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IS IT WORTH BEING SUSTAINABLE? ANALYSIS AND COMPARISON OF ESG AND MSCI INDICES

RELATORE:

CH.MO PROF. PARIGI BRUNO MARIA

LAUREANDO:

MATTEO CARRARO
Matricola N. 1237808

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This thesis focuses on ESG indices, about which still too little is known. The centre of attention of this study is the comparison of the performance of ESG and non-ESG indices and their interdependence. Especially this last analysis has been carried out through the implementation of an alternative method, known as the Wild Bootstrap, which allows to resample the residuals obtained from the cointegration analysis while maintaining the heteroschedasticity, previously verified through the GARCH model. Portfolio diversification will be considered in order to draw conclusions.

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Chapter 1

Introduction

Environmental, social, and corporate governance (ESG)-based investments have sparked a surge of interest among academics and practitioners in recent years, as a growing number of investors have expanded their business valuation criteria to include non-financial elements. ESG-friendly investing techniques can assist investors avoid ”sin” corporations (alcohol, tobacco, and gambling industries) that may offer a larger, perceived or real, financial risk owing to their environmental, social, or community policies in a reliable and efficient manner. In order to fulfill the growing demand for ESG-related investments, fund managers have introduced new financial products. Existing research has suggested that shareholders' and investors' risk exposures are linked to their enterprises' ESG profiles, and that, as a result, stakeholders would benefit from investments that incorporate ESG performance factors, as stated by Edmans (2011) and Jacobsen et al. (2019). According to Bloomberg, Europe alone has ”nearly 12 trillion dollars committed to sustainable investing,” as published in a research on February 8, 2019. Global sustainable assets under management (AUM) was over 30 trillion dollars in 2019. By the end of the same year, members to the Principles of Responsible Investment accounted for more over 80$ trillion in AUM globally. The result is that investors seek non-financial utility from their investment selections as well as financial benefit from portfolios that are compatible with personal and social ideals (Bollen, 2007).

The number of companies evaluating and disclosing environmental (i.e. carbon emissions, water consumption, waste generation, etc.), social (i.e. employee, product, customer-related, etc.), and governance (i.e. political lobbying, anti-corruption, board diversity, etc.) data, collectively known as ESG data, has increased exponentially over the last twenty-five years. By 2016, approximately 9,000 firms have issued sustainability or integrated reports, up from less than 20 in the early 1990s.

Investor interest in ESG data expanded quickly as well. Signatories to the United Nations Principles for Responsible Investment (PRI), which were established in 2006, agreed to include ESG factors into their investment analysis and ownership policies and practices. The principles has over 1,400 signatories as of 2016, with about 60$ trillion in assets under control. In 2010, Bloomberg terminals added ESG data, further demonstrating the institutionalization of ESG data. According to Milton Friedman, a company's primary commitment is to maximize shareholder profits. Most firms that have been concentrated on profit maximization have ignored environmental, social, and governance (ESG) obligations for decades. ESG duties were not only seen to have little impact on financial success, but they were also seen as a possible burden on the latter, as they were linked to cost rises. Nonetheless, environmental, social, and governance concerns have had an impact on the profitability, as well as the financial viability, of some companies in the previous two decades. The growing prevalence of catastrophic weather events, which damage infrastructure and disrupt global markets, drew attention, as did the 2008 financial crisis, which affected both the private and public sectors. Indeed, the subprime crisis had three effects: first, it brought attention to the importance of investors' decisions and therefore their intrinsic role; second, it elevated public awareness of social responsibility; and third, it emphasized the necessity of strong governance standards. Consequently, despite the fact that socially responsible investing (SRI) has been around since the 1920s, it has only lately undergone a significant rise in attention and has evolved from a specialist investment practice to a widespread preoccupation.

This thesis focuses on the analysis of indices produced by the MSCI rating agency. Sustainable indices and more general indices are considered. The analysis of the time series of the price of these indices and the returns makes it possible to study how they vary and to compare them over the period of time under consideration. The differences between the two will be explained in Chapter 3. The study is based on an econometric analysis of historical series from a univariate and multivariate point of view. First, prices and returns are considered individually, as a preliminary analysis, and then a study of these series is performed from the point of view of correlation and the influence of a country's asset towards another nation's index, with special attention to sustainable ones. This study aims to focus on portfolio diversification in order to see whether sustainable investments can be an alternative to non-ESG investments, especially in a period of stress such as that caused by COVID19. The time frame considered is from 1 January 2016 to 31 December 2020, so as to consider an initial period of economic stability followed by a sudden severe crisis. The results obtained thus also seek to explain the differences between the various financial instruments and how they perform during such periods.

This study is being conducted in this context, with the goal of determining whether indices that include shares that adhere to ESG principles can effectively diversify the risk present in traditional indices, or whether, on the contrary, the two types of investments

are inextricably linked, making it impossible to diversify one asset by investing in another sustainable. The idea of cointegration was used in this study to examine the relationship between the two variables and, as a result, to investigate the feasibility of diversifying the risk of the general index with a sustainable asset. According to certain research, ESG investments safeguard investors from unforeseeable and potentially disastrous events, such as a financial crisis, which would have a higher impact on general indexes. If a link can be established between the two, this theory will be dismantled since a close association will be identified, and a bad performance of an unsustainable instrument will have an impact on an ESG instrument. For the same country, we'll look at the link between ESG and MSCI indices. Following that, we'll look at the interdependence of these data across countries using the VAR model.
In addition, the performance of the two types of indices will be compared, to verify that sustainable assets are indeed better in terms of return and volatility than non-sustainable ones. It could be observed that the returns are similar. What is considerably different, however, is the riskiness of the assets. A relevant observation is that shocks affecting one type of index cannot be diversified by investing in the counterpart, as there is a very strong relationship between the two.

Chapter 2

Literature analysis

2.0.1 ESG Ratings and Investments

The rise of this emerging movement has led to the growth of a new section of rating agencies, with the top three credit rating agencies (Moody's, SP, and Fitch) beginning to incorporate ESG considerations into their ratings.
ESG ratings are assessments of a company's quality, standard, or performance on environmental, social, or governance concerns. Sustainability rating agencies assess companies and provide data on certain characteristics under the E, S, and G categories, such as pollutant emissions, human rights, and management (Avetisyan and Hockerts 2017). They almost always give a general assessment of a company's performance based on a composite score of individual ESG problems. Many organizations also create ESG and/or sustainability indexes, which are made up of lists of firms chosen from a larger universe of rated companies that fulfill particular ESG criteria. The Dow Jones Sustainability Index (DJSI), the FTSE4Good Index, and the MSCI ESG Indices are just a few examples (Searcy and Elkhawas 2012). Investor demand for ESG data has risen over the last decade, owing to, among other things, greater awareness of the financial relevance of ESG variables and rising client demand, such as from asset owners (van Duuren et al. 2016). ESG ratings are used by investors in a variety of ways, including measuring and managing their ESG-related risk exposure and communicating with investee firms. Similarly, sustainability indexes are frequently used to compare the performance of responsible businesses to that of a larger group of comparable companies, as well as to create responsible investment products (Slager et al. 2012). The reaction of ESG ratings has been varied. Ratings, according to its proponents, alleviate information gaps by providing complete, systematized, and comparable data for a large number of publicly traded companies. As a result, they serve a critical role in assisting stakeholders in understanding, evaluating, and managing the increasingly complex and multi-faceted nature of corporate ethics and sustainability.

(Cappucci, 2018).
On the other hand, given the various approaches used by rating agencies and data providers to account for ESG initiatives, as well as the inherent country-specific particularities and the ESG materiality issue, it is difficult to reach a firm judgment on the subject. In this light, it becomes clear that further standardization of ESG accounting processes is required, allowing investors, policymakers, and scientists to assess ESG performance to its full potential.
Another branch of research looks at the performance of ESG portfolios. Kempf and Osthoff (2007), Statman and Glushkov (2009), Nofsinger and Varma (2014), and Henke (2016) all demonstrate that ESG-firms-based portfolios may deliver a demonstrable performance benefit. Specifically, Kempf and Osthoff (2007) found that buying stocks with high socially responsible ratings and selling equities with low socially responsible ratings leads to large anomalous returns that remain considerable despite transaction costs. Statman and Glushkov (2009) conclude that socially responsible investors outperform conventional investors in terms of returns. Typical socially responsible portfolios, on the other hand, avoid equities linked to cigarettes, alcohol, gambling, weapons, military, and nuclear activities. As a result of this avoidance, socially responsible portfolios have a lower return than conventional portfolios. The return advantage gained by socially responsible portfolios as a result of their lean toward stocks of firms with high social responsibility scores is essentially compensated by the return disadvantage gained by excluding stocks of'shunned' companies. Nofsinger and Varma (2014) find that socially responsible mutual funds outperform their peers, especially during market downturns. Using the Morningstar database and the Domini Social Index, the authors claim that this impact is most noticeable for ESG funds that use positive screening approaches, with the results based only on the socially responsible fund qualities. Henke (2016) emphasizes the outperformance of ESG portfolios during crisis periods in his study of US and Eurozone funds. Even after a huge number of robustness checks, the acquired results retain their relevance. However, Yen et al. (2019) conduct a similar research for Asian stock markets and discover that socially responsible investing (SRI) portfolios outperform exclusively in Japan, while they are undervalued in emerging Asian stock markets.
Auer and Schuhmacher (2016) agree with this last point . The authors find similar results in the Asia-Pacific area and the United States, however in Europe, investment performance might be severely impacted for some industries and ESG criteria. Nonetheless, Friede et al. (2015) found that over 90% of the research found a non-negative link between ESG and corporate financial performance (CFP), with the vast majority showing a clear positive association. Halbritter and Dorfleitner (2015) discovered that the amount and directionality of ESG portfolio overperformance are highly influenced by the rating

source, highlighting the significant disparities across ESG ratings and the need for more harmonization.

Table 2.1: Literature on ESG investing performance: here are reported the studies previously analysed divided by year and the conclusions they reach

Author's name	Year	Nation	Results
Kempf and Osthoff	2007	USA	The findings show that previous SRI ratings are useful information for investors. High anomalous returns may be achieved with a simple trading technique based on publicly available data.
Statman and Glushkov	2009	USA	Socially responsible equities' predicted returns are roughly equivalent to conventional stocks' projected returns.
Nofsinger and Varma	2014	USA	In non-crisis periods, conventional funds outperform SRI fund. But in crisis periods, SRI funds outperform the others.
Halbritter and Dorfleitner	2015	USA	The ESG portfolios do not show significant return differences between companies featuring high and low ESG rating levels. There is actually a relationship between ESG ratings and returns which is exploitable with a trading strategy
Henke	2016	USA and Eurozone	SRI bond funds are attractive investment opportunities that accumulate abnormal returns during market declines.
Auer and Schuhmacher	2016	Asia-Pacific USA Europe	Selecting high (low) ESG stocks does not appear to consistently increase or decrease investment performance relative to the benchmarks and to low (high) ESG stocks.
Yen et al	2019	Asia	Socially responsible investing (SRI) portfolios outperform exclusively in Japan, while they are undervalued in emerging Asian stock markets

The third portion of the literature examines the impact of environmental, social, and governance (ESG) variables on credit ratings. Attig et al.(2013) discover evidence that enterprises with strong social performance benefit from relatively high ratings supplied by credit rating agencies. Devalle et al. (2017), for example, confirm that enterprises with strong environmental and sustainability records benefit from better credit ratings. Kiesel and Lücke (2019) show that ESG performance has a tiny but discernible impact on rating judgments, particularly in the corporate governance pillar. In 3719 Moody's credit rating reports, the writers use the LDA model to identify ESG themes. ESG ratings are complimentary to credit ratings, according to Jang et al. (2020), who focused on the instance of South Korea, since they provide vital non-financial information and help minimize the cost of debt financing, especially for small businesses.
It's difficult to get a firm judgment about the impact of ESG factors on credit ratings. As a consequence, the aforementioned aspects, as well as the observed inconsistent results in the existing literature, emphasize the need of trustworthy and harmonized ESG data.

The sustainability rating industry has risen considerably in response to increased demand for trustworthy ESG data and ESG ratings, and is now in a consolidation phase (Escrig-Olmedo et al., 2019). The notion that ESG evaluations may be incorporated to company risk indicators, allowing for the removal of information asymmetries, has sparked attention. ESG measurement, unlike credit ratings, is rather ambiguous due to the lack of a uniform definition, reporting requirements, and similar features among ESG components and rating providers. Rating agencies are now offering numerous criteria that are comparable to those used in the credit rating market, however ESG ratings are derived from different and conflicting definitions. As a result, there is no universal ESG benchmark, making it difficult to assess and, in some situations, impossible to rate a company's long-term sustainability. According to Billio et al. (2020), rating agencies lack consistent measures in the definition of ESG, and variability in judgment might lead to agencies assigning even opposing ratings to a particular firm. Furthermore, this variability is a concern for the investing sector as a whole, because the identification of sustainable investment portfolios and, as a result, the choice of appropriate benchmarks (ESG indexes) is dependent on the ratings derived from these measurements.
It is common sense that integrating Environmental, Social, and Fair Governance standards reduces a company's vulnerability to reputation, political, and regulatory risk, resulting in decreased cash flow volatility and profitability. You will be less vulnerable in the long term if you do the correct things. Despite the growing popularity of Socially responsible investments (SRI), which is fueled by investors' demand for sustainable products as well as transparent and open information about how they work, the need for asset management

companies (AMCs) to develop more effective strategies that balance trust building, accountability, and ESG informative content and communication remains partially unmet. In order to achieve these requirements for useful content and communication, the European Parliament developed the Key Investor Information Documents (KIIDs) in 2012. These documents are meant to assist potential investors in comparing and selecting funds. AMCs began to voluntarily include additional ESG criteria information in their financial reports in order to meet the growing demand from investors for information about the social and environmental externalises of their asset management practices, as well as to make nonfinancial communication clearer and more transparent. According to recent study, investors in socially responsible funds can benefit from AMCs' ESG activities being communicated. Several AMCs have become considerably more focused on screening the primary ESG criteria - transparency, ethics, impact, environment, society, and governance – as well as the corresponding asset allocation techniques to which they might be added as a result of this. The incorporation of ESG criteria into SRI strategies helps to justify investment decisions, particularly institutional investor decisions, which are critical in the shift to more responsible and sustainable finance as well as more sustainable development.

According to an analysis of Hermes Fund Managers in 2013, the corporate governance factor seemed to be a critical value driver in the performance of firms in the MSCI World Index. The performance of badly governed vs. properly governed corporations was compared in terms of total shareholder return. Hermes discovered no statistically meaningful link between shareholder return and the environmental or social dimensions. Furthermore, there was a significant variation in financial materiality across investment areas for poorly regulated corporations: North American corporations had the least influence. In comparison to other markets, North America may have a more developed corporate governance laws and practice.

Khan et al's (2015) Harvard research examines the materiality of ESG factors for a universe of around 2,300 US enterprises. As an input, the Sustainability Accounting Standards Board (SASB) materiality map technique was applied. Khan et al. created stock portfolios with equal and value weightings, as well as significant and immaterial ESG concerns. The gap between high- and low-performance portfolios is defined as the annual portfolio alphas that are compared. Portfolios with a high score on material ESG criteria and a low score on immaterial elements performed best, according to the findings. According to the study, portfolios with the correct combination of issuers beat portfolios with corporates that score low on significant and immaterial ESG aspects. Furthermore, corporate issuers that score well on material ESG criteria alone outperform those that score well on both material and immaterial ESG aspects. To put it another way, com-

panies that understand the precise, substantial ESG variables that affect their industrial sector generate the highest shareholder value.
The University of Oxford and Arabesque Asset Management conducted a meta-analysis in 2014 that looked at over 190 academic papers on sustainability and its impact on cost of capital, operational performance, and stock prices. The data confirm the notion that incorporating environmental, social, and governance (ESG) considerations into investment decisions has a favorable impact on stock portfolio performance. Despite numerous studies finding no or a negative association between corporate sustainability scores and stock price performance, the majority find a positive relationship, with higher ESG scores leading to greater stock price performance when compared to businesses with lower ESG ratings. The most essential elements contributing to greater stock market success are corporate eco efficiency and environmentally responsible behavior. In terms of the social dimension, research suggests that high employee relations and satisfaction lead to improved stock market success.
Morgan Stanley conducted another investigation (2015). The scope of this study includes about 6,600 US stock mutual funds and approximately 2,900 US equity separately managed accounts (SMAs). The study looked at the differences in returns and volatility between sustainable and conventional strategies across style clusters including big, small, and mid-cap. For 64 percent of the periods studied over the previous seven years, Morgan Stanley found that sustainable mutual funds had equivalent or greater median returns and equal or lower median volatility. When compared to their traditional fund equivalents, they are more cost-effective. When compared to traditional methods, SMAs had equal or greater median returns for 36% of the periods studied and equal or lower median volatility for 72% of the periods studied during the last seven years. In general, sustainable mutual funds and SMAs outperformed their traditional counterparts in terms of return and volatility dispersion.
It is therefore necessary to implement efficient strategies to integrate these issues into financial investments. A clue in this regard is left by the Global Sustainable Investment Alliance (GSIA) Report, according to which the strategies relate to:

- Specific industries or corporations that are unwanted or contentious and whose operations may harm the environment or society are excluded;

- All other factors being equal, the best ESG performing firms within a certain business sector are chosen. It refers to the exclusion of businesses that fail to achieve specified performance benchmarks;

- Only activities relating to the specified subject were included in the targeted investments (clean energy, pollution reduction, low carbon emissions, water resources management, sustainable agricultural activities etc.);

- Private investments in particular initiatives that address social and environmental challenges, such as renewable energy, social housing investments, and so on;

- Inclusion of ESG variables into financial analysis in a systematic and explicit manner. The involvement of ESG rating agencies is critical, given the qualitative and subjective nature of this form of review;

- Shareholder rights are exercised with the goal of influencing business behavior through direct discussion with management and proposal submissions;

- Investing solely in equities that meet the international minimum standards for ethical corporate operations.

Exclusionary screening was the most common approach for open-end funds in 2018. This accomplishment might be attributed to the simplicity with which such a strategy, based on the identification and exclusion of so-called ”nonESG” stocks, could be implemented.
Larry Fink, chairman of BlackRock, is a great illustration of the penultimate criterion, active engagement and influence in the direction of a firm. BlackRock has established itself as a global leader in the cross-cutting field of environmental and sustainable growth, known as ESG, in recent years. It pledged to zero emissions by 2050, including emissions from its investment portfolio, in 2021, and encouraged other corporations to follow suit. The business generated a storm in the spring of 2021 when it voted to replace three directors of oil giant ExxonMobil who were opposed to making a speedy shift to renewable energy sources. In that case, BlackRock had teamed up with a small number of ExxonMobil shareholders who were concerned about the environment. Critics said that this indicated the large fund's affinity with the liberal cause. The Republican world reacted quickly, with Texas passing a measure in June forcing state institutions, such as pension funds, to withdraw from corporations that boycott the fossil fuel sector. Many people have interpreted this action as a carefully veiled warning to BlackRock, which owns a large portion of the state's pension fund. After the money manager advised corporations to cut their emissions to net zero by 2050, West Virginia's treasurer announced that the state's Treasury investment board would no longer employ a BlackRock fund. Riley Moore, a state official, said the attitude hurts West Virginia's economy. It's simple to see how these tactics may be backed up by individuals who have their backs protected and a lot of clout. Otherwise, one would be inundated by counter-measures that might

put a pressure on a sustainable strategy that is opposed by many individuals, particularly those connected to the fossil fuel industry.
Another issue to be addressed, as previously mentioned, is rating agencies' capacity to categorize corporations using ESG indexes. Over the previous two decades, the usage of ESG ratings in investing practice has expanded dramatically, and it has lately soared. ESG evaluations are increasingly widely employed in economics, management, and finance studies as well. Given the difficulty of assessing a company's non-financial or environmental performance, the validity and convergence of these ratings have been hotly contested in the management literature. Many scholars, including Chatterji, Durand, Levine, and Touboul (2016), have documented a lack of consensus among information intermediaries, which stems mostly from two sources: the lack of a shared theoretical framework as well as comparability. These findings suggest that the ratings providers used by enterprises and professional investors may contaminate their long-term financing and investment decisions. The same may be said of academics' judgments based on current empirical investigations.

Table 2.2: Differences in ESG ratings

Company	Sustainalytics	RobeccoSAM	Refinitiv	MSCI
Nissan Motor Co., Ltd	6	77	72	CCC
Verizon Communications Inc	91	20	67	BB
Oracle Corp. Jpn	78	8	63	BB
Goodman Group Unt	86	21	58	AA

The variance in judgments, as well as the different "units of measurement" used to define organizations according to ESG principles, may be seen in table 2.2. Here are reported four companies and their ESG rating according to Sustainalytics, RobeccoSAM, Refintiv and MSCI, which are rating agencies.

Another example of difference and misunderstanding of ESG categories, as reported by the Wall Street Journal in a report posted on January 17, 2022, is Credit Suisse. António Horta-Osório, the company's chairman, had resigned a few days before because he had broken the government's laws against Covid 19. After his predecessor was fired for spying on a coworker, the new CEO was appointed. All of these aspects should be indicative of a poor rating score, with Governance being a critical factor to evaluate. Despite this, the rating agencies can't agree on whether the bank's governance is a concern, much alone what its total ESG score should be in comparison to worldwide rivals. SP Global was the most critical of Credit Suisse's governance among the rating agencies. It assessed the bank only 15% for corporate governance, ranking it 725th out of 747 banks and diversified financial companies rated by SP, considerably below JPMorgan Chase's 83 percent and Goldman Sachs' 89 percent. Credit Suisse received a 57 percent overall score, higher than JPMorgan or Goldman, since SP considers it to be above average in terms of environmental, social, and economic factors (oddly, SP mixes "governance" and "economy" into one broad category for the "G" in ESG).

Refinitiv gives the bank a 95 percent score in its "management" category, which focuses on the board, and an 81 percent score in overall governance, which is comparable to JP-Morgan and Goldman. MSCI is somewhere in the middle. Credit Suisse, like JPMorgan and Goldman Sachs, is rated as having ordinary governance and receives the same single-A grade, the third from the top on a scale of seven. Credit Suisse is ranked in the middle of the world's banks by Sustainalytics, a subsidiary of Morningstar, with a medium ESG risk. It considers JPMorgan to be somewhat riskier than Goldman Sachs. It's hard to distinguish the causes behind the various ratings. Refinitiv's score is high because it isolates "controversies" into a distinct category that has no bearing on the ESG score, whereas others frequently include them. Other distinctions concern the weight given to various components of governance, such as board diversity, board policy, independent directors, and the separation of the chief executive and chairman responsibilities, as well as whether subjective evaluations of what matters should be used. In situations where organizations do not provide data, there is also a distinct approach to whether to infer or estimate, as well as whether a score suffers as a result of the absence of transparency.

Another topic that has received a lot of attention in the literature is the major drivers of differentiable performance. There is emerging evidence that ESG-investing can assist investors manage investment risks. In theory, creating ESG-screened portfolios tries to minimize the portfolio's overall ESG risk by eliminating low ESG-score members from the eligible selection universe. Investors might anticipate ESG-screened portfolios to be safeguarded from ESG-event losses and to have the potential for better realized alpha than unscreened portfolios if the screening is done correctly. During the Global Financial Crisis of 2007, for example, responsible investment served as an insurance policy and outperformed conventional investing (Becchetti et al. 2015). Kumar et al. (2016) evaluates the risk performance of ESG-screening at the business level, demonstrating that firms that include ESG-factors have lower stock volatility than their industry counterparts.

As a result, investors with wealth-protection intentions would be ready to limit the degree to which ESG-related concerns may put their portfolio's economic worth at risk. Another motivation for ESG investment that has been discussed in the literature is to increase diversification options. Chong, Her, and Phillips (2006) found that a non socially responsible fund may not be a feasible alternative for portfolio diversification after incorporating a dynamic measure of risk performance. According to Sherwood and Pollard (2018),

including ESG emerging market equities into institutional portfolios might yield greater returns and reduced downside risk than non-ESG equity investments. ESG-screening may be extended to the portfolio level for diversification by establishing a measure of the portfolio's ESG-risks compared to its peer group (Morningstar, 2019).
It is in this context that this research is carried out, with the aim of verifying whether indices comprising shares that respect ESG principles actually allow diversification of the risk present in normal indices or whether, on the contrary, the two types of investment are closely linked and it is therefore not possible to diversify one asset by investing in another sustainable.

Chapter 3

Data Description

MSCI (Morgan Stanley Capital International) is a major financial services firm in the United States. Capital International began introducing a series of stock indexes relating to international markets in 1969 in New York, and the company was founded in 1970. Since 1986, when Morgan Stanley purchased the license rights to the Capital International indexes and became MSCI's largest shareholder, the name MSCI has been used. With the exception of Great Britain, where the predecessor to today's FTSE was established, MSCI enjoyed a monopoly on world indexes outside of the United States until the end of the 1980s. The acquisition of Barra, a risk management company, for around 816$ million in 2004 marked a watershed moment in the organization's history. Both firms' functions led to the formation of MSCI Barra, which began listed on the New York Stock Exchange (NYSE) in 2007 under the symbol MSCI. MSCI's separation from Morgan Stanley began with this transaction, and it was completed in 2009, when MSCI became a fully independent public business. MSCI has over 160,000 indices that track the performance of the securities included in them and serve as the foundation for ETFs. These indices focus on different geographic areas and different types of stocks (small cap, mid cap, large cap), and they track the performance of the securities included in them.
The main MSCI indices are:

- MSCI Emerging Markets was founded in 1988 and currently covers 25 emerging markets, including China, India, Brazil, and Russia;
- MSCI Frontier Markets: a benchmark for 28 frontier markets, including Bahrain, Croatia, Morocco, and Nigeria;
- The MSCI All Country World Index is the company's flagship index, and it tracks the performance of small and large-cap equities from 23 developed and 26 emerging economies, totaling over 3,000 stocks;

- MSCI EAFE: includes 829 securities from 21 developed markets outside of Canada and the United States.

MSCI indexes are market capitalization-weighted indices, which means that equities are weighted based on their market capitalization. The index gives the most weight to the stock with the largest market capitalization. This reflects the reality that large-capitalization businesses have a bigger economic impact than medium- and small-capitalization businesses. The MSCI family of indexes is evaluated quarterly and rebalanced twice a year. Analysts at MSCI add and remove stocks from indexes to ensure that the index remains an appropriate equity benchmark for the market it represents.
MSCI researches a company's main business as well as potential key concerns in the industry to which it belongs in order to generate ESG indexes, analyzing the risks and possibilities associated with the most pressing issues in terms of corporate social responsibility. The goal of this research is to find any external bad events that could result in an unanticipated expense in the medium to long term, as well as any external possibilities that could be grasped and capitalized in the long run. The research is organized into sectors using the GICS[1] classification system, and it is based on the concept of weighting, which means that the weights assigned to the key factors are calculated based on the external factors that are unique to each sector, as well as the time horizon associated with each factor.
ESG analysis is based on 3 fundamental pillars: environmental, social and governance. Following the evaluation of all of these variables, each pillar will be assigned a score, and the three scores will be combined to produce a weighted score that reflects all of the elements considered. The weighted score will be normalized according to the sector to which it belongs in order to arrive at the final rating: the score obtained is reproportioned each year by taking into account an average of the scores obtained over the last three years by companies belonging to the sector in question, among those belonging to the MSCI ACEI index, establishing the minimum and maximum in a range between the two percentiles 2.5 and 97.5.
Following this procedure, you will receive the company's rating, which might be one of seven types:

- AAA: 8.6 - 10
- AA: 7.1 - 8.5
- A: 5.7 - 7

[1] The Global Industry Classification Standard (GICS) was developed by MSCI in collaboration with SP Dow Jones Indices. This is an approach to define industries and classify securities by industry

- BBB: 4.3 - 5.6
- BB: 2.9 - 4.2
- B: 1.4 - 2.8
- CCC: 0 - 1.3

MSCI collects data via surveying firms' environmental, social, and governance policies and achievements, as well as data from government databases. In the weekly rating update, new information from monitoring is reported. Another important aspect is to assess each company's risks and prospects. This evaluation takes place on two levels:

- A first level considers global patterns, such as the level of worldwide attention paid to climate change issues, the shortage of specific resources, or demographic shifts;
- a second level that evaluates the sector's operations and the entities that make up the sector;

MSCI only considers costs and opportunities after doing these assessments and discovering them if they are fairly expected to convert into significant costs or profits for enterprises. Below are reported the indices that are implemented for this study.

- MSCI GERMANY ESG: this index is based on the MSCI Germany Index, which is its parent index, and comprises big and mid-cap German equities stocks. Nuclear Weapons, Tobacco, Thermal Coal, Nuclear Power, and Unconventional Oil Gas are among the businesses that will be excluded from the index; the main components are ALLIANZ, SAP, MUENCHENER RUECKVERSICH, SIEMENS;
- MSCI SWEDEN ESG: The ESG Sweden Index is based on its parent index and comprises the country's major and mid-cap equities. Firms involved with controversial, civilian and nuclear weapons, tobacco, thermal coal and oil sands production, and companies that are not consistent with the United Nations Global Compact principles are excluded from the index. The major stocks considered are ATLAS COPCO A, INVESTOR B, NORDEA BANK, VOLVO B;
- MSCI NORDIC REGION ESG: large and mid-cap equities from four Developed Markets (DM) countries are included. The index is intended to reflect the performance of an investment strategy that, by shifting away from free-float market cap weights, seeks to gain exposure to companies that have both a strong ESG profile and a positive trend in improving that profile, while using the MSCI Nordics index as a starting point. The main constituents are: NOVO NORDISK B, ATLAS COPCO A, NORDEA BANK, NOKIA CORP;

- MSCI SWITZERLAND ESG: is a capitalization-weighted index that gives exposure to companies that outperform their industry in terms of environmental, social, and governance performance. It is meant for investors seeking a broad and varied market and consists of major and mid-capitalization companies in the Swiss market. Roche Holding Genuss, Lonza Group, Sika, and Swiss RE are just a few of the companies involved;

- The MSCI UK ESG Index is based on the MSCI UK Index and comprises big and mid-cap equities from the UK equity markets. The index is intended to reflect investment strategies and value companies that have a good ESG profile as well as a trend toward strengthening it. Glaxosmithkline, Astrazeneca, HSBC Holdings, and Lloyds Banking Group are some of the important companies that make up this index.

More general indices in which non-sustainable stocks or those that do not meet ESG principles may be considered include:

- MSCI NORDIC: The MSCI Nordic Countries index covers large- and mid-cap companies from Denmark, Finland, Norway, and Sweden, which are all developed markets in northern Europe. The index includes 85 companies and covers roughly 85 percent of each country's free-float adjusted market. Novo Nordisk B, DSV, Nokia, and Volvo are among the major participants;

- The MSCI SWEDEN stock market index measures the performance of Sweden's mid- and large-cap stocks. It consists of 44 businesses and represents for around 85% of the Swedish stock market. The main companies engaged are Atlas Copco A, Nordea Bank, Volvo, and Hexagon B;

- MSCI SWITZERLAND is a stock market index in Switzerland that monitors the performance of mid- and large-cap firms. It is made up of 41 companies and contributes for around 85% of the Swiss stock market. Nestle, Novartis, UBS Group, and Lonza Group are just a few of the significant players;

- MSCI UK is a stock market index that tracks the performance of companies in the United Kingdom. It is made up of 84 enterprises and accounts for around 85% of the free-float adjusted market in the United Kingdom. Astrazeneca, Diageo, BP, and British American Tobacco are among the major participants;

- MSCI GERMANY is a stock market index that tracks the performance of busnesses in Germany. It is made up of 61 companies and accounts for about 85 percent of the German equities market. Sap, Siemens, Allianz, Adidas, and Bayer are among the major participants.

Tables 3.1 and 3.2 show the 10 largest constituents and the stocks in common between an ESG index and the MSCI index for a country.

Table 3.1: Constituents and common shares between ESG and MSCI indices pt.1

INDICES	**TOP 10 CONSTITUENTS**
ESG Germany	SAP, SIEMENS, DEUTSCHE POST, ALLIANZ, INFINEON TECHNOLOGIES, ADIDAS, VONOVIA, DEUTSCHE TELEKOM, MERCK KGAA STAM, SIEMENS ENERGY
MSCI Germany	SAP, SIEMENS, ALLIANZ, DAIMLER, BASF, DEUTSCHE POST, DEUTSCHE TELEKOM, INFINEON TECHNOLOGIES, ADIDAS, BAYER
Common constituents between ESG and MSCI Germany	7/10 are in common
ESG Sweden	ATLAS COPCO A, INVESTOR B, NORDEA BANK, VOLVO B, ERICSSON (LM) B, SANDVIK, HEXAGON B, ASSA ABLOY B, EVOLUTION, ATLAS COPCO B
MSCI Sweden	ATLAS COPCO A, INVESTOR B, NORDEA BANK, VOLVO B, ERICSSON (LM) B, SANDVIK, HEXAGON B, ASSA ABLOY B, EVOLUTION, ATLAS COPCO B
Common constituents between ESG and MSCI Sweden	10/10 are in common
ESG Nordic	NOVO NORDISK B, ATLAS COPCO A, NORDEA BANK, NOKIA CORP, ERICSSON (LM) B, SANDVIK, VESTAS WIND SYSTEMS, ASSA ABLOY B, EQUINOR, ORSTED
MSCI Nordic	NOVO NORDISK B, DSV, ATLAS CORPCO A, INVESTOR B, NORDEA BANK, NOKIA CORP, VOLVO B, ERICSSON (LM) B, SANDVIK, HEXAGON B
Common constituents between ESG and MSCI Nordic	6/10 are in common

Table 3.2: Constituents and common shares between ESG and MSCI indices pt.2

INDICES	TOP 10 CONSTITUENTS
ESG Switzerland	ROCHE HOLDING GENUSS, FIN RICHEMONT NAMEN A, ZURICH INSURANCE GROUP, ABB LTD, LONZA GROUP, SIKA, GIVAUDAN, SWISS RE, GEBERIT, STRAUMANN HOLDING
MSCI Switzerland	NESTLE, ROCHE HOLDING GENUSS, NOVARTIS, FIN RICHEMONT NAMEN A, ZURICH INSURANCE GROUP, UBS GROUP, ABB LTD, LONZA GROUP, SIKA, GIVAUDAN
Common constituents between ESG and MSCI Switzerland	7/10 are in common
ESG UK	GLAXOSMITHKLINE, DIAGEO, ASTRAZENECA, UNILEVER, PLC (GB), HSBC HOLDINGS (GB) RELX (GB), RECKITT, BENCKISER GROUP, NATIONAL GRID, LLOYDS BANKING, GROUP, BP
MSCI UK	ASTRAZENECA, UNILEVER PLC (GB), DIAGEO HSBC HOLDINGS (GB), GLAXOSMITHKLINE, ROYAL DUTCH SHELL A, BP, ROYAL DUTCH SHELL B BRITISH AMERICAN TOBACCO, RIO TINTO PLC (GB)
Common constituents between ESG and MSCI UK	6/10 are in common

All the indices considered here are in dollars. In the following sections, the methodology implemented for the study and the consequent results will be presented.

Chapter 4

Methodology

The fourth chapter of the thesis focuses on the analysis of the time series of the ten indices considered. The first part is based on the study of the univariate analysis of their logarithm of prices. The same analysis was carried out on the returns of ESG and MSCI indices, which are the differences of the log prices and express their changes. The formula to calculate returns is: $r_{t+1} = ln(p_{t+1}) - ln(p_t)$. The autocorrelation was studied on the square of the returns, in order to understand the dependency and to carry out the GARCH model. The study then moves on to cointegration analysis and so multivariate analysis. The method called Wild Bootstrap, proposed by Liu (1988) and Wu (1986), was used for this purpose. Finally, the VAR model was implemented to understand the dependence of the time series over time.

4.0.1 Univariate Analysis

To analyze the performance of the MSCI and ESG indices, the logarithm of prices has been taken. The main advantage of using a logarithmic scale is to identify the importance of movements beyond the absolute values at which they occurred. Analyzing a financial asset with very large variations over time is less difficult using this representation.

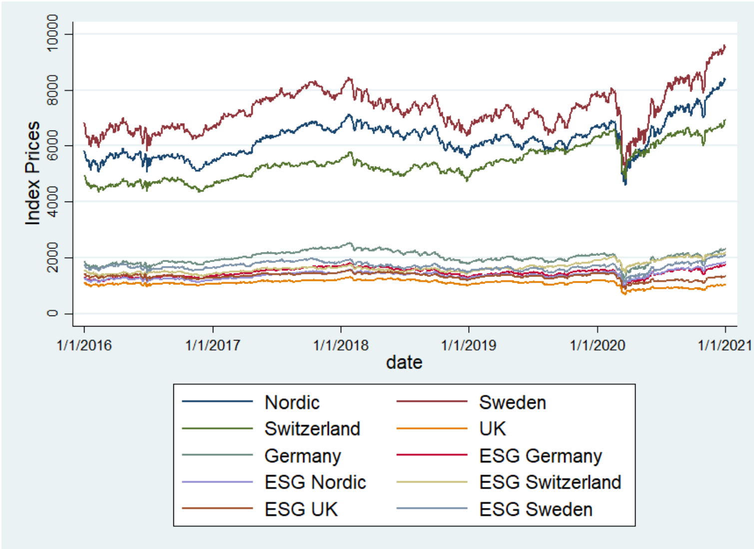

Figure 4.1: Prices

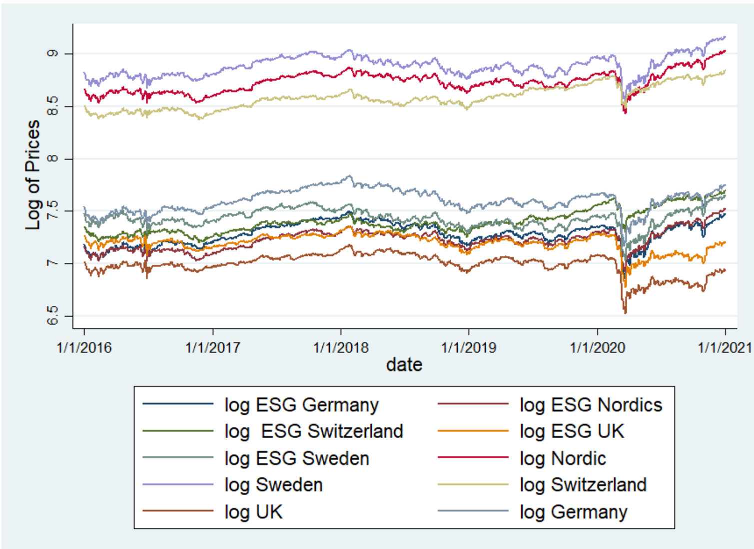

Figure 4.2: log Prices

The figure 4.1 represents the prices from January 1, 2016 to December 31, 2020 of the various indices considered for this study. The 4.2 graph, on the other hand, shows the evolution of the logarithm of prices over the five years.
We can observe how in the second graph the trend is more flattened, precisely because of the presence of a different measurement scale. This is the effect of transforming a number into its respective logarithm. Another additional component is the reduction of volatility in the represented series.

After focusing attention on the two graphs, we turn to our initial analysis. The study was carried out using STATA 14.0, an econometric analysis software. The total number of observations is 1305 for the various prices. The first part focuses on the mean, median, standard deviation, skewness and kurtosis, and normality of the data. The objective for the fist part is to obtain some information regarding the performance of the log prices of the indices and their return. This initial procedure was carried out in order to obtain descriptive statistics of the variables, thus allowing an early comparison. The mean price, in fact, expresses how a certain index behaved during the time period considered. If we use this same indicator for returns, it expresses how much an investor may have earned on a daily basis by putting money into a particular asset. This is very important information for the choice of whether or not to invest in an ESG index or an MSCI index, also integrated with the study of the standard deviation. The latter, in fact, indicates the variability of a price, if applied to the historical series of the log of prices, or how much the returns have varied in the 5 years considered. It is therefore an index of price or return riskiness, as it measures the intensity of the variations undergone by the value of an asset in a given period of time. In other words, volatility indicates the percentage change in the value of a financial instrument: it is a measure of the intensity of the oscillation. This analysis will be applied for ESG and MSCI indices to understand, at least initially, what might be a good investment choice. Skewness, Kurtosis and normality of the distribution are important peculiarities for subsequent investigations. In fact, besides demonstrating how the data in our possession are distributed, they allow us to verify the presence of conditional heteroschedasticity, which will be studied with the GARCH model and will allow us to obtain forecasts on the future variance of an asset. This is a fundamental analysis for a further confirmation of whether an ESG index can be preferred to an MSCI index since, as said before, an investor has a tendency not to keep in his portfolio an investment that is too risky for the return it offers.

In this research dividends are excluded from the analysis. Subsequent studies may also include this indicator to reach further information. They explain how the operating profit of a firm is divided between shareholders, thus becoming an additional source of revenues.

Subsequently the formulas used for this descriptive analysis are reported. The arithmetic mean is defined as follows: given x the variable on which we calculate the summary statistics (MSCI and ESG prices or their returns for us), and denoting as x_i an individual observation, v_i the weight and $V = \sum_{i=1}^{N} v_i$ as the sum of weights, if v_i is normalized to sum to n, $w_i = v_i(n/V)$, then the mean is defined as $\bar{x} = \frac{1}{n}\sum_{i=1}^{n} w_i x_i$. This formula expresses that the ratio of the sum of the logarithms of the prices and returns by their number gives the mean value. The median, on the other hand, represents the central value of the data set considered. The standard deviation expresses the dispersion of the data compared to the mean. This is an indicator of the unpredictability of MSCI and ESG prices and returns: the standard deviation is a representation of the volatility of a certain financial instrument. The formula to obtain this measure is:

- Variance: $s^2 = \frac{1}{n}\sum_{i=1}^{N} w_i(x_i - \bar{x})^2$;
- Standard deviation: $s = \sqrt{s^2}$.

In statistics, skewness is the degree of asymmetry observed in a probability distribution that deviates from the symmetrical normal distribution in a given set of data. When a set of observations has a symmetrical distribution, this means that the left and right sides of the graph contain the same number of values. It reveals how much the quantity of positive and negative log prices and returns are comparable or not in the depiction of a distribution of events. In the absence of such symmetry, we can speak of Skewness. Considering the Skewness coefficient, if it is negative, the distribution is skewed to the left, so negative values; if the coefficient is positive, the distribution is skewed to the right; if it is zero, the distribution follows that of the normal variable, meaning that it is distributed around it mean value. The origin of the term Kurtosis is Greek and means curvature. This coefficient measures the degree of flattening of the distribution. If it is equal to 3 the distribution follows the normal variable. Conversely, a coefficient below 3 indicates that the distribution is more flattened than normal. If the Kurtosis coefficient is greater than 3, the distribution is sharp. It indicates whether the distribution of the indices is dispersed or concentrated. In addition, a test is implemented to check if the distrubution of the log of prices and returns follows the one of the Normal.

Stationarity

To move on and do some inference on ESG and MSCI indices it was necessary to test the stationarity of the data. In fact, if a series in non stationary, then the predictions that are done are misspecified and could lead to wrong interpretations and decisions. Since we are posing from the point of view of an investor between choosing an ESG or non sustainable asset, it would be preferable to be in the best conditions to judge the two asset classes and to invest the money. So stationarity is fundamental for this goal. The study of this feature is done using unit roots tests. They're termed so since they're predicated on looking for a unit root, which would otherwise render the stochastic process non-stationary. A stochastic process is said to be stationary when its probabilistic structure is time invariant. To obtain a stationary process from a non-stationary one, the procedure to be followed is that of differentiation, i.e. subtracting an observation at time t from that at time $t-1$. Returns are the first difference of the logarithm of prices. This explains that, if we obtain a unit root in the logarithm of prices, then we just have to take the first difference of this

variable to obtain another one which is stationary. Stationarity, therefore, is a fundamental concept in order to proceed with the identification of the model and inference analysis of the ESG and MSCI indices and to be able to make predictions on them.
The first test considered is the Zivot and Andrews (1992) test. This test solves a problem present in other unit root tests, namely the structural break. Structural breaks are a visible shift in the trend of a time series caused by a change in the regression parameters. Such changes might occur as a result of a sudden change on a given day or as a result of the coefficients' continuous change over time. These authors proposed a variation of Perron's (1989) test, which assumed that it was impossible to determine when the break point occurred. On the contrary, here, the authors, by means of an algorithm, are able to determine the timing of this event. Zivot Andrews use three models for the determination of unit roots: model A, which allows a one-time change in the level of the series; model B, which allows for a one-time change in the slope of the trend function, and model C, which combines one-time changes in the level and the slope of the trend function of the series.
The three regressions concerning the models are as follows:

Model A: $y_t = c + \alpha y_{t-1} + \beta t + \gamma DU_t + \sum_{j=1}^{k} d_j \Delta y_{t-j} + \varepsilon_t$
Model B: $y_t = c + \alpha y_{t-1} + \beta t + \theta DT_t + \sum_{j=1}^{k} d_j \Delta y_{t-j} + \varepsilon_t$
Model C: $y_t = c + \alpha y_{t-1} + \beta t + \theta DU_t + \gamma DT_t + \sum_{j=1}^{k} d_j \Delta y_{t-j} + \varepsilon_t$.

DU_t is a dummy variable for a mean shift occurring at each possible break date (TB), while DT_t is the corresponding trend shift variable. In particular, $DU_t = 1$ if $t > TB$, 0 otherwise; $DT_t = t - TB$ if $t > TB$, 0 otherwise. y_t is the series to be tested. The null hypothesis in the three regressions is that $\alpha = 0$, which implies that the models have a unit root with a drift that excludes any kind of structural break, while the alternative hypothesis of $\alpha < 0$ implies that the series is a trend-stationary process with a one-time break occurring at an unknown point in time. The method of Zivot and Andrews considers each point as a potential break-date (TB) and performs a regression for each possible break-date sequentially. Then the procedure selects as the choice of break-date (TB) the date that minimises the one-sided t-statistic. The Zivot Andrews test is very important because, as we will see, the presence of a structural break can significantly influence the time series and, if not taken into account, can lead to the incorrect consideration of the data set as stationary when in reality it is not. Crucial, therefore, for our index analysis is the correct specification of whether a series is stationary or not and, consequently, the presence of a structural break. This is defined as a sudden change that can also have long-lasting effects that distort the parameters of our considered series. An example can be the severe crisis resulting from Covid 19. This was an unexpected event that strongly shocked the financial markets. All the more reason, therefore, for the Zivot Andrews test to be fundamental, as it can verify the presence of this upheaval in the data set we have considered and thus allow a correct interpretation by an investor.

Another unit root test was used, the one developed by Dickey and Fuller(1984), called Augumented Dickey Fuller (ADF). The procedure tests whether a variable has a unit root or whether, on the contrary, it follows a random walk. The null hypothesis is always that the variable has a unit root.
The model is assumed to be:

$$y_t = \alpha + y_{t-1} + u_t$$

where u_t is an i.i.d. error term with mean equal to 0. Considering the four cases, in the first and second one α is equal to 0, since it is a random walk without drift. In the third and fourth case α is set to be unrestricted, since it is allowed a drift term.
The Augmented Dickey Fuller fits a model of the form:

$$\Delta y_t = \alpha + \beta y_{t-1} + \delta t + \zeta_1 \Delta y_{t-1} + \zeta_2 \Delta y_{t-2} + ... + \zeta_k \Delta y_{t-k} + \varepsilon_t,$$

where k is the number of lags, α the constant of the regression, δt the time trend. Testing $\beta = 0$ is equivalent to say that $\rho = 1$, or that y_t follows a unit root process.
Hamilton (1994) describes the four different cases in which the augmented Dickey-Fuller test can be applied. Here it is used the first case, where the null hypothesis is that y_t, our data set, follows a random walk without drift, and the ADF model is fit without the constant term and the time trend. α is zero under the null hypothesis. The t-statistic used to test $H_0 : \beta = 0$ does not have a standard distribution.

Another test implemented to study the unit roots of the series is called DF-GLS. Elliott, Rothenberg and Stock (1996) proposed another version of the Dickey Fuller test, with a GLS rationale. This test is similar to Dickey and Fuller's original test, with the exception that the parameters pertaining to the term α are estimated using GLS estimators before the regression is conducted, providing higher decision power in circumstances where $\beta = \beta_0$ and $\beta = \beta_0 + \beta_1 t$.

These tests permit us to have an idea if the data we possess are stationary, meaning that it can be done some inference on them since they show information that remain present even if the time is passing. In fact, from past values we can do some predictions and understand how the MSCI and ESG indices move and behave in the present and future times.

If a process is stationary, it cannot show a regular upward or downward trend: it has be seen that the autocorrelation function of non-stationary data decreases slowly. The autocorrelation of a historical series, as a function of the lag k with which the autocorrelation is calculated, is used to create the correlogram. The correlogram is a graphical tool for assessing a historical series' tendency to evolve in a more or less regular pattern. In this graph each vertical represents the value of the autocorrelation (on the y-axis) as a function of the lag k with which the autocorrelation is calculated (on the x-axis). The correlograms can present the most disparate trends when considering pairs of values $(k, \rho k)$, but to check for stationarity it is needed a graph where there is not a trend and the bars do not pass the significance bands.

Heterosckedasticity

With these procedures it has been possible to determine the stationarity of the returns. The study then moves to another concept which is heteroskedasticity. By recognizing the distinction between unconditional and conditional variance, Engle (1982) overcomes the usual theory in time series of working under the premise of constant variance. The latter can fluctuate over time as a result of previous errors, but the unconditioned variance remains constant. GARCH, therefore, is an auto-regressive model with conditional heteroschedasticity. Analysing the Kernel density distribution it is possible to infer if the model is affected by heteroskedasticity and thus perform a GARCH model to detect this feature. The Kernel density estimator is a graph showing non-parametric density estimation. This curve represents the marginal return distribution, which ranks the returns from largest to smallest, destroying the time sequence. It is compared with the normal distribution with mean 0 and variance 1. A Kernel density estimator gives a value among 0 and 1 to each observation depending on its distance from the window's center and adds the weighted values. The Kernel is the function that determines these weights. A GARCH model permits to infer also the future behaviour of the variance and so the future riskiness of an asset. Comparing how it will develop over time is fundamental in the choice between an ESG or MSCI index, since it is preferred one asset which is not too risky. It can be used for a comparison with the returns during the five years, thus understanding whether it is worth taking the risk of investing in a certain index, given its past performance and its likely future riskiness.

The simplest measure of volatility is the squared return, which illustrates how large the day's return is without considering whether it is positive or negative. Volatile periods are

those with large squared returns. The correlation for the square of the returns was observed, so as to study the dependency in the squares and actually justify the application of the GARCH model.
Very often in the graphical analysis of the logarithm of prices and returns one can find clusters of volatility. This simple fact suggests that there is persistence in variance, or more generally in volatility. This is a very important feature: in fact, the volatility of a market is closely linked to its level of risk, so that the possibility of predicting the volatility is an essential feature of any asset allocation activity. Some financial models overlook the presence of heteroskedasticity. These models produce an elegant closed-form formula but making false assumptions about the underlying process's distribution and stationarity. If a time series has a variance with non-constant behavior, it is called heteroschedastic. To account for this tendency, Robert Engle (1982) created ARCH (autoregressive conditional heteroskedasticity) models in one of his studies. It's a good model for explaining the empirical phenomena of volatility clustering, in which times of high volatility tend to stick around and are followed by periods of relative stability, which also stick around. The premise that the conditional variance is not constant through time, but rather depends on the previous history of X_t, where p is the number of steps back in time that are taken into consideration for the prediction, underlies ARCH(p) models. The idea behind the study of volatility is that returns are serially uncorrelated, but not independent. An attempt is therefore made to use these models to find this dependence. The returns are represented as white noise multiplied by the volatility, and the conditional variance process is given an autoregressive structure:

$$a_t = \varepsilon_t \sigma_t$$
$$\sigma_t{}^2 = \alpha_0 + \alpha_1 at - 1^2 + ... + \alpha_p a_{t-p}{}^2$$

where ε_t (the 'innovations') are unrelated from σ_k for every $k \leq y$ and are i.i.d. with expectation 0 and variance 1. p is the number of lagged innovations squared $at - 1^2$ in the model, $\alpha_0 > 0$, and $\alpha_i \geq 0$ for $i > 0$, for which the conditional variance a_t is finite.
Tim Bollerslev (1986) extended this study and obtained the GARCH model. The GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model is an extension of the ARCH in which the variance of the main regression residuals is described as a function of the delays of the variance of the residuals itself as well as the square of the delayed residuals. The ARCH model has the drawback of requiring a large number of lags, which makes estimation challenging. The GARCH model solves this problem by utilizing an ARMA model to estimate the connection between the values of the squared residuals. As a result, compared to the ARCH model, lagged conditional variance values are added

to the p-regression. That is, the conditional variance is a function of the p most recent values of ${X_t}^2$ and the q most recent variance estimates, attempting to capture both short term impacts related to the development of the variable in question and long term effects related to volatility persistence. The GARCH(p,q) (generalized ARCH) model is given by:

$a_t = \varepsilon_t \sigma_t$
${\sigma_t}^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i {a_{t-i}}^2 + \sum_{i=1}^{q} \beta_i {\sigma_{t-i}}^2.$

The GARCH(1,1) model, in particular, has become widely utilized in financial time series modeling and is included in most statistics and econometric software programs.
The formula for the GARCH(1,1) is: ${\sigma_t}^2 = \alpha_0 + \alpha_1 {a_{t-1}}^2 + \beta_1 {\sigma_{t-1}}^2$.
Using some computations, this study had the possibility to predict the future behaviour of the variance. As previously detected, it is a measure of the riskiness of an asset, since it explains how it developed around the mean. For this reason, understanding this feature for ESG and MSCI indices is fundamental from the point of view of an investor.
In order to check if the model is correct and so the future previsions, the analysis of residuals is conducted. The standardised residuals are derived by dividing the ordinary residuals by their estimated conditional standard deviation and are used for model verification, since the residuals should not show autocorrelation if the model is appropriate.

To summarise what has been done so far, we can say that an initial univariate descriptive analysis, i.e. of the characteristics of the sample considered, has been carried out. This is used to summarise the data studied, i.e. the logarithm of prices and the MSCI and ESG returns, so as to identify the mean, i.e. the value around which the variables considered move; the standard deviation, which identifies how much prices and returns deviate from the mean value; the median indicates which value in the 50th percentile, i.e. in the middle of the distribution. Skewness and Kurtosis coefficients, together with the normality statistic, identify the distribution and explain its shape and probable heteroskedastic components. Unit root tests are implemented to identify the stationarity of the series, i.e. the possibility of deducing from the series information such as the dependence with respect to past values. This study is confirmed by the correlogram. As observed by the presence of volatility clusters in the historical series of returns and the presence of autocorrelation between the squared residuals, we proceed with the subsequent analysis of the dependence of the variance with respect to previous instants of time, identified through the GARCH model, which serves to explain the volatility of returns, a stationary variable for our model, and predicts future behaviours of the riskiness of the assets.

4.0.2 Multivariate Analysis

This last part is also approached from the point of view of an investor, who tries to maximise profit by seeking investments that are not excessively risky and above all diversified. It is precisely for this last point, i.e. diversification, that cointegration analysis and VAR models have been implemented. The multivariate analysis starts with the concept of cointegration. Granger (1983) developed this concept between two or more in general $n > 2$ time series, which was later formalized in the following definition: if a linear combination $\zeta_t = \beta_1 x_{1,t} - \beta_2 x_{2,t}$ that is $I(0)$ exists between two time series $x_{1,t}$ and $x_{2,t}$, both $I(1)$, without drift or trend, then $x_{1,t}$ and $x_{2,t}$ are cointegrated, and $\beta = (\beta_1, \beta_2)$ is denoted as cointegrating vector. This sort of study allows for the establishment of a linear link between non-stationary stochastic processes, allowing for the identification of a stable relationship across time between variables that are not stable separately. In our case the variables considered are MSCI and ESG indices. In particular, whith this test we want to detect if they are cointegrated, thus defining a strict relationship between the two variables and thus not permitting to diversify the risk of the general index with a sustainable asset. One popular belief is that ESG investments protect investors from unexpected and devastating occurrences, such as a financial crisis, which would have a greater impact on general indexes. If we establish a link between the two, this idea will be demolished since a tight relationship will be discovered, and a negative performance of an unsustainable instrument will have effects on an ESG one. We'll look at the correlation between ESG indexes and MSCIs for the same nation in particular. Following that, we'll use the VAR model to investigate the interdependence of these indicators across nations.

Lee and Tse (1996) quantitatively analyze the performance of the rank tests in the presence of generalized autoregressive conditionally heteroskedastic (GARCH) errors. They discover that rank tests have a propensity to overreject the null hypothesis of no cointegration. Sample information pertaining to any conditional heteroskedasticity present is not used in the design of these tests. Bootstrap testing procedures in the multivariate time series setting, that are asymptotically valid in the presence of conditional heteroskedasticity, should be considered.

To infer the cointegration between two variables it has been utilized the ADF test on residuals, which have been resampled using the Wild Bootstrap methodology. The Wild Bootstrap is a bootstrap sample generation approach that does not include resampling the original data or residuals. On the other hand, it creates a bootstrap sample by combining the data with random variables selected from a known distribution. This permits to have a data set which mantains the original heteroskedasticity. Studies show that the Wild Bootstrap is asymptotically justified under a variety of regularity constraints, in the sense that the asymptotic distribution of certain statistics is the same as the asymptotic distribution of their Wild Bootstrap equivalents, thus confirming the validity of this process. To test for cointegration between the ESG indices and the MSCI ones the ADF test is implemented on a resampled data set. For this method the MSCI and ESG indices are regressed in pairs, considering the country on which they are built (MSCI Sweden is regressed with ESG Sweden, for example). After this, the residuals are obtained and it is taken the first difference of them. Another regression is computed between the differenced residuals and the lagged ones. Finally the Wild Bootstrap procedure is implemented for the lagged residual to obtain a statistic that permits to infer a p-value, which is compared to the significance values to obtain inference about cointegration. The methodology developed by Liu(1988) and applied to the lagged residuals will be discussed in Appendix. The results of the Wild Bootstrap ADF test are then compared to the ones of the Johansen cointegration test.

For this purpose, it has been considered the logarithm of prices to calculate the cointegration. This is due to the fact that it is possible to look for cointegration in variables which have unit roots.

Cointegration may be used as an useful tool to diversify investments. In fact, if an index is cointegrated with another one, an economic downturn for a specific instrument may cause a distress situation for the other too. It is useful to see whether MSCI and ESG indices move together or not from the point of view of an investor, since cointegration reduces diversifying properties.

Wild Bootstrap procedure and Johansen test are implemented to see if both detect this feature for stock indices or if they behave differently due to the presence of heteroskedasticity. This is an important feature as, depending on which test we focus, an investor can choose a strategy instead of another one, particularly in a distressed period like the Covid19 crisis.

After this procedure, the study moves to the Vector Autoregressive model. VAR models are dynamic multiple equation time series models in which each variable is related to all other variables lagged by a certain number of periods and do not require any a priori constraints for parameter specification; this allows to summarize the dynamic relationships between the variables that are all considered endogenous. For our analysis the endogenous variables are the MSCI and ESG indices. If previously the cointegration relationship has been detected between two assets in a country, here with this procedure we want to estimate if an index belonging to a country permits to diversify the riskiness of another index of a different country. If a person has invested in the general index of a nation, is it useful from the point of view of diversification to invest in an ESG index in another country? This is because if non-sustainable investments are penalized in one

country, it is very likely that the same trend will be followed in other countries, thus rewarding ESG investments. But are they actually uncorrelated with the general indices, thus allowing proper portfolio diversification? With this last procedure we try to answer to this question, implementing also Impulse Response Function graphs, which permit to detect if a shock of an asset has effects towards other indices.
VAR model fits a multivariate time-series regression of each dependent variable on its own lags as well as all other dependent variables' lags. A VAR is a model in which K variables are stated as linear functions of p of their own lags, p lags of other $K-1$ variables, and perhaps exogenous variables with p delays. A VAR with p delays is sometimes referred to as a $VAR(p)$.
First of all it has been conducted a test for the correct lag selection. Then the Johansen's cointegration test has been conducted to infer the correlating equations between the variables (log prices).
The VAR model expresses the presence of the lagged values of the dependent variables on the right hand side of the equation. The system contains a vector of two or more variables. It is conducted only if the variables are integrated of order one, that is stationary after first difference. In the VAR system, all the variables are endogenous; there are no exogenous variables. The stochastic error terms are called impulses, or innovations or shocks. The dependent variable is a function of its lagged values and the lagged values of other variables in the model. All variables have equal lags. The VAR model is estimated by ordinary least squares (OLS). In general terms, a p-order VAR model , with x_t as exogenous variable, is given by:

$$y_t = v + A_1 y_{t-1} + ... + A_p y_{t-p} + B_0 x_t + B_1 x_{t-1} + ... + B_s x_{t-s} + u_t, \text{ with } t \in \{-\infty, \infty\},$$

where $y_t = (y_{1t}, ..., y_{Kt})'$ is a K x 1 random vector, A_1 through A_p are a K x K matrices of parameters, x_t is an M x 1 vector of exogenous variables, B_0 through B_s are K x M matrices of coefficients, v is a K x 1 vector of parameters, and u_t is assumed to be white noise. The goal of this model is to determine if a variable, in this case the logarithm of a price, is impacted by its lagged values and other indices lagged values. This approach is used to check for probable diversification between ESG and MSCI indexes. VAR models can explain why a shock in one nation has effects in another, restricting the possibility to invest in a different index to diversify the portfolio of assets. Since variables have a time connection, a lagged index may have an affect on another one in the present.

To summarize, this multivariate analysis checks if the variables co-move together thus permitting to infer if a sustainable index can be used as a prevention to shocks in a certain country or if it is cointegrated with the general index, defined as MSCI, and also influenced by other countries, thus not permitting to diversify the risk.

Chapter 5

Analysis and Results

5.0.1 Log of Prices

The first part, defined as descriptive analysis, is focused on the analysis of the logarithm of prices downloaded using Thomson Reuters. As mentioned before, using a logarithmic scale is a way to reduce volatility in the time series to obtain more comparable results. The results are summarised in tables 5.1 and 5.2. To be more clear the values are divided, firstly focusing on ESG data and then to the MSCI.

Table 5.1: Summary of log ESG Statistics

	ESG Germany	ESG Nordics	ESG Switzerland	ESG UK	ESG Sweden
Mean	7,285	7,229	7,401	7,197	7,433
Median	7,288	7,39	7,385	7,210	7,426
St.dev	0,108	0,099	0,112	0,081	0,087
Skewness	-0.488	0,209	0,733	-1,202	-0,460
Kurtosis	2,94	3,047	2,767	5,166	4,450
Normality: Prob>chi2	0,00	0,01	0,00	0,00	0,00

On the left of the table are reported 5.1 the statistics used. On the top are written the ESG indices used for the analysis, all in dollars. In the middle of the table the results are reported. The first row shows the mean of the logarithm of prices in the 5 years considered; in the second row the median value is reported; after that there is the standard deviation of ESG prices; the Skewness and Kurtosis coefficients are reported together with the test for normality, which explains the probability of a distribution to follow the Normal.

Table 5.2: Summary of log MSCI statistics

	MSCI Nordic	MSCI Sweden	MSCI Switzerland	MSCI UK	MSCI Germany
Mean	8,735	8,888	8,586	6,991	7,604
Median	8,741	8,885	8,579	7,001	7,600
St.dev	0,100	0,099	0,110	0,101	0,106
Skewness	0,291	0,159	0,269	-1,109	-0,387
Kurtosis	3,037	2,995	2,218	4,339	3,211
Normality: Prob>chi2	0,00	0,06	0,00	0,00	0,00

Table 5.2 follows the scheme reported for Table 5.1.

As we can see, the mean and median of the log of prices of MSCI indices are higher than their ESG counterparts. The only exception is UK, which has a higher value for the sustainable index than the overall index.
If we then consider the Standard Deviation, which is an expression for volatility of the data, we can see that MSCI indices are more dispersed than ESG ones. In fact, the mean of St.dev. for the general indices is 10,32%, which is higher than the 9,74% of the sustainable ones. This means that the classical investment option is riskier than the second one, since it diverges form the mean of a higher value than the counterpart. The two main differences in the sample are UK and Sweden, with a spread which is around 20%.
With regard to the analysis of the distribution, the coefficients of the Skewness and Kurtosis statistics are observed. In the first case, if the coefficient is negative, this means that the distribution is symmetrical to the left. This is true for the German, English and Swedish ESG index and for the generic index for England and Germany. It must also be said that these values are very close to zero in the normal distribution.
For the analysis of the flattening of the distribution, we can observe that the indices that deviate most from value 3, i.e. that of the normal, are England for both ESG and MSCI and the Swedish sustainable index.
For the analysis of normality of the distribution, all the indices, except MSCI Sweden, are not normally distributed at the 5% significance level.

This first analysis presents an overview of the behaviour of the logarithm of prices both for MSCI and ESG indices for the time period considered. After that we move to the unit root study. As we said in Chapter 4, to check for stationarity permits to do some inference on the model. If the series show a unit root, meaning that they are not stationary, additional studies cannot be done. Many series in the economic and financial domains are non-stationary due to the presence of an underlying trend component. A deterministic or stochastic trend might be used to describe this object. The distinction is in the kind of function that characterizes it: in the former, we discover a non-random connection, but in the latter, we find a function that simply fluctuates in time in a random manner. Because of the presence of a stochastic trend, a difference-stationary time series is produced by subtracting from (Yt) its first lag (Yt-1), as we will see for the returns of the indices. The concept of stationarity coincides with the idea that the future is the same as the past. The first test which has been implemented to detect this feature is the Zivot Andrews unit root test.

Table 5.3: Zivot Andrews Table

ZIVOT-ANDREWS	**t-statistic**	**1% critical value**	**5% critical value**	**10% critical value**	**Break**
ESG Germany	-3,455	-5,34	-4,80	-4,58	obs 712
ESG Nordics	-3,727	-5,34	-4,80	-4,58	obs 716
ESG Switzerland	-4,517	-5,34	-4,80	-4,58	obs 542
ESG UK	-4,136	-5,34	-4,80	-4,58	obs 1082
ESG Sweden	-2,990	-5,34	-4,80	-4,58	obs 576
MSCI Nordic	-3,639	-5,34	-4,80	-4,58	obs 714
MSCI Sweden	-3,229	-5,34	-4,80	-4,58	obs 716
MSCI Switzerland	-4,483	-5,34	-4,80	-4,58	obs 546
MSCI UK	-4,578	-5,34	-4,80	-4,58	obs 1082
MSCI Germany	-3,551	-5,34	-4,80	-4,58	obs 712

Referring to table 5.3, on the left hand side of the table the names of the logarithm of prices are reported. On the top row there are the t-statistic, the critical values and the number of observation when the break is found, which corresponds to a specific date. In fact, the number of observations goes from 1, which is 01/01/2016, to 1305, which is 31/12/2021. In this test the critical values are: -5,34 for $\alpha = 1\%$, -4,80 for $\alpha = 5\%$ and -4,58 for $\alpha = 10\%$.

By comparing the t-statistic, obtained trough the Zivot Andrews test on a single series, with the critical values, it can be observed that for each index the first one is larger than the second number. Consequently we accept the null hypothesis of unit root with a structural break identified by the observation number. This number refers to the observation when the t-statistic reaches the lowest value.

Another test which has been implemented to test for stationarity is the Augmented Dickey Fuller Test. The critical values for this statistic are: -3,430 for $\alpha = 1\%$, -2,860 for $\alpha = 5\%$ and -2,570 for $\alpha = 10\%$. The results are reported in the table 5.4.

Table 5.4: ADF Statistics

ADF TEST	t-statistic	1% critical value	5% critical value	10% critical value	p-value
ESG Germany	-1,896	-3,430	-2,860	-2,570	0,3342
ESG Nordics	-1,207	-3,430	-2,860	-2,570	0,6705
ESG Switzerland	-0,611	-3,430	-2,860	-2,570	0,8684
ESG UK	-2,891	-3,430	-2,860	-2,570	0,0464
ESG Sweden	-2,420	-3,430	-2,860	-2,570	0,1363
MSCI Nordic	-1,118	-3,430	-2,860	-2,570	0,7077
MSCI Sweden	-1,836	-3,430	-2,860	-2,570	0,3629
MSCI Switzerland	-0,783	-3,430	-2,860	-2,570	0,8240
MSCI UK	-2,304	-3,430	-2,860	-2,570	0,1706
MSCI Germany	-2,052	-3,430	-2,860	-2,570	0,2644

For the table 5.4 the same procedure applied for the Zivot Andrews can be used to study the inference of the prices of the indices, with the exception here that the ADF test is implemented. The null hypothesis here is that there is a unit root, hence the series is non stationary. The t-statistic obtained by the test is compared with the critical values. If it is lower than these values, then H_0 is accepted. In addition, it is possible to reach the same results if the p-value is higher than 0,05.

Considering all the indices in the table, except for UK, I accept H_0 of the presence of a unit root. The only one which is different is UK, which has a t-statistic which is smaller than the 10% and 5% critical values. In addition, its p-value is smaller than 5%, so it is possible to reject the null hypothesis. This difference for England can be explained by the presence of the structural break. As we explained in chapter 4, this generates strong changes in the parameters of the time series, thus misspecifying the stationarity of the data.
The latest statistic implemented is the DF-GLS. This type also tests for the presence of unit root in the process. The deterministic parameters are calculated using a Generalized Least Squares (GLS) regression and then subtracted from the original regression, which is then subjected to the ADF test. In this way it is obtained the ADF-GLS test statistic. The tables are reported in Appendix to check the results obtained.
These results may be affected by structural breaks, which let the DF-GLS test fail to accept the null hypothesis in case of unit root. In fact from the tables we can see that some indices refuse the null hypothesis at some critical values, thus considering the data as stationary. For this reason the first test which has been implemented is the Zivot Andrews, which takes into consideration this feature. A structural break, indeed, may lead to false results by ADF and DF-GLS, indicating that a series is stationary even if it has not this feature, and thus doing inferences on the wrong set of data.

An autocorrelation analysis may be used to evaluate the amount to which the values of the time series were determined by their lagged values, which can be used to investigate the stationarity of the data set. The existence of high positive autocorrelation can be seen in the images, indicating that the stochastic process will not remain stable. The correlation coefficients, which are all positive and gradually dropping as the delay grows, surpass the blue dotted lines, which reflect the confidence interval's extremes. This means that a certain price is influenced by its predecessors and not uncorrelated from past values.

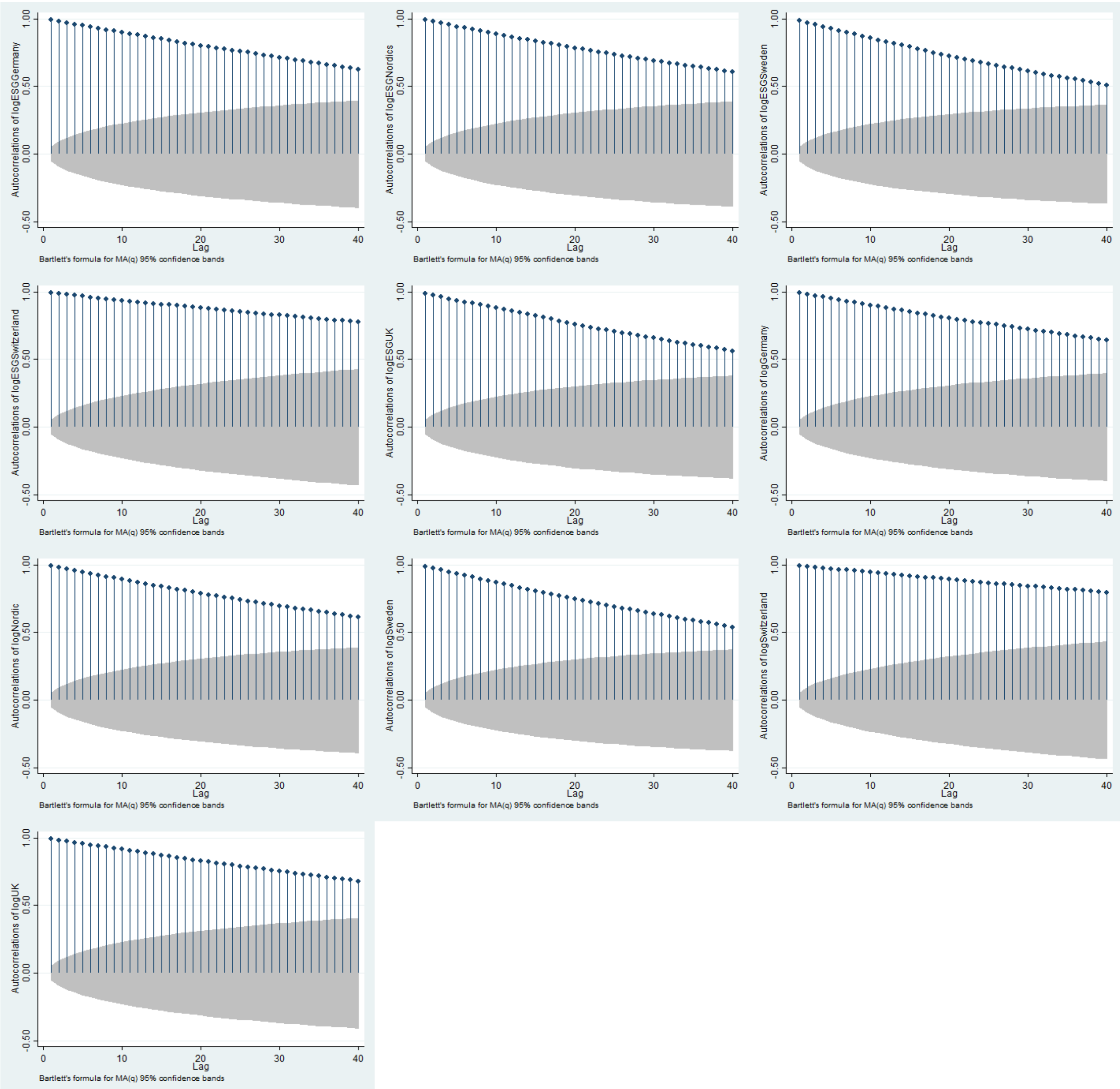

Figure 5.1: Autocorrelation Functions of log prices

Figure 5.1 shows the autocorrelation function of the logarithm of prices. These graphs show that at time t each index is influenced by its previous values. This property is defined as autocorrelation, which is a signal of non stationarity. The stationarity hypothesis states that the stochastic process' mean value and variance are independent of time t. In addition, even $Cov[X_t, X_s]$ should depend only on the distance $|s-t|$ and not on t. Stationarity implies that the properties of the producing process remain unchanged over time, which is necessary for identifying a forecasting model that explains the market's working mechanism, i.e. the dynamics of price variations. Having understood that the series are non stationary, we move now to their first difference which are returns, otherwise we could not do inference on the ten indices.

5.0.2 Returns

To check for stationarity the study moves to the returns of the ten series: $r_{t+1} = ln(p_{t+1}) - ln(p_t)$. Here dividends are not considered. It is analyzed the trend of financial markets and the possible gains that an investor can make through them. Dividends are a practice at the discretion of the company considered. In fact not all of them distribute dividends to shareholders and can be modified at will, even to hide a negative trend of the company in a certain period. Precisely because of the lack of objectivity they have not been considered. Further analysis may also include this element to compare investments, since it is an additional source of revenues and it can influence the choice of investing into a financial instrument.
As a result, the number of observations decreases by one since the return cannot be deduced for the first date.
The analysis starts as before with the descriptive part. The percentage rise in the value of an investment per unit of money initially put in an asset over a specific period of time is referred to as return. For a deeper analysis the annual returns are computed. The formula to obtain them is:
$Annualreturn = [(Dailyreturn + 1)^{258} - 1] \times 100$. It shows that the annual return can be obtained from the daily mean considering the number of trading days, which is 258.

Table 5.5: Summary of ESG returns

	ESG Germany	**ESG Nordics**	**ESG Switzerland**	**ESG UK**	**ESG Sweden**
Mean	0,0002171	0,0002771	0,0002623	-0,0000513	0,0001297
Median	0,0007057	0,0004454	0,0005973	0,0006134	0,0004294
St.dev	0,013	0,012	0,010	0,013	0,014
Skewness	-1,376	-1,268	-1,230	-1,543	-1,395
Kurtosis	23,150	16,301	20,320	24,950	17,717
Normality: Prob>chi2	0,00	0,00	0,00	0,00	0,00
Annual Return %	5,76	7,41	7,00	-1,31	3,40

Table 5.6: Summary of MSCI returns

	MSCI Nordic	MSCI Sweden	MSCI Switzerland	MSCI UK	MSCI Germany
Mean	0,0002782	0,0002565	0,0002579	-0,0000619	0,0001602
Median	0,0003973	0,000552	0,0005401	0,0006383	0,0006925
St.dev	0,012	0,014	0,010	0,013	0,013
Skewness	-1,316	-1,297	-1,447	-1,353	-1,428
Kurtosis	16,844	17,070	21,155	24,630	22,929
Normality: Prob>chi2	0,00	0,00	0,00	0,00	0,00
Annual Return %	7,44	6,84	6,88	-1,58	4,22

For the interpretation of table 5.5 and 5.6 please refer to table 5.1. Here the values refer to the returns of the ten indices. The first row is the mean of daily returns, expressed as a percentage. The second row shows the median value and the third the standard deviation of the returns. Skewness, Kurtosis and the Normal probability give an idea of the distribution of the data. The last row shows the annual returns, obtained with the formula above.

For this analysis, it is very interesting to look at the annual returns of the various indices. The time sample used considers precisely the crisis caused by Covid, in order to observe how the ESG indices behave relative to the general indices. Returns, in fact, show how much an investor can gain from putting her money into one asset. It is a percentage and explains the performance of an index over a certain period. The best performance has been done by MSCI Nordic, but its sustainable correspondent differs of around 0,04%. So their behaviour is quite similar, it cannot be said that annually the sustainable index underperforms the MSCI. The worst performance comes from England, which records negative values for both investments. What is interesting here is that ESG UK has a negative vaue of -1,31% but MSCI UK does worst: its annual return is -1,58%. In this case, even if having a bad performance, the ESG index is safer than the non-sustainable one. The greatest differences between the two investment instruments are Germany and Sweden; in particular the last one has a overll return in a year which doubles the ESG; ESG Germany overperforms MSCI of arund 1,50%, which can result, if we invest a million euros, in 15.400€. There is no substantial difference also with respect to ESG and MSCI in Switzerland.

The average annual return considering all the ESG indices is 4,452, which is relatively lower than the 4,76 of the MSCI ones. If we consider the average daily return, sustainable indices report a value of 0,00016698 and 0,00017818 for MSCIs.

From an investor point of view, it is very important to find an asset which maximizes her profit over a certain period of time. Return is a measure of the income generated by the investment in relation to the capital invested and the duration of the operation. In other words, it can be defined as the risk premium for having invested one's money in a risky financial instrument. This measure of risk is expressed by the standard deviation, which

indicates the volatility of a certain index. Dividends were not taken into account in this analysis, only the price development over the 5-year period. Subsequent analyses might consider this factor as incidental to the selection of an index, as it also influences investment choices. In addition to the return during the year, there is another source of income, namely the distribution of the profit to the shareholders.
The standard deviation is quite similar for all the indexes and it is low, indicating that they do not move consistently from their mean. As a result, this indicates the degree of dispersion of returns around their median and represents the uncertainty associated with the possibility of obtaining a return on investment equal to the median. The smaller the standard deviation, the greater the chance of obtaining a return that is close to the average. The average standard deviation is 0,0124 both for sustainable assets and for MSCIs.
From tables 5.5 and 5.6 we can obtain some considerations. Generally, MSCI indices perform better than ESG ones with respect to annual returns and they have the same standard deviation. ESG instruments, on the contrary, can reduce the losses for an investor, as can be seen for UK.
All the distributions are non normal and skewed to the left. In addition, all the indexes are sharper than the normal distribution. The Kurtosis index is very interesting: if this value is higher than 3, which is the normal distribution, this is an indicator of conditional heterosckedasticity in the model from the Jensen's inequality. In our sample all the MSCI and ESG indices show this feature, which it will be discussed later, from which it is possible to infer the future riskiness of them.
The distribution of data across a continuous interval or time period is visualized using a density plot. This distribution shows graphically the properties described by Skewness, Kurtosis and the coefficient of normality.

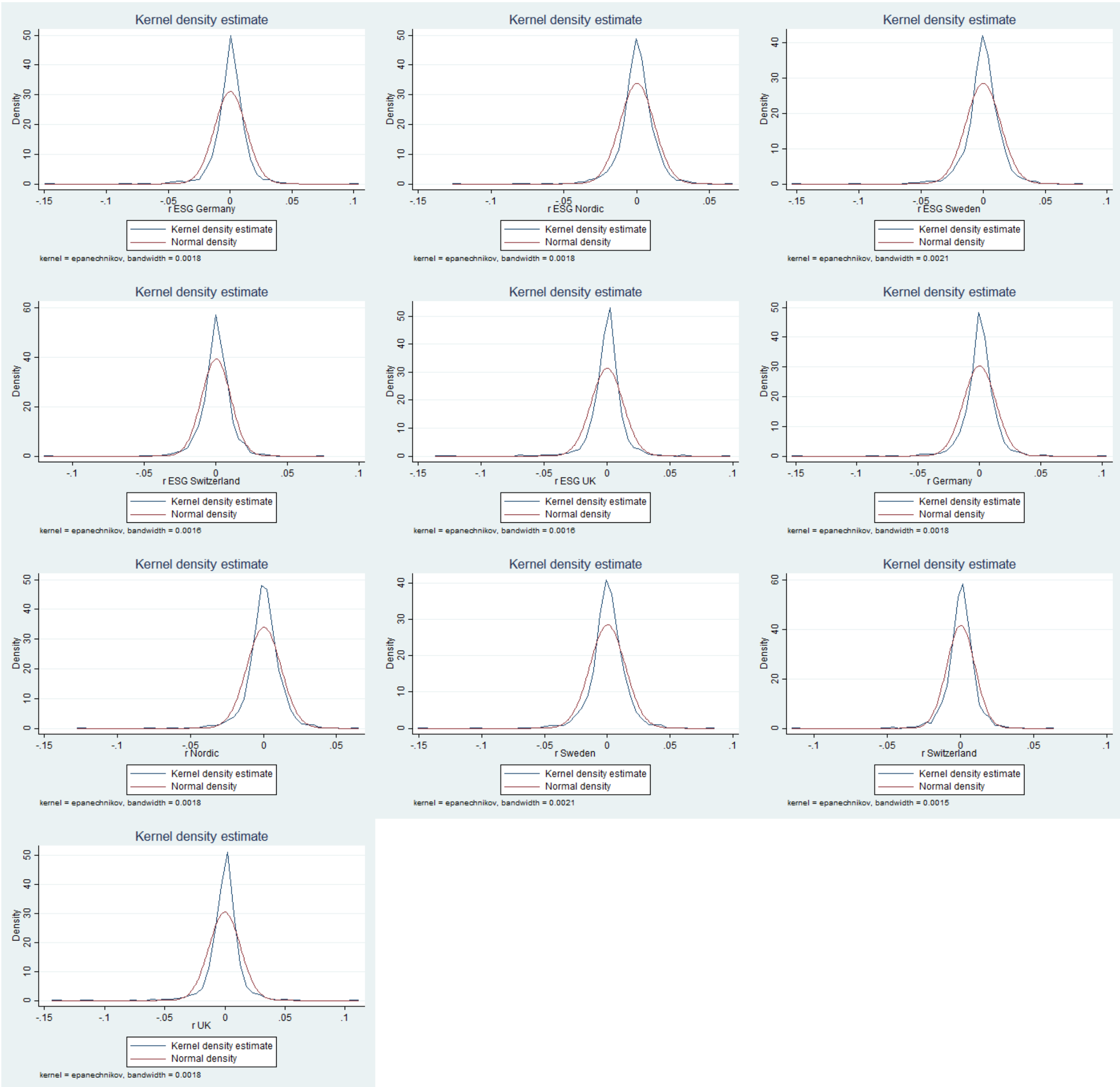

Figure 5.2: Density functions

As we said for the logarithm of prices, a fundamental characteristic of the time series to be detected is stationarity. The analysis then moves to the Zivot Andrews statistic to detect this feature, since we want to have processes on which we can do some inference.

Table 5.7: Zivot Andrews Returns

ZIVOT ANDREWS	t-statistic	1% critical value	5% critical value	10% critical value	Break
MSCI Nordic	-16,197	-5,34	-4,80	-4,58	obs 1091
MSCI Sweden	-16,360	-5,34	-4,80	-4,58	obs 1091
MSCI Switzerland	-18,245	-5,34	-4,80	-4,58	obs 1091
MSCI UK	-16,655	-5,34	-4,80	-4,58	obs 1091
MSCI Germany	-16,247	-5,34	-4,80	-4,58	obs 1089
ESG Germany	-16,398	-5,34	-4,80	-4,58	obs 1089
ESG Nordic	-16,222	-5,34	-4,80	-4,58	obs 1091
ESG Switzerland	-17,567	-5,34	-4,80	-4,58	obs1091
ESG UK	-17,066	-5,34	-4,80	-4,58	obs 1091
ESG Sweden	-16,470	-5,34	-4,80	-4,58	obs 1091

Table 5.7 confirms our initial hypothesis: after obtaining the first difference for a variable, we solve the problem of stationarity. To read it, in fact, we can base on the table 5.3. In the first column there are the t-statistics for the Zivot Andrews test of the returns. These values are compared with the critical values. The break date tells the observation number when it occurs.

Here, the analysis is conducted for the returns of the ESG and MSCI indices. Since the values of the t-statistics are lower than their critical values, it is possible to reject H_0 of unit root, and accept the alternative of stationarity.
This analysis shows a structural break for the 1091-1089 observations, which corresponds to 20th and 24th March, 2020. Those dates represent the starting point for the epidemic of Covid19. In essence, the Zivot-Andrews test is a one-sided unit root test that additionally looks for structural breaks, or a discernible shift in the time series' trend as a result of changes in the regression parameters. Here it results that the series have been influenced by the tremendous effects of the spread of Coronavirus, and it can be detected from the observation of the break. The break could cause the rejection of null hypothesis, considering the series stationary. For this reason the Zivot Andrews test was implemented first.
To confirm the results of stationarity we calculate the ADF test, as done for the log of prices. The results are reported in the table 5.8.

Table 5.8: ADF Test for returns

ADF TEST	t-statistic	1% critical value	5% critical value	10% critical value	p-value
MSCI Nordic	-35,518	-3,430	-2,860	-2,570	0,00
MSCI Sweden	-35,595	-3,430	-2,860	-2,570	0,00
MSCI Switzerland	.35,385	-3,430	-2,860	-2,570	0,00
MSCI UK	-34,945	-3,430	-2,860	-2,570	0,00
MSCI Germany	-34,723	-3,430	-2,860	-2,570	0,00
ESG Germany	-34,481	-3,430	-2,860	-2,570	0,00
ESG Nordic	-35,499	-3,430	-2,860	-2,570	0,00
ESG Switzerland	-35,753	-3,430	-2,860	-2,570	0,00
ESG UK	-34,682	-3,430	-2,860	-2,570	0,00
ESG Sweden	-36,788	-3,430	-2,860	-2,570	0,00

Table 5.4 can be used to describe table 5.8, with the exception that here we talk about returns.

From the theory we know that returns are the first difference of the logarithm of prices. This can be seen from the t-statistics, which are higher than the critical values, or from the p-value, which is significantly smaller than 0,05, that these variables are stationary. For all the tests applied here we can reject the null hypothesis of unit root.
As a final check for stationarity of the time series, the DF-GLS test is implemented. The tables are reported in Appendix, as done for the logarithm of prices.
These tables show that the returns are stationary till a certain lag. This is due to the fact that the series has trend shifts or structural breaks, which have influenced the findings of the DF-GLS tests. A unit root process might easily be mistaken with a trend-stationary I(0) series with structural breakdowns. That's why the first test implemented, the Zivot Andrews, considers structural breaks.
To confirm stationarity, the analysis moves to the autocorrelation function (ACF).

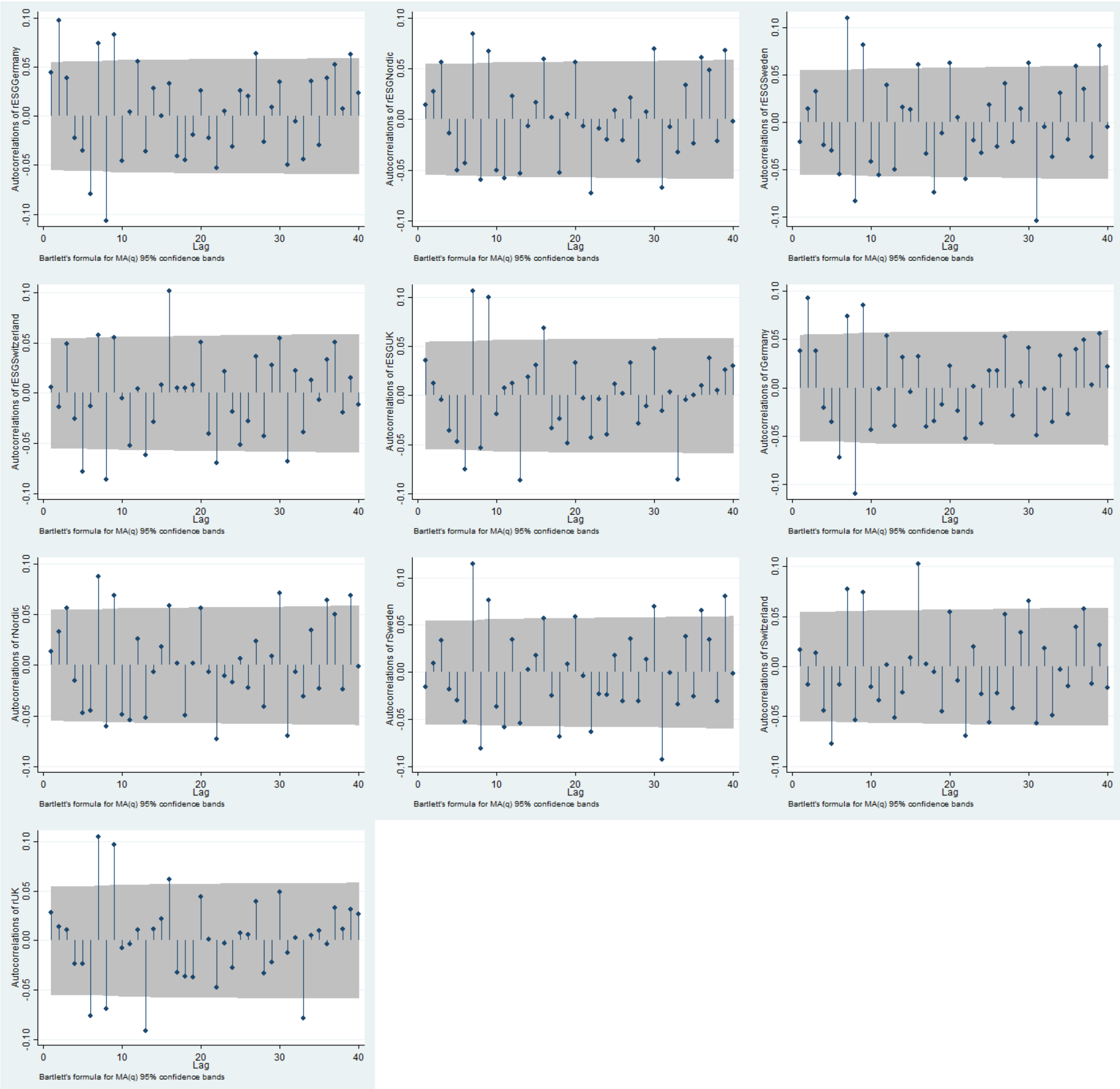

Figure 5.3: Correlogram of returns

Those graphs show that the returns are not conditioned by previous values. It means that the series are uncorrelated from the past. The negligible correlation exhibited in the correlograms and the jagged form (oscillating around zero) of the graph of the transformed series lead to the conclusion that returns are stationary. The majority of the histogram columns do not reach the threshold of significance, as can be shown (indicated by the horizontal blue bands). Without the concept of stationarity it is not possible to do some inference of the data we have. In fact, the arguments which will follow are based on this concept.

After demonstrating the stable behavior of the variable returns R_t, the goal now is to use a conditional heteroschedasticity model to explain the volatility of returns. Then, in the conditional variance equation of the model GARCH, we use a graphical analysis of the autocorrelation function (ACF) of the square of the variable R_t to detect and determine the behavior of the time series. This model is based on the concept that, whereas unconditional variance remains constant through time, conditional variance is a function of the values assumed by the residuals at previous times. It can also be argued from this that, while the historical series of returns has no autocorrelation, the squares of the returns are correlated. This may be seen graphically using the correlogram.

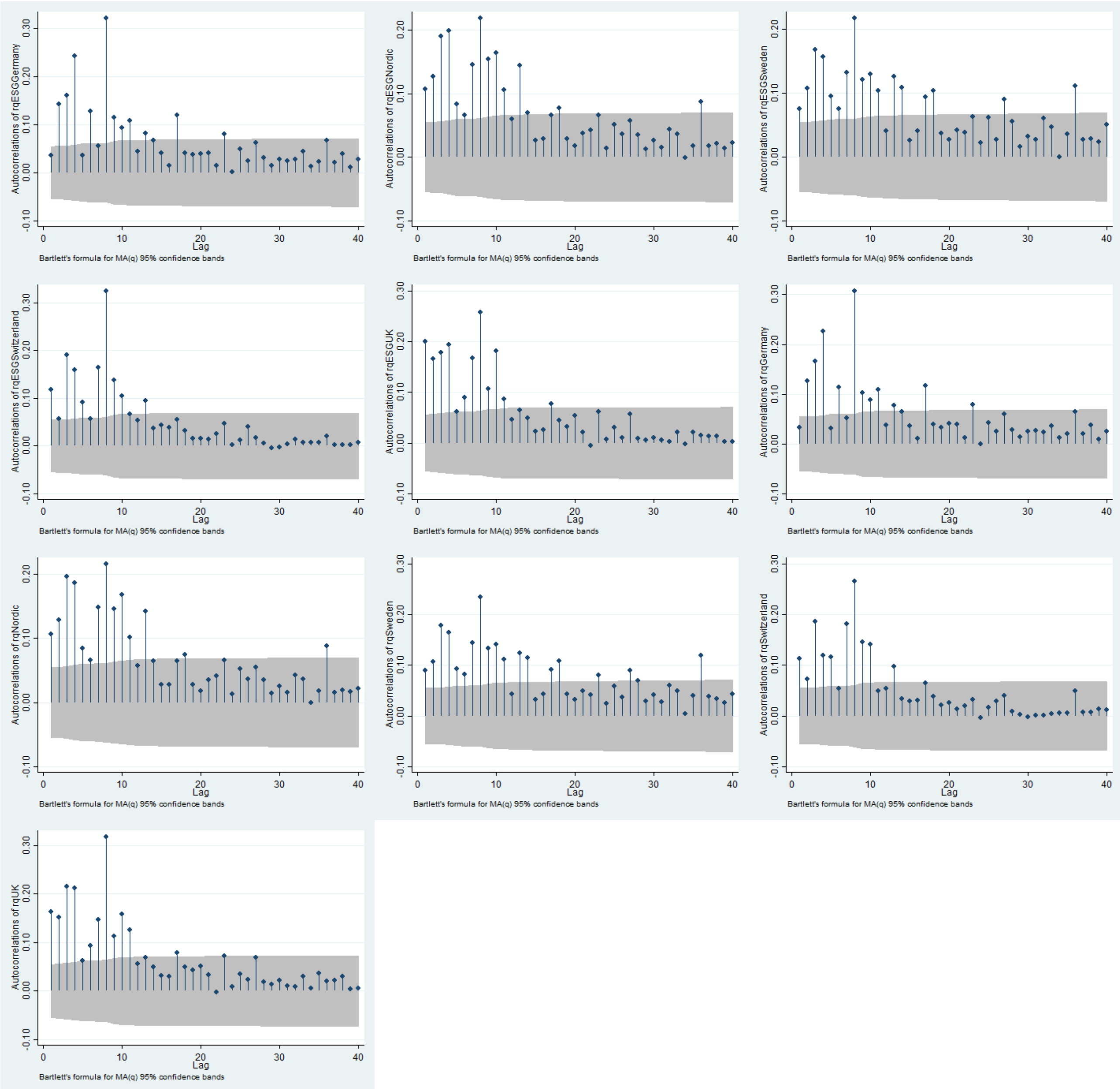

Figure 5.4: AC squared returns

The figure illustrates that the square of the returns at time t and their lagged values are positively associated, indicating that a GARCH(1,1) model is appropriate.

The results for the Generalized AutoRegressive Conditional Heteroskedastic model are reported in tables 5.9 and 5.10. The tables here show the coefficients of the formula that the GARCH model gives us to predict the conditional variance. This is an important feature since, trough those elements, we can predict the behaviour of the riskiness indicator for our MSCI and ESG indices.

Table 5.9: GARCH(1,1) Model MSCI

GARCH(1,1)	arch L1. garch L1. constant coefficients	arch L1. garch L1. constant std.errors	arch L1. garch L1. constant p-value
MSCI Nordic	0,1033084 0,8675839 0,0003848	0,0101083 0,013922 0,0002513	0,000 0,000 0,000
MSCI Sweden	0,1011486 0,8767176 0,000393	0,0093971 0,0137876 0,0002905	0,000 0,000 0,000
MSCI Switzerland	0,1302064 0,8341897 0,0004972	0,0143477 0,01878 0,0002024	0,000 0,000 0,000
MSCI UK	0,1879322 0,798832 0,0002685	0,0187581 0,0189951 0,0002365	0,000 0,000 0,000
MSCI Germany	0,0998179 0,8746793 0,0004365	0,0080124 0,0113541 0,0002736	0,000 0,000 0,000

Table 5.10: GARCH(1,1) Model ESG

GARCH(1,1)	arch L1. garch L1. constant coefficients	arch L1. garch L1. constant std.errors	arch L1. garch L1. constant p-value
ESG Germany	0,1040038 0,8688449 0,0004377	0,0085299 0,0118163 0,0002607	0,000 0,000 0,000
ESG Nordic	0,1017175 0,8685406 0,000382	0,0101408 0,0142406 0,0002532	0,000 0,000 0,000
ESG Switzerland	0,1236202 0,834988 0,0004453	0,0153587 0,0223399 0,0002195	0,000 0,000 0,000
ESG UK	0,1903803 0,7906386 0,0002323	0,0189874 0,0195722 0,0002354	0,000 0,000 0,000
ESG Sweden	0,0935211 0,8866247 0,0002074	0,0087231 0,0134129 0,0002923	0,000 0,000 0,000

In table 5.9 and 5.10 the first column shows α_0, defined as constant, α_1 which is arch L1 and β_1 which is garch L1. In the second column are reported the standard errors of the coefficients obtained from the model. The last one expresses the p-values of the coefficients, to check if they are significant and verifying that the model is correctly specified.

From STATA it is possible to obtain values of the innovations and of the variance at time t. Give these elements, we can derive the value of variance at t, if we pose our self at t-1. After some computations, it is possible to obtain the future Lth variance, considering the first future time t, as: ${\sigma_L}^2 = \frac{\alpha_0[1-(\alpha_1+\beta_1)^{L-1}]}{1-\alpha_1-\beta_1} + (\alpha_1+\beta_1)^{L-1}{\sigma_t}^2$. In the table 5.11 and 5.12 are the results for 1 day future variance and 30 days future variance.

Table 5.11: Predicted variance for MSCI returns

Predicted variance	After 1 day	after 30 days
MSCI Nordic	0,000455728	0,007964851
MSCI Sweden	0,000484334	0,007535691
MSCI Switzerland	0,000581072	0,009119501
MSCI UK	0,000430851	0,006621397
MSCI Germany	0,000553141	0,009085451
Average variance	0,000501025	0,008065378

Table 5.12: Predicted variance for ESG returns

Predicted Variance	After 1 day	After 30 days
ESG Germany	0,000546774	0,008919467
ESG Nordic	0,000453637	0,007526193
ESG Switzerland	0,000515685	0,00762538
ESG UK	0,000393171	0,005320097
ESG Sweden	0,000304132	0,004666774
Average variance	0,000442679	0,006811582

In tables 5.11 and 5.12 are reported the predicted variances using the GARCH(1,1) model of the MSCI and ESG indices. Here it is considered 1 day in the future and 30 future days.

In general can be observed from table 5.12 and 5.11 that MSCI indices are riskier than ESG ones. Indeed the table reports the values of the predicted variance, obtained trough the formula written above, for 1 day in the future and 30 days in the future for each index. Here the results may be affected from the volatility clusters phenomenon, which explains that high volatile periods tend to be followed by periods with the same peculiarity. The Covid19 crisis is of course a period of great uncertainty and consequently the results above take this into account. The values obtained show that after a day MSCI is a little riskier than ESG, and after 30 days after 30 days this difference increases.
As a result, the null hypothesis of no GARCH effects may be rejected. The GARCH model, which states that variance is dependent on the past, may be accepted, validating volatility clusters. The presence of the volatility clustering phenomenon indicates that stock's returns are represented by a leptokurtic distribution function, which has a higher concentration of values in the center and tails than a Gaussian distribution.
The standardised residuals are derived by dividing the ordinary residuals by their estimated conditional standard deviation and are used for model verification since the residuals should not show autocorrelation if the model is good. This means that the GARCH model manages to remove the autocorrelation in the squared returns and is a good choice for our model.

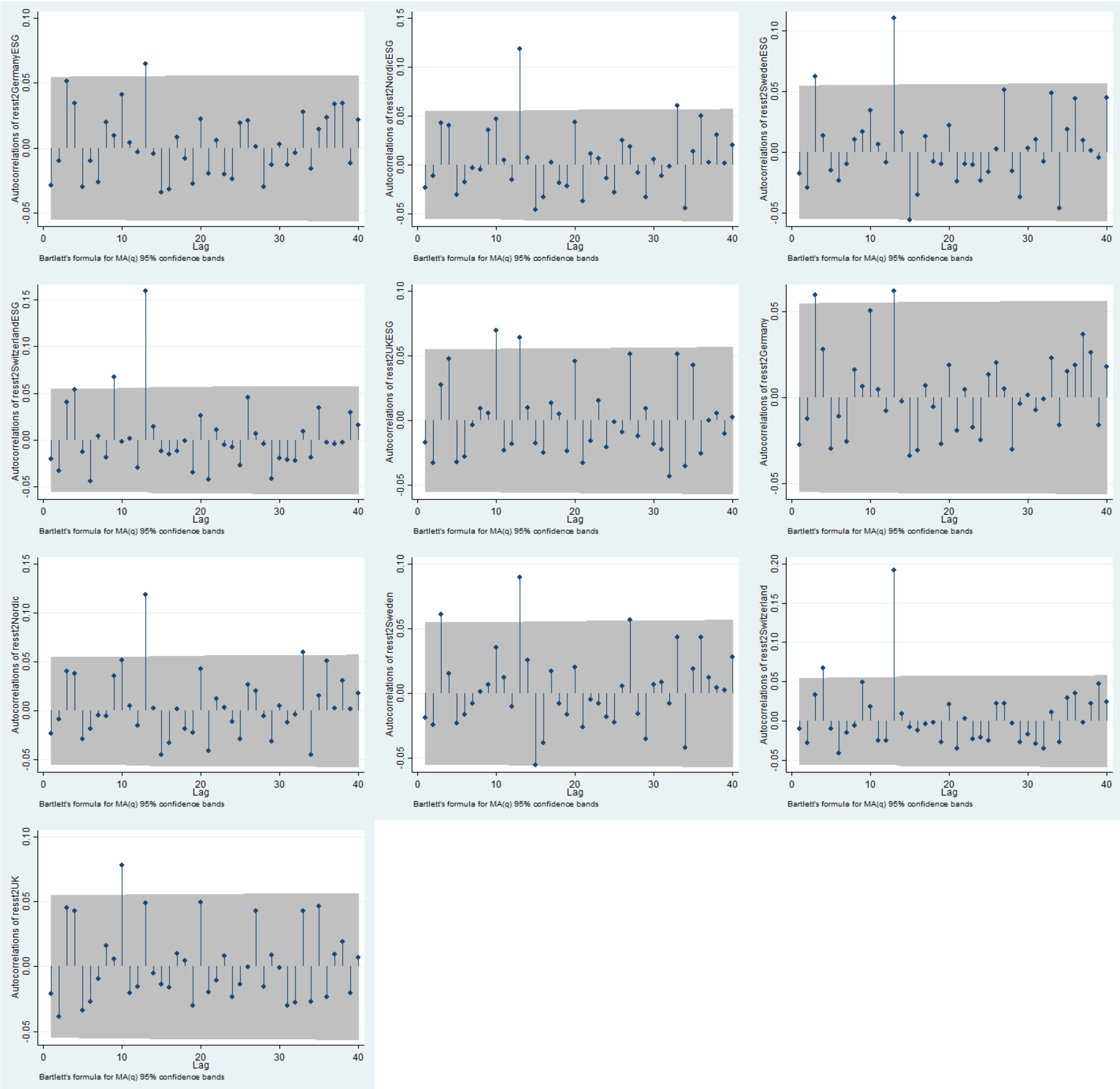

Figure 5.5: ACF standardized residuals

After having observed the presence of heteroschedasticity in the time series and having predicted future behaviour of the riskiness of an index, we move on to the cointegration analysis. As various studies have shown, the classical methodologies do not allow us to obtain a true analysis. It is therefore necessary to apply an alternative procedure to resolve the presence of heteroskedasticity. In particular, the Wild Bootstrap, implemented for cumulative ADF (CADF) is used to study the dependence over time between two assets. This feature is important if we consider portfolio diversification. As theory explains, an investor seeks to put her money into assets which do not move together, since a shock in one of them causes an alteration of the others. Here it is investigated if ESG can be a good instrument for the reduction of riskiness in ones portfolio, or if general assets are strictly connected with them. The table 5.13 shows the results obtained.

Table 5.13: Wild Boostrap on Cointegrated ADF

Wild Bootstrap CADF	**p-value**
MSCI Nordic and ESG Nordics	0,0040
MSCI Germany and ESG Germany	0,0911
MSCI UK and ESG UK	0,0440
MSCI Sweden and ESG Sweden	0,0661
MSCI Switzerland and ESG Switzerland	0,0260

Table 5.13 reports the p-values of the cointegration analysis using the Wild Bootstrap procedure. For this test, the null hypothesis is that there is no cointegration. The alternative, instead, is the presence of cointegration. As seen for the ADF to check for stationarity, this procedure gives a t-statistic and a p-value. Here the last one is compared with 0,05 and 0,10. If a p-value is lower than these two indicators, then it is possible to reject H_0 of no cointegration between MSCI and ESG indices.

Results here show that at at 10% all the cases studied present the tendency of cointegration. This means that the series tend to follow a common behaviour, thus not permitting the diversification. Indeed, even if we saw that MSCI indices are riskier than ESG ones, since they are cointegrated, a shock in one asset is immediately transmitted to its sustainable counterpart. An investor who has put his money in an ESG index and an MSCI index, and unfortunately an unforeseen event occurs in the markets, such as the pandemic crisis, will lose his money in both cases, because the two asset classes will move together.

These results are compared with the trace statistic of the Johanesn's cointegration test. Theory says that, in presence of heteroskedasticity, this indicator tends to behave incorrectly. For this reason the results are reported in table 5.14.

Table 5.14: Johansen cointegration test

Johansen test	trace statistic	5% critical value
MSCI Nordic and ESG Nordic	rank 0: 14,5668	15,41
MSCI Germany and ESG Germany	rank 0: 8,6447	15,41
MSCI UK and ESG UK	rank 0: 13,0488	15,41
MSCI Sweden and ESG Sweden	rank 0: 8,6107	15,41
MSCI Switzerland and ESG Switzerland	rank 0: 6,5582	15,41

Table 5.14 shows the trace statistic, which is the result of the Johansen test, at rank 0, which is the one of no cointegration and the critical values of this test. For all the critical values the trace statistic obtained is always lower, thus accepting the null hypothesis of no cointegration.

This comparison was made in order to observe how two tests investigating the same subject behave differently in the case of heteroschedasticity. This peculiarity, however, is fundamental for an investor, as we have shown before, because when choosing investments she might make a bad choice in terms of portfolio diversification and consequent risk reduction. The second test shows how the indices are uncorrelated, causing the indices to be wrongly considered and leading an investor to consider ESG investment as a good way to diversify the portfolio. If, on the contrary, heteroschedasticity is considered, as the Wild Bootstrap does, the results are the opposite, showing an impossibility of sustainable indices to reduce the risk of non-sustainable ones through diversification.

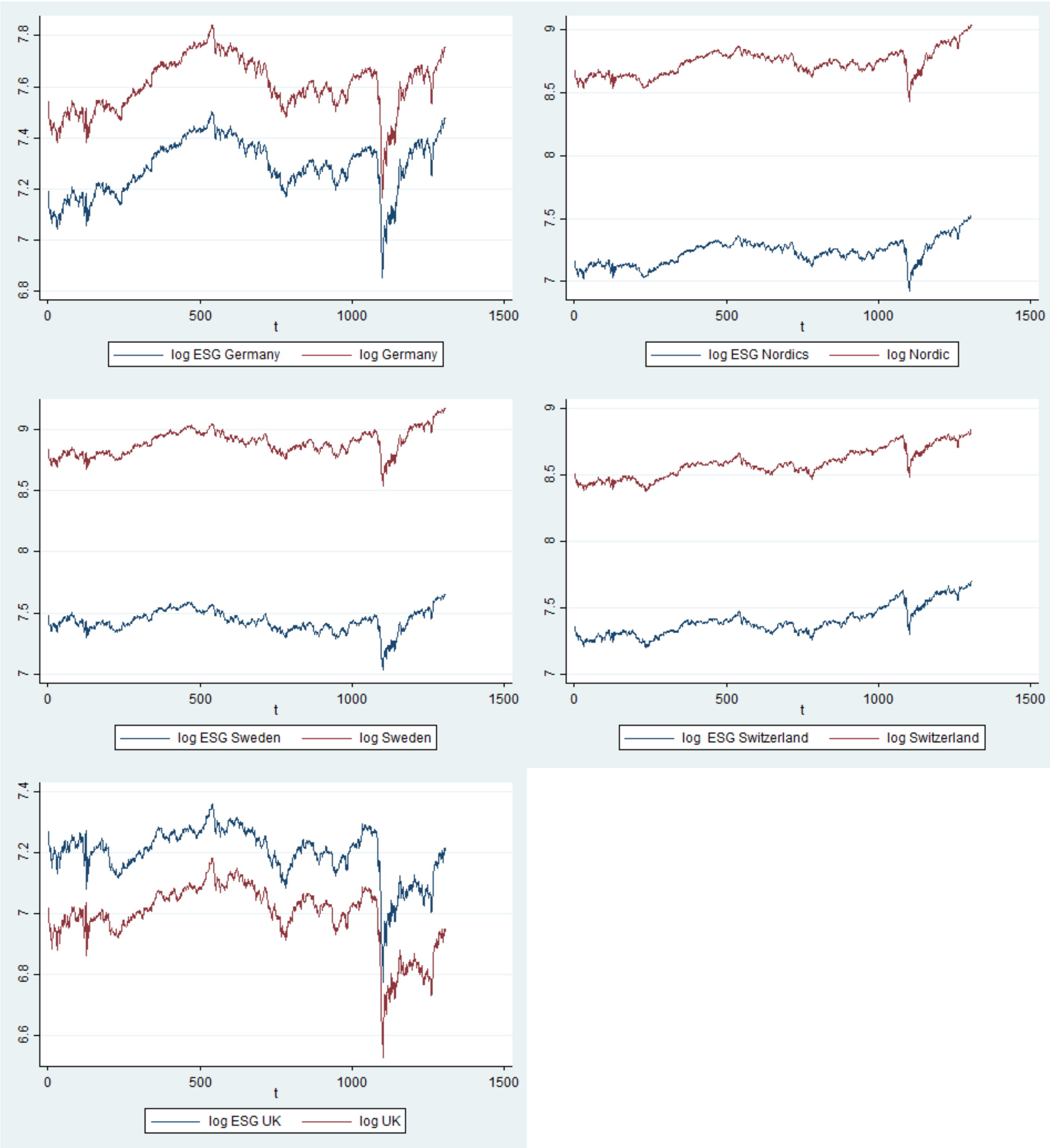

Figure 5.6: Comparison of graphs

Here are reported the logarithm of prices in pairs of the same nation, on the y axis. The time frame, denoted as t, is from 01/01/2016 to 31/12/2020, written on the x axis as the number of observations from 0 to 1305.

Also from a graphical analysis it can be seen that the two series have a tendency to move together over time, confirming the Wild Bootstrap result of cointegration between the MSCI and ESG indices. Prices, indeed, are reported in graph 5.6 and show a tendency to co-move together, with falls in one value which are reflected in the same behaviour of the other index. This graphical feature represents the concept of cointegration between sustainable e non sustainable indices.

The vector autoregressive (VAR) model is a simple multivariate time series model that connects current observations of a variable to previous observations of that variable and other variables in the system. Through this analysis we can observe if an index is caused by past values of another asset. Having found that an ESG index cannot be used to diversify the risk associated with the MSCI index of the same country, in this analysis we ask whether, instead, it is possible to reduce the riskiness of investments in other countries. To do this, we use the VAR model. All the tables relating to this argument are reported in Appendix.
The results show that there is an interdependence between the variables, i.e. the ESG and MSCI indices. It is not surprising that the markets are interconnected, but the thing to note here is that proper diversification between a sustainable index and one that is non ESG cannot be applied, not only within the same country, but also between different nations. This feature is also seen from the impulse response function graphs 5.7 and 5.8. They show how the performance of an index responds to a sudden shock in another financial instrument. The y-axis refers to the percentage change, the x-axis to the time span considered, i.e. 30 days. Here the first one 5.7 tells us that a sudden change in some conditions of an ESG index has a strong effect on another MSCI index. Graph 5.8 studies the inverse relationship, so how a change in MSCI indices has an impact on ESG ones. Both are very important for the detection of interdependence between these variables and predict how they variate in case of an unexpected event.

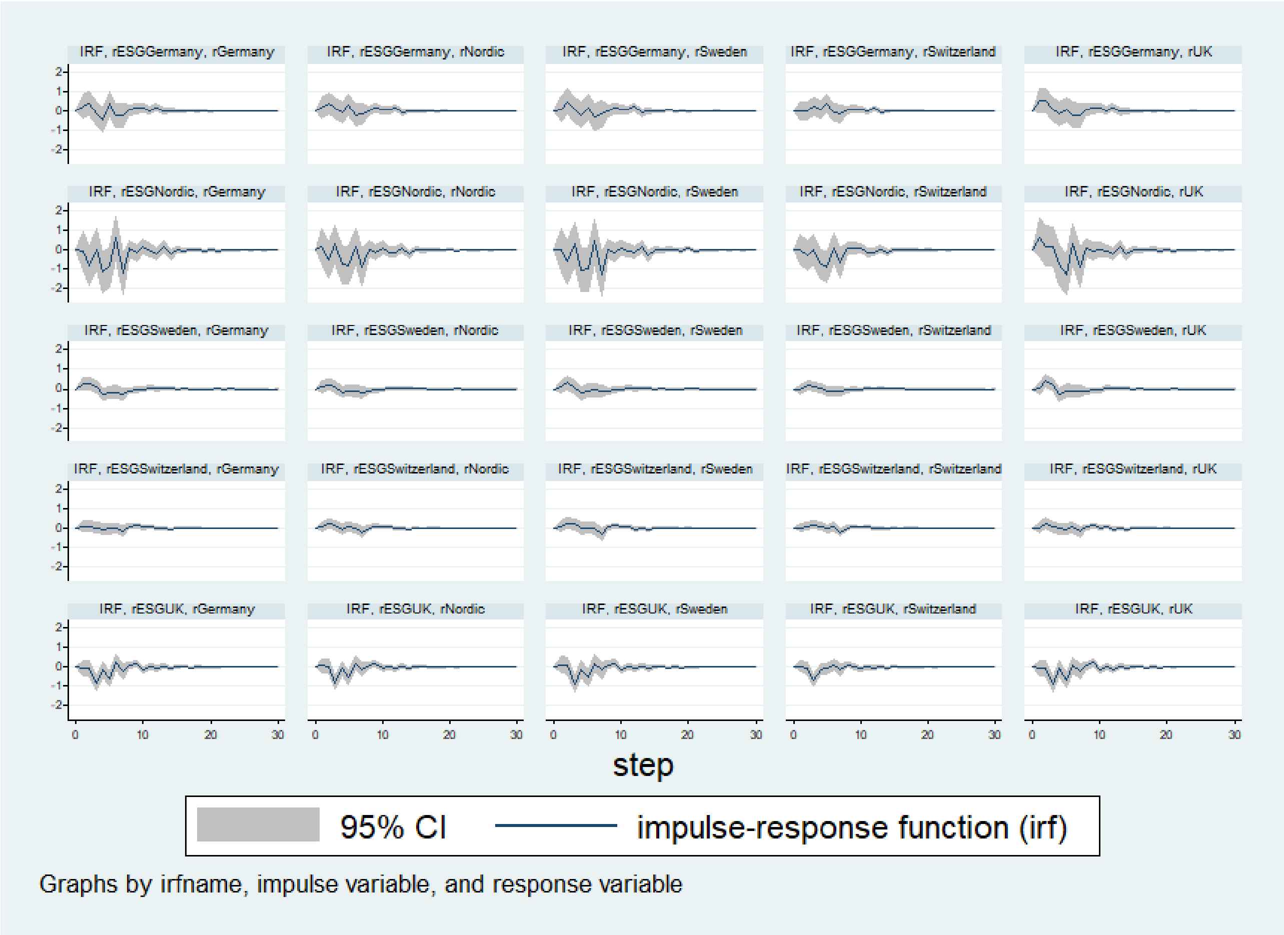

Figure 5.7: Impulse response function of ESG shocks to MSCI indices

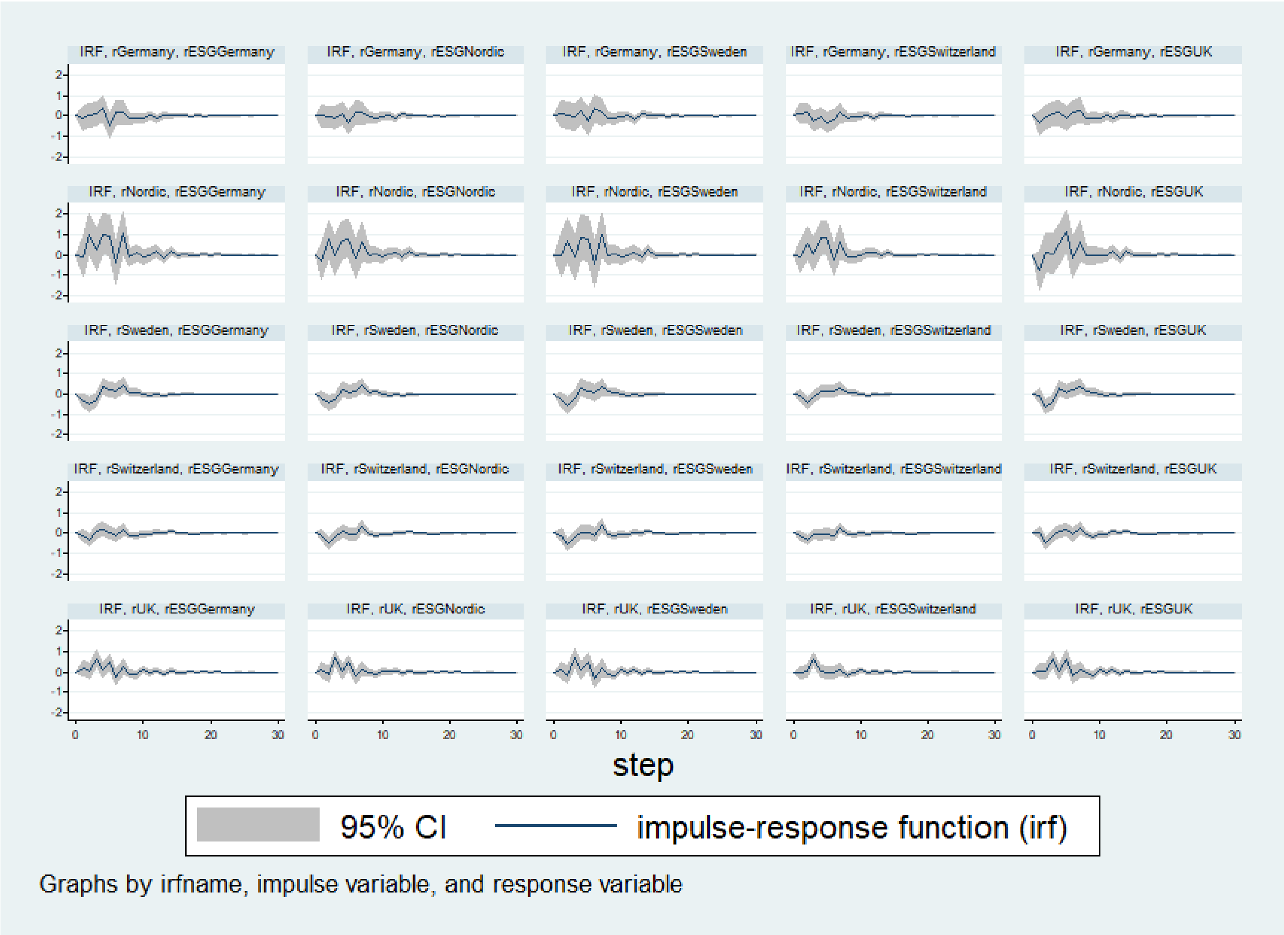

Figure 5.8: Impulse response function of MSCI shocks to ESG indices

All the studies which have been conducted for this thesis lead us to a conclusion: ESG indices cannot be used to diversify the risk of MSCI ones, even if they are less risky.

Chapter 6

Conclusions

Sustainability is a highly topical and important issue that is increasingly linked to the world of finance. It has become a method of measuring corporate performance that goes beyond traditional concepts and canons. As a result, a great deal of attention has been paid to what companies actually do in this regard, and investment judgements have increasingly been based on these aspects, in addition to the classic profitability ones. For this reason, rating agencies have started to publish more and more reports on certain indicators that express the behaviour of a business with regard to these issues. It is from this that the concept of ESG ratings, i.e. assessments of environmental, social and good governance compliance, has developed. It is rare, in fact, to find homogeneous classifications between the various agencies, as each uses different standards and indicators, and conflicting judgements can be found with reference to the same company. This research investigates the performance of ESG (sustainable) and MSCI (non-sustainable) indices in order to provide an objective assessment of the two classes of financial instruments. Here, we studied how ESG indices perform compared to MSCI indices from an investor's point of view. The investor bases her decisions on the risk, reward and dependence between two assets.

The results obtained here show that ESG indices perform substantially better than MSCI indices in terms of volatility. Indeed, given the same return, what influences an investment decision is the risk associated with it. However, this risk cannot be diversified between a sustainable and a non-sustainable asset class. In fact, a very high correlation was found between indices from the same and different countries. The theory that investing in a sustainable financial instrument protects investors against possible losses compared to a non-ESG index, perhaps as a result of climate change or governments' decisions to punish 'sinful' companies, as defined by those that do not respect the principles of sustainability, therefore falls apart. Because of this very strong relationship between the two, a deterioration in the performance of one index would also have repercussions on another. The analysis, therefore, based on a period of severe stress such as that of the financial crisis caused by the Covid, shows that such risk diversification is not possible. A sustainable index is therefore a good investment alternative to an MSCI, as it can reduce the losses and shows less present and future variability. In terms of diversification, however, the relationship between the two indices is very close. All the more so after analysing the common stocks within them. In order to allow for a reduction in risk, they should be adjusted and consider non-shared companies.

Appendix A

Skewness, Kurtosis and Normality tests

In this section are reoprted the formula for calculating Skewness, Kurtosis and the Normality test

Defining m_r as the rth moment about the mean $\bar{x}$: $m_r = \frac{1}{n}\sum_{i=1}^{N} w_i(x_i - \bar{x})^r$. The coefficient of skewness is defined as $m_3 m_2^{-\frac{3}{2}}$. The coefficient of kurtosis is $m_4 m_2^{-2}$. To assess whether the data are normally distributed or not, the test described by D'Agostino, Belanger and D'Agostino (1990) is implemented, with the empirical correction made by Royston (1991). We define as g_1 g1 the coefficient of skewness and b_2 the coefficient of kurtosis, and n the sample size. To perform the test of skewness, D'Agostino et al.(1990) use these formulas:
$Y = g_1\{\frac{(n+1)(n+3)}{6(n-2}\}^{\frac{1}{2}}$
$\beta_2(g_1) = \frac{3(n^2+27n-70)(n+1)(n+3)}{(n-2)(n+5)(n+7)(n+9)}$
$W^2 = -1 + [2\{\beta_2(g_1) - 1\}]^{\frac{1}{2}}$
and $\alpha = \{\frac{2}{W^2-1}\}^{\frac{1}{2}}$.
The distribution of the test statistic $Z_1 = \frac{1}{\sqrt{\ln W}} \ln[\frac{Y}{\alpha} + \{(\frac{Y}{\alpha})^2 + 1\}^{\frac{1}{2}}]$ is approximately standard normal under the null hypothesis that the data are distributed normally. To perform the kurtosis test the authors computed:
$E(b_2) = \frac{3(n-1)}{n+1}$
$var(b_2) = \frac{24n(n-2)(n-3)}{(n+1)^2(n+3)(n+5)}$
$X = \frac{\{b_2 - E(b_2)\}}{\sqrt{var(b_2)}}$
and $A = 6 + \frac{8}{\sqrt{\beta_1(b_2)}}[\frac{2}{\sqrt{\beta_1(b_2)}} + \{1 + \frac{4}{\beta_1(b_2)}\}^{\frac{1}{2}}]$.
The distribution of the test statistic $Z_2 = \frac{1}{\sqrt{\frac{2}{9A}}}[(1 - \frac{2}{9A} - \{\frac{1-\frac{2}{A}}{1+X\sqrt{\frac{2}{A-4}}}\}^{\frac{1}{3}}]$ is approximately standard normal under the null hypothesis that the data are distributed normally.
The test for normality proposed by the authors is $K^2 = Z_1^2 + Z_2^2$. This has a χ^2 distribution

with 2 degrees of freedom under the null of normality.

Royston proposed some adjustments to the test of normality. Denoting with $\phi(x)$ the cumulative standard normal distribution function for x, indicating the inverse cumulative standard normal function with $\phi^{-1}(p)$, define the following terms:

$Z_c = -\phi^{-1}\{exp(-\frac{1}{2}K^2)\}$

$Z_t = 0.55n^{0.2} - 0.21$

$\alpha_1 = [-5 + 3.46\ln(n)]exp[-1.37\ln(x)]$

$b_1 = 1 + [0.854 - 0.148\ln(n)]exp[-0.55\ln(n)]$

$\alpha_2 = \alpha_1 - \{\frac{2.13}{[1-2.37\ln(n)]}\}Z_t$

and $b_2 = \frac{2.13}{[1-2.37\ln(n)]} + b_1$.

If $Z_c < -1$ set $Z = Z_c$; else if $Z_c < Z_t$ set $Z = \alpha_1 + b_1 Z_c$; else set $Z = \alpha_2 + b_2 Z_c$. Define $P = 1 - \phi(Z)$. Then, $K^2 = -2\ln(P)$ is approximately distributed as χ^2 with 2 degrees of freedom.

Appendix B

Wild Bootstrap Procedure

Suppose $\{Y_i, X_i\}_{i=1}^{n}$ is an i.i.d. sequence of random variables, with $Y_i \in \mathbb{R}$, $X_i \in \mathbb{R}^m$ and satisfying the linear relationship:

$Y_t = X_i{}'\beta_0 + \varepsilon_i$. (1)
Letting $\hat{\beta}$ denote the OLS estimate of β_0 and $e \equiv (Y_i - X_i{}'\hat{\beta})$, For some randomly generated i.i.d. sequence $\{W_i\}_{i=1}{}^{n}$ that is independent of $\{Y_i, X_i\}_{i=1}{}^{n}$ and satisfies $E[W_i] = 0$ and $E[W_1{}^2] = 1$, the wild bootstrap creates fresh residuals of the form $\varepsilon_i{}^* \equiv W_i e_i$. The Standard Normal, Rademacher, and the two-point distribution proposed in Mammen (1993) are some of the most popular distributions for W_i. Under these assumptions on $\{W_i\}_{i=1}{}^{n}$ it follows that:

$E[\varepsilon_i{}^* | \{Y_i, X_i\}_{i=1}{}^{n}] = 0$
$E[(\varepsilon_i{}^*) | \{Y_i, X_i\}_{i=1}{}^{n}] = e_i{}^{n}$. (2)

As a result, $\varepsilon_i{}^*$ is mean independent of $\{Y_i, X_i\}_{i=1}{}^{n}$ and captures the heteroscedasticity pattern present in the original sample. This characteristic, first highlighted in Wu (1986), allows the wild bootstrap to stay consistent even when heteroscedasticity or model misspecification are present.
The dependent variables $\{Y_i, X_i\}_{i=1}{}^{n}$ are generated by

$Y_i^* = X_i{}'\hat{\beta} + \varepsilon_i{}^*$ (3)

in the Wild bootstrap resampling procedure, and then using OLS to produce a bootstrap estimate $\hat{\beta}^*$ on the sample $\{Y_i, X_i\}_{i=1}{}^{n}$. The unknown distribution of $\sqrt{n}(\hat{\beta} - \beta_0)$ is then estimated using the distribution of $\sqrt{n}(\hat{\beta}^* - \hat{\beta})$ conditional on $\{Y_i, X_i\}_{i=1}{}^{n}$. The wild bootstrap is a straightforward approach to generate crucial values for inference since the

former distribution may be estimated through simulation. Drawing on considerations in Mammen (1993), it is argued why the wild bootstrap is consistent.
Standard OLS algebra and the relationships (1) and (3) imply that:

$\sqrt{n}(\hat{\beta}-\beta_0) = {H_n}^{-1}\frac{1}{\sqrt{n}}\sum_{i=1}^{n} X_i\varepsilon_i,\ \sqrt{n}(\hat{\beta}^{*}-\hat{\beta}) = {H_n}^{-1}\frac{1}{\sqrt{n}}\sum_{i=1}^{n} X_i{\varepsilon_i}^{n}$ (4)

where $H_n \equiv n^{-1}\Sigma_i X_i {X_i}'$. When $\hat{\beta}$ is the maximum likelihood estimator of a normal model, H_n is the Hessian of the likelihood, and $\sigma_i X_i \varepsilon_i$ is the gradient (or score) at the true parameter value β_0. The equations in (4) should converge to a normal limit since both the full sample score contributions $(\{X_i\varepsilon_i\}_{i=1}{}^{n})$ and their bootstrap equivalents $(\{X_i{\varepsilon_i}^{*}\}_{i=1}{}^{n})$ are appropriately centered. As a result, the wild bootstrap's consistency is dependent on whether these bounds are the same or, in other words, if the asymptotic variances concur. However, since $E[{W_i}^2] = 1$ and $\{X_i\}_{i=1}{}^{n}$ is independent of $\{Y_i, X_i\}_{i=1}{}^{n}$, we may write:

$E[(\frac{1}{\sqrt{n}}\sum_{i=1}^{n} X_i\varepsilon_i)(\frac{1}{\sqrt{n}}\sum_{i=1}^{n} X_i\varepsilon_i)'] = E[X_i{X_i}'{\varepsilon_i}^2$ (5)
$E[(\frac{1}{\sqrt{n}}\sum_{i=1}^{n} X_i{\varepsilon_i}^{*})(\frac{1}{\sqrt{n}}\sum_{i=1}^{n} X_i{\varepsilon_i}^{*})'|\{Y_i, X_i\}_{i=1}{}^{n}] = \frac{1}{n}\sum_{i=1}^{n} X_i X_i' {e_i}^2$, (6)

By usual reasoning, this suggests that the second moments do indeed agree asymptotically. As a result, the distributions of $\sqrt{n}(\hat{\beta}-\beta_0)$ and $\sqrt{n}(\hat{\beta^{*}}-\hat{\beta})$ converge to the same normal limit, and the consistency of the wild boot-strap is instantaneous. While the wild bootstrap's ability to asymptotically match the first two moments of the complete sample score establishes its validity, it does not explain why it typically outperforms a normal approximation. When the bootstrap is able to match higher moments of the score, improvements occur. If $E[{W_i}^3] = 1$, for example, the third moments match asymptotically, and the wild bootstrap provides a refinement above the normal approximation to a studentized statistic by incorporating a skewness adjustment. The extra constraint that $E[{W_i}^3] = 1$ is met, for example, by the weights provided in Mammen (1993), as well as for $W_i = (V_i - 2)$ with V_i based on a Gamma distribution with mean 2 and variance 1. Alternatively, for symmetric distributions, the Rademacher one, which satisfies $E[W_i] = E[{W_i}^3] = 0$ and $E[{W_i}^2] = E[{W_i}^4] = 1$, can match the first four moments and give an extra refinement.

Appendix C

DF-GLS of prices

Considering the tables from C.1 to C.10, the settings are the same. On the left we have the lags at which the GLS detrended ADF is computed. For each lag we obtain a t-statistic, as in the ADF test, which is compared with the corresponding critical values. Here the null is the presence of a unit root, which indicates stationarity for the series. If the t-statistic is higher than the critical values, then H_0 is accepted; otherwise it is refused.

Table C.1: DF-GLS of ESG Germany price

	DF-GLS tau	**1%**	**Critical**	**5%**	**Critical**	**10%**	**Critical**
[lags]	**Test Statistic**		**Value**		**Value**		**Value**
22	-2.226		-3.480		-2.829		-2.543
21	-2.352		-3.480		-2.830		-2.545
20	-2.393		-3.480		-2.832		-2.546
19	-2.276		-3.480		-2.833		-2.547
18	-2.332		-3.480		-2.834		-2.548
17	-2.443		-3.480		-2.835		-2.549
16	-2.438		-3.480		-2.836		-2.550
15	-2.525		-3.480		-2.838		-2.551
14	-2.429		-3.480		-2.839		-2.552
13	-2.378		-3.480		-2.840		-2.553
12	-2.384		-3.480		-2.841		-2.554
11	-2.321		-3.480		-2.842		-2.555
10	-2.352		-3.480		-2.843		-2.556
9	-2.425		-3.480		-2.844		-2.557
8	-2.214		-3.480		-2.845		-2.558
7	-2.448		-3.480		-2.847		-2.559
6	-2.272		-3.480		-2.848		-2.560
5	-2.412		-3.480		-2.849		-2.561
4	-2.493		-3.480		-2.850		-2.562
3	-2.611		-3.480		-2.851		-2.563
2	-2.515		-3.480		-2.852		-2.564
1	-2.284		-3.480		-2.853		-2.565

The test statistic for ESG Germany obtained using the DF-GLS is compared with the critical values. For this case it is always higher than the critical values, thus accepting the null hypothesis of unit root.

Table C.2: DF-GLS of ESG Nordic price

[lags]	DF-GLS tau Test Statistic	1%	Critical Value	5%	Critical Value	10%	Critical Value
22	-2.242		-3.480		-2.829		-2.543
21	-2.417		-3.480		-2.830		-2.545
20	-2.462		-3.480		-2.832		-2.546
19	-2.193		-3.480		-2.833		-2.547
18	-2.306		-3.480		-2.834		-2.548
17	-2.400		-3.480		-2.835		-2.549
16	-2.297		-3.480		-2.836		-2.550
15	-2.280		-3.480		-2.838		-2.551
14	-2.185		-3.480		-2.839		-2.552
13	-2.171		-3.480		-2.840		-2.553
12	-2.204		-3.480		-2.841		-2.554
11	-2.221		-3.480		-2.842		-2.555
10	-2.386		-3.480		-2.843		-2.556
9	-2.537		-3.480		-2.844		-2.557
8	-2.318		-3.480		-2.845		-2.558
7	-2.461		-3.480		-2.847		-2.559
6	-2.227		-3.480		-2.848		-2.560
5	-2.339		-3.480		-2.849		-2.561
4	-2.447		-3.480		-2.850		-2.562
3	-2.514		-3.480		-2.851		-2.563
2	-2.363		-3.480		-2.852		-2.564
1	-2.258		-3.480		-2.853		-2.565

The test statistic for ESG Nordic obtained using the DF-GLS is compared with the critical values. For this case it is always higher than the critical values, thus accepting the null hypothesis of unit root.

Table C.3: DF-GLS of ESG Switzerland price

	DF-GLS tau	1%	Critical	5%	Critical	10%	Critical
[lags]	Test Statistic		Value		Value		Value
22	-1.672		-3.480		-2.829		-2.543
21	-1.765		-3.480		-2.830		-2.545
20	-1.848		-3.480		-2.832		-2.546
19	-1.690		-3.480		-2.833		-2.547
18	-1.718		-3.480		-2.834		-2.548
17	-1.709		-3.480		-2.835		-2.549
16	-1.669		-3.480		-2.836		-2.550
15	-1.581		-3.480		-2.838		-2.551
14	-1.469		-3.480		-2.839		-2.552
13	-1.545		-3.480		-2.840		-2.553
12	-1.660		-3.480		-2.841		-2.554
11	-1.678		-3.480		-2.842		-2.555
10	-1.797		-3.480		-2.843		-2.556
9	-1.805		-3.480		-2.844		-2.557
8	-1.686		-3.480		-2.845		-2.558
7	-1.877		-3.480		-2.847		-2.559
6	-1.738		-3.480		-2.848		-2.560
5	-1.776		-3.480		-2.849		-2.561
4	-1.936		-3.480		-2.850		-2.562
3	-2.027		-3.480		-2.851		-2.563
2	-1.913		-3.480		-2.852		-2.564
1	-1.925		-3.480		-2.853		-2.565

The test statistic for ESG Switzerland obtained using the DF-GLS is compared with the critical values. For this case it is always higher than the critical values, thus accepting the null hypothesis of unit root.

Table C.4: DF-GLS of ESG UK price

	DF-GLS tau	**1%**	**Critical**	**5%**	**Critical**	**10%**	**Critical**
[lags]	**Test Statistic**		**Value**		**Value**		**Value**
22	-3.197		-3.480		-2.829		-2.543
21	-3.266		-3.480		-2.830		-2.545
20	-3.256		-3.480		-2.832		-2.546
19	-3.080		-3.480		-2.833		-2.547
18	-3.306		-3.480		-2.834		-2.548
17	-3.433		-3.480		-2.835		-2.549
16	-3.313		-3.480		-2.836		-2.550
15	-3.360		-3.480		-2.838		-2.551
14	-3.126		-3.480		-2.839		-2.552
13	-3.046		-3.480		-2.840		-2.553
12	-3.176		-3.480		-2.841		-2.554
11	-3.180		-3.480		-2.842		-2.555
10	-3.196		-3.480		-2.843		-2.556
9	-3.243		-3.480		-2.844		-2.557
8	-2.900		-3.480		-2.845		-2.558
7	-3.105		-3.480		-2.847		-2.559
6	-2.774		-3.480		-2.848		-2.560
5	-3.001		-3.480		-2.849		-2.561
4	-3.076		-3.480		-2.850		-2.562
3	-3.211		-3.480		-2.851		-2.563
2	-3.241		-3.480		-2.852		-2.564
1	-3.174		-3.480		-2.853		-2.565

The test statistic for ESG UK obtained using the DF-GLS is compared with the critical values. For this case it is always higher than the 1% critical values, thus accepting the null hypothesis of unit root.

Table C.5: DF-GLS of ESG Sweden price

	DF-GLS tau	1%	Critical	5%	Critical	10%	Critical
[lags]	Test Statistic		Value		Value		Value
22	-2.268		-3.480		-2.829		-2.543
21	-2.451		-3.480		-2.830		-2.545
20	-2.438		-3.480		-2.832		-2.546
19	-2.170		-3.480		-2.833		-2.547
18	-2.337		-3.480		-2.834		-2.548
17	-2.491		-3.480		-2.835		-2.549
16	-2.489		-3.480		-2.836		-2.550
15	-2.433		-3.480		-2.838		-2.551
14	-2.333		-3.480		-2.839		-2.552
13	-2.287		-3.480		-2.840		-2.553
12	-2.325		-3.480		-2.841		-2.554
11	-2.292		-3.480		-2.842		-2.555
10	-2.453		-3.480		-2.843		-2.556
9	-2.575		-3.480		-2.844		-2.557
8	-2.308		-3.480		-2.845		-2.558
7	-2.498		-3.480		-2.847		-2.559
6	-2.220		-3.480		-2.848		-2.560
5	-2.371		-3.480		-2.849		-2.561
4	-2.413		-3.480		-2.850		-2.562
3	-2.503		-3.480		-2.851		-2.563
2	-2.426		-3.480		-2.852		-2.564
1	-2.349		-3.480		-2.853		-2.565

The test statistic for ESG Sweden obtained using the DF-GLS is compared with the critical values. For this case it is always higher than the critical values, thus accepting the null hypothesis of unit root.

Table C.6: DF-GLS of MSCI Nordic price

	DF-GLS tau	1%	Critical	5%	Critical	10%	Critical
[lags]	Test Statistic		Value		Value		Value
22	-2.166		-3.480		-2.829		-2.543
21	-2.337		-3.480		-2.830		-2.545
20	-2.378		-3.480		-2.832		-2.546
19	-2.121		-3.480		-2.833		-2.547
18	-2.240		-3.480		-2.834		-2.548
17	-2.327		-3.480		-2.835		-2.549
16	-2.225		-3.480		-2.836		-2.550
15	-2.209		-3.480		-2.838		-2.551
14	-2.111		-3.480		-2.839		-2.552
13	-2.105		-3.480		-2.840		-2.553
12	-2.130		-3.480		-2.841		-2.554
11	-2.140		-3.480		-2.842		-2.555
10	-2.292		-3.480		-2.843		-2.556
9	-2.439		-3.480		-2.844		-2.557
8	-2.220		-3.480		-2.845		-2.558
7	-2.365		-3.480		-2.847		-2.559
6	-2.132		-3.480		-2.848		-2.560
5	-2.243		-3.480		-2.849		-2.561
4	-2.340		-3.480		-2.850		-2.562
3	-2.410		-3.480		-2.851		-2.563
2	-2.263		-3.480		-2.852		-2.564
1	-2.148		-3.480		-2.853		-2.565

The test statistic for MSCI Nordic obtained using the DF-GLS is compared with the critical values. For this case it is always higher than the critical values, thus accepting the null hypothesis of unit root.

Table C.7: DF-GLS of MSCI Sweden price

	DF-GLS tau	1%	Critical	5%	Critical	10%	Critical
[lags]	**Test Statistic**		**Value**		**Value**		**Value**
22	-2.365		-3.480		-2.829		-2.543
21	-2.560		-3.480		-2.830		-2.545
20	-2.562		-3.480		-2.832		-2.546
19	-2.305		-3.480		-2.833		-2.547
18	-2.440		-3.480		-2.834		-2.548
17	-2.548		-3.480		-2.835		-2.549
16	-2.519		-3.480		-2.836		-2.550
15	-2.501		-3.480		-2.838		-2.551
14	-2.395		-3.480		-2.839		-2.552
13	-2.376		-3.480		-2.840		-2.553
12	-2.413		-3.480		-2.841		-2.554
11	-2.399		-3.480		-2.842		-2.555
10	-2.574		-3.480		-2.843		-2.556
9	-2.674		-3.480		-2.844		-2.557
8	-2.437		-3.480		-2.845		-2.558
7	-2.625		-3.480		-2.847		-2.559
6	-2.344		-3.480		-2.848		-2.560
5	-2.478		-3.480		-2.849		-2.561
4	-2.512		-3.480		-2.850		-2.562
3	-2.583		-3.480		-2.851		-2.563
2	-2.503		-3.480		-2.852		-2.564
1	-2.446		-3.480		-2.853		-2.565

The test statistic for MSCI Sweden obtained using the DF-GLS is compared with the critical values. For this case it is always higher than the 5% critical values, thus accepting the null hypothesis of unit root.

Table C.8: DF-GLS of MSCI Switzerland price

	DF-GLS tau	**1%**	**Critical**	**5%**	**Critical**	**10%**	**Critical**
[lags]	**Test Statistic**		**Value**		**Value**		**Value**
22	-2.228		-3.480		-2.829		-2.543
21	-2.314		-3.480		-2.830		-2.545
20	-2.320		-3.480		-2.832		-2.546
19	-2.200		-3.480		-2.833		-2.547
18	-2.299		-3.480		-2.834		-2.548
17	-2.313		-3.480		-2.835		-2.549
16	-2.259		-3.480		-2.836		-2.550
15	-2.156		-3.480		-2.838		-2.551
14	-2.050		-3.480		-2.839		-2.552
13	-2.136		-3.480		-2.840		-2.553
12	-2.194		-3.480		-2.841		-2.554
11	-2.217		-3.480		-2.842		-2.555
10	-2.305		-3.480		-2.843		-2.556
9	-2.355		-3.480		-2.844		-2.557
8	-2.163		-3.480		-2.845		-2.558
7	-2.312		-3.480		-2.847		-2.559
6	-2.127		-3.480		-2.848		-2.560
5	-2.186		-3.480		-2.849		-2.561
4	-2.340		-3.480		-2.850		-2.562
3	-2.480		-3.480		-2.851		-2.563
2	-2.453		-3.480		-2.852		-2.564
1	-2.485		-3.480		-2.853		-2.565

The test statistic for MSCI Switzerland obtained using the DF-GLS is compared with the critical values. For this case it is always higher than the critical values, thus accepting the null hypothesis of unit root.

Table C.9: DF-GLS of MSCI UK price

	DF-GLS tau	1%	Critical	5%	Critical	10%	Critical
[lags]	Test Statistic		Value		Value		Value
22	-2.520		-3.480		-2.829		-2.543
21	-2.606		-3.480		-2.830		-2.545
20	-2.579		-3.480		-2.832		-2.546
19	-2.418		-3.480		-2.833		-2.547
18	-2.588		-3.480		-2.834		-2.548
17	-2.712		-3.480		-2.835		-2.549
16	-2.637		-3.480		-2.836		-2.550
15	-2.694		-3.480		-2.838		-2.551
14	-2.529		-3.480		-2.839		-2.552
13	-2.487		-3.480		-2.840		-2.553
12	-2.608		-3.480		-2.841		-2.554
11	-2.631		-3.480		-2.842		-2.555
10	-2.667		-3.480		-2.843		-2.556
9	-2.681		-3.480		-2.844		-2.557
8	-2.406		-3.480		-2.845		-2.558
7	-2.603		-3.480		-2.847		-2.559
6	-2.341		-3.480		-2.848		-2.560
5	-2.540		-3.480		-2.849		-2.561
4	-2.546		-3.480		-2.850		-2.562
3	-2.627		-3.480		-2.851		-2.563
2	-2.617		-3.480		-2.852		-2.564
1	-2.565		-3.480		-2.853		-2.565

The test statistic for MSCI UK obtained using the DF-GLS is compared with the critical values. For this case it is always higher than the critical values, thus accepting the null hypothesis of unit root.

Table C.10: DF-GLS of MSCI Germany price

	DF-GLS tau	**1%**	**Critical**	**5%**	**Critical**	**10%**	**Critical**
[lags]	**Test Statistic**		**Value**		**Value**		**Value**
22	-2.267		-3.480		-2.829		-2.543
21	-2.387		-3.480		-2.830		-2.545
20	-2.448		-3.480		-2.832		-2.546
19	-2.329		-3.480		-2.833		-2.547
18	-2.387		-3.480		-2.834		-2.548
17	-2.476		-3.480		-2.835		-2.549
16	-2.471		-3.480		-2.836		-2.550
15	-2.562		-3.480		-2.838		-2.551
14	-2.473		-3.480		-2.839		-2.552
13	-2.414		-3.480		-2.840		-2.553
12	-2.425		-3.480		-2.841		-2.554
11	-2.368		-3.480		-2.842		-2.555
10	-2.411		-3.480		-2.843		-2.556
9	-2.475		-3.480		-2.844		-2.557
8	-2.266		-3.480		-2.845		-2.558
7	-2.507		-3.480		-2.847		-2.559
6	-2.334		-3.480		-2.848		-2.560
5	-2.461		-3.480		-2.849		-2.561
4	-2.538		-3.480		-2.850		-2.562
3	-2.648		-3.480		-2.851		-2.563
2	-2.553		-3.480		-2.852		-2.564
1	-2.335		-3.480		-2.853		-2.565

The test statistic for MSCI Germany obtained using the DF-GLS is compared with the critical values. For this case it is always higher than the critical values, thus accepting the null hypothesis of unit root.

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Appendix D

DF-GLS for returns

Table D.1: DF-GLS MSCI Nordic return

[lags]	DF-GLS tau Test Statistic	1%	Critical Value	5%	Critical Value	10%	Critical Value
22	-1.796		-3.480		-2.829		-2.543
21	-1.812		-3.480		-2.830		-2.544
20	-1.791		-3.480		-2.831		-2.546
19	-1.813		-3.480		-2.833		-2.547
18	-1.920		-3.480		-2.834		-2.548
17	-1.967		-3.480		-2.835		-2.549
16	-1.956		-3.480		-2.836		-2.550
15	-2.024		-3.480		-2.838		-2.551
14	-2.155		-3.480		-2.839		-2.552
13	-2.310		-3.480		-2.840		-2.553
12	-2.433		-3.480		-2.841		-2.554
11	-2.508		-3.480		-2.842		-2.555
10	-2.716		-3.480		-2.843		-2.556
9	-2.825		-3.480		-2.844		-2.557
8	-2.896		-3.480		-2.846		-2.558
7	-3.305		-3.480		-2.847		-2.559
6	-3.476		-3.480		-2.848		-2.560
5	-4.348		-3.480		-2.849		-2.561
4	-4.909		-3.480		-2.850		-2.562
3	-5.623		-3.480		-2.851		-2.563
2	-6.843		-3.480		-2.852		-2.564
1	-9.592		-3.480		-2.853		-2.565

The test statistic for the returns of MSCI Nordic obtained using the DF-GLS is compared with the critical values. Here the results are controversial, since till lag 5 it is accepted the alternative hypothesis of stationarity, otherwise it is refused. This is due to the presence of structural breaks.

Table D.2: DF-GLS MSCI Sweden return

	DF-GLS tau	1%	Critical	5%	Critical	10%	Critical
[lags]	Test Statistic		Value		Value		Value
22	-1.754		-3.480		-2.829		-2.543
21	-1.759		-3.480		-2.830		-2.544
20	-1.749		-3.480		-2.831		-2.546
19	-1.763		-3.480		-2.833		-2.547
18	-1.848		-3.480		-2.834		-2.548
17	-1.889		-3.480		-2.835		-2.549
16	-1.875		-3.480		-2.836		-2.550
15	-1.909		-3.480		-2.838		-2.551
14	-2.002		-3.480		-2.839		-2.552
13	-2.136		-3.480		-2.840		-2.553
12	-2.231		-3.480		-2.841		-2.554
11	-2.292		-3.480		-2.842		-2.555
10	-2.464		-3.480		-2.843		-2.556
9	-2.541		-3.480		-2.844		-2.557
8	-2.640		-3.480		-2.846		-2.558
7	-3.010		-3.480		-2.847		-2.559
6	-3.102		-3.480		-2.848		-2.560
5	-3.947		-3.480		-2.849		-2.561
4	-4.422		-3.480		-2.850		-2.562
3	-5.206		-3.480		-2.851		-2.563
2	-6.456		-3.480		-2.852		-2.564
1	-9.054		-3.480		-2.853		-2.565

The test statistic for the returns of MSCI Sweden obtained using the DF-GLS is compared with the critical values. Here the results are controversial, since till lag 5 it is accepted the alternative hypothesis of stationarity, otherwise it is refused. This is due to the presence of structural breaks.

Table D.3: DF-GLS MSCI Switzerland return

	DF-GLS tau	1%	Critical	5%	Critical	10%	Critical
[lags]	**Test Statistic**		**Value**		**Value**		**Value**
22	-1.822		-3.480		-2.829		-2.543
21	-1.868		-3.480		-2.830		-2.544
20	-1.853		-3.480		-2.831		-2.546
19	-1.883		-3.480		-2.833		-2.547
18	-2.022		-3.480		-2.834		-2.548
17	-2.027		-3.480		-2.835		-2.549
16	-2.062		-3.480		-2.836		-2.550
15	-2.133		-3.480		-2.838		-2.551
14	-2.358		-3.480		-2.839		-2.552
13	-2.526		-3.480		-2.840		-2.553
12	-2.654		-3.480		-2.841		-2.554
11	-2.708		-3.480		-2.842		-2.555
10	-2.901		-3.480		-2.843		-2.556
9	-3.088		-3.480		-2.844		-2.557
8	-3.256		-3.480		-2.846		-2.558
7	-3.787		-3.480		-2.847		-2.559
6	-4.001		-3.480		-2.848		-2.560
5	-5.002		-3.480		-2.849		-2.561
4	-5.947		-3.480		-2.850		-2.562
3	-6.791		-3.480		-2.851		-2.563
2	-8.264		-3.480		-2.852		-2.564
1	-11.381		-3.480		-2.853		-2.565

The test statistic for the returns of MSCI Switzerland obtained using the DF-GLS is compared with the critical values. Here the results are controversial, since till lag 7 it is accepted the alternative hypothesis of stationarity, otherwise it is refused. This is due to the presence of structural breaks.

Table D.4: DF-GLS MSCI UK return

	DF-GLS tau	**1%**	**Critical**	**5%**	**Critical**	**10%**	**Critical**
[lags]	**Test Statistic**		**Value**		**Value**		**Value**
22	-2.059		-3.480		-2.829		-2.543
21	-2.094		-3.480		-2.830		-2.544
20	-2.108		-3.480		-2.831		-2.546
19	-2.149		-3.480		-2.833		-2.547
18	-2.346		-3.480		-2.834		-2.548
17	-2.362		-3.480		-2.835		-2.549
16	-2.362		-3.480		-2.836		-2.550
15	-2.408		-3.480		-2.838		-2.551
14	-2.567		-3.480		-2.839		-2.552
13	-2.815		-3.480		-2.840		-2.553
12	-3.004		-3.480		-2.841		-2.554
11	-3.006		-3.480		-2.842		-2.555
10	-3.180		-3.480		-2.843		-2.556
9	-3.417		-3.480		-2.844		-2.557
8	-3.617		-3.480		-2.846		-2.558
7	-4.295		-3.480		-2.847		-2.559
6	-4.483		-3.480		-2.848		-2.560
5	-5.739		-3.480		-2.849		-2.561
4	-6.271		-3.480		-2.850		-2.562
3	-7.434		-3.480		-2.851		-2.563
2	-9.127		-3.480		-2.852		-2.564
1	-12.279		-3.480		-2.853		-2.565

The test statistic for the returns of MSCI UK obtained using the DF-GLS is compared with the critical values. Here the results are controversial, since till lag 8 it is accepted the alternative hypothesis of stationarity, otherwise it is refused. This is due to the presence of structural breaks.

Table D.5: DF-GLS MSCI Germany return

	DF-GLS tau	1%	Critical	5%	Critical	10%	Critical
[lags]	Test Statistic		Value		Value		Value
22	-1.752		-3.480		-2.829		-2.543
21	-1.775		-3.480		-2.830		-2.544
20	-1.778		-3.480		-2.831		-2.546
19	-1.779		-3.480		-2.833		-2.547
18	-1.834		-3.480		-2.834		-2.548
17	-1.863		-3.480		-2.835		-2.549
16	-1.864		-3.480		-2.836		-2.550
15	-1.888		-3.480		-2.838		-2.551
14	-1.937		-3.480		-2.839		-2.552
13	-2.019		-3.480		-2.840		-2.553
12	-2.114		-3.480		-2.841		-2.554
11	-2.158		-3.480		-2.842		-2.555
10	-2.330		-3.480		-2.843		-2.556
9	-2.490		-3.480		-2.844		-2.557
8	-2.586		-3.480		-2.846		-2.558
7	-3.005		-3.480		-2.847		-2.559
6	-3.050		-3.480		-2.848		-2.560
5	-3.744		-3.480		-2.849		-2.561
4	-4.133		-3.480		-2.850		-2.562
3	-4.744		-3.480		-2.851		-2.563
2	-5.642		-3.480		-2.852		-2.564
1	-7.563		-3.480		-2.853		-2.565

The test statistic for the returns of MSCI Germany obtained using the DF-GLS is compared with the critical values. Here the results are controversial, since till lag 5 it is accepted the alternative hypothesis of stationarity, otherwise it is refused. This is due to the presence of structural breaks.

Table D.6: DF-GLS ESG Germany return

	DF-GLS tau	1%	Critical	5%	Critical	10%	Critical
[lags]	**Test Statistic**		**Value**		**Value**		**Value**
22	-1.778		-3.480		-2.829		-2.543
21	-1.805		-3.480		-2.830		-2.544
20	-1.807		-3.480		-2.831		-2.546
19	-1.810		-3.480		-2.833		-2.547
18	-1.878		-3.480		-2.834		-2.548
17	-1.911		-3.480		-2.835		-2.549
16	-1.905		-3.480		-2.836		-2.550
15	-1.931		-3.480		-2.838		-2.551
14	-1.985		-3.480		-2.839		-2.552
13	-2.078		-3.480		-2.840		-2.553
12	-2.171		-3.480		-2.841		-2.554
11	-2.221		-3.480		-2.842		-2.555
10	-2.407		-3.480		-2.843		-2.556
9	-2.587		-3.480		-2.844		-2.557
8	-2.685		-3.480		-2.846		-2.558
7	-3.123		-3.480		-2.847		-2.559
6	-3.180		-3.480		-2.848		-2.560
5	-3.924		-3.480		-2.849		-2.561
4	-4.309		-3.480		-2.850		-2.562
3	-4.942		-3.480		-2.851		-2.563
2	-5.848		-3.480		-2.852		-2.564
1	-7.807		-3.480		-2.853		-2.565

The test statistic for the returns of ESG Germany obtained using the DF-GLS is compared with the critical values. Here the results are controversial, since till lag 5 it is accepted the alternative hypothesis of stationarity, otherwise it is refused. This is due to the presence of structural breaks.

Table D.7: DF-GLS ESG Nordic return

	DF-GLS tau	**1%**	**Critical**	**5%**	**Critical**	**10%**	**Critical**
[lags]	**Test Statistic**		**Value**		**Value**		**Value**
22	-1.807		-3.480		-2.829		-2.543
21	-1.823		-3.480		-2.830		-2.544
20	-1.802		-3.480		-2.831		-2.546
19	-1.824		-3.480		-2.833		-2.547
18	-1.931		-3.480		-2.834		-2.548
17	-1.984		-3.480		-2.835		-2.549
16	-1.972		-3.480		-2.836		-2.550
15	-2.041		-3.480		-2.838		-2.551
14	-2.174		-3.480		-2.839		-2.552
13	-2.328		-3.480		-2.840		-2.553
12	-2.459		-3.480		-2.841		-2.554
11	-2.534		-3.480		-2.842		-2.555
10	-2.742		-3.480		-2.843		-2.556
9	-2.844		-3.480		-2.844		-2.557
8	-2.915		-3.480		-2.846		-2.558
7	-3.324		-3.480		-2.847		-2.559
6	-3.502		-3.480		-2.848		-2.560
5	-4.372		-3.480		-2.849		-2.561
4	-4.946		-3.480		-2.850		-2.562
3	-5.652		-3.480		-2.851		-2.563
2	-6.891		-3.480		-2.852		-2.564
1	-9.680		-3.480		-2.853		-2.565

The test statistic for the returns of ESG Nordic obtained using the DF-GLS is compared with the critical values. Here the results are controversial, since till lag 6 it is accepted the alternative hypothesis of stationarity, otherwise it is refused. This is due to the presence of structural breaks.

Table D.8: DF-GLS ESG Switzerland return

	DF-GLS tau	**1%**	**Critical**	**5%**	**Critical**	**10%**	**Critical**
[lags]	**Test Statistic**		**Value**		**Value**		**Value**
22	-1.846		-3.480		-2.829		-2.543
21	-1.916		-3.480		-2.830		-2.544
20	-1.893		-3.480		-2.831		-2.546
19	-1.896		-3.480		-2.833		-2.547
18	-2.054		-3.480		-2.834		-2.548
17	-2.116		-3.480		-2.835		-2.549
16	-2.180		-3.480		-2.836		-2.550
15	-2.286		-3.480		-2.838		-2.551
14	-2.591		-3.480		-2.839		-2.552
13	-2.824		-3.480		-2.840		-2.553
12	-3.004		-3.480		-2.841		-2.554
11	-3.032		-3.480		-2.842		-2.555
10	-3.289		-3.480		-2.843		-2.556
9	-3.482		-3.480		-2.844		-2.557
8	-3.755		-3.480		-2.846		-2.558
7	-4.373		-3.480		-2.847		-2.559
6	-4.531		-3.480		-2.848		-2.560
5	-5.583		-3.480		-2.849		-2.561
4	-6.583		-3.480		-2.850		-2.562
3	-7.367		-3.480		-2.851		-2.563
2	-8.946		-3.480		-2.852		-2.564
1	-12.627		-3.480		-2.853		-2.565

The test statistic for the returns of ESG Switzerland obtained using the DF-GLS is compared with the critical values. Here the results are controversial, since till lag 9 it is accepted the alternative hypothesis of stationarity, otherwise it is refused. This is due to the presence of structural breaks.

Table D.9: DF-GLS ESG UK return

	DF-GLS tau	1%	Critical	5%	Critical	10%	Critical
[lags]	**Test Statistic**		**Value**		**Value**		**Value**
22	-2.030		-3.480		-2.829		-2.543
21	-2.052		-3.480		-2.830		-2.544
20	-2.065		-3.480		-2.831		-2.546
19	-2.100		-3.480		-2.833		-2.547
18	-2.261		-3.480		-2.834		-2.548
17	-2.265		-3.480		-2.835		-2.549
16	-2.272		-3.480		-2.836		-2.550
15	-2.311		-3.480		-2.838		-2.551
14	-2.457		-3.480		-2.839		-2.552
13	-2.686		-3.480		-2.840		-2.553
12	-2.883		-3.480		-2.841		-2.554
11	-2.888		-3.480		-2.842		-2.555
10	-3.072		-3.480		-2.843		-2.556
9	-3.330		-3.480		-2.844		-2.557
8	-3.489		-3.480		-2.846		-2.558
7	-4.132		-3.480		-2.847		-2.559
6	-4.377		-3.480		-2.848		-2.560
5	-5.643		-3.480		-2.849		-2.561
4	-6.265		-3.480		-2.850		-2.562
3	-7.336		-3.480		-2.851		-2.563
2	-8.969		-3.480		-2.852		-2.564
1	-11.914		-3.480		-2.853		-2.565

The test statistic for the returns of ESG UK obtained using the DF-GLS is compared with the critical values. Here the results are controversial, since till lag 8 it is accepted the alternative hypothesis of stationarity, otherwise it is refused. This is due to the presence of structural breaks.

Table D.10: DF-GLS ESG Sweden return

[lags]	**DF-GLS tau Test Statistic**	**1%**	**Critical Value**	**5%**	**Critical Value**	**10%**	**Critical Value**
22	-1.783		-3.480		-2.829		-2.543
21	-1.785		-3.480		-2.830		-2.544
20	-1.781		-3.480		-2.831		-2.546
19	-1.794		-3.480		-2.833		-2.547
18	-1.866		-3.480		-2.834		-2.548
17	-1.889		-3.480		-2.835		-2.549
16	-1.873		-3.480		-2.836		-2.550
15	-1.894		-3.480		-2.838		-2.551
14	-1.969		-3.480		-2.839		-2.552
13	-2.071		-3.480		-2.840		-2.553
12	-2.164		-3.480		-2.841		-2.554
11	-2.220		-3.480		-2.842		-2.555
10	-2.375		-3.480		-2.843		-2.556
9	-2.457		-3.480		-2.844		-2.557
8	-2.543		-3.480		-2.846		-2.558
7	-2.896		-3.480		-2.847		-2.559
6	-2.988		-3.480		-2.848		-2.560
5	-3.773		-3.480		-2.849		-2.561
4	-4.226		-3.480		-2.850		-2.562
3	-4.975		-3.480		-2.851		-2.563
2	-6.124		-3.480		-2.852		-2.564
1	-8.572		-3.480		-2.853		-2.565

The test statistic for the returns of ESG Sweden obtained using the DF-GLS is compared with the critical values. Here the results are controversial, since till lag 5 it is accepted the alternative hypothesis of stationarity, otherwise it is refused. This is due to the presence of structural breaks.

Appendix E

VAR model

These tables show in bold the variable considered in the analysis, i.e. the index. It is compared with the other indices to check their dependence over time. For explanatory purposes, consider the first table rNordic, i.e. the return if one invests in the ESG Nordic index, is considered as a dependent variable with respect to the others, i.e. the various ESG and MSCI indices, including itself. As mentioned above, this dependent variable is compared to the past values of all indices. In the table, however, only the significant ones are shown, i.e. those that explain a dependency between the assets. For our example, i.e. the Nordic ESG return, the only significant ones were found with Sweden, Switzerland and the UK (both ESG and MSCI), respectively for their lags of 2 days, expressed by L.2 for Sweden and Switzerland, and 3 and 5 days for the UK indices.

Table E.1: VAR Model MSCI Nordic

	Coef.	P>z
rNordic		
rSweden		
L2.	-.4164999	0.012
rSwitzerland		
L2.	-.5027869	0.000
rUK		
L3.	.6408019	0.000
L5.	.5018306	0.004
rESGUK		
L3.	-.7303515	0.000
L5.	-.5636331	0.001

Here is the table of the VAR model for the returns of MSCI Nordic. The second lag of the returns of MSCI Sweden has an effect of positive coefficient on the returns of MSCI Nordic. The same is for the returns of MSCI Switzerland and MSCI UK. The coefficients of ESG UK returns are negative. Here are reported also the p-values to check if the coefficients are significative.

Table E.2: VAR Model MSCI Sweden

	Coef.	P>z
rSweden		
rSweden		
L2.	-.565022	0.004
rSwitzerland		
L2.	-.5985303	0.000
L7.	.3593518	0.029
rUK		
L3.	.6721235	0.001
L5.	.5230626	0.011
L6.	-.4158545	0.045
rESGNordic		
L7.	-1.246.276	0.025
rESGSwitzerland		
L7.	-.3104571	0.029
rESGUK		
L3.	-.7818161	0.000
L5.	-.5860614	0.005

MSCI Sweden is influenced by the second lag value of Sweden itself (negative coefficient), by Switzerland at lags 2 (negative coefficient) and 7 (positive coefficient), by UK at lags 3, 5 (positive coefficients) and 6 (negative coefficient), by ESG Nordic at lag 7 (negative coefficient), by ESG Switzerland at lag 7 and by ESG UK at lags 3 and 5 (negative coefficients).

Table E.3: VAR Model MSCI Switzerland

	Coef.	P>z
rSwitzerland		
rNordic		
L5.	.8429844	0.026
rSweden		
L2.	-.4170421	0.002
rSwitzerland		
L2.	-.344056	0.002
rUK		
L3.	.5265674	0.000
rGermany		
L5.	-.4507407	0.044
rESGNordic		
L5.	-.9153375	0.017
rESGSwitzerland		
L7.	-.2097839	0.034
rESGUK		
L3.	-.6196471	0.000

Considering MSCI Switzerland, it is influenced by lag 5 of Nordic, lag 2 of Sweden, lag 2 of Switzerland itself, lag 5 of Germany, lag 5 of ESG Nordic, lag 7 of ESG Switzerland and lag 3 of ESG UK.

Table E.4: VAR Model MSCI UK

	Coef.	P>z
rUK		
rSweden		
L2.	-.643995	0.000
L4.	.419648	0.023
rSwitzerland		
L2.	-.5094248	0.001
rUK		
L3.	.5997697	0.002
L5.	.6715951	0.000
rESGNordic		
L5.	-1.182.955	0.022
rESGUK		
L3.	-.803291	0.000
L5.	-.7385338	0.000
rESGSweden		
L2.	.3516426	0.027
L4.	-.3698671	0.020

MSCI UK is affected by lag 2 and lag 4 of Sweden, lag 2 of Switzerland, lag 3 and 5 of UK, lag 5 of ESG Nordic, its lag 3 and 5 and by Sweden at lag 2 and 4.

Table E.5: VAR Model ESG Nordic

	Coef.	P>z
rESGNordic		
rSweden		
L2.	-.4279056	0.010
rSwitzerland		
L2.	-.4965665	0.000
L7.	.2829305	0.041
rUK		
L3.	.6303169	0.000
L5.	.4887142	0.005
rESGUK		
L3.	-.7138574	0.000
L5.	-.5479866	0.002

Lag 2 of Sweden, Lag 2 and 7 of Switzerland, lag 3 and 5 of UK and lag 3 and 5 of ESG UK influence ESG Nordic.

Table E.6: VAR Model MSCI Germany

	Coef.	P>z
rGermany		
rNordic		
L7.	1.015.377	0.046
rSweden		
L2.	-.4622161	0.012
rSwitzerland		
L2.	-.3553277	0.021
rUK		
L3.	.6463744	0.001
L5.	.5246348	0.007
rGermany		
L5.	-.6182073	0.041
rESGNordic		
L4.	-1.064.295	0.041
L7.	-1.186.859	0.022
rESGUK		
L3.	-.7428422	0.000
L5.	-.6117884	0.002

The seventh lag of Nordic, the second of Sweden and Switzerland, the third and fifth of UK and ESG UK, the fifth of Germany and the fourth and seventh of ESG Nordic have an impact on MSCI Germany.

Table E.7: VAR Model ESG Germany

	Coef.	P>z
rESGGermany		
rNordic		
L7.	104.481	0.036
rSweden		
L2.	-.4763294	0.008
L4.	.3737853	0.039
rSwitzerland		
L2.	-.3545208	0.018
rUK		
L3.	.6291948	0.001
L5.	.4960969	0.009
L6.	-.3940761	0.038
rGermany		
L5.	-.6246784	0.034
rESGGermany		
L5.	.6137811	0.042
rESGNordic		
L7.	-1.224.147	0.016
rESGUK		
L3.	-.7342029	0.000
L5.	-.5874875	0.002

ESG Germany in influenced by lag 7 of Nordic, lag 2 and 4 of Sweden, lag 2 of Switzerland, lag 3 and 5 of UK and ESG UK and also lag 6 of UK, lag 5 of Germany and ESG Germany and lag 7 of ESG Nordic.

Table E.8: VAR Model ESG Switzerland

	Coef.	P>z
rESGSwitzerland		
rNordic		
L4.	.8482041	0.035
L5.	.831098	0.039
rSweden		
L2.	-.4441826	0.002
rSwitzerland		
L2.	-.3519519	0.004
rUK		
L3.	.5794102	0.000
rESGNordic		
L4.	-.9945152	0.015
L5.	-.9419081	0.022
rESGUK		
L3.	-.6799573	0.000

Lags 4 and 5 of Nordic, 2 of Sweden and Switzerland, 3 of UK and ESG UK and 4 and 5 of ESG Nordic determine ESG Switzerland.

Table E.9: VAR Model ESG UK

	Coef.	P>z
rESGUK		
rNordic		
L5.	102.676	0.037
rSweden		
L2.	-.6103138	0.001
rSwitzerland		
L2.	-.5149766	0.000
rUK		
L3.	.5537605	0.003
L5.	.6727701	0.000
rESGNordic		
L5.	-1.088.637	0.030
rESGUK		
L3.	-.7601524	0.000
L5.	-.7623791	0.000
rESGSweden		
L2.	.3174827	0.041
L4.	-.3120841	0.044

ESG UK is affected by lag 5 of Nordic, lag 2 of Sweden and Switzerland, lag 3 and 5 of UK, lag 5 og ESG Nordic, its lags 3 and 5 and lag 2 and 4 of ESG Sweden.

Table E.10: VAR Model ESG Sweden

	Coef.	P>z
rESGSweden		
rSweden		
L2.	-.5732202	0.004
rSwitzerland		
L2.	-.5764613	0.000
L7.	.3402444	0.039
rUK		
L3.	.666039	0.001
L5.	.5758817	0.005
L6.	-.488241	0.019
rESGNordic		
L7.	-1.147.828	0.038
rESGSwitzerland		
L7.	-.3031225	0.033
rESGUK		
L3.	-.7867601	0.000
L5.	-.646116	0.002

For ESG Sweden there is an interaction between this index and the second lag of MSCI Sweden, second and seventh lag of Switzerland, third, fifth and sixth lag of UK, seventh lag of ESG Nordic and ESG Switzerland and third and fifth lag of ESG UK.

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