmaps are the output of this method, as can be seen in Figures 1 to 7 (below). The warmer (colder) the color, the higher (lower) the coherence. Time is represented on the horizontal axis in days, and frequency is on the vertical axis. The Covid-19 crisis occurred between days 807 and 871, while the Ukraine crisis occurred between days 1345 and 1370. The white striped line shows the area ("cone of influence") where the results are reliable. The higher (lower) the frequency, the longer (shorter) the investment horizon. The arrows pointing to the right (left) show a positive (negative) correlation. If the arrow points upwards (downwards), the first (second) series leads the second (first). In this model, the first series is always the ESG portfolio while the second is the non-ESG portfolio. If no arrows are present, the series are not correlated (and therefore not co-moving).

Figure 1 below shows the wavelet coherence between the global S&P ESG and non-ESG portfolios. The heatmap shows that the two series are positively correlated and co-moving for the low and medium frequencies. However, there are spots of no coherence on higher frequencies. There is a short period of no coherence during the Covid and Ukraine crisis on high frequencies, but these intervals are not an exception, as there are other intervals during the entire period. Interestingly, there is also a larger interval of no coherence on the medium-high frequency during the Covid recovery period. As such, this portfolio pair does not suggest that ESG stocks are a safe haven during crises, but they may function as a hedge in the long investment horizon.

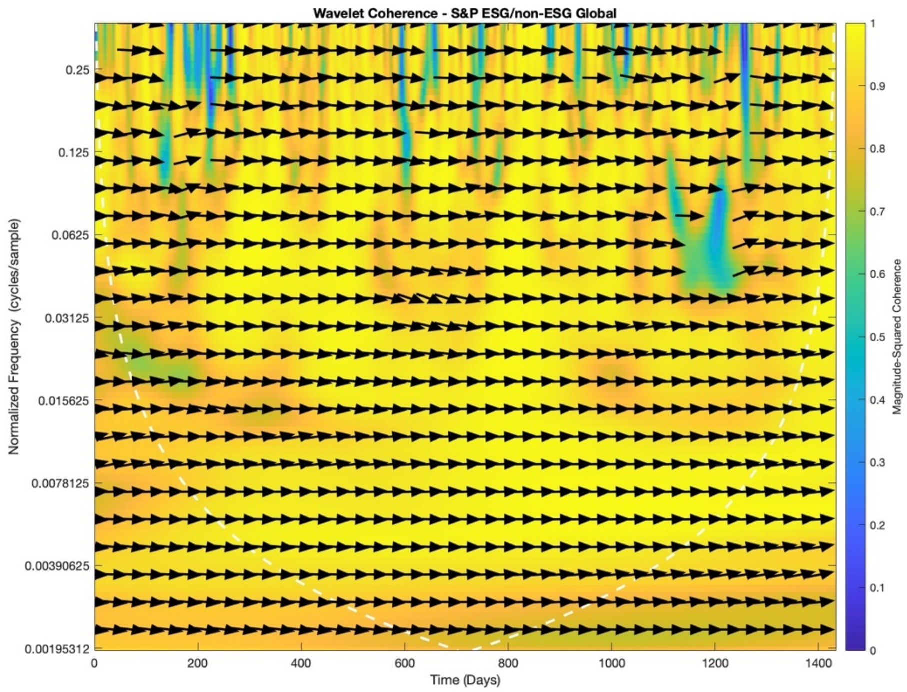

Figure 1: Wavelet coherence - S&P ESG/non-ESG Global portfolios

Figure 2 below shows the alternative global portfolio pair (Refinitiv). The results are similar to those of the previous portfolio pair on lower frequencies, but there is less coherence on the higher frequencies. There is no evidence that the ESG portfolio may function as a safe haven during crises, as there are no major coherence gaps during those periods. Given the non-coherence intervals are frequent and regular on high frequencies, there is evidence that this ESG portfolio may function as a long-term hedge. Furthermore, there is also a non-coherence gap on the medium-high frequencies showing that the ESG portfolio had temporary hedging properties. Therefore, based on the evidence presented, Hypothesis 3 could not be rejected, while Hypothesis 4 can be rejected. These findings are partially in line with the principal component method.

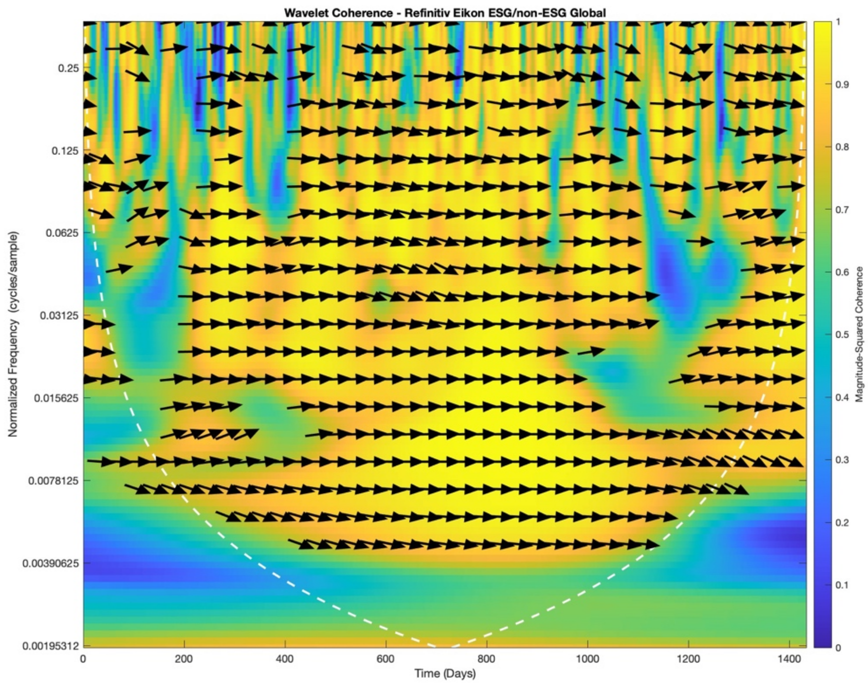

Figure 2: Wavelet coherence - Refinitiv ESG/non-ESG Global portfolios

Figures 3 and 4 (see below) show the wavelet coherence graphs of developed and emerging markets separately. As can be seen in both figures, the output suggests a near-perfect coherence and co-movement throughout the entire period examined. In this setting, ESG stocks do not function as a hedge or a safe haven. Furthermore, there is no evidence of a lag in either of the ESG classes, which implies that there is no difference between the ESG and non-ESG stocks in terms of market reaction. This suggests that the results on a global scale may be more variable due to the variability between stocks from developed and emerging markets and, thereby, the regional aspect rather than the ESG factor itself. In this setting, neither of the two hypotheses could be rejected.

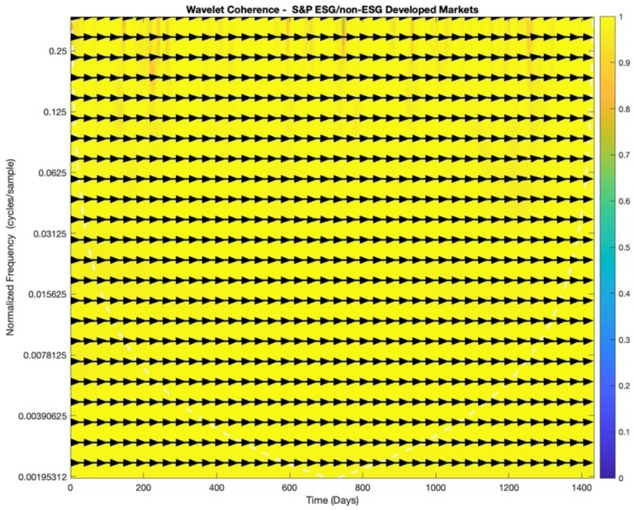

Figure 3: Wavelet coherence - S&P ESG/non-ESG Developed Markets

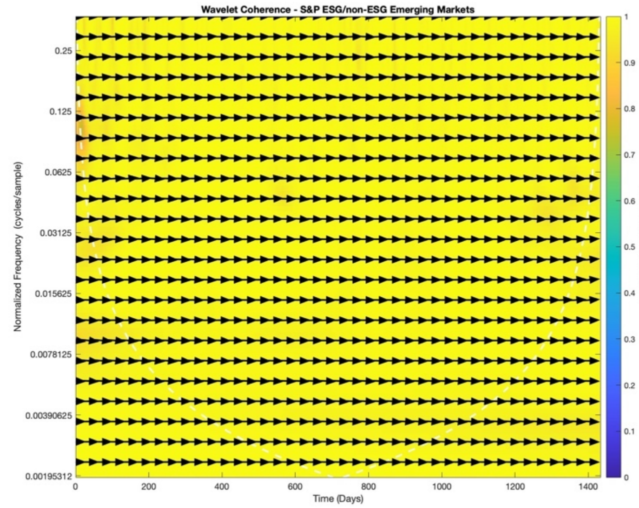

Figure 4: Wavelet coherence - S&P ESG/non-ESG Emerging Markets

Figures 5, 6, and 7 show the wavelet coherence graphs of the Environmental, Social, and Governance dimensions when isolated. As shown in the figures, the intervals of no-coherence are short and frequent on higher frequencies and similar across the three ESG dimensions. All three figures also provide evidence that the co-movement between the ESG and non-ESG pairs also occurred during the Covid crisis, which means that the ESG stocks could not have functioned as a safe haven in that period. However, there is a small interval in the beginning of the Ukraine crisis where the two series are not coherent. Nevertheless, the non-coherence occurs only in the high-frequency areas of the graphs. The most co-movement is present in the Governance dimension, whereas the least co-movement is found in the Environmental dimension. There is a period of non-coherence between the two series (Environmental dimension) during the recovery period on the medium-high frequency but not during Covid and the Ukraine war. A similar, albeit smaller pattern, can be found in the Social dimension. In addition, the Environmental dimension's non-coherence was present also for lower frequencies in the past two years. Therefore, given the results presented, the separate dimension ESG portfolios do not possess safe haven properties during crises, but hedging possibilities were present in the Environmental and Social dimensions during Covid recovery.

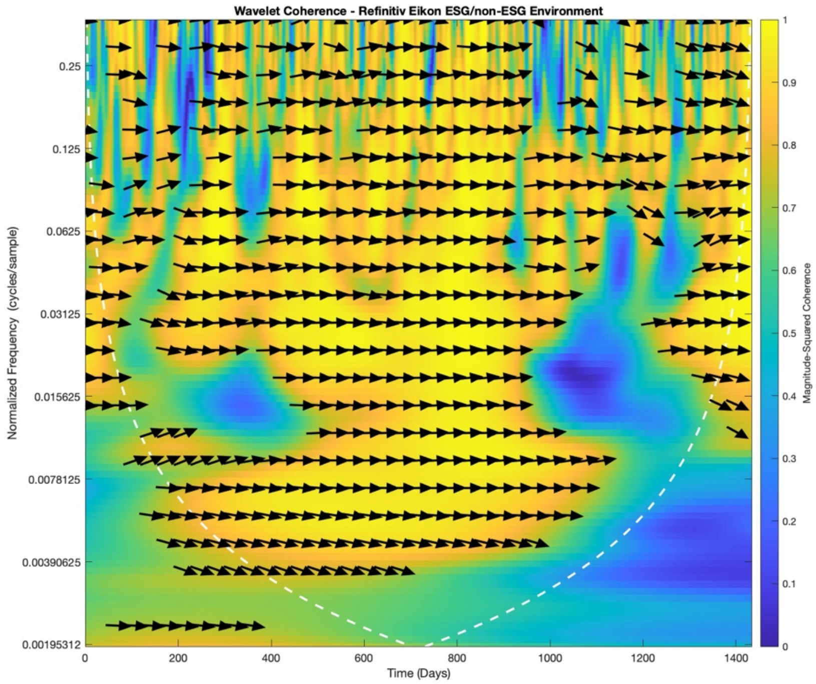

Figure 3: Wavelet coherence - Refinitiv ESG/non-ESG Environmental

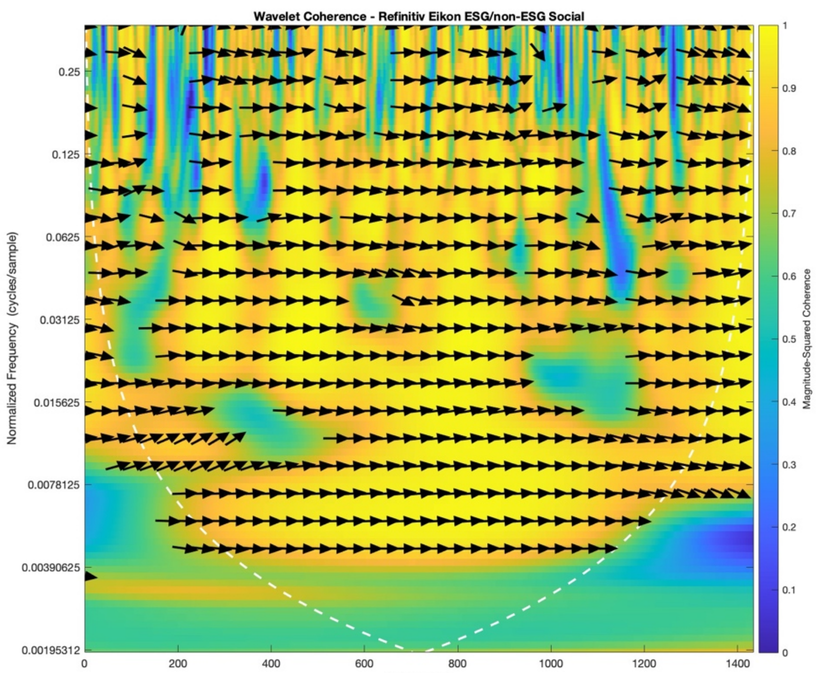

Figure 4: Wavelet coherence - Refinitiv ESG/non-ESG Social

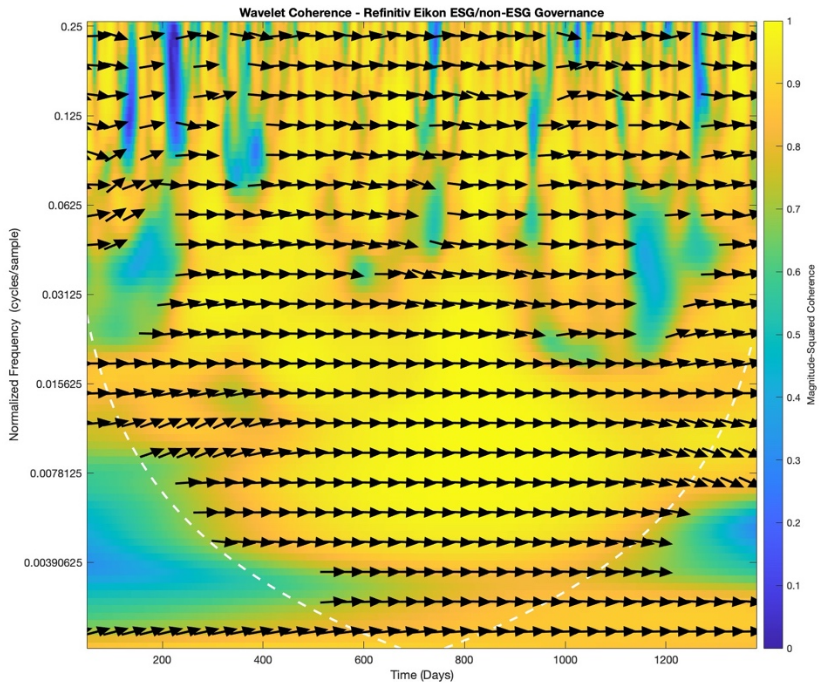

Figure 5: Wavelet coherence - Refinitiv ESG/non-ESG Governance

In conclusion, the wavelet coherence graphs show that ESG stocks have hedging properties in some intervals. These properties are mostly present on the medium to long-investment horizons, while there is evidence the portfolios almost perfectly co-move in the short term. Therefore, Hypothesis 3 cannot be rejected but Hypothesis 4 can. This conclusion is partially in conflict with the principal components method. This discrepancy could stem from the different definitions of a crisis, as the principal component model used both the volatilities and arbitrary crisis periods. In contrast, wavelet coherence only used the arbitrary crisis periods.

The wavelet coherence method also tests whether ESG stocks possess diversifying capabilities (Hypothesis 5). As shown in the graphs, the ESG stocks' ability to serve as a diversifier depends on the market and portfolio. A stock is a good diversifier when it is positively, yet not perfectly correlated with the asset it aims to diversify (Baur & Lucey, 2010). The diversifying properties of ESG stocks are visible in the S&P and Refinitiv ESG Global portfolios on medium-high frequencies but not on the S&P ESG Developed and Emerging portfolios. The Refinitiv ESG Environmental portfolio had diversifying properties on medium-high frequencies between 2018 and 2020 but not before and after. The Governance portfolio can function as a diversifier on the same frequencies since 2021. The Social portfolio does not have any long periods where it can function as a diversifier on any of the frequencies shown. Therefore, some portfolios can function as diversifiers for the whole period of interest or at least a large part of it, the null hypothesis cannot be supported. This finding is in line with the results of the DCC-GARCH analysis.

5.5 Robustness tests

This section discusses the results of the robustness tests conducted to ensure the validity of the results. This section is split into four parts, whereby each part analyzes the results of the robustness tests of one of the methods employed.

5.5.1 Multi-factor models

I chose to assess the robustness of the three-factor Fama French Model in two ways. First, I chose to run the Fama-French five-factor model on the global, developed, and emerging markets separately. Second, I use the Sustainalytics portfolio on the original three-factor model.

I tested the robustness of the results of Hypothesis 1 using both methods. The five-factor Fama-French model of both S&P and Refinitiv ESG global portfolios confirmed that the ESG spread is significant even after including additional factors. However, the results of the same model used on the S&P ESG developed markets portfolio are less convincing. The ESG factor is significant only on the 10% significance level for both the Covid and Ukraine war periods, with ESG equities underperforming the market for all periods but the Ukraine war. Moreover, the emerging markets ESG factor is significant for all periods, except for the Covid crisis, and its coefficient is negative. I also ran the Sustainalytics portfolio during the Ukraine war period, which confirmed that the ESG spread was positive and significant for global portfolios. I chose not to use the results from this portfolio for previous periods, as the Sustainalytics score became available only from 2021 onwards. In summary, there are differences in the impact of the ESG factor, depending on the scope of a portfolio, as there are significant differences in the treatment of ESG equities between the global, developed, and emerging markets. Therefore, the robustness holds for the global portfolio, but the results are not valid once the portfolio focuses on a specific market.

The first part of the second hypothesis can be tested using both methods too. The Sustainalytics portfolio has confirmed the persistence of the null hypothesis during the Ukraine war period, such that there are no significant differences in performance between ESG and non-ESG equities. The Fama-French five-factor model confirmed the persistence on the global, developed, and emerging markets. Therefore, the finding that there is no performance difference between ESG and non-ESG stocks during the crisis is robust.

I used the Fama-French five-factor model to assess the robustness of the results pertaining to the second part of the second hypothesis. I tested the model only on the global sample. The results confirmed that the performance of the Environmental, Social, and Governance portfolios remains comparable after including additional factors in the model. As a result, the findings of this hypothesis test are robust.

5.5.2 Volatility

To estimate the robustness of the DCC-GARCH model, I split the sample data into developed and emerging markets using the S&P portfolios. As Table 14 shows, the autocorrelation between ESG and non-ESG portfolios in both markets remains high; therefore, the results of the hypothesis remain robust. However, several changes can be observed in the table. Namely, the lambdas for emerging markets become insignificant after the start of the covid pandemic. Only λ_1 remains significant at the 10% level in the “after” period. For the emerging markets portfolio, the factor that shows the magnitude of lag-dependent correlation loses its significance completely, meaning that more of the correlation between the ESG and non-ESG portfolios in emerging markets depends on shocks, if the significance threshold is relaxed. Moreover, for developed markets, the lagged coefficient of the ESG portfolio is not significant in either of the periods. Therefore, the results presented are not robust once the global portfolio is split into regional samples.

Table 14: DCC-GARCH – Robustness check (Developed and Emerging markets)

	S&P ESG - Developed			**S&P ESG - Emerging**		
Variable	Before	After	Total	Before	After	Total
L.1	- 0.1089	- 0.4466	- 0.2097	1.0799***	- 0.0632	- 0.3962
S&P non-ESG - Developed	0.1834	0.4856	0.2661	-	-	-
S&P non-ESG - Emerging	-	-	-	- 0.9486***	0.0977	0.3321
ARCH	0.1066***	0.1214***	0. 0976***	0.0317***	0.0713***	0.0557***
GARCH	0.8193***	0.8097***	0. 8794***	0.9503***	0.8602***	0.9116***
Constant	0.0000***	0.0000***	0.0000***	0.0000 ***	0.0000***	0.0000***
λ_1	0.0505**	0.1302***	0.0522***	0.0181**	0.0945*	0.0192***
λ_2	0.8924***	0.7174***	0.9323***	0.9754***	0.0176	0.9792***
Corr. ESG-non-ESG	0.9937***	0.9943***	0.9939***	0.9953***	0.9957***	0.9908***
N	804	628	1,433	804	628	1,433
Log-Likelihood	7701.97	5327.77	13008.4	6788.37	4935.06	11703.85
χ^2	15.74***	8.77*	22.89***	12.39**	10.40**	11.09**

***p<0.01; **p<0.05; *p<0.10

Another way to test the presence of serial autocorrelation is through the Ljung-Box test. This test was developed by Ljung and Box (1978). It uses the squared standardized residual to test for serial autocorrelation (Metsileng, Moroke, & Tsoku, 2020). The results of the test are displayed below in Table 15. While the test demonstrates a strong autocorrelation present in the global and developed portfolios, both the ESG and non-ESG emerging markets portfolios are shown not to be autocorrelated. This result supports the notion that emerging markets are different from global one, and the results from tests run on regional portfolios should not be considered.

Table 15: DCC-GARCH – Robustness check (Ljung Box test)

Portfolio	Q-Statistic	p-value
S&P ESG Top	40.0854	0.0000***
S&P non-ESG	32.7321	0.0000***
Refinitiv ESG Top	11.2875	0.0000***
Refinitiv non-ESG	12.5037	0.0004***
S&P ESG Top – Developed	38.2277	0.0000***
S&P non-ESG – Developed	35.7723	0.0000***
S&P ESG Top – Emerging	1.1261	0.2886
S&P non-ESG – Emerging	0.8205	0.3650

***p<0.01; **p<0.05; *p<0.10

5.5.3 Regression models – principal components

The objective of this section is to test the assumptions on which is the principal components model-based. Table 16 (below) shows the effect of additional variables on the principal component regression. The main assumption of the principal regression model was that the return of the non-ESG counterpart is the only variable that affects the return of the ESG portfolio. As seen in the table below, this assumption does not hold once more variables are added to the model. For all ESG portfolios, there is at least one additional variable that, if changed, will change the return of the ESG portfolio. Despite the main assumption of the principal components model not holding after additional variables have been added, the results of the principal components model have remained unchanged and robust.

Table 16: Effect of additional variables on the principal component regression

Variable	ESG Portfolio						
	S&P	Refinitiv	S&P Developed	S&P Emerging	Refinitiv E	Refinitiv S	Refinitiv G
Bloomberg Agg.	(-)	(-)	(-)	(-)**	(-)*	(-)	(-)
Corporate bonds	(-)*	(-)***	(-)	(+)	(-)***	(-)**	(-)
S&P 500 Bonds	(+)*	(+)	(+)	(+)	(+)	(+)	(-)
HY Bonds	(+)**	(+)***	(+)	(+)***	(+)***	(+)**	(+)***
Gold	(+)	(-)	(-)	(+)*	(-)**	(-)	(-)
Oil	(+)	(+)**	(+)	(+)***	(+)**	(+)	(+)
US Dollar	(-)	(-)***	(-)***	(-)***	(-)***	(-)***	(-)***
Swiss Franc	(+)	(+)	(+)	(+)	(-)*	(-)	(+)
Safe haven / Hedge	Y	Y	Y	Y	Y	Y	Y

***p<0.01; **p<0.05; *p<0.10, (+) - positive coefficient, (-) – negative coefficient, Y – same result as in the base equation, N – different result from the base equation

5.5.4 Wavelet coherence

Provided the wavelet coherence method is not trying to establish causality in this case, no robustness tests will be performed. The two available robustness tests for this method are the Granger causality test and the Toda-Yamamoto causality test.

6. Discussion and Conclusion

This paper analyzed investors' behavior in the markets in times of crises and their preferences for investing in ESG stocks. As such, I used existing research to develop five hypotheses to test the research question. I tested those hypotheses on a self-constructed dataset which consists of ESG and non-ESG portfolios. I constructed these portfolios using the ESG scores from two rating agencies: S&P and Refinitiv Eikon. In total, I used the stock price and ESG scores of 1,549 unique companies to construct the portfolios. Over three-quarters of all companies originated in developed markets. I subjected the portfolio data was to multiple tests: the Fama-French regressions, the DCC-GARCH model, the principal components regression, and the wavelet coherence model.

The first hypothesis claimed that the ESG factor did not contribute to abnormal returns. The analysis revealed that on the global scale, the opposite is true and the ESG factor contributes to abnormal returns. As such, the first hypothesis could not be supported. The robustness test confirmed the validity of the results in the global setting. The subsequent robustness check revealed that the results are not valid once the developed and emerging markets are separated.

The second hypothesis contains three sub-hypotheses that theorize the performance differences between conventional stocks during normal times, crises, and also the differences in volatilities between individual ESG dimensions. The results show that while there are differences between ESG and conventional stocks during crises, the differences between the two types of stocks are not significant in normal times. In addition, there are no differences in volatility between individual ESG dimensions. The results of the Fama-French model are robust in global settings but not when developed and emerging markets split. The findings of DCC-GARCH are robust. Correspondingly, the second hypothesis can only be partially supported.

The third hypothesis stated that ESG stocks do not possess safe haven properties. The principal component regression results show that ESG stocks can function as safe havens in times of high volatility. Thus, the hypothesis cannot be supported. However, when looking only at the arbitrarily established crisis periods, all ESG portfolios functioned as a weak safe haven during the Covid crisis but co-moved with conventional stocks during the Ukraine war. Furthermore, the wavelet coherence results suggest that it is the case only on high frequencies (long investment horizon). Therefore, in this case, the hypothesis holds.

The fourth hypothesis theorized that ESG stocks do not have hedging properties. This time, the principal component regression and wavelet coherence conclusions are identical, such that certain ESG stocks can be used as a hedge against conventional stocks in certain settings. Therefore, the hypothesis cannot be supported. Finally, according to the last hypothesis, ESG stocks do not possess diversifying properties. The results of the DCC-GARCH model and wavelet coherence find a positive yet not perfect correlation between ESG and conventional stocks, so the hypothesis cannot be supported. The results of the principal components regression are robust, although the main assumption that the return of ESG stocks is solely dependent on the return of conventional stocks does not hold.

The abovementioned findings allow to formulate an answer to the research question. While investors do not consider ESG stocks to be any different in normal times, the discrepancy in performance and volatility increases in times of increased market volatility. The hedging, diversifying, and limited safe haven properties serve as evidence of such. Moreover, investors perceive the Environmental and Social dimensions as more distinct than the Governance dimension. However, it is challenging to form a prediction about investor behavior in the future. This paper's findings suggest that there are additional factors that determine investor behavior in times of high market volatility since investors behaved differently during the Covid crisis compared to the Ukraine war crisis.

The analysis has provided some additional insights. First, it shows slight discrepancies in results between the portfolios constructed using the S&P and Refinitiv ESG scores. The Fama-French factor models better the S&P portfolios better, while there is more opportunity to hedge or use ESG stocks as a safe haven when using wavelet coherence. The Refinitiv ESG portfolio have a lower autocorrelation in the DCC-GARCH model but do not fare as well in the principal components regression. One of the possible explanations for this discrepancy could be the methodology used by the rating agencies to award the score. While Refinitiv Eikon uses only publicly available information, S&P uses both public and private information. As such, the ESG scores of the same company may differ. Second, the robustness checks and the wavelet coherence performed on developed and emerging markets suggest that the variation between ESG and conventional stocks is present only in global markets, as the differences disappear once the markets are separated from one another. This finding implies the regionality aspect plays a role in the interactions, and that the regionality and sustainability aspects reinforce each other in some way.

Moreover, this paper brings several contributions to existing literature. First, it utilizes portfolios of stocks selected from the sustainability leaders in each sector, while previous research used existing sustainability indices instead. This method aims to provide less bias in selecting sustainability leaders while striving to maintain a balanced sample representing all market sectors. Second, the paper analyzes the last most recent crisis periods and provides additional insight into how ESG stocks are perceived by investors in normal and crisis times. Also, this paper runs both the principal components regressions and the wavelet coherence model on the same dataset. It allows for a closer comparison of the accuracy of the two methods and the degree of salience each method provides. In this sense, the two methods do not function as substitutes but rather as complements, as each method performs better in certain aspects. For once, the principal components regression is better at quantifying the degree (weak or strong) of the hedge or a safe haven. At the same time, wavelet coherence provides more detail on when ESG stocks are a safe haven or a hedge depending on one's investment horizon. Third, the finding that the ESG factor contributes to abnormal returns is in line with the findings of Derwall et al. (2005), Kumar et al. (2016), Sherwood & Pollard (2018), as well as Omura et al. (2021). Sharma et al. (2021) have also found a high correlation and close co-movement between ESG stocks and conventional stocks. The finding that performance is driven by Environmental and Social dimensions supports Díaz et al. (2021). Furthermore, this paper's findings on safe haven properties align with that of Rubbaniy et al. (2022) and Kuang (2021) on hedging properties. Finally, the results support those of Jain et al. (2019) regarding diversifying properties of ESG stocks.

There are several limitations to this research. Most of the limitations stem from the data selection and transformation process, which creates the possibility of a sampling bias. I have selected the companies based on their presence in an index. As indices usually include large-cap companies, the results of this research are likely to be different for medium- and small-cap companies, which are size categories not included in the data. This problem is further fueled by the ESG scores due to a possible information bias. First, not all (large cap) companies had an ESG score available for both crises, and their availability differed by the rating provider. Second, ESG scores are nowadays under scrutiny concerning their validity. As there are only a few providers, it becomes difficult to control for the quality and validity. Therefore, I used the ESG scores assuming that the companies' sustainability ratings reflect the actual situation. In addition, due to the scarcity of available ESG scores for 2022 at the time of data retrieval, I assumed that the companies' scores did not change and remained the same as in December 2021. This assumption may result in imprecision in the results retrieved for the Ukraine war.

Further, as most of the indices I worked with come from developed markets, there is a possibility of a selection bias, as the indices I used omitted certain countries (e.g., Russia, due to Western sanctions). Moreover, as I employed the best-in-class approach, I aimed to include a balanced proportion of companies from each sector rather than including companies based solely on their reported ESG score. Therefore, the results may differ when another portfolio creation technique is used. The next concern is the definition of crisis periods, as previous research still needs to unite on the perceived start date of the Covid-19 shock. Similarly, although I chose the end dates of both crises based on the recovery state of given indices (S&P 500 for the Covid crisis and FTSE and Euronext 100 for the Ukraine war), there is nevertheless a degree of arbitrariness present. As a result, choosing a different period length, albeit for the same period of interest, may yield disparate results. Further evidence for this disparity is the difference in the results of principal regression models. The results diverged when times of proven high volatility were used while in the other instance, the model ran on the arbitrary period. Another limitation could be the methods used. For once, as shown by the robustness tests, the main assumption of the principal component regression model did not hold. Therefore, the results obtained from the analysis may not be as precise when run on another sample of data, despite being robust on this sample, as there was omitted variable bias identified. Another method-related limitation is the difficulty quantifying the wavelet coherence analysis results, as its output is only visual.

Based on the limitations presented, there are several suggestions to improve future research on the properties of ESG stocks. First, new research could include a sample of companies that represents the overall market better by including smaller companies. On the same note, a larger sample and a more balanced representation of different countries and regions, especially in emerging markets would aid in providing a truer depiction of the situation in global and regional markets. Second, more stringency could be put on the definition of crisis periods. This would allow for the retrieval of more precise results. Third, future research could extend the research period to other crises and map the development of investor attitudes towards ESG stocks over a longer time frame. In addition, forthcoming research could use other types of financial assets and sustainability ratings. Fourth, more analysis could be done on the lags (feedback effect) between ESG stocks and conventional stocks, as done by Baur & McDermott (2016) but on a more recent sample.

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Appendix

Table 17: Overview of financial assets used for the analysis

Equity			
Index	**Identifier**	**Market type**	**N**
S&P 500	SPX	Developed	503
STOXX Global ESG Leaders	SXWESGP		394
Nikkei 225	NKY		225
FTSE 100	UKX		100
Euronext 100	N100		100
DAX	DAX		40
Dow Jones Industrial Average	INDU		30
Shanghai Shenzhen CSI300 Index	SHSZ300	Emerging Markets	300
STOXX Emerging Markets 50	EDE5P		50
S&P Latin America 40	SPLAC		41
Bloomberg World Energy Index	BWENRS	Mixed	170
Bloomberg World Mining Index	BWMING		130
Bloomberg World Oil & Gas Index	BWOILP		28
Total observations			2,111
Total traded companies			1,759
Total traded companies with available data			**1,549**

Sovereign and corporate bond indices, commodities, and currencies		
Name	**Identifier**	**Type**
Bloomberg Global Aggregate Index	LEGATRUU	Sovereign and corporate bonds
S&P 500 Bond Index	SP500BDT	Corporate bonds
iBoxx EUR Corporate Bonds Index	N/A	
iBoxx EUR Liquid High Yield	N/A	
Gold United States Dollar Spot	XAU	Gold
Generic 1st Crude Oil, Brent	CO1	Oil
United States Dollar	USD	Currency
Swiss Franc	CHF	Currency

Table 18: Descriptive statistics of ESG portfolios – part I

Portfolio	Mean (%)	St. dev.	Minimum (%)	Maximum (%)	Sharpe ratio
Panel A: Full period (January 1st, 2017, to June 30th, 2022)					
S&P ESG Top	0.0576	0.0105	- 9.6446	8.4464	0.73
S&P ESG Top Developed	0.0533	0.0108	- 9.8777	8.7924	0.64
S&P ESG Top Emerging	0.0913	0.0135	- 6.0979	5.3036	0.93
S&P ESG Bottom	0.0681	0.0116	- 11.6426	8.3034	0.79
Refinitiv ESG Top	0.0219	0.0094	- 10.2997	8.0016	0.26
Refinitiv ESG Bottom	0.0663	0.0121	- 11.1337	7.1324	0.72
Panel B: Pre-Covid period (prior to February 1st, 2020)					
S&P ESG Top	0.0718	0.0070	- 3.1194	3.0513	1.21
S&P ESG Top Developed	0.0644	0.0070	- 3.3646	3.7807	1.05
S&P ESG Top Emerging	0.1002	0.0114	- 4.7403	4.1581	1.06
S&P ESG Bottom	0.0758	0.0076	- 3.8866	4.5371	1.18
Refinitiv ESG Top	0.0408	0.0064	- 2.6807	2.5328	0.66
Refinitiv ESG Bottom	0.0879	0.0099	- 4.8182	4.9597	1.04
Panel C: Covid period (February 1st to April 30th, 2020)					

S&P ESG Top	-0.0351	0.0311	- 9.6446	8.4464	
S&P ESG Top Developed	-0.0570	0.0329	- 9.8777	8.7924	
S&P ESG Top Emerging	0.0357	0.0233	- 6.0979	5.3036	N/A
S&P ESG Bottom	-0.0340	0.0327	- 11.6426	8.3034	
Refinitiv ESG Top	-0.1589	0.0267	- 10.2997	8.0016	
Refinitiv ESG Bottom	0.0139	0.0295	- 11.1337	7.1324	
Panel D: Post-Covid (May 1st, 2020, to January 31st, 2022)					
S&P ESG Top	0.0761	0.0091	- 4.6664	4.1273	1.49
S&P ESG Top Developed	0.0835	0.0090	- 4.8419	2.9422	1.67
S&P ESG Top Emerging	0.1056	0.0143	- 5.5470	5.3036	1.25
S&P ESG Bottom	0.1035	0.0105	- 4.7168	3.3754	1.82
Refinitiv ESG Top	0.0446	0.0084	- 4.0034	3.0744	0.84
Refinitiv ESG Bottom	0.0793	0.0107	- 5.2379	5.0023	1.28
Panel E: Ukraine war (February 24th to March 31st, 2022)					
S&P ESG Top	0.2346	0.0146	- 2.3785	3.8931	
S&P ESG Top Developed	0.2359	0.0153	- 2.8052	3.4924	
S&P ESG Top Emerging	-0.1844	0.0220	- 4.3341	4.6241	
S&P ESG Bottom	0.3675	0.0155	- 3.0535	2.6724	N/A
Refinitiv ESG Top	0.0889	0.0155	- 2.7836	3.8082	
Refinitiv ESG Bottom	0.1251	0.0136	- 2.8001	2.7472	
Panel F: War recovery (April 1st to June 30th, 2022)					
S&P ESG Top	-0.2317	0.0141	- 3.5359	2.7909	
S&P ESG Top Developed	-0.2700	0.0158	- 3.8067	2.9986	
S&P ESG Top Emerging	0.0426	0.0141	- 3.9715	3.2129	
S&P ESG Bottom	-0.3041	0.0178	- 4.2909	2.9242	N/A
Refinitiv ESG Top	-0.2273	0.0111	- 2.9566	3.2370	
Refinitiv ESG Bottom	-0.2683	0.0156	- 5.1755	3.3031	
Panel G: Crisis periods combined (Covid period & Ukraine war)					
S&P ESG Top	0.0428	0.0274	- 9.6446	8.4464	
S&P ESG Top Developed	0.0276	0.0288	- 9.8777	8.7924	
S&P ESG Top Emerging	-0.0279	0.0229	- 6.0979	5.3036	N/A
S&P ESG Bottom	0.0819	0.0287	- 11.6426	8.3034	
Refinitiv ESG Top	-0.0873	0.0240	- 10.2997	8.0016	
Refinitiv ESG Bottom	0.0460	0.0259	- 11.1337	7.1324	

Table 19: Descriptive statistics of ESG portfolios – part II

Portfolio	Mean (%)	St. dev.	Minimum (%)	Maximum (%)	Sharpe ratio
Panel A: Full period (January 1st, 2017, to June 30th, 2022)					
Refinitiv ESG Top - E	0.0426	0.0108	- 10.5071	9.0924	0.49
Refinitiv ESG Top - S	0.0382	0.0101	- 10.0607	8.1347	0.47
Refinitiv ESG Top - G	0.0319	0.0102	- 10.7154	9.4767	0.37
Panel B: Pre-Covid period (prior to February 1st, 2020)					
Refinitiv ESG Top - E	0.0593	0.0073	- 2.9795	2.7649	0.91
Refinitiv ESG Top - S	0.0530	0.0069	- 2.9211	2.8350	0.84
Refinitiv ESG Top - G	0.0486	0.0066	- 3.1656	2.5971	0.80
Panel C: Covid period (February 1st to April 30th, 2020)					
Refinitiv ESG Top - E	-0.1332	0.0301	- 10.5071	9.0924	N/A

Refinitiv ESG Top - S	-0.0676	0.0263	- 10.0607	8.1347	
Refinitiv ESG Top - G	-0.1494	0.0308	- 10.7154	9.4767	
Panel D: Post-Covid (May 1st, 2020, to January 31st, 2021)					
Refinitiv ESG Top - E	0.0723	0.0099	- 5.0060	3. 4964	1.23
Refinitiv ESG Top - S	0.0645	0.0094	- 3.5868	2.8024	1.12
Refinitiv ESG Top - G	0.0629	0.0089	- 4.9069	4.0260	1.21
Panel E: Ukraine war (February 25th to March 30th, 2022)					
Refinitiv ESG Top - E	0.0050	0.0207	- 3.6798	5.2023	
Refinitiv ESG Top - S	0.1415	0.0192	- 3.4094	5.0401	N/A
Refinitiv ESG Top - G	0.1079	0.0154	- 2.3072	4.0079	
Panel F: War recovery (April 1st to June 30th, 2022)					
Refinitiv ESG Top - E	-0.1934	0.0128	- 3.4533	3.1907	
Refinitiv ESG Top - S	-0.2740	0.0135	- 3.3631	3.1582	N/A
Refinitiv ESG Top - G	-0.2525	0.0130	- 3.4981	3.0319	
Panel G: Crisis periods combined (Covid period & Ukraine War)					
Refinitiv ESG Top - E	-0.0933	0.0276	- 10.5071	9.0924	
Refinitiv ESG Top - S	-0.0072	0.0244	- 10.0607	8.1347	N/A
Refinitiv ESG Top - G	-0.0751	0.0272	- 10.7154	9.4767	

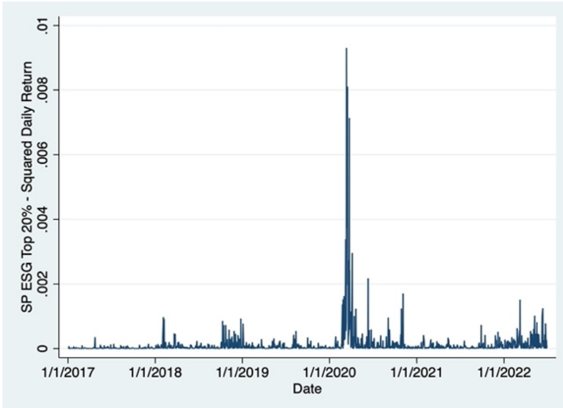

Figure 8: Squared daily returns of S&P ESG Global

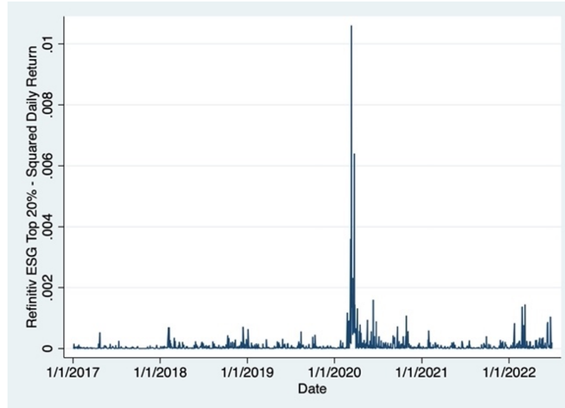

Figure 9: Squared daily returns of Refinitiv ESG

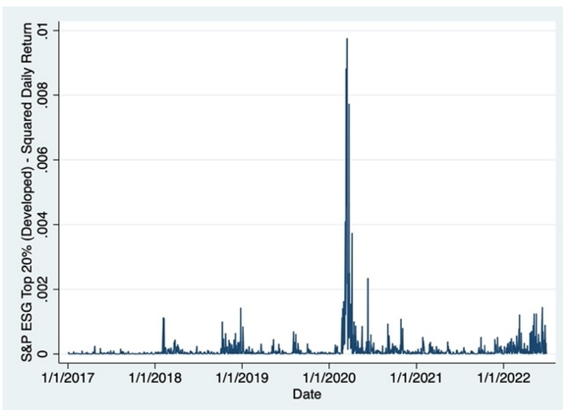

Figure 6: Squared daily returns of S&P ESG Developed

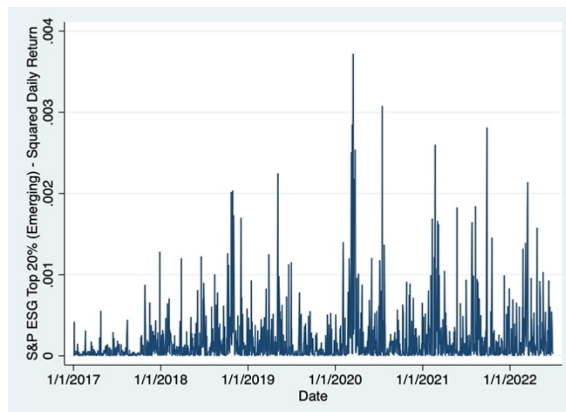

Figure 11: Squared daily returns of S&P ESG Emerging

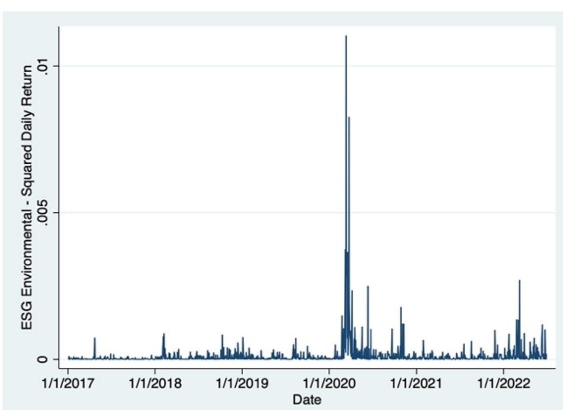

Figure 12: Squared daily returns of Refinitiv ESG Environmental

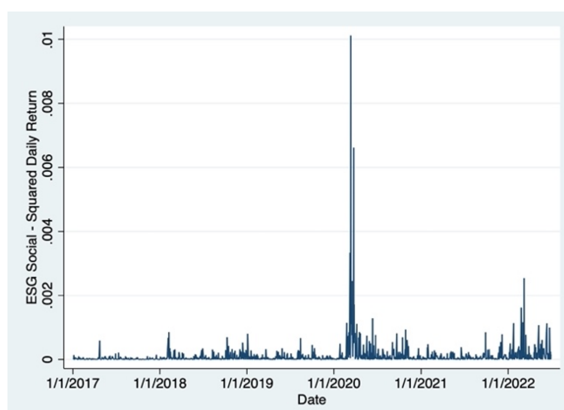

Figure 13: Squared daily returns of Refinitiv ESG Social

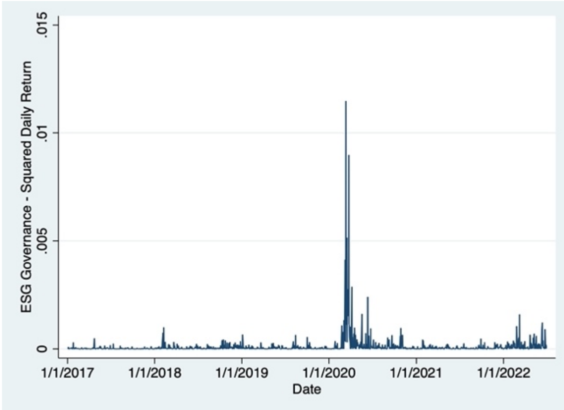

Figure 14: Squared daily returns of Refinitiv ESG Governance

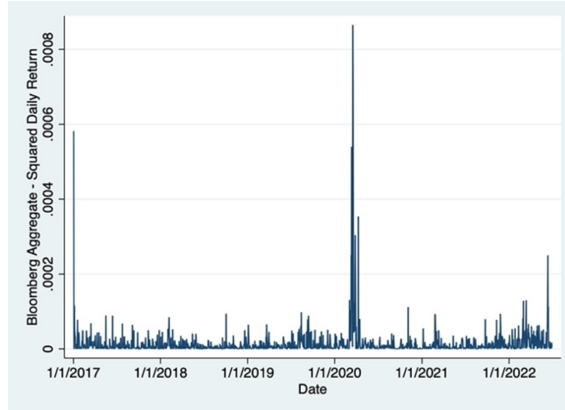

Figure 15: Squared daily returns of Bloomberg Aggregate Bond Index

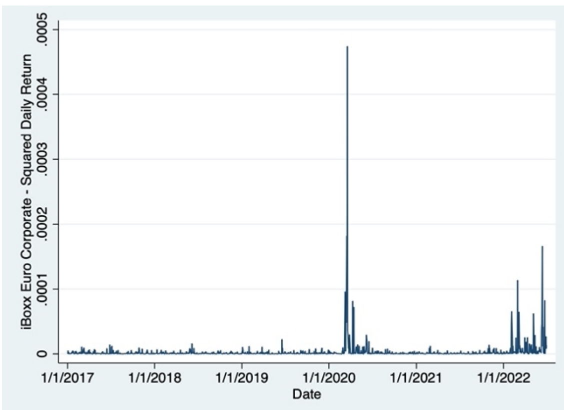

Figure 16: Squared daily returns of iBoxx Euro Bonds

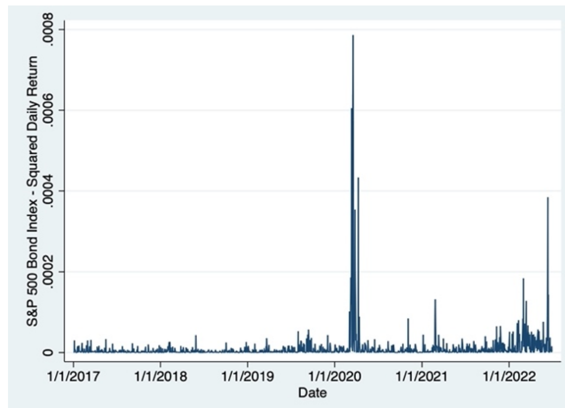

Figure 17: Squared daily returns of the S&P 500 Bond index

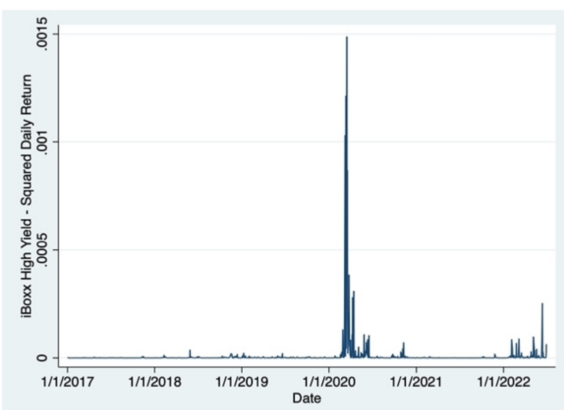

Figure 18: Squared daily returns of iBoxx High-Yield Bonds

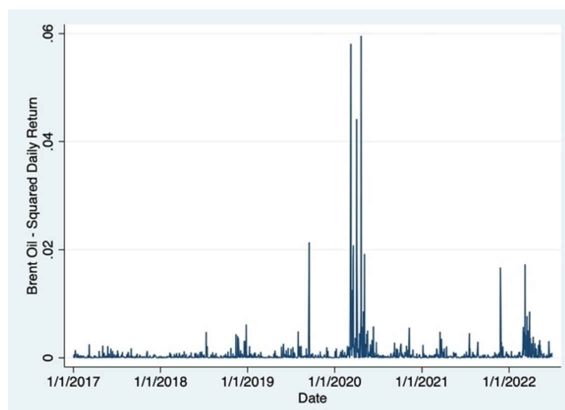

Figure 19: Squared daily returns of Brent Oil

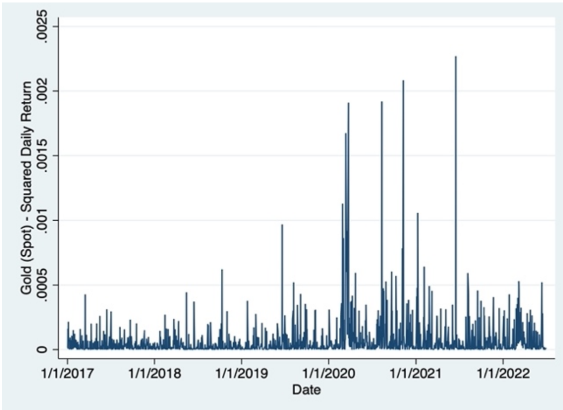

Figure 20: Squared daily returns of Gold

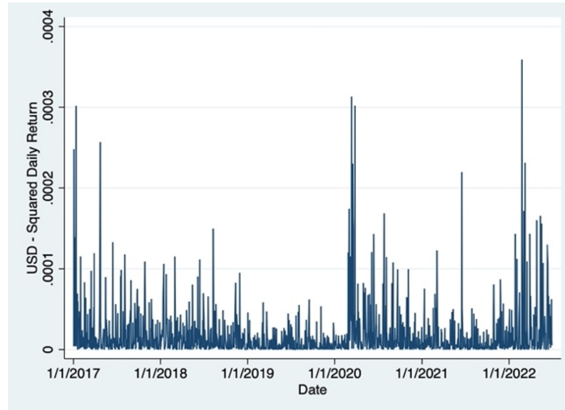

Figure 21: Squared daily returns of US Dollar

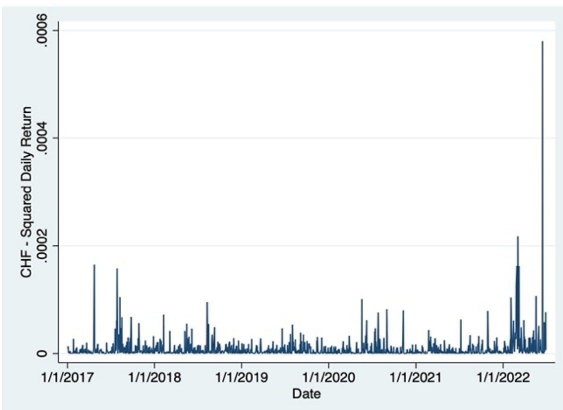

Figure 22: Squared daily returns of Swiss franc

Table 20: Descriptive statistics of non-ESG portfolios

Portfolio	**Mean (%)**	**St. dev.**	**Minimum (%)**	**Maximum (%)**	**Sharpe ratio**
Panel A: Full period (January 1st, 2017, to June 30th, 2022)					
S&P non-ESG	0.0508	0.0108	- 10.0512	8.7659	0.60
Refinitiv non-ESG	0.0581	0.0109	- 9.7584	8.1604	0.70
S&P non-ESG Developed	0.0495	0.0108	- 10.0030	8.7340	0.59
S&P non-ESG Emerging	0.0974	0.0145	- 6.0040	5.9063	0.92
Panel B: Pre-Covid period (prior to February 1st, 2020)					
S&P non-ESG	0.0620	0.0070	- 3.4412	3.9424	1.01
Refinitiv non-ESG	0.0700	0.0075	- 3.8303	3.2980	1.09
S&P non-ESG Developed	0.0609	0.0069	- 3.4374	3.9413	0.99
S&P non-ESG Emerging	0.1052	0.0126	- 5.2405	4.7761	0.99
Panel C: Covid period (February 1st to April 30th, 2020)					
S&P non-ESG	-0.0670	0.0329	- 10.0512	8.7659	N/A
Refinitiv non-ESG	-0.0426	0.0293	- 9.7584	8.1604	
S&P non-ESG Developed	-0.0725	0.0329	- 10.0030	8.7340	
S&P non-ESG Emerging	0.0830	0.0230	- 5.8041	5.1234	
Panel D: Post-Covid (May 1st, 2020, to January 31st, 2022)					

S&P non-ESG	0.0825	0.0090	- 4.8201	3.2207	1.66
Refinitiv non-ESG	0.0936	0.0096	- 4.2010	3.9737	1.73
S&P non-ESG Developed	0.0817	0.0090	- 4.8585	3.2139	1.64
S&P non-ESG Emerging	0.1013	0.0155	- 6.0040	5.9063	1.07
Panel E: Ukraine war (February 24th to March 31st, 2022)					
S&P non-ESG	0.2099	0.0152	- 2.9591	3.2656	
Refinitiv non-ESG	0.2028	0.0193	- 2.6213	5.0659	
S&P non-ESG Developed	0.2178	0.0152	- 2.9061	3.2555	N/A
S&P non-ESG Emerging	-0.2156	0.0242	- 4.7619	5.4054	
Panel F: War recovery (April 1st to June 30th, 2022)					
S&P non-ESG	-0.2687	0.0149	- 3.8092	3.0493	
Refinitiv non-ESG	-0.3084	0.0189	- 4.2846	3.6381	N/A
S&P non-ESG Developed	-0.2743	0.0149	- 3.7853	3.0285	
S&P non-ESG Emerging	0.1123	0.0243	- 4.0285	3.3961	
Panel G: Crisis periods combined (Covid period & Ukraine war)					
S&P non-ESG	0.0130	0.0288	- 10.0512	8.7659	
Refinitiv non-ESG	0.0283	0.0267	- 9.7584	8.1604	N/A
S&P non-ESG Developed	0.0114	0.0289	- 10.0030	8.7340	
S&P non-ESG Emerging	-0.0033	0.0232	- 6.0040	5.9063	

Table 21: Descriptive statistics for bonds, commodities, and currencies

Portfolio	**Mean (%)**	**St. dev.**	**Minimum (%)**	**Maximum (%)**
Panel A: Full period (January 1st, 2017, to June 30th, 2022)				
Bloomberg Global Agg.	-0.0071	0.0038	- 2.9414	2.4116
iBoxx Euro Corporate	-0.0030	0.0018	- 2.1774	1.0665
iBoxx High Yield	0.0009	0.0028	- 3.8572	1.9638
S&P 500 Bonds	0.0081	0.0032	- 2.8032	2.0820
Gold	0.0350	0.0083	- 4.7640	4.3701
Brent Oil	0.0788	0.0256	- 24.4036	21.0186
US Dollar	0.0013	0.0042	- 1.7375	1.8946
Swiss Franc	0.0054	0.0029	- 1.2852	2.4081
Panel B: Pre-Covid period (prior to February 1st, 2020)				
Bloomberg Global Agg.	0.0126	0.0033	- 0.9702	2.4116
iBoxx Euro Corporate	0.0104	0.0011	- 0.3995	0.4764
iBoxx High Yield	0.0131	0.0011	- 0.6151	0.4817
S&P 500 Bonds	0.0239	0.0020	- 0.7560	0.7288
Gold	0.0420	0.0063	- 2.1042	3.1121
Brent Oil	0.0150	0.0177	- 6.9946	14.6131
US Dollar	-0.0051	0.0039	- 1.7367	1.5747
Swiss Franc	0.0011	0.0027	- 1.2852	1.0232
Panel C: Covid period (February 1st to April 30th, 2020)				
Bloomberg Global Agg.	-0.0263	0.0089	- 2.9414	1.8816
iBoxx Euro Corporate	-0.0600	0.0047	- 2.1774	0.9028
iBoxx High Yield	-0.1547	0.0109	- 3.8572	1.9638
S&P 500 Bonds	-0.0024	0.0088	- 2.8032	2.0820
Gold	0.1069	0.0162	- 4.7640	4.3701
Brent Oil	-0.9143	0.0720	- 24.4036	21.0186

US Dollar	0.0278	0.0063	- 1.7375	1.7694
Swiss Franc	0.0178	0.0020	- 0.4774	0.5763
Panel D: Post-Covid (May 1st, 2020, to January 31st, 2022)				
Bloomberg Global Agg.	-0.0189	0.0030	- 0.9649	1.0562
iBoxx Euro Corporate	0.0009	0.0014	- 0.8100	0.5426
iBoxx High Yield	0.0248	0.0018	- 0.9328	1.0435
S&P 500 Bonds	0.0020	0.0027	- 0.9307	1.1486
Gold	0.0303	0.0093	- 4.7640	2.7984
Brent Oil	0.2985	0.0222	- 12.9287	13.8603
US Dollar	-0.0084	0.0038	- 1.2985	1.4822
Swiss Franc	0.0028	0.0026	- 1.0197	0.8897
Panel E: Ukraine war (February 24th to March 31st, 2022)				
Bloomberg Global Agg.	-0.0904	0.0058	- 1.1400	0.9018
iBoxx Euro Corporate	-0.0585	0.0036	- 0.8064	1.0665
iBoxx High Yield	-0.0341	0.0032	- 0.9483	0.4974
S&P 500 Bonds	-0.0464	0.0063	- 1.3563	0.9173
Gold	0.0801	0.0128	- 2.1838	2.3016
Brent Oil	0.4514	0.0544	- 13.1583	8.7941
US Dollar	0.0608	0.0073	- 1.5207	1.8946
Swiss Franc	0.0562	0.0064	- 1.2753	1.4760
Panel F: War recovery (April 1st to June 30th, 2022)				
Bloomberg Global Agg.	-0.1131	0.0047	- 1.5807	1.0637
iBoxx Euro Corporate	-0.1186	0.0035	- 1.2892	0.9086
iBoxx High Yield	-0.1562	0.0034	- 1.5931	0.6007
S&P 500 Bonds	-0.1113	0.0051	- 1.9608	1.1967
Gold	-0.1073	0.0077	- 2.2854	1.6797
Brent Oil	0.0953	0.0259	- 5.7389	6.2551
US Dollar	0.0990	0.0053	- 1.2485	1.2867
Swiss Franc	0.0487	0.0049	- 0.7174	2.5081
Panel G: Crisis periods combined (Covid period & Ukraine war)				
Bloomberg Global Agg.	-0.0448	0.0081	- 2.9414	1.8816
iBoxx Euro Corporate	-0.0596	0.0044	- 2.1774	1.0665
iBoxx High Yield	-0.1199	0.0093	- 3.8572	1.9637
S&P 500 Bonds	-0.0151	0.0081	- 2.8032	2.0820
Gold	0.0992	0.0153	- 4.0907	4.3701
Brent Oil	-0.5197	0.0676	- 24.4036	21.0186
US Dollar	0.0373	0.0066	- 1.7375	1.8946
Swiss Franc	0.0289	0.0038	- 1.2753	1.4760

Table 22: Correlations ESG portfolios, non-ESG portfolios, and other financial assets for the pre-Covid period – part I

Variable	1	2	3	4	5	6	7	8
1 S&P ESG Top	1.00							
2 Refinitiv ESG Top	0.83	1.00						
3 S&P ESG Top - Developed	0.96	0.81	1.00					
4 S&P ESG Top - Emerging	0.41	0.41	0.39	1.00				
5 S&P non-ESG	0.93	0.78	1.00	0.40	1.00			
6 Refinitiv non-ESG	0.91	0.83	0.94	0.45	0.94	1.00		
7 S&P non-ESG - Developed	0.93	0.79	1.00	0.38	1.00	0.94	1.00	
8 S&P non-ESG - Emerging	0.39	0.39	0.37	1.00	0.38	0.43	0.36	1.00
9 Bloomberg Global Aggregate	-0.20	-0.15	-0.24	-0.10	-0.24	-0.21	-0.24	-0.10
10 Corporate Bonds	-0.01	-0.04	0.00	0.04	0.00	-0.01	0.00	0.03
11 S&P 500 Bonds	-0.16	-0.10	-0.20	-0.06	-0.21	-0.17	-0.21	-0.06
12 High Yield Bonds	0.38	0.40	0.37	0.36	0.36	0.38	0.36	0.34
13 Gold	-0.05	-0.04	-0.09	0.03	-0.10	-0.07	-0.09	0.02
14 Oil	0.24	0.22	0.24	0.18	0.24	0.21	0.24	0.17
15 US Dollar	-0.13	-0.28	-0.11	-0.14	-0.09	-0.17	-0.09	-0.12
16 Swiss Franc	-0.22	-0.25	-0.21	-0.11	-0.21	-0.26	-0.21	-0.10

Table 23: Correlations ESG portfolios, non-ESG portfolios, and other financial assets for the pre-Covid period – part II

Variable	9	10	11	12	13	14	15	16
9 Bloomberg Global Aggregate	1.00							
10 Corporate Bonds	0.49	1.00						
11 S&P 500 Bonds	0.89	0.50	1.00					
12 High Yield Bonds	-0.02	0.24	0.03	1.00				
13 Gold	0.38	0.23	0.42	-0.03	1.00			
14 Oil	-0.10	-0.02	-0.07	0.20	0.05	1.00		
15 UD Dollar	-0.06	0.17	-0.06	-0.04	-0.40	-0.03	1.00	
16 Swiss Franc	0.15	0.24	0.16	-0.16	0.07	-0.07	0.38	1.00

Table 24: Correlations ESG portfolios, non-ESG portfolios, and other financial assets for the Covid period – part I

Variable	1	2	3	4	5	6	7	8
1 S&P ESG Top	1.00							
2 Refinitiv ESG Top	0.94	1.00						
3 S&P ESG Top - Developed	0.99	0.93	1.00					
4 S&P ESG Top - Emerging	0.64	0.68	0.62	1.00				
5 S&P non-ESG	0.99	0.93	1.00	0.62	1.00			
6 Refinitiv non-ESG	0.98	0.96	0.98	0.68	0.97	1.00		
7 S&P non-ESG - Developed	0.99	0.93	1.00	0.61	1.00	0.97	1.00	
8 S&P non-ESG - Emerging	0.62	0.66	0.59	1.00	0.60	0.66	0.59	1.00
9 BB Global Aggregate	-0.04	0.04	-0.07	0.21	-0.08	-0.02	-0.08	0.20
10 Corporate Bonds	0.36	0.36	0.34	0.55	0.34	0.37	0.33	0.53
11 S&P 500 Bonds	0.22	0.29	0.20	0.39	0.19	0.25	0.19	0.37
12 High Yield Bonds	0.62	0.65	0.60	0.78	0.60	0.64	0.60	0.76
13 Gold	0.31	0.32	0.30	0.33	0.31	0.34	0.31	0.34
14 Oil	0.41	0.41	0.41	0.45	0.41	0.42	0.41	0.45
15 US Dollar	-0.10	-0.16	-0.09	-0.18	-0.09	-0.15	-0.09	-0.17
16 Swiss Franc	-0.27	-0.26	-0.26	-0.26	-0.27	-0.32	-0.27	-0.25

Table 25: Correlations ESG portfolios, non-ESG portfolios, and other financial assets for the Covid period – part II

Variable	9	10	11	12	13	14	15	16
9 Bloomberg Global Aggregate	1.00							
10 Corporate Bonds	0.70	1.00						
11 S&P 500 Bonds	0.93	0.74	1.00					
12 High Yield Bonds	0.55	0.82	0.71	1.00				
13 Gold	0.28	0.34	0.33	0.35	1.00			
14 Oil	-0.04	0.29	0.07	0.39	0.16	1.00		
15 UD Dollar	-0.61	-0.37	-0.60	-0.30	-0.25	0.12	1.00	
16 Swiss Franc	0.00	-0.13	-0.06	-0.15	-0.29	-0.01	0.35	1.00

Table 26: Correlations ESG portfolios, non-ESG portfolios, and other financial assets for the post-Covid period – part I

Variable	1	2	3	4	5	6	7	8
1 S&P ESG Top	1.00							
2 Refinitiv ESG Top	0.81	1.00						
3 S&P ESG Top - Developed	0.95	0.79	1.00					
4 S&P ESG Top - Emerging	0.25	0.27	0.26	1.00				
5 S&P non-ESG	0.91	0.77	0.99	0.29	1.00			
6 Refinitiv non-ESG	0.87	0.85	0.92	0.38	0.92	1.00		
7 S&P non-ESG - Developed	0.91	0.77	0.99	0.26	1.00	0.92	1.00	
8 S&P non-ESG - Emerging	0.23	0.25	0.23	1.00	0.27	0.35	0.23	1.00
9 BB Global Aggregate	0.02	-0.08	-0.02	-0.02	-0.03	-0.03	-0.03	-0.01
10 Corporate Bonds	0.16	0.12	0.15	0.05	0.15	0.14	0.15	0.04
11 S&P 500 Bonds	0.12	0.04	0.08	0.01	0.07	0.08	0.07	0.01
12 High Yield Bonds	0.36	0.44	0.36	0.23	0.36	0.41	0.36	0.20
13 Gold	0.12	0.10	0.09	0.10	0.09	0.11	0.08	0.09
14 Oil	0.34	0.38	0.36	0.16	0.36	0.36	0.36	0.14
15 US Dollar	-0.17	-0.33	-0.17	-0.15	-0.16	-0.28	-0.16	-0.13
16 Swiss Franc	-0.06	-0.15	-0.09	-0.08	-0.10	-0.15	-0.10	-0.07

Table 27: Correlations ESG portfolios, non-ESG portfolios, and other financial assets for the post-Covid period – part II

Variable	9	10	11	12	13	14	15	16
9 Bloomberg Global Aggregate	1.00							
10 Corporate Bonds	0.41	1.00						
11 S&P 500 Bonds	0.91	0.48	1.00					
12 High Yield Bonds	0.05	0.52	0.18	1.00				
13 Gold	0.20	0.12	0.19	-0.03	1.00			
14 Oil	-0.19	-0.05	-0.10	0.17	-0.02	1.00		
15 UD Dollar	0.02	0.02	-0.01	-0.19	-0.42	-0.08	1.00	
16 Swiss Franc	0.22	0.16	0.19	-0.14	0.10	-0.17	0.27	1.00

Table 28: Correlations ESG portfolios, non-ESG portfolios, and other financial assets for the Ukraine war period – part I

Variable	1	2	3	4	5	6	7	8
1 S&P ESG Top	1.00							
2 Refinitiv ESG Top	0.82	1.00						
3 S&P ESG Top - Developed	0.98	0.79	1.00					
4 S&P ESG Top - Emerging	0.30	0.39	0.29	1.00				
5 S&P non-ESG	0.96	0.79	1.00	0.31	1.00			
6 Refinitiv non-ESG	0.94	0.89	0.95	0.41	0.95	1.00		
7 S&P non-ESG - Developed	0.97	0.78	1.00	0.28	1.00	0.94	1.00	
8 S&P non-ESG - Emerging	0.30	0.39	0.29	1.00	0.32	0.42	0.29	1.00
9 BB Global Aggregate	-0.06	-0.18	-0.07	0.39	-0.06	-0.05	-0.07	0.37
10 Corporate Bonds	-0.07	-0.25	-0.09	0.19	-0.09	-0.12	-0.09	0.17
11 S&P 500 Bonds	0.14	0.00	0.13	0.42	0.14	0.16	0.13	0.41
12 High Yield Bonds	0.40	0.49	0.41	0.71	0.43	0.51	0.42	0.69
13 Gold	-0.63	-0.65	-0.64	0.14	-0.63	-0.69	-0.64	0.11
14 Oil	-0.45	-0.37	-0.46	0.20	-0.45	-0.46	-0.46	0.18
15 US Dollar	-0.58	-0.85	-0.55	-0.50	-0.55	-0.70	-0.54	-0.49
16 Swiss Franc	-0.52	-0.78	-0.52	-0.13	-0.52	-0.61	-0.52	-0.16

Table 29: Correlations ESG portfolios, non-ESG portfolios, and other financial assets for the Ukraine war period – part II

Variable	9	10	11	12	13	14	15	16
9 Bloomberg Global Aggregate	1.00							
10 Corporate Bonds	0.67	1.00						
11 S&P 500 Bonds	0.95	0.64	1.00					
12 High Yield Bonds	0.29	0.39	0.35	1.00				
13 Gold	0.25	0.18	0.05	-0.17	1.00			
14 Oil	0.19	0.13	0.01	0.02	0.61	1.00		
15 UD Dollar	-0.05	0.15	-0.17	-0.57	0.38	0.30	1.00	
16 Swiss Franc	0.31	0.41	0.19	-0.17	0.56	0.49	0.73	1.00

Table 30: Correlations ESG portfolios, non-ESG portfolios, and other financial assets for the war recovery period – part I

Variable	1	2	3	4	5	6	7	8
1 S&P ESG Top	1.00							
2 Refinitiv ESG Top	0.89	1.00						
3 S&P ESG Top - Developed	0.98	0.85	1.00					
4 S&P ESG Top - Emerging	0.40	0.38	0.39	1.00				
5 S&P non-ESG	0.96	0.84	1.00	0.40	1.00			
6 Refinitiv non-ESG	0.93	0.87	0.95	0.51	0.95	1.00		
7 S&P non-ESG - Developed	0.96	0.84	1.00	0.38	1.00	0.95	1.00	
8 S&P non-ESG - Emerging	0.36	0.33	0.35	0.99	0.36	0.47	0.34	1.00
9 BB Global Aggregate	0.19	0.19	0.16	0.00	0.16	0.12	0.16	-0.01
10 Corporate Bonds	0.38	0.36	0.37	0.16	0.37	0.39	0.37	0.16
11 S&P 500 Bonds	0.31	0.30	0.28	0.10	0.28	0.27	0.28	0.09
12 High Yield Bonds	0.45	0.51	0.43	0.39	0.43	0.54	0.43	0.35
13 Gold	0.09	0.21	0.05	0.21	0.05	0.14	0.05	0.20
14 Oil	0.21	0.14	0.19	0.23	0.19	0.26	0.19	0.21
15 US Dollar	-0.41	-0.56	-0.35	-0.05	-0.32	-0.39	-0.33	0.00
16 Swiss Franc	-0.14	-0.07	-0.17	-0.05	-0.17	-0.14	-0.17	-0.04

Table 31: Correlations ESG portfolios, non-ESG portfolios, and other financial assets for the war recovery period – part III

Variable	9	10	11	12	13	14	15	16
9 Bloomberg Global Aggregate	1.00							
10 Corporate Bonds	0.69	1.00						
11 S&P 500 Bonds	0.93	0.70	1.00					
12 High Yield Bonds	0.32	0.46	0.38	1.00				
13 Gold	0.21	0.06	0.25	0.15	1.00			
14 Oil	0.00	-0.07	0.01	0.16	0.38	1.00		
15 UD Dollar	-0.09	0.01	-0.20	-0.26	-0.46	-0.10	1.00	
16 Swiss Franc	0.29	0.12	0.13	-0.10	0.23	0.04	0.14	1.00

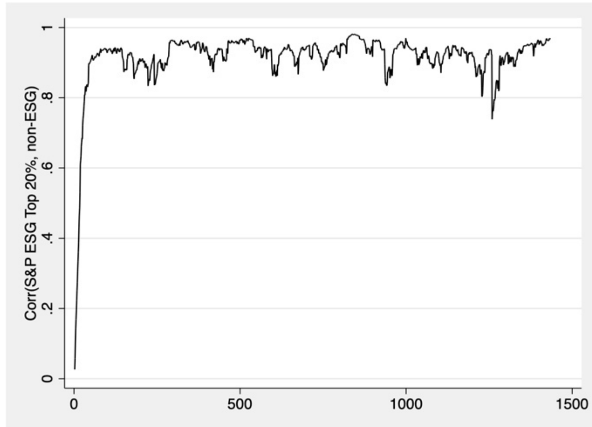

Figure 23: Autocorrelation between S&P ESG and non-ESG Global portfolios during the whole period

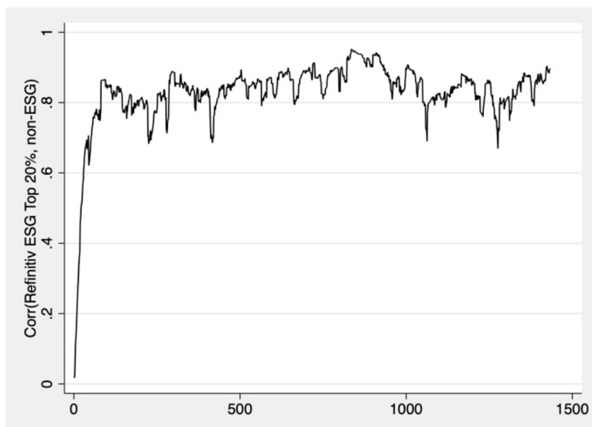

Figure 24: Autocorrelation between Refinitiv ESG and non-ESG Global portfolios during the whole period

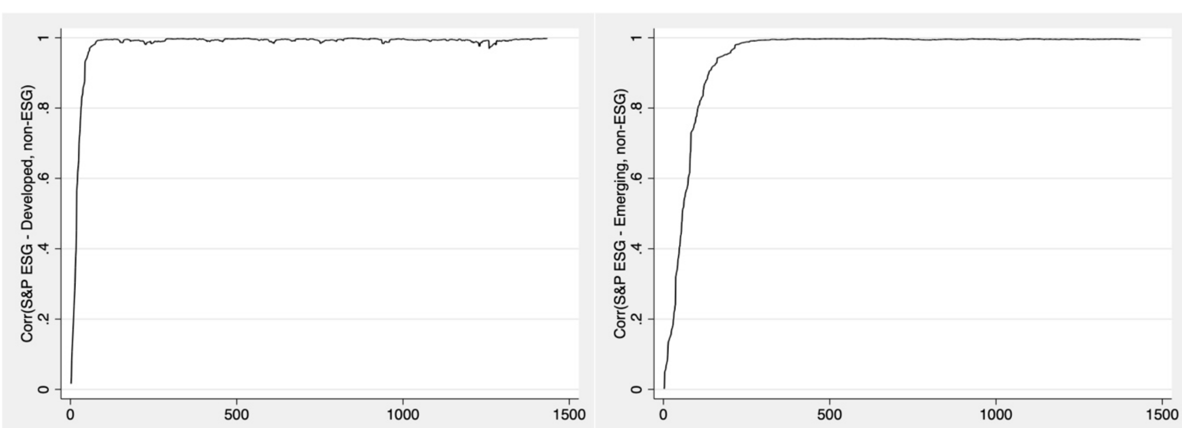

Figure 25: Autocorrelation between S&P ESG and non-ESG developed and emerging markets portfolios during the whole period

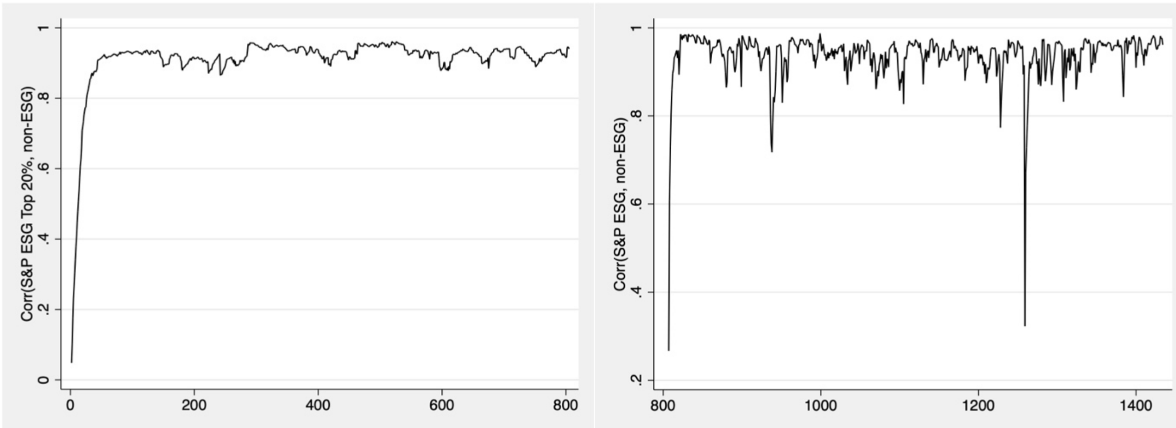

Figure 26: Autocorrelation between S&P ESG and non-ESG portfolios before and after Covid

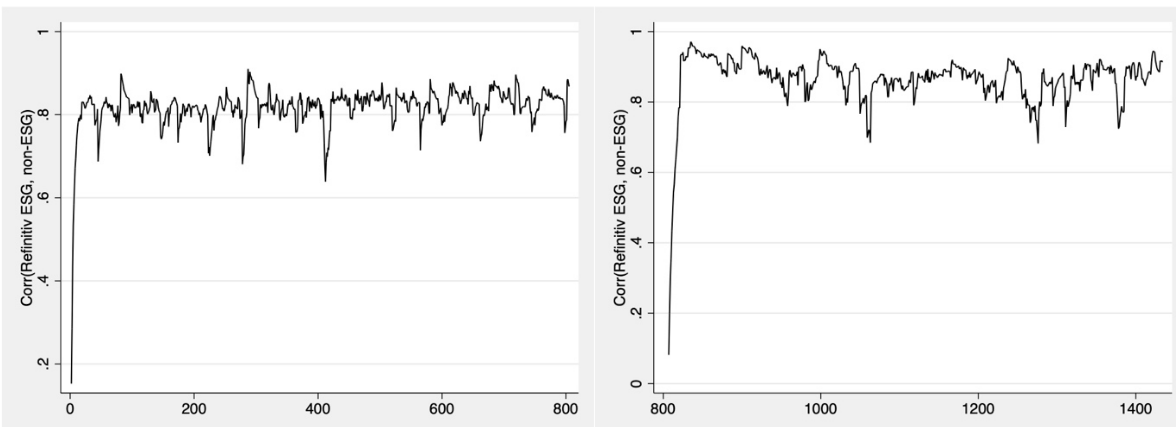

Figure 27: Autocorrelation between Refinitiv ESG and non-ESG portfolios before and after Covid