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**Analysis and comparison of ESG and MSCI indexes in terms of portfolio allocation**

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Firma (signature) Andrea Donato Martella

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# Chapter 1
# Introduction

Environmental, social and governance (ESG)-based investments have been in recent years a topic of strong interest among academics and researchers, as a consequence of the growing number of investors which include non-financial elements in their investment decision. The company's evaluation of ESG data has increased exponentially over the last twenty years, in particular disclosing data regards environmental (i.e. waste generation, carbon emissions, etc.), social (i.e. customer-related, product, employee, etc.), and governance (i.e. board diversity, political lobbying, etc.). Companies are increasing their ESG awareness and many of them have conducted management roadshows with investors to present their ESG practices and started to report their ESG efforts in their annual reports.

As reported by Jacobsen et al. (2019) and Edmans (2011), the investors' and shareholders' risk exposure are related to their enterprises' ESG profiles, and the incorporation of ESG criteria in the business valuation would benefit the shareholders' investment. One of the main topics analyzed is the relationship between ESG score and financial performance, in particular this relationship has been considered from several point of view and has been the subject of numerous analyses, with some of them presented in this thesis. In case of positive ESG-financial performance relation, the results available in the literature are often contradictory and not conclusive.

The aim of this thesis is to analyze the comparison among the two investment strategies; the traditional investment, which does not consider the ESG criteria as relevant element in the investment decision, and the ESG investment, which takes into account the ESG criteria as significant feature for the investment decision. The analysis is conducted in terms of portfolio allocation, therefore different methods are applied for the computation of the moments and several strategies are selected for better and deeper analysis.

In particular, in the Chapter 2 we present the financial literature related to the ESG criteria and sustainable investments, are developed the main items that characterize the development of the sustainable investment and we also include a brief survey of the existing literature. The major subjects presented are related to the risk and performance of the ESG and traditional investments and the cost and benefits related to them. We also report the results across countries and across different time windows trying to understand the relationship between the traditional and sustainable investments. In addition, has been examined the role of the rating agencies in providing the ESG score and the divergences related to it.

In the Chapter 3 we describe the methodology applied in this thesis based on the model of Markowitz. We explain the "Mean-Variance criterion", which refers to the aim of investors to achieve high expected return and, simultaneously, low risk. The Mean-Variance criterion, together with the principle of diversification, allows to determine the set of portfolios, called "Efficient Frontier", which are efficient combination of risk and return.

Chapter 4 focuses on the data description, analyzing in details the various indexes selected for the study, in particular MSCI indexes, which are market-weighted indexes. The intention behind the MSCI indexes selection is to find a proper measure in order to better represents the market condition. In this chapter we pointed out the main stocks of the indexes, their sector and country weights with the intention of highlight the index composition to be more precise in the analysis.

In the Chapter 5 we presented the results obtained and the methods and strategies applied. Firstly, we compute the descriptive analysis of the single indexes and then has been applied the model of Markowitz for the computation of the Efficient Frontiers, the optimal portfolios and the relative's portfolio compositions of the traditional and ESG portfolios, applying all the strategies and the method selected. The outcomes of these optimal portfolios are measured with the cumulated percentage return and several performance measure in order to make a proper comparison among them.

# Chapter 2
# Literature analysis

Sustainable investment refers to a variety of asset classes that share the same concern for their environmental, social and governance aspect. This is an investment strategy that acts taking into account the investor attention to ethic, ecology and community without compromise financials performance (Brzeszczynski and McIntosh 2014). Nowadays companies are increasingly embracing ESG policies in many ways like conducting management roadshows with their investors and reporting their ESG efforts in their annual reports. ESG awareness is spreading embracing also public interest groups, employees, customers and government regulators (Vives and Wadhwa 2012).

The reasons why investors care about ESG investing are explained by Broadstock et al. (2021). First reason involves the ethical aspect in the investment decision to whom people are willing to dedicate effort. The second is related to the enhancement of the managed portfolio performance, potentially increase in returns and reduction of portfolio risk.

In the stock market PRI (Principles for Responsible Investment) signatories handle roughly 60 trillion US Dollars in assets under management or half of the total global institutional assets base (PRI 2015a). This development clearly shows the commitment of financial markets toward ESG criteria within investment decisions. Even though those outcomes are promising, the shift of traditional investors toward sustainable investment practices proceeds slowly (G. Friede et al. 2015 and PRI 2015b). In addition to that, less than 25% of investment professionals take into account extra-financial information in their investment strategies (EY 2015) and just about one tenth of global professionals are educated on how to deal with ESG criteria in investment strategies (CFA Institute 2015).

A significant number of organizations develop ESG and/or sustainability indexes, which are composed by a list of firms selected from a wide universe of rated companies that satisfy particular ESG criteria.

Kinder, Lydenberg, Domini, and Co launched in May 1990 the world’s first sustainability index, Domini 400 social, thus the sustainable indices are still in an early stage (Gerard et al. 1997a, 1997b) and in the following years new sustainable indexes (Vigeo, Jantzi, Ethibel, FTSE4Good, Humanix, KLD Analytics, E. Capital, and Dow Jones) are born due to the increasing acceptance of SRIs (socially responsible investments) (Fowler and Hope 2007).

In January 2007 one of the most famous rating agencies, MSCII, started to include in their database ESG scores for a large cross-section of firms. Each company is evaluated according to three complementary criteria:

- Environmental, meaning the implementation of climate change reduction policies, reducing greenhouse gas emissions, being efficient in the use of energy and natural resources (water, raw materials, forests ...) not polluting and protecting biodiversity.
- Social, related to the quality of the work environment and the supply chain, the development of human resources, the attention to gender equality, diversity and inclusion.
- Governance, which includes governance and behavior of corporate, ethics and transparency, control policies and procedures; in the case of joint-stock companies, the rights of the shareholders, the composition, independence and remuneration of the board of directors, etc.

For each criteria a score between 0 and 10 simply express how every firm is doing on those ESG key issues.

Nowadays firms are starting to integrate corporate sustainability in their business strategy mainly looking for the consequential better risk adjusted returns that it involves (Broadstock et al. 2021). Given the potential of this type of investment, many researches tried to understand its return and volatility, doing also comparisons among the general market indices and sustainability indices. The literature available so far has focused on the return and volatility linkages and comparisons among the sustainability and general market indices; some of those studies are explained below. Skare and Golja (2012) using econometric model show that CSR (Corporate Social Responsibility) company on average enjoy better financial performance than non-CSR company. The regression results prove the presence of strong positive relation between corporations' financial performances and socially responsible behavior. In fact, an increase of CSR by a unit, corporations' financial performance (FP) increases by 1.797925. Charlo et al. (2015) instead focus on the risk point of view and found that for the same systematic level of risk the socially responsible companies obtain higher profit. The research also explains the positive relationship between CSR companies and leverage, meaning easier access to credit for companies with better ESG rating. Martinez-Ferrero and Frias-Aceituno (2013) deepen the direction of causality, thus the influence of CSR on financial performance or FP on CSR. The result they found is the existence of a positive and bidirectional relationship between CSR and FP. The better financial performance of CSR companies than those with traditional management strategies is also declared by Pilar Marti et al. (2015), which stated that there is no real consensus due to differences regards: the definition of CFP and CSR, methodological issues and characteristics of samples analyzed. Alshehhi et al. (2018) analyzed the overall literature regarding the way corporate sustainability affect corporate financial performance and discovers that 78 percent of the publications agreed on a positive relationship between those two factors.

A research on an aggregation of 2000 empirical studies (Friede et al. 2015) shows that approximately nine tenth of studies find a nonnegative ESG–CFP (corporate financial performance) relation. The research also focuses on nonportfolio, meaning bond and real estate investment, and portfolio studies. The relevance of the distinction became evident because the share of positive results in the identifiable portfolio-related studies shrinks considerably (15.5%) in comparison to the second one (56.7%). Studies with neutral or mixed findings increase proportionately in portfolio-based studies (37%) with respect to nonportfolio-based studies (18,8%). Instead, the share of negative studies increases marginally in portfolio-based studies (11.0%) compared to other one (5.8%). The overall results show that in case of nonportfolio-based studies the ESG-CFP relation moves towards a positive relation, instead in case of portfolio-based studies the ESG-CFP relation moves towards a mixed or neutral relation. The results of portfolio-based studies are affected by the different constraint and assets selection in the portfolio allocation.

The study conducted by Melas et al. (2016) shows that the active returns obtained from their target factors, obtained by their optimal allocation, are not significantly affected after the integration of ESG factors into a defensive strategy that take the lowest level of risk. Active returns related to investment quality, profitability, earnings quality, residual volatility and dividend yield remained rather high and statistically relevant after the ESG enhancements.

Investors, who wish to use ESG strategies into their investment decision, are generally seeking to include long-term risk considerations, for instance, avoiding investments in companies that do not consider ESG policies into their investment decision. In addition Melas et al. (2016) show the trade-off between the decrease in target factor exposure and increase in ESG score for six strategies, each one with a different risk exposure. It shows that significant improvements in the ESG profile of these strategies, up to 30%, is related to a change in target factor exposure ranging between 7% and 22%. In case of more considerable ESG improvement are achieved, the decrease in target factor exposure becomes greater. Instead, the influence on target factor exposure ranging from 23% to 54% in case the ESG enhancement reaches 50%.

Due to the different risk exposure not all strategies evaluated were affected to the same magnitude by the ESG enhancement. In particular, considering the minimum volatility strategies, the ESG enhancement has the lowest impact on the target factor exposure that decreased only by 7% for a 30% ESG improvement and even for a 50% ESG improvement, volatility factor exposure is reduced only by 23%. In addition, the other strategies evaluated experienced more significant target factor exposure reductions, ranging between 13% and 22% for a 30% ESG improvement.

Another investigation conducted by Morgan Stanley (2015) includes about 6,600 US stock mutual funds and approximately 2,900 US equity separately managed accounts (SMAs). The study examined the differences in volatility and returns between traditional and sustainable strategies across style clusters including big, small, and mid-cap. Morgan Stanley showed that for 64% of the periods studied over the previous seven years, sustainable mutual funds had equal or greater median returns and equivalent or lower median volatility. Instead, when the comparison is made between their traditional fund equivalents, they are more cost-effective. Furthermore, SMAs had equivalent or greater median returns compared to traditional methods for 36 percent of the periods studied and same or lower median volatility for 72 percent of the periods studied during the last seven years. In conclusion, SMAs and sustainable mutual funds outperformed their traditional counterparts relatively to return and volatility dispersion.

These results discredit the common idea (Lopez et al. 2007; Hong and Kacperczyk 2009; Lee et al. 2018; de Souza Cunha and Samanez 2013) that the sustainable strategies lead to lower financial returns in comparison to conventional investment. The studies above show that there is no significant difference in the performance between conventional indices and sustainable indices, being the latter a good substitute to the traditional indexes, and this is in part similar to the findings of other studies for example, la Torre et al. (2020); Santis et al. (2016) and Charlo et al. (2017).

In conclusion, even though the relationship between ESG measure and financial performance has been widely analyzed, the results are subjected to debate and are not conclusive (Lassala et al. 2017).

The literature has also focused on the major drivers of differentiable performance. There is emerging evidence that ESG-investing can support investors handle investment risks. The creation of ESG-screened portfolios attempting to minimize the portfolio's overall ESG risk by eliminating low ESG-score members from the allowable selection universe. Doing the screening properly, investors might anticipate ESG-screened portfolios to be protected from ESG-event losses.

In order to satisfy fiduciary duties and manage risk the Forum for Sustainable and Responsible Investment (SIF) argues that some investors embrace SRI strategies. Investors adopted the ESG criteria to assess the management quality and the probability of resilience of their portfolio companies when facing challenges in the future. The ESG factors has become a significant driver for enterprises as well as for shareholders and asset managers (Orsato et al. 2015). It brings to investment that may lead to relevant social and environmental advantages, such as clean technology portfolios and community development loan funds. The reduction in potential risks, such as litigation risk, tax risk, compliance risk, and honor risk, could allow investors to yield long-term financial returns (Riedl and Smeets, 2017; Revelli and Viviani, 2015; Derwall et al., 2011; Døskeland and Pedersen, 2015; Dam and Scholtens, 2015).

Several studies wonder if socially responsible investment strategies, in contrast to traditional investment strategies, can enhance long-term financial performance. Some of those researches state that difference between the financial performance of traditional investments and SRI investments is not significant. Further studies have found that abnormal returns should not be expect by trading portfolios with low and high ESG rated firms because ESG portfolios are not indicative of a relevant difference in the returns between companies with low and high ESG rating levels (see, e.g., Halbritter and Dorfleitner, 2015; Renneboog et al., 2008; Schroder, 2007; Utz, 2014).

By analyzing the risk measure, Kumar et al. (2016) evaluates the risk performance of ESG-screening at the business level, demonstrating that firms including ESG-factors have lower stock volatility than their industry competitors. Those findings open a new field in which scholars deepen their researches in a wider way.

Broadstock et al. (2021) examined the COVID-19 crisis and displayed that trading activity for CSI300 (Chinese stock market index) constituents intensified in the pandemic period, both in terms of value of trades and volume. Splitting the sample into low-ESG and high-ESG firms, both sub-samples experience intensification of trade activity, especially among low-ESG firms. This imply that during turbulent market pandemic period, high-ESG firms are relatively more resilient and that investors were more patient and didn't sell their shares to avoid losses.

As result, diversification gains for conventional stock portfolios could be given by doing sustainable investments (Balcilar et al. 2017; Brzeszczynski and McIntosh 2014). In such a way investors with wealth-protection intentions would be ready to reduce the degree to which ESG-related concerns may put their portfolio's economic worth at risk. Sherwood and Pollard (2018) found that including ESG emerging market equities into institutional portfolios might yield greater returns and reduced downside risk than non-ESG equity investments. According to Chong et al. (2006) conventional fund may not provide a viable alternative for portfolio diversification after incorporating a dynamic measure of risk performance. ESG-screening may be expanded to the portfolio level for diversification by developing a measure of the portfolio's ESG-risks likened to its peer group (Morningstar, 2019).

New studies results support the idea that high sustainability firms benefit lower downside risk and are resilient during troubled periods. Albuquerque et al. (2020) elaborate a theoretical framework exhibiting conditions under which companies can reduce systematic risk exposure, using CSR investments to provide product portfolio diversification and enhance product differentiation. Ilhan et al. (2019) show that firms with poor ESG profiles, measured by higher carbon emissions, have higher tail risk and in addiction Hoepner et al. (2019) evidence how the involvement of ESG issues reduces downside risk.

The scholars delve their studies comparing results across regions and countries, such as Yen et al.

(2019) which conduct research in Asian stock markets and discover that SRI (socially responsible investing) portfolios outperform only in Japan, while they are undervalued in emerging Asian stock markets.

Expanding the boundaries, there is a vast studies on the Australian markets (Tularam et al. 2010; Lokuwaduge and Heenetigala 2017), Europe's Sustainability Index (Ortas et al. 2014; Charlo et al. 2015, 2017; del Mar Miralles-Quiros et al. 2017; Lopez et al. 2007; Pilar Marti et al. 2015; Stolowy and Paugam 2018) and U.S.' Sustainability Indices (Lopez et al. 2007; Antonakakis et al. 2016; Giannarakis et al. 2011; Mensi et al. 2017; la Torre et al. 2016). Nevertheless, there is not enough literature about the economies of developing countries (Talan and Sharma 2019). Alshehhi et al. (2018) after consulting the literature trends connected to the relation between corporate financial performance and corporate sustainability, and argue that the number of comparable publications from the developing countries remain behind those of the developed countries, implying the need for more research in the economies of the developing economies.

Some researchers have examined potential differences in the ESG–CFP relation across regions. It is been hypothesized that the ESG–CFP relation across countries is mainly affected by a higher humane orientation (del Mar Miras-Rodríguez et al. 2015). Other findings show that the ESG–CFP relationship for US assets is considerably higher compared to non-US assets (Allouche and Laroche 2005; Dixon-Fowler et al. 2013). On the other hand, a few researchers also discover significantly higher effects for studies done around the world (Albertini 2013; Golicic and Smith 2013).

Friede et al. (2015) detect two main patterns in their collected data. First, developed markets excluding North America present a smaller share of positive results. This contrast is most evident between developed Europe (26.1% positive) and North America (42.7% positive). Developed Asia/Australia possess a positive share of 33.3%, though with the largest share of negatives as well at 14.3%. The total sample excluding North American stands at 27.8% positive share. The above study discovers a greater share of portfolio-based studies within the Asian/Australian and European sample that potentially biases the data. Nevertheless, positive ratio for Europe and Asia/Australia combined rise to 45.6% and for North America to 51.5%, when not consider all portfolio studies for the developed market samples. This shows that the previous gap between the two samples shrinks significantly – from 14.9 to 5.9 percentage points.

Second, the Emerging Markets sample exhibits, with 65.4 percentage, a considerable larger share of positive outcomes over developed markets while considering only nonportfolio studies, the ratio increases up to 70.8 percentage. Based on 52 single studies in Emerging Markets solely focused on equity-linked studies, the spread to developed markets is considerable.

According to Broadstock et al. (2021) China is at the beginning in the development of ESG investing.

In developed markets, institutional investors are fundamentals in influencing ESG investment practices and supporting ESG performance within their managed portfolios and in challenging companies towards the enhancement of their ESG performance. In China, the most investment activity come from retail investors and only in recent time they are incorporating ESG into their investment decision, so institutional investors remain relatively few causing a weak demand for ESG products.

In addiction a study conducted by the MSCI (2016) assesses ESG score distributions for selected countries and show that the country scores reveal that European companies compared to their peers in Japan tend to have better ESG characteristics. The distribution of sector scores confirms that there were no major biases in the way companies were assessed relative to their sector peers. These results are confirmed by the Swiss Finance Institute (2020) too, revealing how U.S. markets show higher performance than European markets over the sample period, which explains why financial performance of the ACWI portfolio is not as good as in the United States.

The academics focused also into analysis across time and in particular in different time window. As shown into Bennani et al. (2018) and Drei et al. (2019) studies, both active and passive ESG investment underperformed over the period 2010-2013, on the other hand it overperformed over the period ranging between 2014 and mid-2019 in both North America and Europe. They also claimed that the social pillar was underappreciated but has tended to earn traction in the recent years.

Melas et al. (2016) examine instead the stability of credit score over time and show that ESG ratings remained stable 68 percent of the time over the period analyzed. The main annual changes in ratings were downgrade or upgrade by one unit, while the change in ratings by two or more units was about 8 percent.

The research conducted by Fiede et al. (2015) that aggregating evidence from more than 2000 empirical studies show the absence of indications to support the learning hypothesis until 2012. The time-invariant relation was subjected to several trend tests which all fail to identify a time dependent change of the correlation factors for every year since the mid of the 1990s.

The same research focus also on the contribute of each ESG factors. The highest proportion is found in G criteria with 62.3 percentage of all cases. Governance linked aspect, conversely, indicate a 9.2 percentage of negative ESG-CFP relation, the highest one. Environmental studies offer the best relation (58.7– 4.3%, positive and negative) in case of subtracting negative findings from positive ones. In terms of social criteria, the outcomes show the weakest relation (55.1%-5.1%) between positive and negative results.

Guéant et al. (2021) try to answer which ESG metric should be used to increase portfolio performance. The answer was far from being simple because the three components of the ESG score may influence differently the portfolio performance at different times, and therefore the huge amount of extra-financial data requires a drastic simplification in order to creating a single metric, which can be designed in many different ways.

Due to the resilience of high-ESG index, in terms of downside risk, during the turbulent periods, the literature focused on the effect of crisis on ESG investments.

Nofsinger and Varma (2014) explain that during market downturns in particular, the socially responsible mutual funds outperform their peers. The scholars, after assessing the Domini Social Index and Morningstar database, argue that the impact of this crisis is most noticeable for ESG funds that use positive screening approaches, with the outcomes based only on the socially responsible fund qualities. Henke (2016) in his studies of Eurozone and US funds during crisis periods underlines the higher performance of ESG portfolios and this result retain his significance even after a huge number of robustness checks.

Analyzing the pre-crisis period from 2003 to 2007 that characterized the raise in Socially Responsible Investment around the world, Ortas and Moneva (2011) studied the market reaction to the company's inclusion in, and exclusion from, the Dow Jones Sustainability Stoxx Index, and conclude that investors value the non-excluded companies more in achieving a good level of social and financial performance of the company. Studying the pre-crisis period from 1999 to 2004, Lopez et al. (2007) say that corporate social responsibility practices over the short term, impact negatively on the company's financial performance, even though this influence is reduced over the longer term. Relating to the period 2008–2013, thus including the global financial crisis of 2008, Ortas et al. (2014) find that social and responsible investment strategies as less risky compared to the conventional investment. At the same time Lins et al. (2017) analyzed the financial performance of U.S non-financial firms and found that those with high ESG scores have better financial performance than traditional firms. In the bank industry too, Cornett et al., (2016) find a positive relation between the U.S. banks' financial performance, during the global financial crisis, and their ESG score.

Becchetti et al. (2015) conclude that during the Global Financial Crisis of 2007, responsible investment behaved as an insurance policy and yield better results than conventional investing in the majority of developed country, especially in U.S and Europe.

Taking into account the post-crisis period from 2012–2016, Alexandre and Francisco (2018) assess the firms listed on the Brazilian stock market with respect to the corporate sustainability index, and consider human resource, environmental and organizational management as the baseline for the implementation of the sustainable practices.

During the COVID-19 pandemic the severe decrease in global equity values suggest a strong negative feeling among investors about market uncertainty. Broadstock et al. (2021) wondered whether during times of instability the transmission of negative sentiment was across all forms, or if it is feasible that ESG performance behave as a valid signal to systematically move away from negative risk. They perform a test of the internal validity of the results by benchmarking against the empirical relationship between ESG score and stock returns in time of crisis, versus "regular" periods. In conclusion of their study the relevance of ESG performance strengthened during times of instability, and is mitigated in regular periods, therefore investors in China's stocks assign higher relevance to ESG performance.

The overall results in terms of performance comparison between SRI funds and conventional peers are explain by Guèant et al. (2021), showing that SRI funds did not perform better or worse than their conventional peers. By the way, according to them, this conclusion is based on weak grounds: all the studies analyzed are based on the objectionable underlying assumption, particularly in this highly competitive industry, that the managers of SRI and non-SRI funds have the same ability for execution, risk management, stock picking and so on. Furthermore, there is no consensus on the consequences of the different types of screens or screening intensity given the different samples of funds used, the different periods of time analyzed, the different countries selected, and the different definitions of the ratings for the same screen in the different researches.

Nowadays investors demand for accurate and meaningful ESG ratings due to the growth of the sustainability rating industry in response to the increase of sustainable investment strategies worldwide (Escrig-Olmedo et al., 2019). Due to stakeholders' demands of accurate information regarding company performance, in 2018 the SRI market has risen exponentially and particularly in Europe where SRI assets constitute roughly 11 trillion euros (Eurosif, 2018).

The integration of ESG aspects into socially responsible investment helps to support investment decisions, particularly the investment strategies of institutional investor, which are critical to move towards more responsible and sustainable finance as well as more sustainable development (Friede et al. 2015). Additionally Schmidt et al. (2020) underly that professional investors' and firms' sustainable financing and investment strategies are potentially contaminated by the assessments of their ratings' providers.

The spread of COVID-19 pandemic and the policies linked to it increase the attention toward ESG measures, thus the European Commission sets the definition of corporate social responsibility (CSR) related to the responsibility of organizations for their influence on society (European Commission, 2020). Exceeding collective agreements and relevant mandatory requirements, businesses should aim to "have in place a process to integrate social, environmental, ethical, consumer, and human rights concerns into their business operations and core strategy in close collaboration with their stakeholders" (European Commission, 2020).

In April 2021, the European Commission disclosed a draft directive on non-financial reporting. The existing NFRD (Non-Financial Reporting Directive) will be replaced by the CSRD (Corporate Sustainable Reporting Directive), and it will enforce not only more reporting obligations but also extend the areas and the list of entities covered by that reporting. All big companies, not only listed ones, that meet specific financial and employment criteria, will be subject to this obligation. The new directive will come into force in 2024 and will apply to data reporting for 2023, all of that after its adoption by the Member States and its implementation into national legislation.

The COVID-19 pandemic shows that not only the company financial condition affects its creditworthiness but also non-financial measures play a key role.

Several authors in the financial literature examine the impact of ESG variables on credit ratings, some of them are Attig et al. (2013) that find out that enterprises with high social performance benefit from relatively high ratings supplied by credit rating agencies. Those results are confirmed also by Devalle et al. (2017), which exhibit that better credit ratings bring benefits to enterprises with high environmental and sustainability records.

It's difficult to achieve a firm judgment about the effect of ESG criteria on credit ratings in fact the observed inconsistent results in the existing literature highlight the need of trustworthy and standardized ESG data.

The comparison of results received for Moody's and Fitch subsamples suggests a positive relation of ESG measures on internal credit ratings (Bongaerts 2014; Chodnicka-Jaworska 2019; Behn et al. 2014; Chodnicka-Jaworska 2018). The significant relation of ESG measures on credit ratings is mainly due to default probability of companies, cash flow of borrowers and sector risk thus higher ESG score should enhance the company credit ratings (Chodnicka-Jaworska 2021). On the contrary, another portion of scholars state a negative relationship between ESG–CSR measures and the cost of capital. This negative influence is mainly due to three reasons. The fist regards the possibility of managers exploiting ESG to distract from inappropriate accounting inaccuracies or company behavior (Kim et al. 2014). The second is about the fact that a high level of ESG performance requires a rise in the fixed costs of firms and higher cost maintenance relations with stakeholders (e.g., Luis Perez-Batres et al. 2012). The third is related to the agency conflicts, caused by large investments in ESG, between shareholders who would have to bear the associated costs and managers benefitting from overinvestments (Goss and Roberts 2011). Focusing on the relation between the each ESG criteria, Chodnicka-Jaworska (2021) exhibit that the influence of the single ESG criteria on Moody's long-term issuer credit ratings have different relevance. Starting with the environmental pillar, its score is relevant for the utilities and energy sector so the influence of this measure is strictly connected to regulations regarding pollution reduction and conservation of energy and water. While the corporate governance pillar score is significant exclusively for the materials sector, such as gold, aluminum and iron mining. Instead, the social pillar score is meaningful purely for the industrial sector assessing the company's capacity to receive trust and loyalty from its customers, workforce, and society through the application of right management strategies. In addition, it reflects key factors in defining its ability to create long-term shareholder value such as the company's reputation and the health of its license to operate.

In financial literature the divergence of ratings providers in issuing different ESG score for the same firm was a debated subject by the scholars.

In a research conducted by Schmidt (2021) they acquire and assess ESG ratings from seven well-known ESG ratings providers for S&P 500 companies in the time range from 2010 to 2017. The data they used come from Bloomberg, KLD (now MSCI), Asset 4 (now Refinitiv ESG), Inrate, FTSE, Sustainalytics (now Morningstar) and MSCI IVA. The ESG rating disagreement is much deepened in this research in comparison to the studies of Christensen et al. (2019) which use data from only three ratings providers, and the studies of Berg et al. (2020) which do not focus on the time-series dimension. They reported that in the sample of S&P 500 firms the average pairwise correlation between the ESG ratings of the seven rating providers is about 0.45. In particular, the average pairwise correlation is highest for the environmental dimension (0.46) and lowest for the governance (0.16). The research shows that this disagreement to be higher for the largest companies in the S&P 500 (potentially due to the complexity in the measurement) and for companies not having a credit rating (perhaps due to lower quality information). Furthermore, more profitable companies strive to have lower ESG rating disagreement (maybe because more resources are dedicated to ESG policies and ESG disclosures). The importance of ESG ratings has led then to be frequently used in management, economics and finance research. The management literature debate critically the validity and convergence of these ratings given the complexity of measuring a company's non-financial or ESG performance.

The idea that ESG evaluations may be incorporated to company risk indicators has sparked attention, in fact companies have increased their information disclosure trying to reduce the information asymmetries. The lack of a reporting requirements, single definition and similar features among rating providers makes ESG measurement, unlike credit ratings, rather ambiguous. Although ESG ratings are obtained from conflicting and different definitions, rating agencies are giving several criteria equivalent to those utilized in the credit rating market. Therefore, the fact that there is no universal ESG benchmark, make difficult to properly measure and even impossible to rate a company's long-term sustainability.

The reasons this disagreement exists was studied by Berg et al. (2020) who propose a decomposition

of the ESG rating disagreement sources dividing the ESG ratings of six providers into finer categories and obtaining three sources of ESG rating divergence. In first place, underlining that the difference in categories utilized by rating providers can lead to disagreement, they define this disagreement as scope divergence. Then they defined as measurement divergence the fact that rating providers quantify identical categories differently. At the end, they present the results from rating providers attaching different weights to the several categories when generating an aggregated ESG rating, as weight divergence. In conclusion, they summarize that most of the differences discovered are mostly caused by scope divergence and measurement, unlike weight divergence that has low influence. The same scholars pay also their attention on the divergences in the singles ESG measures. Stating with the E measure, they illustrate that this rating is more measurable and objective due to the common consensus on the aspects relevant in the environmental field, and to the more systematic regulation that aim to quantify these components. In fact, there is now an agreement that greenhouse gas emissions are a significant parameter to evaluate a company's environmental performance. Similar methods are used to also measure water and electricity use. Although there could be some problems in the measurement of emissions (voluntary reporting, missing emissions data/imputation, scaling of emissions), there is at least some basic orientation on how to quantify these (for example, the greenhouse gas emission protocol). Relating to social and governance criteria, rating providers are less in agreement on what the most relevant factors would be and in addition there is a worse understanding of how the real impacts of these issues should be determined. The effects and consequences of differences and misunderstanding of ESG categories could be explained by the Credit Suisse case. As described by the Wall Street Journal in a report posted on January 17, 2022, the company's chairman, António Horta-Osório, had resigned due to his violation of the government's laws against Covid 19, and this after Tidjane Thiam, his predecessor, was fired for spying on a coworker. All of these events should cause a worsening in rating score, being governance measure an important factor in the rating score. Although this events, the rating agencies can't agree on if they should be concerned by bank's governance and even less what the overall ESG score should be compared to competitors around the world. The implications of this events are converted into different rating agencies interpretation. Among the rating agencies assessments, SP Global was the most critical in the measurement of Credit Suisse's governance. This agency evaluates the bank only 15 percentage for corporate governance, placing it 725th out of 747 banks, ranking it below Goldman Sachs' 89% and JPMorgan Chase's 83%. Credit Suisse obtained a 57% overall score, higher than Goldman and JPMorgan, as SP evaluate it over the average about ESG criteria (in particular, SP combines "economy" and "governance" into one general category for the "governance" in ESG).
Refinitiv assigns the bank a 95% score in its "management" measure, which focuses on the board,

and an 81% score in general governance, similar to Goldman and JPMorgan. Meanwhile MSCI evaluation of the measure can be found in the middle, being the Credit Suisse governance assessed as ordinary receives the same grade of JPMorgan and Goldman Sachs. Having a medium ESG risk Credit Suisse is classified in the middle of the world's banks by Sustainalytics. Instead, the Refinitiv's score is high due to the fact that it separates "controversies" placing them into a distinct category that do not affect the ESG score, while they are commonly considered by other rating agencies. Further distinctions are related to the weight that different elements of governance have, such as board policy, board diversity, independent directors, and the responsibilities given to the chief executive or chairman. As a result of the absence of transparency, there is also a different approach to whether to estimate or infer in circumstances where data are not provided by organizations. Therefore, the complexity in the design and the measurement makes hard to distinguish the causes behind the divergences in ESG rating.

In conclusion, investors should take into account that ESG measures are still not the greatest predictors of ESG risk. The big firms with a very large assets value are still high indexed in widespread ESG indexes, even though they are not on top of the institutions which utilize ESG criteria in their strategy. Thus, more researches need to be done on this topic in order to develop a clearer and more trustworthy ESG score (Chodnicka-Jaworska 2021).

# Chapter 3

# Data Description

Morgan Stanley Capital International (MSCI) is the world leader financial services company in the providing investment data and analytics services to investors. In 1969, Capital International started to establish a series of stock indexes linked to international markets, but since 1986, has been used the name MSCI once Morgan Stanley acquired the license rights to the Capital International indexes getting the major shareholder. Until the end of the 1980s, MSCI was the most important company on world indexes outside of the United States, to the exclusion of UK, in which was instituted the forerunner of today's FTSE. The turning point for the history of the organization was the acquisition, in 2004 for roughly 816$ million, of a risk management company called Barra. In the following years the company strategy has aimed to acquire other companies, such as Investment Property Databank, GMI rating and Real Capital Analytics, to improve his business activity. The year 2007 coincide with the MSCI's separation from Morgan Stanley becoming a fully independent company in 2009, and the listing of the company on the New York Stock Exchange (NYSE) under the symbol MSCI. The MSCI indexes are over 160,000, which focus on various types of stocks (small cap, mid cap, large cap) and several geographic areas, in addition they track the performance of the securities included in them and function as base for ETFs.

The MSCI indexes are market value-weighted indexes, a stock market indexes in which individual components of the indexes are incorporated in quantities that correspond to their total market capitalization. The index assigns higher weight to the index component with the higher market capitalization. The effect of this form of index design led to the fact that large-cap companies have a higher impact than the mid- and small- cap companies on the index value.

The aim of MSCI is to ensure that the indexes represent properly and appropriately the market situation, therefore the analysts examined the indexes quarterly and rebalanced twice a year.
Nowadays investors utilize ESG criteria and climate data to support their investment decision and the sustainable investing is growing exponentially. MSCI assess the company's primary business along with potential key concerns in the industry to which it belongs with the aim to create ESG indexes,

examining the risks and the potential of the ESG criteria related to corporate social responsibility. The research utilizes the GICS[1] classification system with a non-overlapping size and style segmentation and it is built on the weighting concept, meaning that the weights attributed to the relevant element are relied on the external factors that are exclusive for each sector.

In terms of ESG analysis is the MSCI ESG Rating that measure the company's management of financially significant opportunities and ESG risk. This evaluation is based on three fundamental pillars: environmental, social and governance. Is attributed a score to each pillar and the three scores are merged together creating a unique weighted score that summarize all the factors examined. Subsequently the weighted score will be normalized depending on the sector to which it belongs with the intention to achieve a final rating. The definitive score is assessed and reproportioned each year evaluating the average of the scores realized over the last three years by competitors in the same sector, ranging between the two percentiles 2.5 and 97.5.
The company's rating, according to this method, might be one of those seven:

- AAA: 8.6 - 10
- AA: 7.1 - 8.5
- A: 5.7 – 7
- BBB: 4.3 - 5.6
- BB: 2.9 - 4.2
- B: 1.4 - 2.8
- CCC: 0 - 1.3

MSCI obtains data through government databases examination and the monitoring of firms' governance, social, and environmental policies and achievement. The relevant element is to evaluate each company's risks and prospects and new monitoring information are reported in the weekly rating up-date. This assessment is conducted on two levels:

- The first stage focus on the global patterns, meaning the attention on climate change topic worldwide, demographic shifts and the absence of particular resources;
- At second stage is examinated the industry activities and the companies that belong to this

[1] Global Industry Classification Standard (GICS) was developed by MSCI and S&P Global, which classify stocks in a common framework

industry;

The following indexes are the one implemented for this research and in particular those explained below are members of MSCI ESG LEADERS index series, based on data from MSCI ESG Research. Those indexes are established for investors searching a broad, diversified sustainability benchmark with reasonably low tracking error to the underlying stock market. The companies considered by those indexes are large and mid-cap, moreover they are those with the highest ESG performance in comparison to their peers.

- MSCI EAFE ESG LEADERS: this index is based on companies across Developed Markets countries around the world, except for Canada and US. The main stocks are: ASML HLDG, ROCHE HOLDING GENUSS, ASTRAZENECA, NOVO NORDISK B, COMMONWEALTH BANK OF AUS, SONY GROUP CORP, TOTALENEGIES, SAP, UNILEVER (GB), GLAXOSMITHKLINE;
- MSCI EMERGING MARKET ESG LEADERS: The index is relied on companies across 24 Emerging Markets countries. The main constituents are: TAIWAN SEMICONDUCTOR MFG, TENCENT HOLDINGS LI (CN), ALIBABA GRP HLDG (HK), RELIANCE INDUSTRIES, INFOSYS, MEITUAN B, CHINA CONSTRUCTION BK H, HOUSING DEV FINANCE CORP, MEDIATEK INC, TATA CONSULTANCY;
- MSCI USA ESG LEADERS: The index considers only companies in the US market. The principal stocks are: MICROSOFT CORP, TESLA, ALPHABET A, ALPHABET C, NVIDIA, JOHNSON & JOHNSON, VISA A, PROCTER & GAMBLE CO, MASTERCARD A, HOME DEPOT;
- MSCI CANADA ESG LEADERS: the index includes companies exclusively in Canadian market. The major stocks are: ROYAL BANK OF CANADA, TORONTO-DOMINION BANK, BANK NOVA SCOTIA, CANADIAN NATL RAILWAY, ENBRIDGE, SHOPIFY A, BROOKFIEL ASSET MAN A, BANK MONTREAL, CANADIAN NAT RESOURCES, CP RAILWAY

The following are the traditional indexes, meaning those that do not meet ESG principals. They are stock indexes which measure the performance of mid and large capitalization segment of the market. The indexes include roughly 85 percentage of the free float-adjusted market capitalization in the countries considered.

- MSCI EAFE Index: it covers companies across 21 Developed Countries worldwide, with the exception of Canada and US. The primary stocks are: NESTLE, ASML HLDG, ROCHE HOLDING GENUSS, LVMH MOET HENNESSY, SHELL, TOYOTA MOTOR CORP, NOVARTIS, ASTRAZENECA, NOVO NORDISK B, BHP GROUP (AU);

- The MSCI EMERGING MARKET Index: it incorporates the companies belonging to 24 Emerging markets countries. The primary constituents are: TAIWAN SEMICONDUCTOR MFG, TENCENT HOLDING LI (CN), ALIBABA GRP HLDG (HK), SAMSUNG ELECTRONICS CO, MEITUAN B, RELIANCE INDUSTRIES, JD.COM (UK), CHINA CONSTRUCTION BK H, INFOSYS, VALE ON;
- MSCI USA Index: it contains lonely US market companies. The main stocks are: APPLE, MICROSOFT CORP, AMAZON.COM, ALPHABET A, ALPHABET C, TESLA, NVIDIA, META PLATFORMS A, UNITEDHELTH GROUP, JOHSON & JOHNSON;:
- MSCI CANADA Index: solely Canadian companies are included in this index. The principal constituents are: ROYAL BANK OF CANADA, TORONTO-DOMINION BANK, BANK NOVA SCOTIA, CANADIAN NATL RAILWAY, ENBRIDGE, SHOPIFY A, BROOKFIELD ASSET MAN A, BANK MONTREAL, CANADIAN NAT RESOURCES, CP RAILWAY;

In conclusion, has been selected two indexes as benchmarks in order to make some comparison with the above indexes. The benchmarks are the following:

- MSCI ACWI ESG LEADERS Index: It is composed by companies with high ESG performance relative to their peers. The index is constituted by mid and large cap companies across 24 Emerging Markets and 23 Developed Markets countries. The main stocks are: MICROSOFT CORP, TESLA, ALPHABET A, ALPHABET C, NVIDIA, TAIWAN SEMICONDUCTOR MFG, JOHNSON & JOHNSON, VISA A, PROCTER & GAMBLE CO, MASTERCARD A;

- MSCI ACWI Index: it is composed by companies that do not meet ESG criteria and consider mid and large cap companies that belong to 25 Emerging Market and 23 Developed Market countries. The principal constituents are: APPLE, MICROSOFT CORP, AMAZON.COM, ALPHABET A, ALPHABET C, TESLA, NVIDIA, TAIWAN SEMICONDUCTOR MFG, META PLATFORM A, UNITEDHEALTH GROUP;

Tables 3.1, 3.2 and 3.3 show the sector and country weights of the indexes, all of them are considered in dollars.

**Table 3.1**: Sector and country weights of traditional and ESG indexes pt.1

| **SECTOR WEIGHTS** | **COUNTRY WEIGHTS** |
|---|---|
| **MSCI EAFE ESG LEADERS Index** | |
| Financials 17,9%<br>Health Care 15,2%<br>Industrials 14,7%<br>Consumer Discretionary 10,8%<br>Materials 8,9%<br>Other 32,5% | Japan 23,8%<br>United Kingdom 13,9%<br>France 10,7%<br>Switzerland 10%<br>Australia 7,7%<br>Other 33,9% |
| **MSCI EAFE Index** | |
| Financials 17,5%<br>Industrials 15,4%<br>Health Care 12,7%<br>Consumer Discretionary 12,2%<br>Consumer Staples 10,5%<br>Other 31,7% | Japan 22,7%<br>United Kingdom 15,5%<br>France 11,5%<br>Switzerland 10,3%<br>Germany 8,5%<br>Other 31,5% |
| **MSCI EM ESG LEADERS Index** | |
| Information Technology 22,2%<br>Financials 21,4%<br>Consumer Discretionary 15,1%<br>Communication Service 12,4%<br>Materials 7,4%<br>Other 21,5% | China 30,1%<br>Taiwan 23,5%<br>India 13,2%<br>South Korea 6,8%<br>South Africa 6,1%<br>Other 20,3% |
| **MSCI EM Index** | |
| Financials 21,2%<br>Information Technology 19,2%<br>Consumer Discretionary 14,9%<br>Communication Service 10,6%<br>Materials 8,4%<br>Other 25,7% | China 35,4%<br>Taiwan 14,5%<br>India 12,7%<br>South Korea 11,3%<br>Brazil 4,9%<br>Other 21,2% |

**Table 3.2**: Sector and country weights of traditional and ESG indexes pt.2

| **SECTOR WEIGHTS** |
|---|
| **MSCI US ESG LEADERS Index** |
| Information Technology 28,7%<br>Health Care 13,5%<br>Consumer Discretionary 12,8%<br>Financials 11,3%<br>Communication Services 11,3%<br>Other 22,4% |
| **MSCI US Index** |
| Information Technology 28,2%<br>Health Care 13,2%<br>Consumer Discretionary 11,9%<br>Financials 11,3%<br>Consumer Staples 9,6%<br>Other 25,8% |
| **MSCI CANADA ESG LEADERS Index** |
| Financials 37,8%<br>Industrials 13,6%<br>Materials 13,5%<br>Energy 11,9%<br>Information technology 6,8%<br>Other 16,4% |
| **MSCI CANADA Index** |
| Financials 38,7%<br>Energy 16,5%<br>Materials 11,6%<br>Industrials 11,2%<br>Information technology 7,5%<br>Other 14,5% |

**Table 3.3**: Sector and country weights of traditional and ESG benchmarks

| **SECTOR WEIGHTS** | **COUNTRY WEIGHTS** |
|---|---|
| **MSCI ACWI ESG LEADERS Index** | |
| Information Technology 22,3% | United States 60,3% |
| Financials 15,0% | Japan 5,8% |
| Health Care 12,3% | China 3,6% |
| Consumer Discretionary 12,3% | United Kingdom 3,4% |
| Communications Service 9,4% | Canada 3,4% |
| Other 28,7% | Other 23,5% |
| **MSCI ACWI Index** | |
| Information Technology 22,3% | United States 60,6% |
| Financials 14,8% | Japan 5,6% |
| Health Care 11,7% | United Kingdom 3,8% |
| Consumer Discretionary 11,6% | China 3,7% |
| Communications Service 9,6% | Canada 3,1% |
| Other 30% | Other 23,2% |

# Chapter 4

# Methodology

Currently, wealth allocation plays a key role in the decision making of investor and through the use of several forecasts of risk and return it allows the creation of financial portfolios. The portfolio allocation theory tries to determine the optimal investment decisions for the investor in a risky background using different models. According to this theory the degree of risk tolerance, the objectives defined and the investment horizon of the investor are the main factors that affect the optimal allocation strategy.

The most popular model of portfolio allocation is born in 1952, exhibited in Harry Markowitz's Ph.D., a research that in 1990 earned him, Merton Miller and William F. Sharpe, the Nobel Prize in Economic Science. Markowitz (1952) is considered the pioneer of Modern Portfolio Theory and defined by Mangram (2013) as the process of portfolio construction that aim to maximize the return and at the same time to minimize the risk. Markowitz's research assumes that the rational agent in the definition of the portfolio choice utilize the mean-variance criterion.

One of Markowitz's intuition was the discover of the relation between the level of risk and the level of return, factors that the combination of which generate the "Efficient Frontier". Another significant intuition was the diversification principle stating that in diversified portfolios unsystematic risks became negligible while the systematic risks remain relevant.
The agent, being rational, utilizes correlation among various assets to diversify its wealth for achieving a better risk- return trade-off.

### 4.1 The Efficient Frontier

The efficient frontier is composed by a set of optimal risk-return combinations or in other word by a set of efficient portfolios meaning that there are no other portfolios that for the same or lower amount of risk offer higher returns. Another definition of efficient frontier is given by the Corporate Finance Institute according to which it is a set of investment portfolios that for a given level of risk offers the utmost returns. The agent's degree of risk tolerance sets the position of portfolios on the efficient frontier.

The efficient frontier can be composed in two ways:

- $N > 1$ risky assets without a risk-free asset;
- $N$ risky assets and one risk-free asset with deterministic return $r_f$.

#### 4.1.1 The Efficient Frontier without Risk-Free asset

As reported in Barucci and Fontana (2017) notation's, given the following conditions:

- $N > 1$ risky assets that yield random returns ( $\tilde{r}_1, \dots, \tilde{r}_N$);
- $e = (e_1, \dots, e_N)^T$ the vector of expected returns;
- $V \in \mathbb{R}^{N \times N}$ the variance-covariance matrix, assumed to be positive definite, of the random vector $\tilde{r}$

A single portfolio included in the whole set of portfolios $\Delta_N$ is determined by the vector $w \in \mathbb{R}^N$ for which $\sum_{n=1}^{N} w_n = 1$ is valid, where $w_n$ reflects the weight of wealth invested in the n-th asset.

Markowitz in his research did not expose how the calculation of variance and expected returns has to be done. The computation of these estimates could be done by using different methods: sample moments, rolling window approach, equilibrium moments (such as the Capital Asset Pricing Model) and exponential smoothing (which gives more weights to recent observation and lower weights to further one.

The set of efficient portfolios can be described by a dual representation. The first representation is based on the research of optimal portfolio $w_n \in \Delta_N$ that minimize the variance (measure of risk) for a given level of expected return $\mu \in \mathbb{R}$. This optimal portfolio is represented by the solution of

$$\min_{w \in \mathbb{R}^N} w^T V w$$

under the two constraints

$$w^T e = \mu \quad \text{and.} \quad w^T \mathbf{1} = 1$$

The first one is related to the target return $\mu$ while the second make sure that the total wealth is distributed.

The second representation focus on the research of the efficient portfolio that maximizes the expected return μ for a selected level of variance. This optimal portfolio is represented by the solution of

$$\max_{w \in \mathbb{R}^N} w^T e,$$

Under the following constraints

$$w^T V w = \overline{\sigma}^2 \quad \text{and} \quad w^T 1 = 1$$

The discussion below is based on the first representation.

Selecting any $\mu \in \mathbb{R}$ , the solution to the minimization problem is defined as

$$w^* = g + h\mu.$$

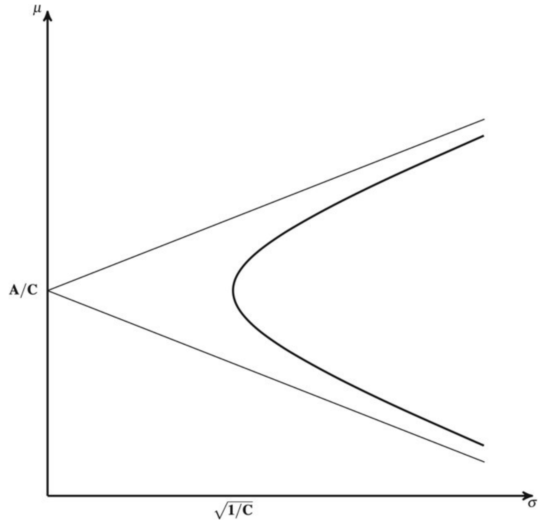
For each target return selected, several portfolio solutions can be found. In fact, the portfolio frontier is composed by the set of all these portfolios solutions.

The variance of this portfolio could be determined as

$$\sigma^2(\tilde{r}_{w^*}) = \frac{C}{D}\left(\mathbb{E}[\tilde{r}_{w^*}] - \frac{A}{C}\right)^2 + \frac{1}{C} = \frac{1}{D}(C\mathbb{E}[\tilde{r}_{w^*}]^2 - 2A\mathbb{E}[\tilde{r}_{w^*}] + B)$$

so expressed as a quadratic function of the target return allowing the portfolio frontier in the variance-expected return plane $(\sigma^2, \mu) \in (0, +\infty) \times \mathbb{R}$ to be depicted by a parabola with vertex $(1/C, A/C)$, as reported by Barucci and Fontana (2017). The use of standard deviation $\sigma$ which share the same unit of return can make the comprehension of the graph less complex. As Barucci and Fontana (2017) said, the portfolio frontier in the standard deviation - expected return plane $(\sigma^2, \mu) \in (0, +\infty) \times \mathbb{R}$, is expressed by a hyperbola centered in the point $(0, A/C)$ and with asymptotes $\mu = A/C \pm \sqrt{D/C}\,\sigma$. The EF is commonly displayed in the plane $(\sigma, \mu)$ allowing it takes the form of a hyperbola.

Figure 1 - Portfolio frontier in the variance-expected return plane Data source: Barucci and Fontana (2017, p.81)




The efficient frontier is composed by efficient portfolios for which the two conditions below hold:

- Does not exist a portfolio $\widehat{\mathrm{P}}$ with equal expected return and lower risk of $\mathrm{P}^*$
- Does not exist a portfolio $\widehat{\mathrm{P}}$ with higher expected return and equal risk of $\mathrm{P}^*$

The dominance method states that in the comparison of two different portfolios $\widehat{\mathrm{P}}$ and $\mathrm{P}^*$ with different weights, if

$$\mathrm{r}_{\mathrm{P}^*} \geq \mathrm{r}_{\widehat{\mathrm{P}}} ,$$
$$\sigma_{\mathrm{P}^*} \leq \sigma_{\widehat{\mathrm{P}}}$$

and at least one inequality is strict, $\mathrm{P}^*$ is preferred to $\widehat{\mathrm{P}}$ ($\mathrm{P}^*$ dominates $\widehat{\mathrm{P}}$).

So, for a given level of return, lower risk is preferred and for a given level of volatility, higher returns are preferred.

As exibited by Barucci and Fontana (2017), the Efficient Portfolio Frontier (EPF) is the set of portfolios lying in the part of the portfolio frontier that dominates the rest of portfolios in accordance with the mean-variance criterion:

$$EPF = \{\mathrm{w}^* \in PF \text{ such that } \mathbb{E}[\tilde{\mathrm{r}}_{\mathrm{w}^*}] \geq A/C\}.$$

Analyzing the above equation and the Figure 1, it's evident that a given value $\sigma$ is related to two values of $\mu$. Thus, the upper branch of the hyperbola dominating the lower one represents the efficient frontier.

Even the missing fulfillment of at least one equation, make the identification of optimal investment decision more difficult. The dominance method doesn't allow comparisons between different portfolios based on different expected return and volatility. Therefore, the risk aversion coefficient of the agent acquires relevance in order to determine the agent's optimal decision.

The model assumes that given the initial wealth and free available information, the rational risk-averse agent intention is to maximize his own utility. Agents apply the E-V criteria, following the mean and variance of returns distribution.

The preferences of the agents such as the risk aversion coefficient η and on the set of efficient portfolios affect the optimal solution. The tangency between the agent's indifference curves and the EF represent the optimal investment choice for a rational agent.
In all the portfolio that compose the EF, there are two in particular that are in practice significantly utilized.

The first one is the Global Minimum Variance (GMV or V) portfolio that aim to minimize the variance, respecting the admissibility constraint but without a specified target return. His mathematical representation would be:

$$\min_{w \in \mathbb{R}^N} w^T V w,$$

under the single constraint

$$w^T \mathbf{1} = 1$$

The GMV portfolio lies on the graph in the vertex of the parabola with expected return $\mathbb{E}[\tilde{r}_{wGMV}] = A/C$ and variance $\sigma^2(\tilde{r}_{wGMV}) = 1/C$. The optimal weight is represented in this solution as $w_{GMV} = \frac{V^{-1}1}{1^T V^{-1} 1}$. The second one is the Maximum Trade-Off (T) portfolio which aim to maximize the expected return over the volatility, always complying with the admissibility constraint. The MS portfolio can be mathematically represented as:

$$\max_{w \in \mathbb{R}^N} \frac{w^T e}{\sqrt{w^T V w}}$$

under the constraint

$$w^T \mathbf{1} = 1$$

In this solution the optimal weights is expressed as $w_T = \frac{V^{-1}e}{\mathbf{1}^T V^{-1} e}$, the related expected return as $\mathbb{E}[\tilde{r}_{wT}] = B/A$ and the variance as $\sigma^2(\tilde{r}_{wT}) = B/A$

The tangency between the agent's indifference curves and the EF represent again the optimal investment choice for a rational agent. The solution is expressed by a vector obtained by $w^* = \frac{A}{\eta} w_T - \frac{A-\eta}{\eta} w_{GMV}$, therefore the risk aversion coefficient η, the GMV and MS weights influence the agent investment decision.

### 4.1.2 The Efficient Frontier with Risk-Free asset

The second case in which the efficient frontier can be expressed, as reported by Barucci and Fontana (2017) notation's, is the one composed:

- $N > 1$ risky assets yielding random returns $(\tilde{r}_1, \ldots, \tilde{r}_N)$;
- 1 risk-free asset with deterministic return $r_f$.

Therefore, the vector $w = (w_1, \ldots, w_n)^T \in \mathbb{R}^N$, where $w_n$ is the fraction of wealth invested in the n-th risky asset, for $n = 1, \ldots, N$, while $1 - \sum_{n=1}^{N} w_n$ is the fraction of wealth invested in the risk-free asset describe a portfolio contained in the entire set of portfolios $\Delta_{N+1}$.

Consequently, for a given expected return $\mu \in \mathbb{R}$ the mathematical representation of the minimization problem is

$$\min_{w \in \mathbb{R}^N} w^T V w,$$

under the constraint

$$w^T e + (1 - w^T \mathbf{1}) r_f = \mu.$$

The μ expression contains the admissibility constraint being the sum of $w^T$ and $(1 - w^T \mathbf{1})$ is equal to 1.

Adding one asset (risk-free asset) to the initial universe of N risky assets, the combinations of risk and return widen. The diversification effect shifts the EF to the left obtaining new investment opportunities with higher return and lower volatility. Moreover, this second scenario enable the full allocation of the total wealth in the risk-free asset obtaining zero volatility.

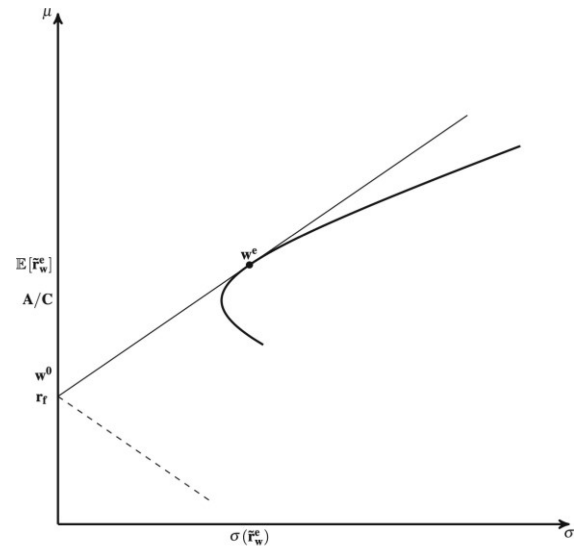
For any $\mu \in \mathbb{R}$, the solution to the minimization problem is represented by

$$w^* = \frac{\mu - r_f}{K} V^{-1}(e - r_f 1).$$

As the target return varies, the minimization problem provides different portfolio solutions.

In the standard deviation-expected return plane $(\sigma, \mu) \in (0, +\infty) \times \mathbb{R}$ the portfolio frontier is defined by two half-lines originating from the point $(0, r_f)$, with slope $\sqrt{K}$ and $-\sqrt{K}$ where the half-line with positive slope stands for the efficient part of the portfolio frontier. An investment in $r_f$ dominates the portfolios with return lower than $r_f$, in fact in the plane moving towards right along the straight line implies a specific part of the wealth allocated in the risky assets.

Figure 2 - Portfolio frontier with a risk-free asset, Data source: Barucci and Fontana (2017, p.92)




The Sharpe ratio SR(w) of a given a portfolio $w \in \mathbb{R}^N$, which quantify portfolio's performance, is expressed as the ratio between the return risk premium of a portfolio and the standard deviation of the related random return:

$$SR(w) := \frac{\mathbb{E}[\tilde{r}_w] - r_f}{\sigma(\tilde{r}_w)}$$

In the standard deviation – expected return plane, the slope of the straight line which connects the point $(0, r_f)$ to the point $(\sigma(\tilde{r}_w), \mathbb{E}[\tilde{r}_w])$ is represented by the Sharpe Ratio.

The portfolio weight is $w_T = \frac{V^{-1}(e-1r_f)}{1^T V^{-1}(e-1r_f)}$.

The optimal weights for the risky assets after maximizing the utility function are:

$$w = \frac{1}{\eta} V^{-1}(e - 1r_f)^T = \frac{A-Cr_f}{\eta} w_T.$$

The optimal portfolio is constituted by the tangency portfolio and the risk-free asset. According to the agent risk aversion coefficient the investor decides whether to assign more wealth towards one of the two constituents of the portfolio since the optimal choice is represented by the tangency of the investor's indifference curves and the EF.

# Chapter 4

# Analysis and Results

The analysis uses the indexes explained in the previous chapter and is conducted using monthly basis data in US dollars from October 1$^{st}$, 2007 to April 1$^{st}$, 2022 downloaded using Thomson Reuters and all the computations and analysis are done using MATLAB.

Table 5.1: Descriptive analysis

| | Mean | Median | StDev | Min | Max | Skew | Kurt |
|---|---|---|---|---|---|---|---|
| EAFE ESG | 0,144222699 | 0,613000528 | 5,36327099 | -20,05798045 | 14,6225303 | -0,462758647 | 4,65692085 |
| EM ESG | 0,407345839 | 0,300809467 | 6,18710819 | -22,87890969 | 20,482309 | -0,19301538 | 4,56583147 |
| USA ESG | 0,76698118 | 1,547039739 | 5,25556584 | -20,19163933 | 16,5241876 | -0,811252145 | 5,63014525 |
| CANADA ESG | 0,445379506 | 0,732112424 | 6,47856822 | -25,37283162 | 22,8640251 | -0,557103125 | 6,11773106 |
| EAFE | 0,110863251 | 0,698792217 | 5,38567279 | -20,03991838 | 14,8499917 | -0,483916624 | 4,65142296 |
| EM | 0,177153347 | 0,224837862 | 6,47958785 | -25,67039866 | 22,2442536 | -0,195323991 | 5,17623048 |
| USA | 0,770524236 | 1,697023613 | 5,26667474 | -20,35295473 | 15,5590606 | -0,770718626 | 5,32996935 |
| CANADA | 0,326816499 | 0,531269754 | 6,45539126 | -26,07116371 | 23,0283413 | -0,586900007 | 6,4938814 |
| ACWI | 0,453172927 | 0,873108011 | 5,29745979 | -19,50978233 | 15,3155836 | -0,677437225 | 5,18845319 |
| ACWI ESG | 0,494551318 | 0,913702416 | 5,17503182 | -19,6338655 | 14,7721943 | -0,727226091 | 5,29101749 |

The Table 5.1 exhibits the descriptive analysis using the overall time interval data for the computation of the moments. The ESG Indexes' mean is higher than their traditional peers with the exception of USA Index, on the other hand the volatility of ESG Indexes is lower than the traditional ones with the exception of USA Index. The traditional indexes present a higher skewness in comparison of the ESG indexes with again the only exclusion of USA Index.

Table 5.2: Indexes correlation coefficients

| | EAFE ESG | EM ESG | USA ESG | CANADA ESG | EAFE | EM | USA | CANADA | ACWI | ACWI ESG |
|---|---|---|---|---|---|---|---|---|---|---|
| EAFE ESG | 1 | 0.8524 | 0.8886 | 0.8452 | 0.9968 | 0.8697 | 0.8981 | 0.8412 | 0.9662 | 0.9668 |
| EM ESG | 0.8524 | 1 | 0.7874 | 0.822 | 0.8582 | 0.9855 | 0.7906 | 0.8212 | 0.8796 | 0.8776 |
| USA ESG | 0.8886 | 0.7874 | 1 | 0.8569 | 0.8877 | 0.7962 | 0.9943 | 0.8537 | 0.964 | 0.9682 |
| CANADA ESG | 0.8452 | 0.822 | 0.8569 | 1 | 0.8616 | 0.8632 | 0.8598 | 0.9915 | 0.9045 | 0.8958 |
| EAFE | 0.9968 | 0.8582 | 0.8877 | 0.8616 | 1 | 0.879 | 0.8985 | 0.8571 | 0.9696 | 0.9678 |
| EM | 0.8697 | 0.9855 | 0.7962 | 0.8632 | 0.879 | 1 | 0.8018 | 0.8605 | 0.896 | 0.8889 |
| USA | 0.8981 | 0.7906 | 0.9943 | 0.8598 | 0.8985 | 0.8018 | 1 | 0.8544 | 0.972 | 0.9715 |
| CANADA | 0.8412 | 0.8212 | 0.8537 | 0.9915 | 0.8571 | 0.8605 | 0.8544 | 1 | 0.8999 | 0.8913 |
| ACWI | 0.9662 | 0.8796 | 0.964 | 0.9045 | 0.9696 | 0.896 | 0.972 | 0.8999 | 1 | 0.9978 |
| ACWI ESG | 0.9668 | 0.8776 | 0.9682 | 0.8958 | 0.9678 | 0.8889 | 0.9715 | 0.8913 | 0.9978 | 1 |

The Table 5.2 shows the correlation coefficients among the indexes analyzed, in particular between ESG indexes and traditional indexes themselves and also among ESG indexes and traditional indexes. What firstly emerges is the positive value for all the correlation coefficients with a minimum value of 0,7874 (white cell of the table). Focusing on the correlation among the ESG indexes themselves can be seen the positive correlation for EAFE ESG Index and the other ESG indexes of around 0,85 with a slightly higher value for ESG USA Index. The ESG CANADA Index has the correlation of roughly 0,85 for the other indexes with a lower value for EM ESG Index. The USA ESG Index has the correlation coefficients in line with previous result (0,85) with exception of EM ESG Index which decrease down to 0,7874. Moving towards the correlations among the traditional indexes themselves the results share the same characteristics with a slightly higher value. Also in terms of correlation between traditional and ESG indexes the results share the same features, in addition the correlation coefficients among ESG indexes and the respective traditional one are very high. The correlation coefficients of the benchmarks in relation to the indexes are over 0,87 with higher value for EAFE and USA indexes and lower value for EM and CANADA indexes in both ESG and traditional form.

The research is composed by the analysis of several strategies and each of them has the same roadmap structure, meaning the division into two sections: strategic asset allocation and monthly tactical choice. The first section is characterized by the graphical representation of the multiple Efficient Frontiers categorized by the different methods applied (Sample Moments, RW, EWMA) and by the different composition of the EF (traditional and ESG indexes). The second section refers to the evolution of the portfolio composition, the computation and graphical representation of the cumulated returns and the computation of the performance measures.

The methods used for the computation of Markowitz inputs are the following:

- Sample Moments: it considers the first 60 prices and compute the moments, mean and variance, based on that data. Then for the subsequent period, the $61^{st}$, is added the relative observation to the 60 initial data, therefore the dataset is composed by 61 observations on which are computed the moments. For each following periods is added the observation of the relative period to the dataset and is computed the relative moments, therefore at the end of the time horizon the dataset is composed by all the observations. The intuition behind this method is to update the initial dataset each period obtaining an updated dataset on which compute the Markowitz inputs.

- Rolling Window: as Sample Moments, it starts with the first 60 prices for the computation of the moments, then for each subsequent period is added an observation and simultaneously is removed the first observation. In this way there is a shift each period keeping the time interval constant to 60 observations. The intuition behind this method is to update the dataset each period without being bound to the too old observations.

- Exponential Weighted Moving Average: it uses the same characteristics of the Rolling Window, meaning constant number of observations in the dataset and subsequent shift on the whole-time horizon. The additional component that characterizes this method is the weighted of the observation, it means more weight to recent observation than the one distant in time. There is a parameter that adjust the weights of the observations and it is the smoothing factor $\lambda \in (0.9, 0.99)$; the lower is the parameter the higher is the significance of the weights of the recent observations than the one distant in time; instead, the higher is the parameter the lower is the significance of the weights on the recent observations than the one distant in time, meaning more similar to the equal observations' weights. The insight of this method is to assign more importance to recent observations than those far away.

The performance measure used in the research are the following:

- Sharpe Ratio: the return per unit of total risk

$$\mathrm{Sh} = \frac{\mathbb{E}[\mathrm{R_t}]}{\mathbb{V}[\mathrm{R_t}]}$$

- Sortino Ratio: the return per unit of downside risk

$$\mathrm{So} = \frac{\mathbb{E}[\mathrm{R_t}]}{\mathbb{V}[\mathrm{R_t} \mathrm{I}\ (\mathrm{R_t} < 0)]}$$

- Treynor Ratio: the return per unit of systematic risk ($\beta$)

$$\mathrm{Tr} = \frac{\mathbb{E}[\mathrm{R_t}]}{\beta}$$

  Where $\beta$ represents the volatility of the portfolio in comparison to the benchmark

- Value – at – risk: it is a quantile of the returns density and it satisfy

$$\int_{-\infty}^{\mathrm{VaR}(\propto)} \mathrm{f}(\mathrm{R_t})\mathrm{dR_t} = \propto$$

  Where $\propto$ = 5% and the probability of observing returns below the VaR($\propto$) equals $\propto$ and f($\cdot$) is a density function.

- Expected shortfall: is calculated by averaging all of the returns in the distribution that are worse than $\mathrm{VaR}(\propto)$ where $\propto = 5\%$

$$\mathrm{ES}(\mathrm{R_t}, \propto) = \mathbb{E}[\mathrm{R_t} | \mathrm{R_t} \leq \mathrm{VaR}(\propto)]$$

The ratio is computed by taking the average of returns in the worst 5% of cases.

The drawdown identifies the largest losses and the time to recover from losses, better strategy has small losses and quick recovery. Firstly are identified the losses, therefore returns below zero, then are selected the worst drawdown for the computation of the particular ratio.

- Calmar Ratio: the return per unit of the maximum drawdown.
- Sterling Ratio: the return per unit of extreme risk, taken the k largest drawdowns, k=5 in this research.
- Farinelli – Tibiletti Ratio: is a ratio of average gains to average losses with respect to a target, each of them raised by a powerd index.

$$\mathrm{FT}(\tau, \mathrm{p}, \mathrm{q}) = \frac{\mathbb{E}[\max(0, \mathrm{R_t} - \tau)^{\mathrm{p}}]^{\frac{1}{\mathrm{p}}}}{\mathbb{E}[\max(0, \tau - \mathrm{R_t})^{\mathrm{q}}]^{\frac{1}{\mathrm{q}}}}$$

**5.1 Sample Moments Method**

In this paragraph are showed the analysis results using the Sample Moments method and the two strategies applied are:

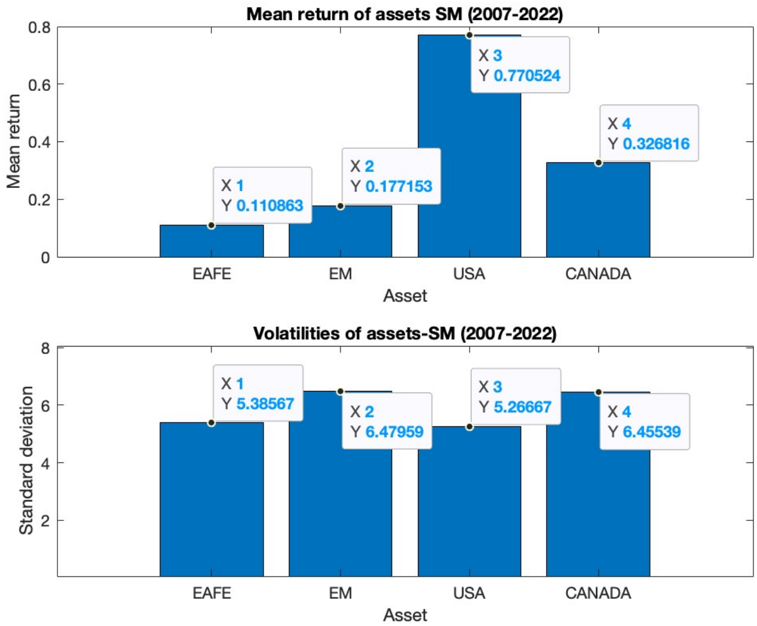
- No Short Selling strategy, only positivity constraint;
- Short Selling strategy or Unconstraint strategy, possibility of short selling.

The two set of portfolios studied are:

- Traditional portfolios which are made by only traditional indexes: EAFE Index, EM Index, USA Index and CANADA Index;
- ESG portfolios which are composed by only ESG indexes: EAFE ESG Index, EM ESG Index, USA ESG Index and CANADA ESG Index.

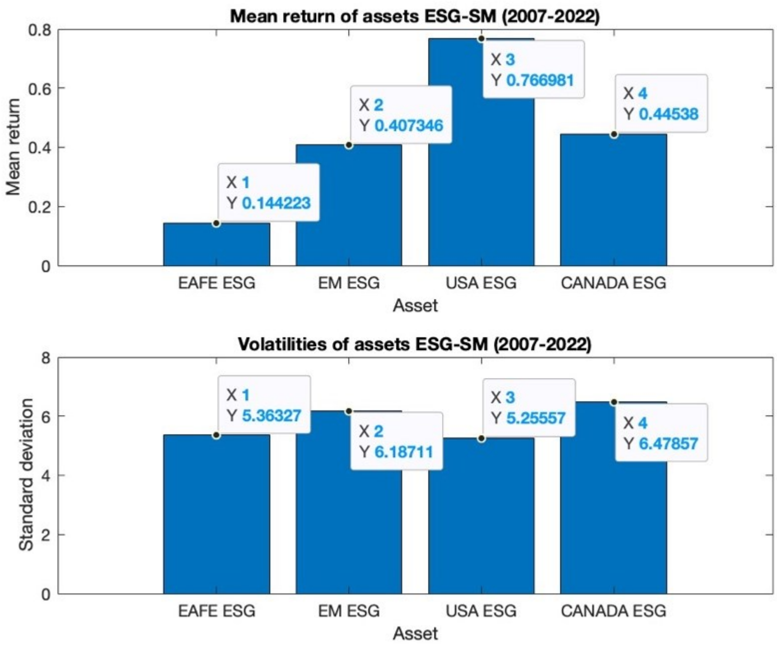
The first section focuses initially on the computations of the mean and variance relating to traditional indexes.

Figure 5.1: Mean and volatility of traditional indexes




The figure 5.1 shows the first two moments of the traditional indexes which are explained by the Y, instead the X is related to the position of the index, therefore 1 is the first index and so on. The rough outcome is the higher performance and lower volatility of USA Index in comparison with the other indexes. The CANADA Index shows the second-best mean return and second worst volatility, instead the EM Index has the third best mean return and worst volatility. Even with a volatility slightly similar to USA Index, the EAFE Index has a very poorly mean return, the worst one.

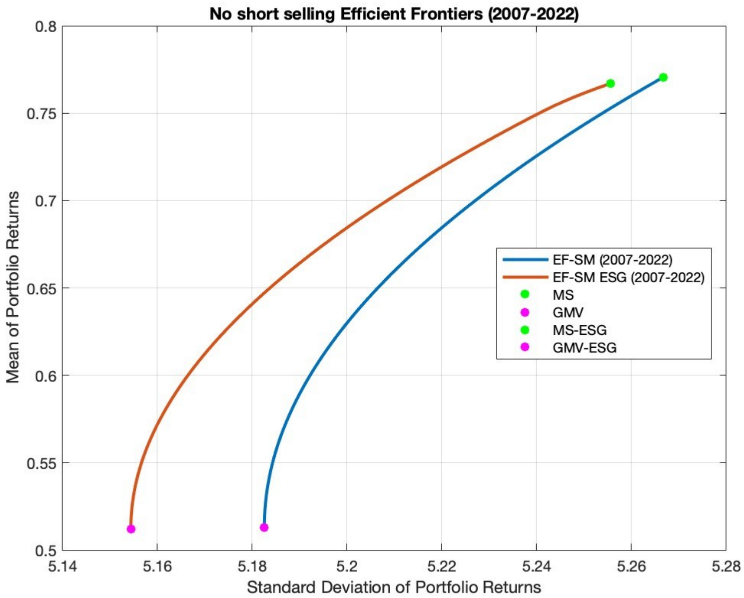
Figure 5.2: Mean and volatility of ESG indexes



The figure 5.2 shows the ESG indexes moments and still the USA ESG Index is the best one, but with a worsening in the mean return and improving in volatility, instead the other indexes improve their performance and also their volatility, with exception of CANADA ESG Index that worsens his volatility but significantly improve his return. The EM ESG Index is the one who mostly improve his returns and volatility, on the contrary the EAFE ESG Index is the one which improve less his moments.

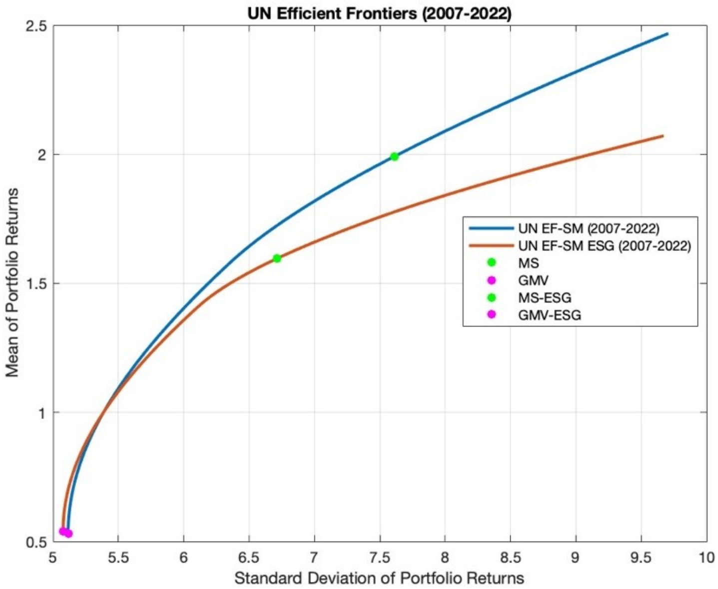
The further figures describe the portfolios strategies object of analysis.

Figure 5.3: ESG and traditional efficient frontiers – No short selling strategy




In case of No Short Selling strategy, Figure 5.3, the ESG EF is shifted towards left, resulting in a lower riskiness of the EF and increasing the volatility the gap between the two EFs is reduced. In terms of optimal portfolios, the ESG GMV portfolio (pink dot) sems it dominates the traditional GMV portfolio, since for the same level of return the former bears a lower risk, but the return of traditional GMV portfolio is slightly higher than the traditional one, therefore the ESG GMV portfolio doesn’t dominate the traditional one. In case of MS portfolio (green dot), the difference in riskiness is reduced and in addition there is a slight better performance of traditional portfolio, therefore there is not a clear portfolio dominance. In this situation even if the ESG EF is shifted towards left, the ESG optimal portfolios don’t dominate the traditional one.

Figure 5.4: ESG and traditional efficient frontiers – Short selling strategy

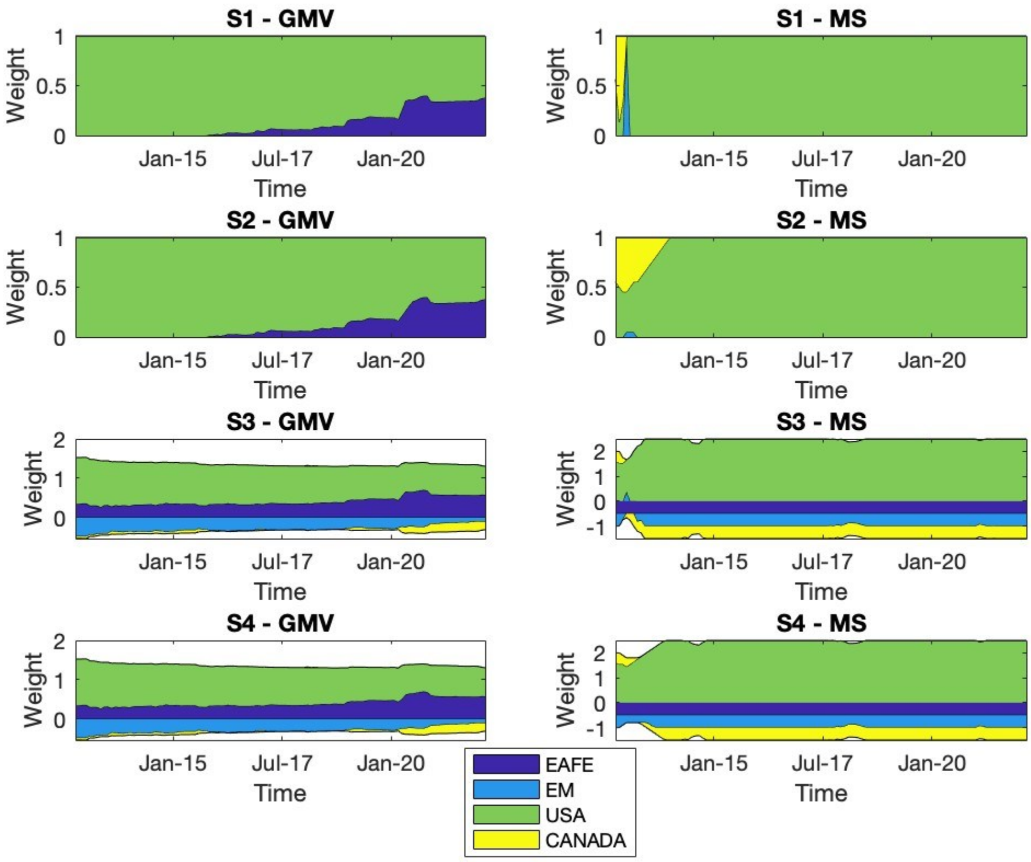



Analyzing the Figure 5.4, the case of Short Selling strategy, firstly the ESG EF dominates the traditional one, then across 5.4 of volatility, the traditional EF dominates the ESG one, then after this point the gap between the two EFs starts to increase over the increase of volatility. In terms of efficient portfolios, the ESG GMV portfolio dominates the traditional one, even if they are very close each other. The two MS portfolios, instead, are not comparable since the traditional portfolio has higher performance than ESG portfolio but at the same time the traditional one has a very high volatility.

Now, moving towards the Monthly Tactical Choice section, it's possible to see the portfolio composition of the optimal portfolios. In order to improve the research two constraints has been added: transaction cost (equal to 0,125%) and turnover constraint. Therefore, the resulting strategies are the following:

- S1: No Short Selling;
- S2: No Short Selling, transaction cost and turnover constraint;
- S3: Short Selling;
- S4: Short Selling, transaction cost and turnover constraint

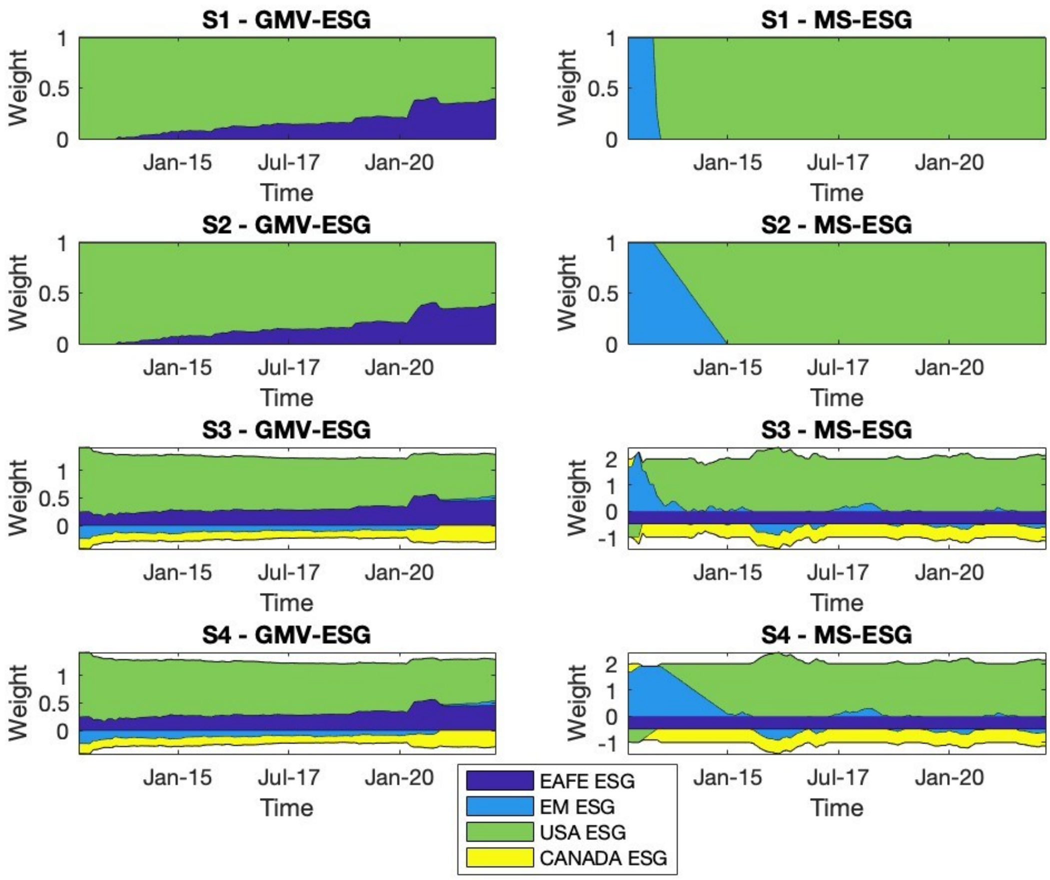
Figure 5.5: Compositions of traditional portfolios




The main result of the Figure 5.5 is the dominance of USA Index in all portfolios and the slight similarity between all GMV portfolios and between all MS portfolios. In particular the GMV similarity is between S1 and S2, No Short Selling strategy, moreover between S3 and S4, Short Selling strategy. In relation to MS similarity, it is verified for all the time horizon for S3 and S4, instead S1 and S2 share the same characteristics with exception of the first years of the time horizon. The consistent presence of EAFE Index in GMV portfolios is driven by the comparable riskiness of it with USA Index, especially after the pandemic crisis. The short position for the EM Index in the S3 and S4 strategies is driven by his very high volatility and his low return, and since the correlation with USA Index is high, the USA Index is preferred.

On the other hand, MS portfolios are all totally composed by the USA Index, with the exception of the CANADA Index in first few years. Also here, in the S3 and S4 strategies, there is a short position for CANADA Index and EM Index, because since they have lower return and higher volatility than USA Index, and since they are very correlated with the USA Index, it is preferred as long position and both CANADA Index and EM Index take a short position. In terms of the additional constraints, transaction cost and turnover constraint, they do not highly affect the portfolio composition.

Figure 5.6: Compositions of ESG portfolios




In the Figure 5.6, which exhibits the ESG portfolios composition, shows that also in ESG portfolios there is an USA Index dominance in the composition and the slight similarity between ESG GMV portfolios and between ESG MS portfolios. The similarity for ESG GMV portfolios is between S1 and S2, and with the introduction of the lower bound also S3 and S4 are quite similar. In terms of MS portfolios, S1 and S2 have the presence of EM ESG Index for the first years and for S2, differently from S1, this presence last until January 2015. The same happens for S3 and S4, which share the same characteristics for all the time horizon with exception of the first years where the presence of EM ESG Index remains until January 2015.

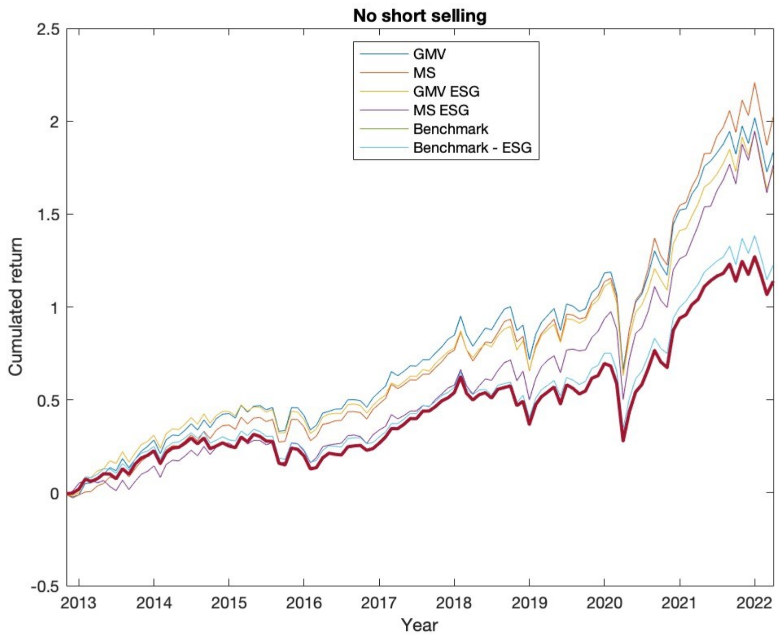
The ESG GMV portfolios are characterized by the almost similar index composition of traditional one, with the only difference in the Short Selling strategy (S3-S4), where the CANADA ESG Index has a higher short position and EM ESG Index has a lower weight in the short position in comparison to the respective indexes in the traditional form. This result is mainly due to the improvement of EM ESG Index moments and worsening in the CANADA ESG Index moments.

In terms of ESG MS portfolios there is a massive presence of EM ESG Index in the first years of the time horizon and after that there is not a short position on this index but more or less it is neutral. The neutral presence of EM ESG Index in comparison to the short position of the EM Index, is due to the

improvement of the EM ESG Index both in terms of return and volatility. The CANADA ESG Index is instead the main index in a short position since his highly correlation with the US ESG Index and his worsening in volatility and not a very high return.
Also in the ESG portfolios, the presence of additional constraints, transaction costs and turnover constraints, is not relevant for the portfolios composition.

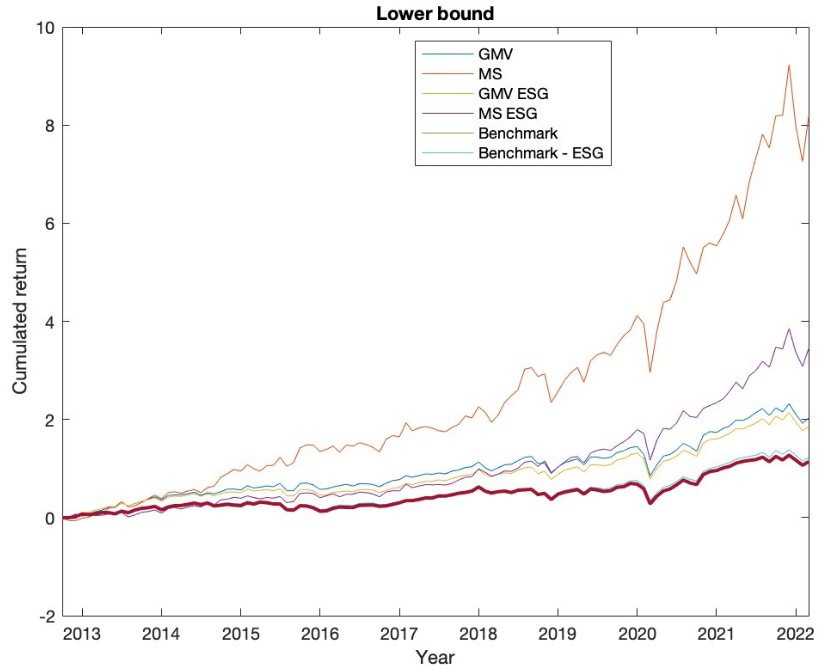
The following tables show the percentage cumulated returns over the time horizon selected. The strategies presented are the No Short Selling (S1) and Short Selling (S3), because results of the strategies with the additional constraints are in line with those strategies without them.

Figure 5.7: Portfolios percentage cumulated returns of No Short Selling strategy




The Figure 5.7 focuses on No Short Selling strategy, what is possible to see is the similar path of all strategies, with some divergences among the different strategies. In terms of GMV portfolios (blue and yellow line) the path is almost identical between the two portfolios with a slight better performance of traditional portfolio; with regards to MS (orange and purple line), the traditional portfolios overperform the ESG portfolios for all the time horizon. In particular, the divergency in portfolio performance between MS portfolios lasts mainly until the end of 2019, because after that period the divergency is deduced or is kept constant over the remaining period.

Figure 5.8: Portfolios percentage cumulated returns of Short Selling strategy




In case of Short Selling strategy, Figure 5.8, the GMV portfolios maintain their similarity with a slight overperformance by traditional GMV portfolios. As regards MS portfolios, the divergency is quite huge and continues to rise over the entire time horizon.

All portfolios in all strategies have, at the end of the time horizon, a better cumulated return than the benchmark (red and light blue). This result is due to the benchmark composition (Table 3.3) because it is composed by only roughly 60% of USA Index, instead those strategies are composed by more than 90% of USA Index for almost all the whole-time horizon; therefore, the benchmark underperforms all the strategies analyzed.

Another common feature among all portfolios is the portfolio's reaction in a stress situation or period of crisis. During those periods the ESG portfolios' downturns are more contained than the traditional one and this effect can be seen during the end of 2018, the beginning and the end of 2020, then again during the beginning of 2022. In those periods, the traditional portfolios overperformances are reduced and start to increase just after the stress period. Considering the time interval $1^{st}$ February to $1^{st}$ September 2020, respectively the two highest peaks, and within that time interval there is the lowest peak $1^{st}$ April, therefore the cumulated returns path shows a decrease from the first highest peak to the lowest peak and a subsequent increase from the lowest peak to the second highest peak. In particular in the Short Selling strategy the traditional GMV portfolio exhibits a cumulated return decrease of 0.5989 and subsequent increase of 0.6657, instead the ESG GMV portfolio reveals a decrease of 0,5293 with an increase of 0.5839. In the Short Selling strategy with transaction cost and turnover constraint the GMV portfolios results have a slightly higher value in comparison to the Short Selling strategy. Analyzing the Short Selling strategy, the traditional MS portfolio presents a cumulated return decrease of 1.1654 and subsequent increase of 1.4286, differently instead the ESG MS portfolio which shows a lower decrease of 0.6254 and a lower increase of 0.6483. In the Short Selling strategy with transaction cost and turnover constraint the MS portfolio results have a lower intensity with respectively lower decrease and subsequent lower increase.

These results are confirmed also by the No Short selling strategy and No Short selling strategy with transaction costs and turnover constraint, but with a lower intensity in the performance reduction and subsequent performance improvement.

Table 5.3: Performance measures

| Strategy | Sh | So | Tr | VaR | ES | Cal | Ste | FT |
|---|---|---|---|---|---|---|---|---|
| Benchmark | 0,183415481 | 0,215364614 | 0,754844131 | 0,129679819 | 0,081640209 | 0,030641755 | 0,045137948 | 0,673348756 |
| Benchmark-ESG | 0,195557521 | 0,22595335 | 0,807520587 | 0,142761093 | 0,087526244 | 0,033649618 | 0,050318077 | 0,683513074 |
| GMV SM-no short selling | 0,23542833 | 0,273213069 | 0,989774781 | 0,178831716 | 0,107361953 | 0,041801421 | 0,07027865 | 0,74562918 |
| GMV SM-no short selling, trans costs and turnover | 0,235854319 | 0,27435462 | 0,991530889 | 0,179578918 | 0,107810538 | 0,041976077 | 0,070803736 | 0,747104278 |
| GMV SM-lower bound | 0,243078601 | 0,293041763 | 1,061272936 | 0,169128497 | 0,112079995 | 0,043988098 | 0,069727248 | 0,770995106 |
| GMV SM-lower bound, transaction cost and turnover | 0,243283655 | 0,293737829 | 1,061900713 | 0,16953023 | 0,11234622 | 0,044092584 | 0,070089184 | 0,771875124 |
| MS SM-no short selling | 0,243665802 | 0,282018529 | 1,035609409 | 0,189042104 | 0,112154415 | 0,044243227 | 0,074863541 | 0,756670799 |
| MS SM-no short selling, trans costs and turnover | 0,234169399 | 0,275432236 | 0,99075272 | 0,181813681 | 0,107865954 | 0,042551494 | 0,072000976 | 0,747940522 |
| MS SM-lower bound | 0,345275461 | 0,52632745 | 1,881641986 | 0,271089481 | 0,180544858 | 0,094701085 | 0,128334223 | 1,044857189 |
| MS SM-lower bound, transaction cost and turnover | 0,338305368 | 0,517759064 | 1,833055439 | 0,283729968 | 0,178329938 | 0,092395963 | 0,125210435 | 1,034935306 |
| GMV-ESG SM-no short selling | 0,233027875 | 0,272796563 | 0,982005049 | 0,180554837 | 0,107484678 | 0,041316663 | 0,06840176 | 0,743742341 |
| GMV-ESG SM-no short selling, trans costs and turnover | 0,233369656 | 0,273862566 | 0,983361013 | 0,181260388 | 0,107904695 | 0,041478115 | 0,068931399 | 0,745101053 |
| GMV-ESG SM-lower bound | 0,241978156 | 0,287660594 | 1,038752762 | 0,168339277 | 0,110549468 | 0,044240184 | 0,071996382 | 0,763021303 |
| GMV-ESG SM-lower bound, transaction cost and turnover | 0,242162591 | 0,288193466 | 1,039382526 | 0,168651115 | 0,110754253 | 0,044322136 | 0,072288121 | 0,763698215 |
| MS-ESG SM-no short selling | 0,228443208 | 0,270258056 | 0,978711645 | 0,180660508 | 0,105587808 | 0,041289039 | 0,069620768 | 0,742549956 |
| MS-ESG SM-no short selling, trans costs and turnover | 0,211164666 | 0,250004664 | 0,910071149 | 0,15293006 | 0,096528479 | 0,038166475 | 0,064355562 | 0,717414284 |
| MS-ESG SM-lower bound | 0,281223922 | 0,382415957 | 1,410433498 | 0,223523486 | 0,134919535 | 0,064638436 | 0,105070895 | 0,880939148 |
| MS-ESG SM-lower bound, transaction cost and turnover | 0,234218051 | 0,335726398 | 1,203041642 | 0,188995646 | 0,11547266 | 0,053659503 | 0,058892414 | 0,826537546 |

In conclusion of this section has been explained in the Table 5.3 the performance measure of all the strategies. The results are in line with what emerges from the cumulated returns and EFs. The GMV portfolios obtain very similar performances with a little overperformance by traditional GMV portfolio. In terms of MS portfolios, the traditional portfolios overperform the ESG ones in all the strategies analyzed and the gap of MS portfolios, meaning the difference in performance between traditional MS portfolio and ESG MS portfolio, is higher than GMV portfolios' gap, driven by the very high performance of traditional MS portfolio.

### 5.2 Rolling window and EWMA

In this paragraph has been used for the computation of mean and variance the following methods:

- Rolling Window;
- EWMA, with $\lambda = 0{,}98$;
- EWMA, with $\lambda = 0{,}95$;

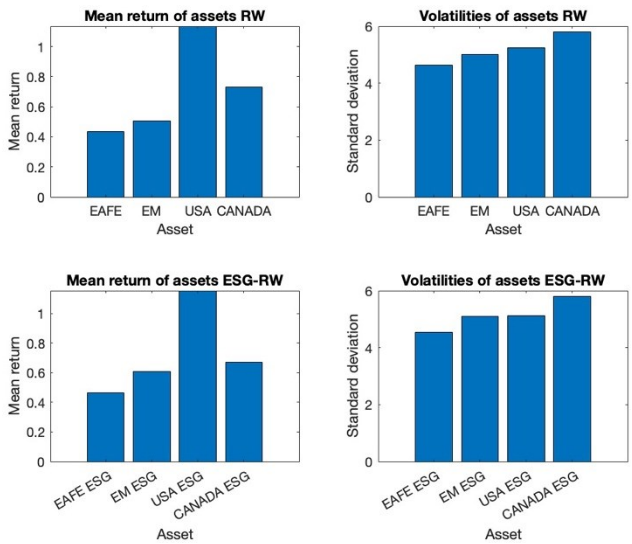
As the previous analysis the two strategies applied are:

- No Short Selling strategy;
- Short Selling strategy or Unconstraint strategy;

Firstly are computed the returns for all the rolling windows, obtaining 114 mean return for each index, then on this data are computed the overall mean and variance which are based on the 114 mean return.

It's possible to see the following results:

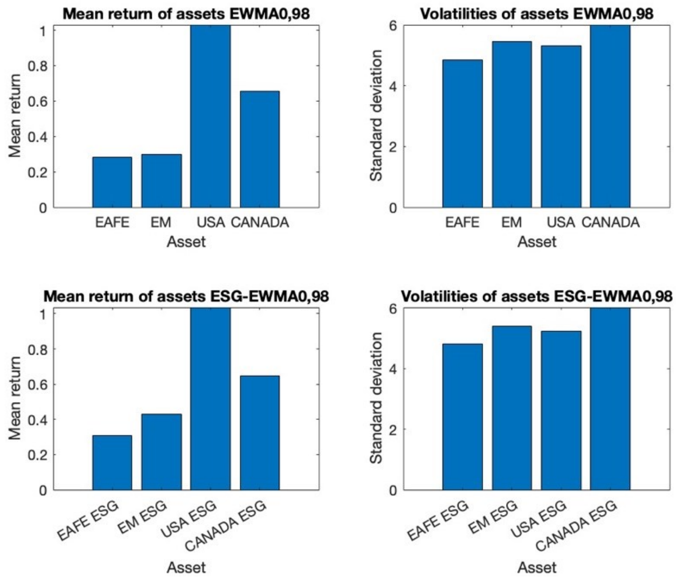
Figure 5.9: Overall mean and volatility of ESG and traditional indexes computed with Rolling Window




The general result that arises from the Figure 5.9 is the slightly similarity in the performance of the traditional indexes and ESG indexes, with a performance improvement by all the ESG indexes with exception of USA ESG Index which is slightly lower than the USA Index. In terms of volatility the ranking is the same for traditional and ESG assets, meaning highest volatility for CANADA, then USA, EM and at the end EAFE. The only difference is in the EM and USA indexes volatility, because in the traditional indexes the difference between them is evident, instead in the ESG indexes they are quite similar. Making a comparison with the Sample Moments results (Figure 5.1 and Figure 5.2), it is possible to observe that USA Index performance is still the best one; on the contrary, the US Index is no more the one with lowest volatility. The other indexes maintain the same characteristics of the previous method, in particular lowest performances and lowest volatilities by EAFE indexes, the second highest performances and highest volatilities by CANADA indexes, instead for EM indexes the performance and volatilities are between the one of CANADA and EAFE indexes.

The same process is applied for the both EWMA cases for the computation of the overall mean and variance and the following results are obtained by using the EWMA method with $\lambda = 0{,}98$

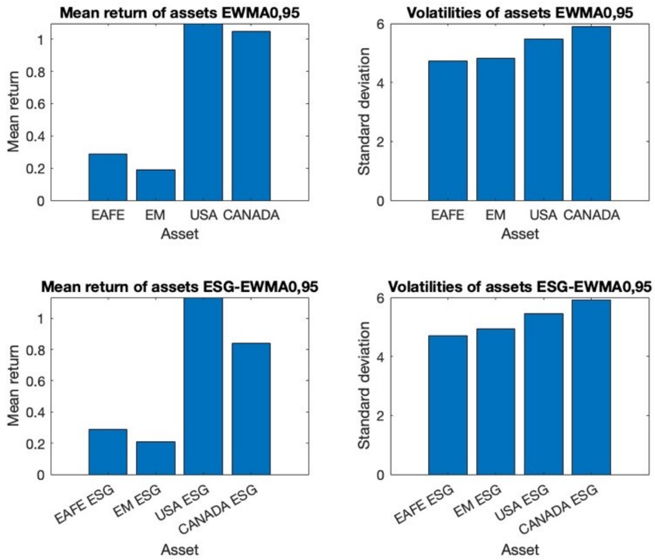
Figure 5.10: Overall mean and volatility of ESG and traditional indexes computed with EWMA 0,98




What is showed in the Figure 5.10 is the comparison of the mean and volatility of traditional and ESG indexes. As in the RW the mean returns of ESG indexes are higher than the ones of traditional indexes with exception of USA ESG Index, moreover the ESG index that mostly improve his performance in comparison to the respective traditional one is the EM index. In terms of volatility, the one of the ESG indexes are lower than the one of traditional indexes with exception of CANADA ESG Index. In both cases the USA indexes are the best one in terms of mean return and the second in terms of volatility, instead is the EAFE indexes that have the best volatility but the worst returns. The CANADA indexes, in both cases, have the highest volatility and the second-best mean return, instead the EM indexes have the second highest volatility and second worst mean returns. Comparing these results with the ones obtained with the RW, they share the same ranking for the mean returns but with different intensity, and also in terms of volatility the ranking is the same with the inversion of USA indexes, that became the second best, with the EM indexes, which became the third best.

Analyzing the third method, EWMA with $\lambda = 0,95$, are achieved the outcomes below.

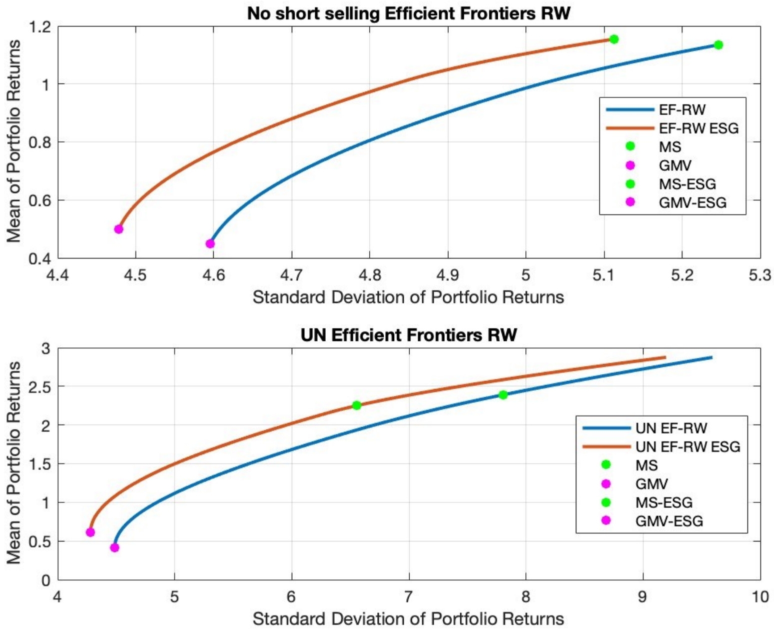
Figure 5.11: Overall mean and volatility of ESG and traditional indexes (EWMA 0,95)




In the Figure 5.11 are showed the mean returns and the volatilities of the traditional and ESG indexes. In particular the mean return ranking is the same for the traditional and ESG indexes, with a mean return of EAFE ESG and EM ESG indexes higher than the respective traditional indexes, instead the mean return of USA ESG and CANADA ESG indexes lower than the respective traditional indexes. Also in terms of volatility the ranking is the same for the traditional and ESG indexes, with a lower volatility intensity for the ESG indexes in comparison to the traditional one, with exception of CANADA ESG Index that has an higher volatility than the traditional one.
In comparison of the RW method, in these results the CANADA indexes have a higher mean returns and at the same time the EM indexes have a lower mean return. The EAFE and USA indexes are at the same level of the RW in terms of mean returns and volatility.

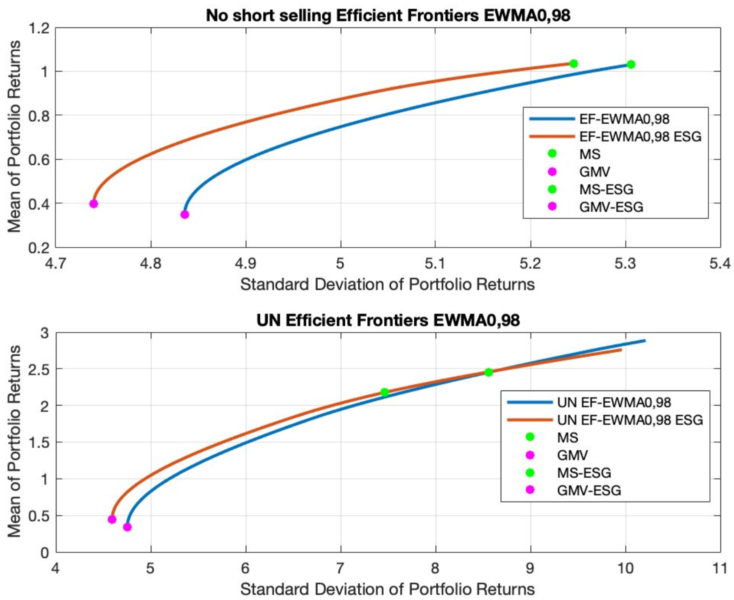
The graphical representation of the Efficient Frontiers and the optimal portfolios are exhibited in the subsequent section.

Figure 5.12: No Short Selling and Short Selling efficient frontiers computed with RW



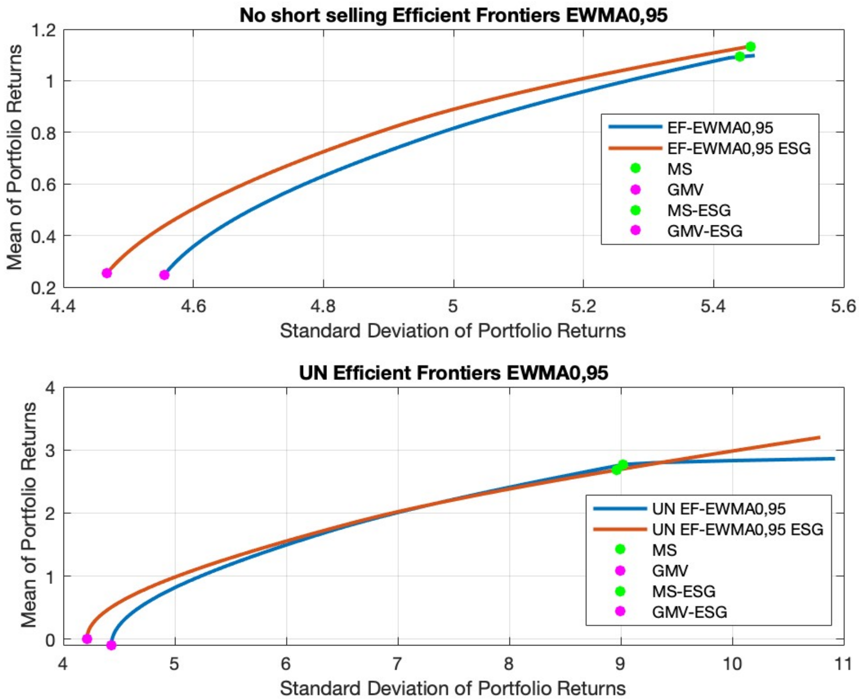

Analyzing the Figure 5.12, which focuses on the RW method, is possible to see that in both strategies the ESG EF is shifted towards left with respect to the traditional EF and increasing the volatility the gap between the two EFs is reduced. Focusing on the GMV portfolios, the ESG GMV portfolios dominate the traditional GMV portfolios in both strategies, meaning that the ESG portfolios have lower risk and higher return in comparison to the traditional one. With regards to MS portfolios, in No Short Selling strategy ESG MS portfolio dominates the traditional one, instead in Unconstraint strategy the traditional one has both higher return and volatility.

Figure 5.14: No Short Selling and Short Selling efficient frontiers computed with EWMA0,98



In the Figure 5.14, the case of EWMA0,98, the ESG EFs are shifted towards left in comparison to the traditional EFs even if this shit has a lower intensity than the one in the RW, and as the previous methos increasing the volatility the gap between the two EFs is reduced. As the RW method also here the ESG GMV portfolios dominate the traditional one in both strategies and only in No Short Selling strategy, the ESG MS portfolio dominates the traditional MS portfolio.

Figure 5.15: No Short Selling and Short Selling efficient frontiers computed with EWMA0,95

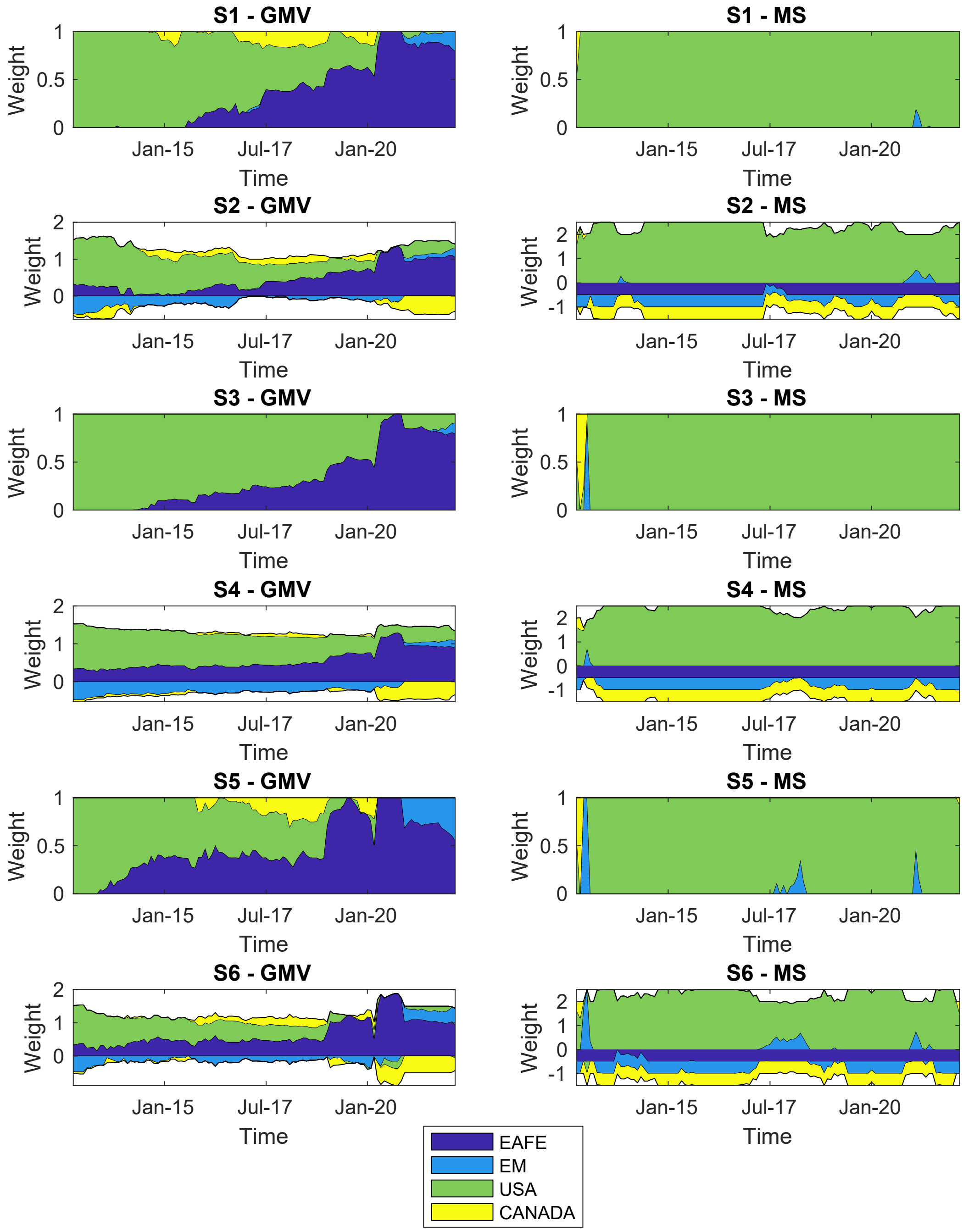



The results obtained by the EWMA0.95, Figure 5.15, are slightly similar to the ones obtained by the EWMA0.98 for the GMV portfolios. In particular the ESG EFs are shifted toward left in comparison to the traditional one and increasing the volatility the gap between the two EFs is reduced. The ESG GMV portfolios dominate the traditional one even if the dominance has lower magnitude, instead the results related to the MS portfolios are different among the two strategies. In the No Short Selling strategy, the ESG MS portfolio gains a higher performance and higher volatility than the traditional portfolio, instead in Unconstraint strategy is the traditional MS portfolio which achieves the higher performance and higher volatility than ESG MS portfolio.

Here, the analysis examines the portfolio composition of the various method and strategies:

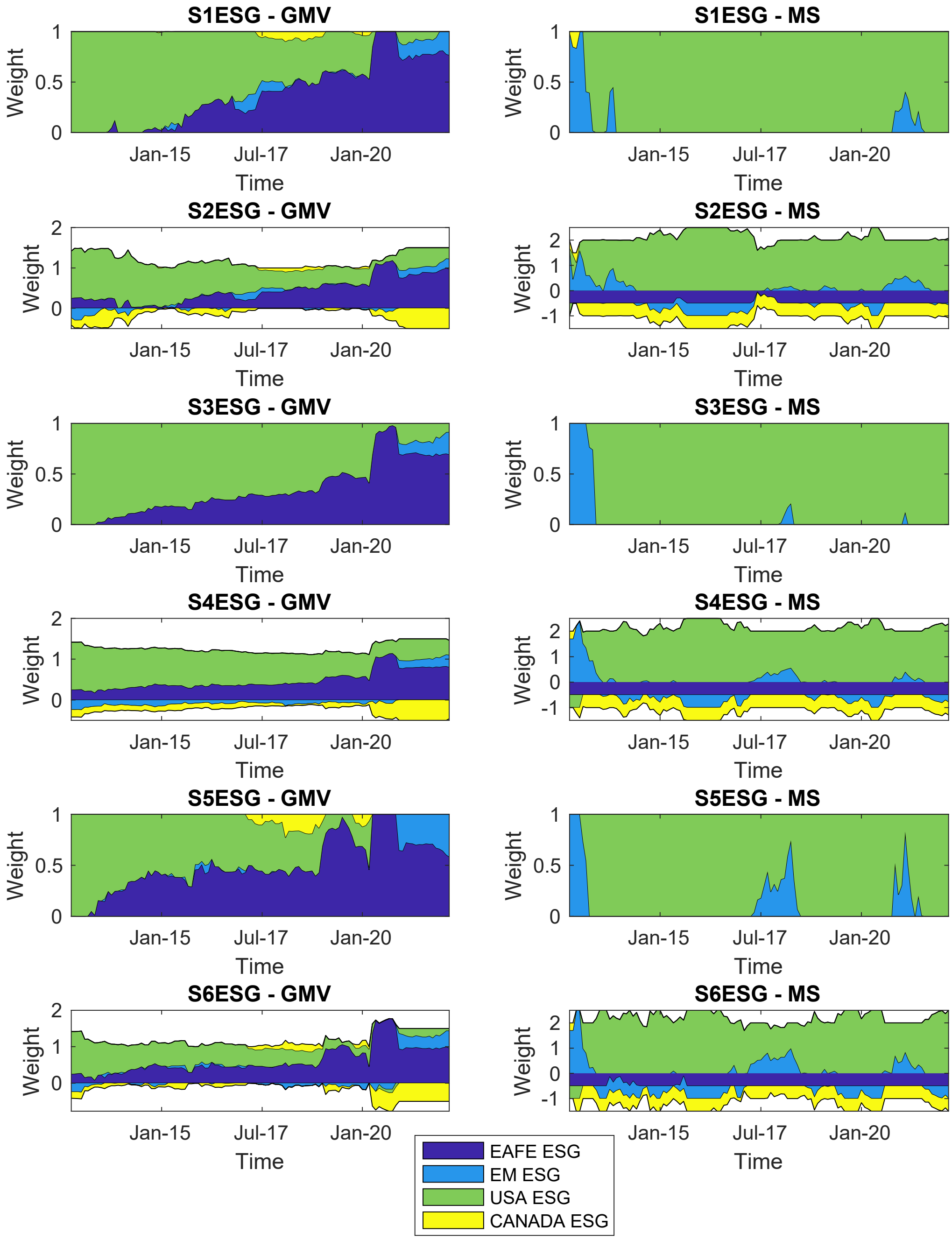
- S1: Rolling Window method and No Short Selling strategy
- S2: Rolling Window method and Short Selling strategy
- S3: EWMA0,98 method and No Short Selling strategy
- S4: EWMA0,98 method and Short Selling strategy
- S5: EWMA0,95 method and No Short Selling strategy
- S6: EWMA0,95 method and Short Selling strategy

**Figure 5.16**: Composition of traditional portfolios



Starting with the analysis related to the composition of traditional portfolios, Figure 5.16, it's clear that in all of GMV portfolios there is a consistent presence of USA Index until the beginning of 2020, then it is reduced or even disappears in some strategies. Again in all GMV strategies, there is a significant presence of EAFE Index which continues to rise over time, in particular this presence is higher than the Sample Moments case analyzed in the previous section. This result is mainly driven by the lower EAFE Index volatility in comparison to the other indexes and also the correlation coefficient is positive and significant (around 0.87) in comparison to the other indexes. The EM Index starts to be included at the beginning of 2020, previously being in a short position for Short Selling strategy and it is not included in the No Short Selling strategy. Also the presence of this index is driven by the same reason of the EAFE Index, therefore it is very correlated with the other indexes and in comparison it has the second lowest volatility. The CANADA Index is included for a slight weight from the beginning of 2015 to the end of 2021 and for the Short Selling strategy it has a short position from the beginning of 2020 to the end of the time horizon. The presence of the CANADA Index for the rest of the time horizon is absent for the No Short Selling strategy, instead short position for the Short Selling strategy. This result is linked to the positive and consistent correlation with the other indexes, which have a better volatility, and also to a very high volatility of the index, even if it is the second-best index in terms of return.
The composition of MS portfolios is very similar among all the strategies in terms of long position, but also for the Short Selling strategies (S2, S3, S4) the composition is slight similar among the short positions. In particular there is a massive presence of USA Index in the long position of the portfolios with some occasional inclusions of EM Index. The EAFE Index is always absent in the No Short Selling strategies and it has always a short position for the Short Selling strategies. Also the CANADA Index has the same characteristics, absence for No Short Selling strategies and short position for Short Selling strategies, with exception of the first months of the S3 and S5 strategies.

**Figure 5.17**: Composition of ESG portfolios



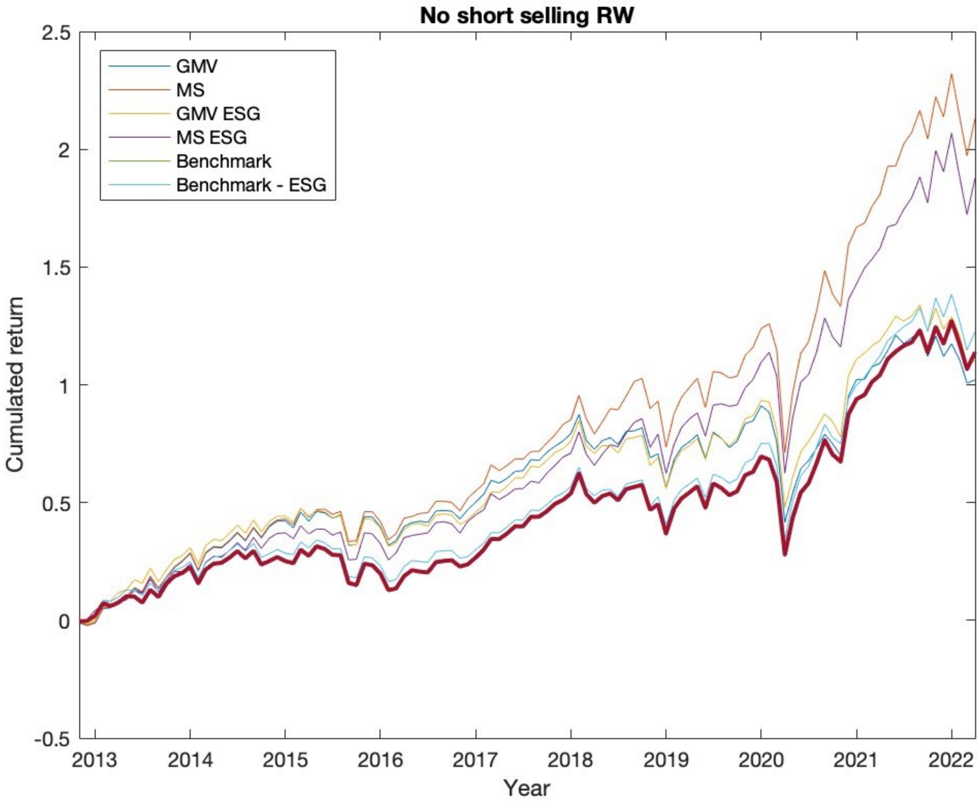
The Figure 5.17 demonstrates that the composition of the ESG portfolios shares almost all the main aspects of the traditional portfolios with some differences. The USA ESG Index has a significant presence in all GMV ESG portfolios until the beginning of 2020, then it is reduced or even disappears completely (S5ESG). Also here there is a consistent presence in the GMV ESG portfolios of EAFE ESG Index which continues to rise overtime from the end of 2014 for the same reasons explained before, even if the correlations coefficients are lower than the traditional one. The EM ESG Index has a considerable presence after the pandemic crisis in all the GMV ESG portfolios, with a lower magnitude for S2ESG and S4ESG strategies. In the same period, that is after the pandemic crisis, the CANADA ESG Index has a maximum short position in the GMV portfolios with Short Selling strategies (S2ESG, S4ESG, S6ESG).

As the GMV ESG portfolios also the MS ESG portfolios share almost all the main features of the traditional portfolios, again with some variations. The common characteristic among all the MS portfolios is the massive presence of USA ESG Index for all the entire time horizon, excluding the first years of the time horizon. In relation to the Short Selling strategies (S2ESG, S4ESG, S6ESG), the common feature is the short position of both EAFE ESG Index and CANADA ESG Index for almost all the time horizon selected. The EM ESG Index has a massive presence for the first years and then for the No Short Selling strategies it has some occasional inclusion, such as during the pandemic crisis, instead for the Short Selling strategies it switches between short position, neutral position and long position.

Comparing the traditional and the ESG portfolio composition the main result is the higher presence of EM ESG Index in both MS and GMV portfolios, instead the weights of the other indexes are almost the same.

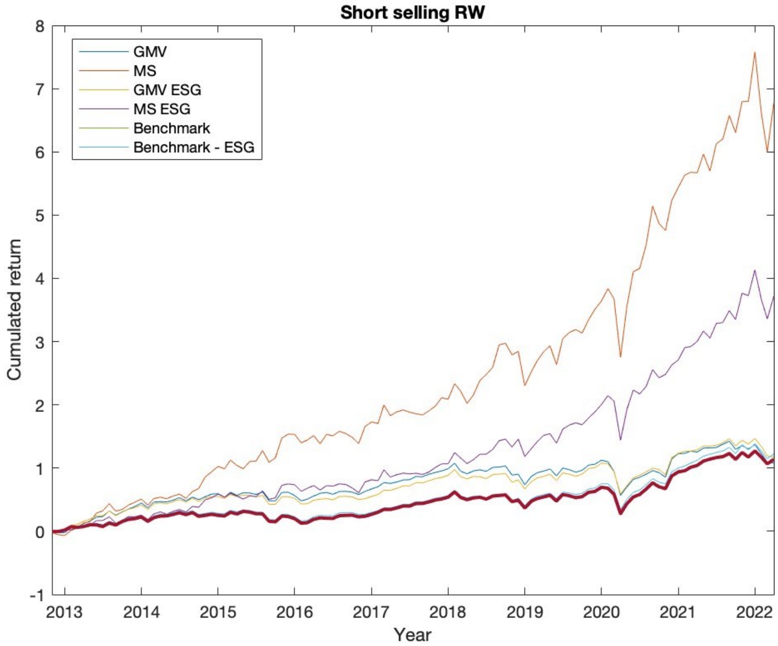
In the computation of the percentage cumulated returns the graphical results are exhibited below.

Figure 5.18: Portfolios percentage cumulated returns of No Short Selling strategy using RW




In the Figure 5.18, which displays the percentage cumulated returns of the No Short selling strategy using RW method, there is a clear gap between the GMV portfolios and MS portfolios and it is a different result with respect to the Sample Moment method. The ESG GMV portfolio and the traditional one have a quite similar path, differently of Sample Moment case, here the ESG GMV portfolio overperform from the end of 2019 to the end of time horizon. The traditional MS portfolio continues to overperform the ESG one at a slight lower intensity than the Sample Moment method. The benchmarks are located below the MS portfolios and around the GMV portfolios.

Figure 5.19: Portfolios percentage cumulated returns of Short Selling strategy using RW




Examining the Figure 5.19, the Short Selling strategy, the results that emerge are the same of the previous strategy. In particular, GMV portfolios have similar trend and from the end of 2019 to the end of the time horizon the ESG GMV portfolio overperforms the traditional one. The MS portfolios overperform hugely the GMV portfolios and the benchmark because of the high presence of USA Index in their compositions.

The gap between the traditional MS portfolio and ESG MS portfolio is slightly reduced with respect to the gap obtained using Sample Moments method. As in the Sample Moments method, during the stress period the ESG portfolios downturns are more contained than the traditional ones. In particular, the pandemic crisis was a turning point for the GMV portfolios because after it the ESG GMV portfolio starts to overperform the traditional GMV portfolio.

In case of EWMA0,98 method, the results obtained from both strategies are the same of the RW approach. The only relevant difference between the two methods is the improving of the percentage cumulated return in the GMV portfolios, which become stable over the benchmark.

In the last method, EWMA0,95, the general results found by both strategies are in line with the RW outcomes with some differences. One of them is the lower percentage cumulated returns by the GMV portfolios, which after the beginning of 2020 achieve a percentage cumulated returns lower than the benchmarks in both strategies. The further difference is the increase in the gap between the percentage cumulated returns of the two portfolios, ESG GMV portfolios and traditional GMV portfolios.

In particular, the ESG GMV portfolios increase their overperformance in comparison to the traditional one.

Focusing on the period of crisis, the RW and EWMA portfolios' reaction in a stress situation is very similar to the sample moments method, therefore traditional portfolios' downturns have a higher magnitude than the ESG ones. As the previous method the stress periods are the end of 2018, the beginning and the end of 2020 and the beginning of 2022. Analyzing the same time interval of the previous method, $1^{st}$ February to $1^{st}$ September 2020, the cumulated returns have an initial highest peak with a subsequent lowest peak in $1^{st}$ April 2020 and again a second highest peak in the end of the time interval, therefore there is an initial decrease and subsequent increase in the cumulated returns trend. In particular in all the methods analyzed, RW, EWMA0.98 and EWMA0.95, all traditional MS portfolios have a higher decrease and subsequent higher increase with respect to ESG MS portfolios in both No Short Selling and Short Selling strategies. This reduction in the traditional portfolios overperformance and consequent high traditional portfolio recovery is higher for the Short Selling strategy than the No Short Selling one in terms of strategy, instead in terms of method the magnitude of the initial decrease and consequent increase is for the RW the highest one and for the EWMA0,95 the lowest one.

The results of the GMV portfolios are different across methods and strategies. In the RW case in both strategies, Short Selling and No Short Selling strategies, the cumulated returns of traditional and ESG GMV portfolios are very closed each other until the pandemic crisis and after it the ESG GMV portfolios start to overperform the traditional one and this overperformance continue to increase. In the EWMA0.98 case and in the Short Selling strategy the traditional GMV portfolio overperformance decrease over the pandemic time period but then it starts to increase reaching the overperformance value pre-pandemic. Considering the other strategy, the No Short Selling strategy, the pandemic crisis is the point in time in which the traditional GMV portfolio overperformance has been converted in ESG GMV portfolio overperformance even if at low overperformance value. In last case, EWMA0.95, the GMV portfolios share the same characteristics for both No Short Selling and Short Selling strategies. In particular, the ESG GMV portfolios overperform the traditional one still at the beginning of the pandemic crisis with an increase in the overperformance during the pandemic period and after it the overperformance is kept constant.

Table 5.4: Performance measures of RW, EWMA0,98 and EWMA0,95

| Strategy | Sh | So | Tr | VaR | ES | Cal | Ste | FT |
|---|---|---|---|---|---|---|---|---|
| Benchmark | 0,183415481 | 0,215364614 | 0,754844131 | 0,129679819 | 0,081640209 | 0,030641755 | 0,045137948 | 0,673348756 |
| Benchmark-ESG | 0,195557521 | 0,22595335 | 0,807520587 | 0,142761093 | 0,087526244 | 0,033649618 | 0,050318077 | 0,683513074 |
| GMV RW-no short selling | 0,171349935 | 0,200937611 | 0,729219366 | 0,12089716 | 0,075031653 | 0,027182884 | 0,03999258 | 0,658256092 |
| GMV RW-short selling | 0,171543475 | 0,205186915 | 0,754079951 | 0,119566057 | 0,07699341 | 0,028139181 | 0,040385016 | 0,665095151 |
| GMV EWMA0,98-no short selling | 0,197740561 | 0,235529258 | 0,836221596 | 0,14315373 | 0,088244142 | 0,032936045 | 0,05298514 | 0,699089526 |
| GMV EWMA0,98-short selling | 0,194595291 | 0,228724211 | 0,854271406 | 0,133567135 | 0,086362624 | 0,033089797 | 0,049137823 | 0,689875303 |
| GMV EWMA0,95-no short selling | 0,14303967 | 0,166248082 | 0,60961494 | 0,096609425 | 0,060446499 | 0,021012272 | 0,029412201 | 0,615818205 |
| GMV EWMA0,95-short selling | 0,127792144 | 0,149533306 | 0,570478083 | 0,085120751 | 0,05405374 | 0,019453174 | 0,025765427 | 0,598591557 |
| MS RW-no short selling | 0,249839737 | 0,289377954 | 1,056529364 | 0,194600986 | 0,115452374 | 0,045544222 | 0,077064942 | 0,766168163 |
| MS RW-short selling | 0,331649363 | 0,494057394 | 1,773698651 | 0,252512523 | 0,17178255 | 0,088773909 | 0,123904962 | 1,011245652 |
| MS EWMA0,98-no short selling | 0,243520131 | 0,282006062 | 1,035095621 | 0,188963278 | 0,112107649 | 0,044224778 | 0,074832325 | 0,75667552 |
| MS EWMA0,98-short selling | 0,338431294 | 0,505629591 | 1,81861043 | 0,260470038 | 0,175051047 | 0,091218927 | 0,124897756 | 1,022151626 |
| MS EWMA0,95-no short selling | 0,24106162 | 0,279153849 | 1,025195501 | 0,18704922 | 0,110972082 | 0,043776814 | 0,074074329 | 0,752904074 |
| MS EWMA0,95-short selling | 0,322144348 | 0,481939901 | 1,734296801 | 0,259956468 | 0,166007692 | 0,084890409 | 0,12062393 | 0,994684345 |
| GMV-ESG RW-no short selling | 0,182752883 | 0,218390912 | 0,778721739 | 0,127014052 | 0,08148685 | 0,031239531 | 0,046946628 | 0,678772017 |
| GMV-ESG RW-short selling | 0,186853976 | 0,222179026 | 0,811042187 | 0,123686385 | 0,084011214 | 0,032642183 | 0,048478962 | 0,682159109 |
| GMV-ESG EWMA0,98-no short selling | 0,196838083 | 0,233162715 | 0,833748898 | 0,14413229 | 0,088558154 | 0,034159833 | 0,054629014 | 0,695457886 |
| GMV-ESG EWMA0,98-short selling | 0,200761939 | 0,235362692 | 0,868719035 | 0,132486021 | 0,089209578 | 0,03533678 | 0,054843811 | 0,697235128 |
| GMV-ESG EWMA0,95-no short selling | 0,15718262 | 0,186051012 | 0,672358351 | 0,104910672 | 0,068010107 | 0,025585572 | 0,037572668 | 0,640695949 |
| GMV-ESG EWMA0,95-short selling | 0,142150603 | 0,165764671 | 0,629878033 | 0,091775953 | 0,061199054 | 0,023519935 | 0,031779903 | 0,615584582 |
| MS-ESG RW-no short selling | 0,239240392 | 0,272101935 | 1,024593246 | 0,186779021 | 0,109163799 | 0,042687394 | 0,071978647 | 0,74348642 |
| MS-ESG RW-short selling | 0,287172231 | 0,396644886 | 1,486453555 | 0,235204778 | 0,142233558 | 0,067159549 | 0,113976409 | 0,898177221 |
| MS-ESG EWMA0,98-no short selling | 0,232088393 | 0,270809331 | 0,992664899 | 0,182576146 | 0,10670741 | 0,041726849 | 0,070358993 | 0,742458437 |
| MS-ESG EWMA0,98-short selling | 0,276127958 | 0,385148748 | 1,418280805 | 0,223741337 | 0,133747039 | 0,064648925 | 0,104759309 | 0,88355835 |
| MS-ESG EWMA0,95-no short selling | 0,22929743 | 0,262291886 | 0,989385262 | 0,178563228 | 0,104362043 | 0,040809717 | 0,067065007 | 0,730989472 |
| MS-ESG EWMA0,95-short selling | 0,273853427 | 0,379617537 | 1,449236249 | 0,223099473 | 0,130371407 | 0,064611729 | 0,100931915 | 0,876982129 |

The Table 5.4 shows the last analysis of this section and it is related to the computations of the performance measures where the outcomes obtained support the results exhibited before. The traditional MS portfolio overperforms the ESG MS portfolio in all the methods and the ESG GMV portfolio overperforms the traditional one, with exception of the GMV EWMA0,98 and GMV-ESG EWMA0,98 with the No Short Selling strategy, even if the traditional portfolios overperformance is not significant. Comparing these results with the ones obtained by the Sample Moments method what emerges is the reduction in the traditional MS portfolios overperformance, instead according to GMV portfolios, the traditional GMV overperformances for the Sample Moments method is changed in a ESG GMV overperformances for the RW and EWMA methods, with exception of the No Short Selling strategy using EWMA0,98.

## 5.3 Diversification strategy

The optimal portfolios studied present some limitations in the portfolio composition that have been developed and improved in this paragraph. In particular in the MS portfolios, and with lower intensity also in the GMV portfolios, the portfolio composition is constituted massively by few indexes, mainly USA Index. The aim of this paragraph is to increase the portfolio diversification through the implementation of multiple strategies, adding some constraints, in order to increase the weights of the remaining assets. The three macro strategies are the following:

- Upper Bound and No Short Selling strategy: it consists in the no short selling constraint and the upper bound constraint in order to limit the severe weight of only few indexes. Has been created four strategies through the use of four upper bound limits set to: 0.8 – 0.7 – 0.6 – 0.5;
- Upper Bound and Short Selling strategy: it includes the short selling constraint and the upper bound constraint with a degree of: 0.8 – 0.7 – 0.6 – 0.5;
- Upper Bound, No Short selling and Minimum Investment strategy: it is the same of first case with the inclusion of a lower bound of 0.1, meaning a minimum mandatory investment in all indexes. The purpose of this strategy is to bind the long position of all indexes, this is due to the fact that in some cases of the previous two macro strategies the weight reduction of the main index is balanced by a weight increase of only one index.

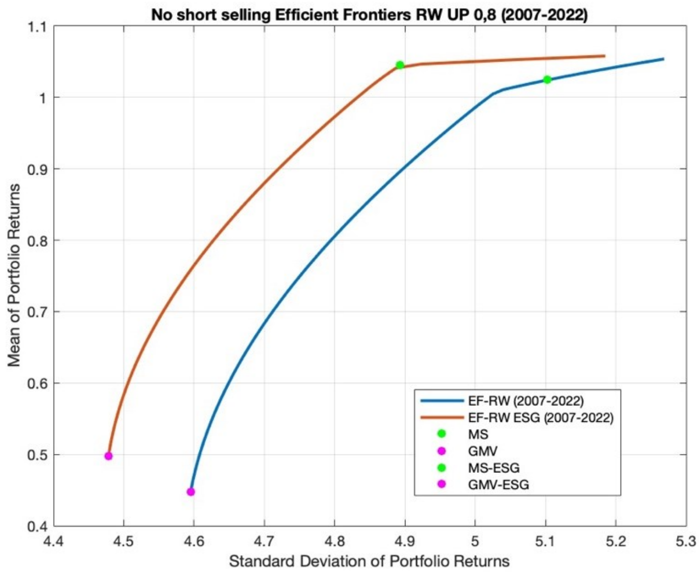
The macro strategies just explained have been analyzed using the methods previously implemented:

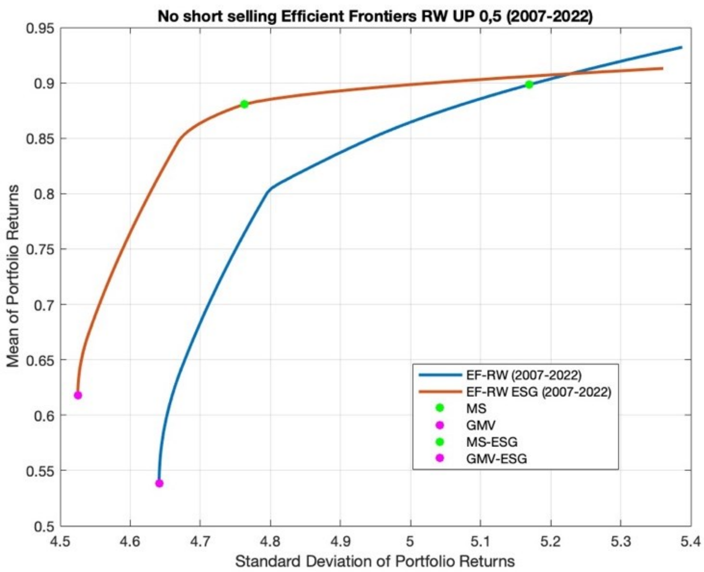
- Rolling Window;
- EWMA 0,98;
- EWMA 0,95.

### 5.3.1 Upper Bound and No Short Selling strategy

The introduction of the upper bound constraint has an important role on the two EFs and on the optimal portfolios computed with the Rolling Window approach. The Figure 5.20 shows that the ESG EF is more shifted toward left in all the upper bound strategies (0.8, 0.7, 0.6, 0.5) and in particular lower is the upper bound higher is the shift towards left. Considering the GMV portfolios, is possible to notice that ESG GMV portfolios dominate the traditional ones and this dominance is stronger than the base case (the one without upper bound constraint) and become stronger when the upper bound decrease. The MS portfolio reduces slightly his performance when the upper bound decreases and also reduce the volatility consistently.

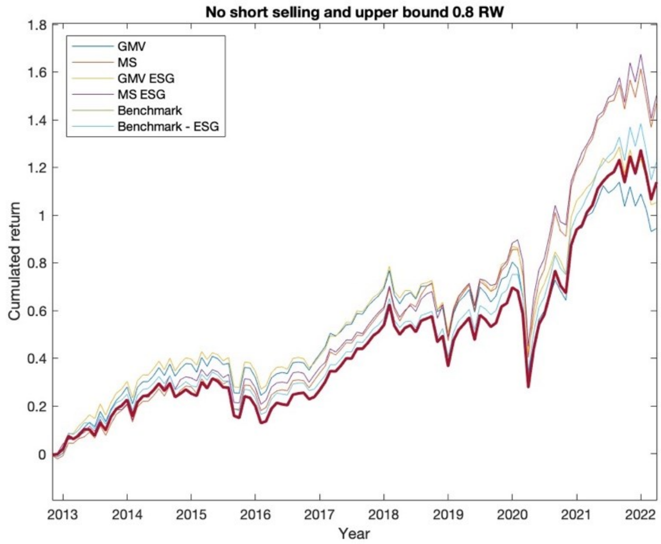
Figure 5.20: No Short Selling EFs with upper bound constraint using RW

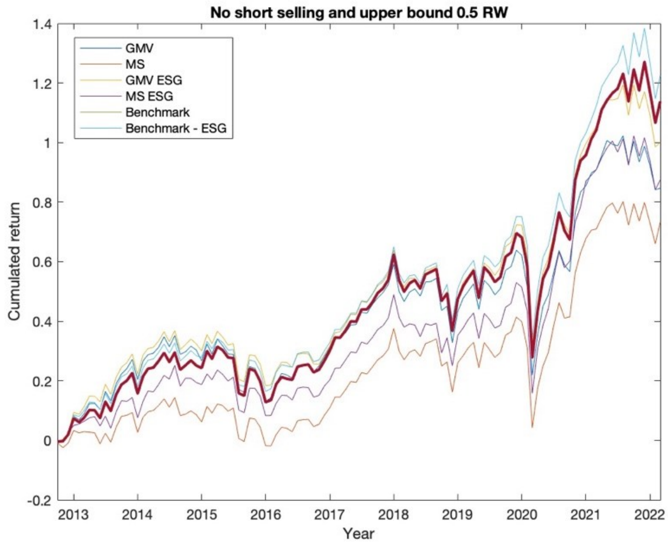


The portfolios composition of all those strategies is characterized by a reduction of the major index weight and an increase of the second major index weight. The two indexes that take the role of major index are USA Index and EAFE Index, in some case also EM Index, in both traditional and ESG form.

Figure 5.21: Portfolios percentage cumulated returns with upper bound constraint using RW




The EF results are confirmed by the cumulated returns results, explained by the Figure 5.21, because the reduction of upper bound constraint is related to an overall performance reduction of MS portfolios and the ESG MS portfolio overperformance. The overall performance reduction is due to the weight reduction in the best index, the USA Index; instead, the ESG MS portfolio overperformance is related to the fact that the other indexes introduced, ESG EAFE Index and ESG EM Index, overperform their respective traditional peers. The upper bound reduction has an effect also on GMV portfolios, particularly the overperformance increases by ESG MS portfolio, in consequence of the increase of the EAFE Index weight which overperforms his traditional peer. Comparing the optimal portfolios with the benchmark emerges that for the upper bound reduction the GMV portfolios reduce their performance slightly and remain close to the benchmark, instead MS portfolios are affected significantly and in the 0.6 and 0.5 upper bound strategy perform even worse than the benchmark.

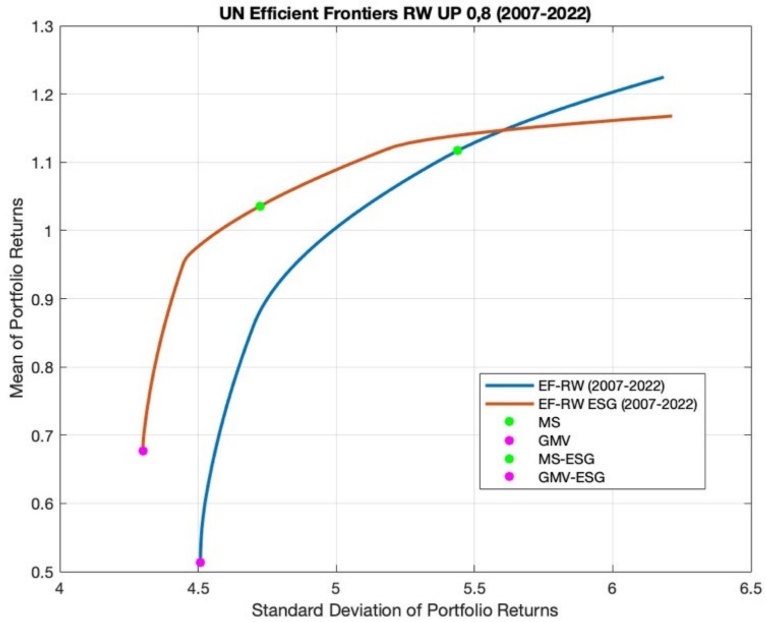
Using the EWMA0,98 approach all the results are the same of Rolling Window approach but with lower intensity. The ESG GMV portfolio overperformance increases in relation of the reduction of the upper bound constraint, but with lower magnitude. On the other hand, the ESG MS portfolio overperformance increases at the same intensity of Rolling Window approach.

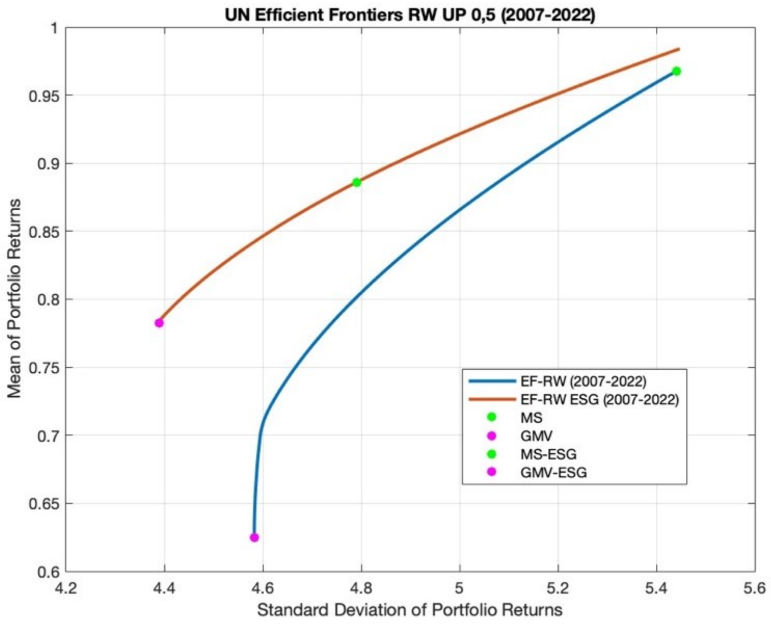
The last method, EWMA0,95, shows the same results of Rolling Window but at a different intensity. The ESG GMV portfolio increases his overperformance at a higher magnitude than RW, meanwhile the ESG MS portfolio increase in overperformance is lower than the previous two methods.

### 5.3.2 Upper Bound and Short Selling strategy

In the case of Short Selling strategy, the inclusion of the upper bound constraint plays a key role in the ESG and traditional portfolios comparison. The Figure 5.22, which illustrates the Short Selling strategy utilizing RW, shows that the reduction of the upper bound constraint leads to a shift of the EF towards left, therefore a stronger ESG GMV portfolios dominance and the ESG MS portfolios reduce both their performance and volatility.

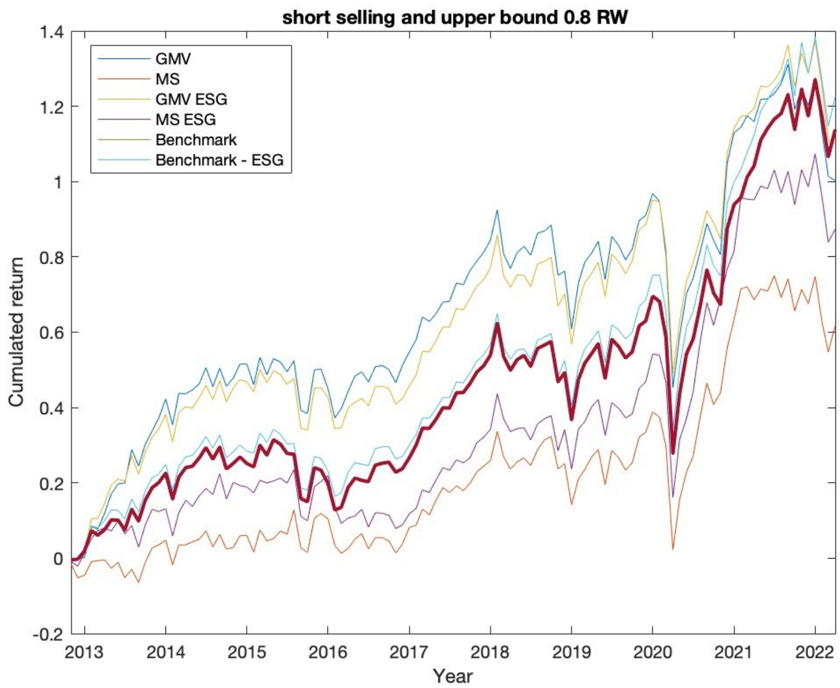
Figure 5.22: Short Selling EFs with upper bound constraint using RW

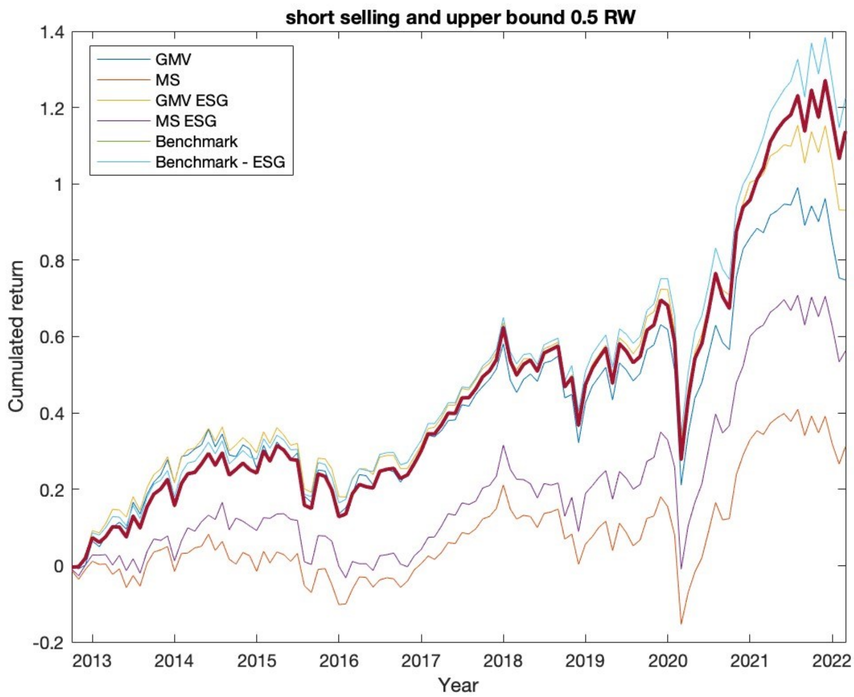


The portfolios composition of the GMV portfolios is characterized by presence of USA Index and EAFE Index in both traditional and ESG cases. The MS portfolios are constituted by USA Index mainly and the remaining weights are EAFE Index and EM Index for traditional portfolios and ESG EM Index for ESG portfolios, with some isolated CANADA Index weights for both traditional and ESG portfolios.

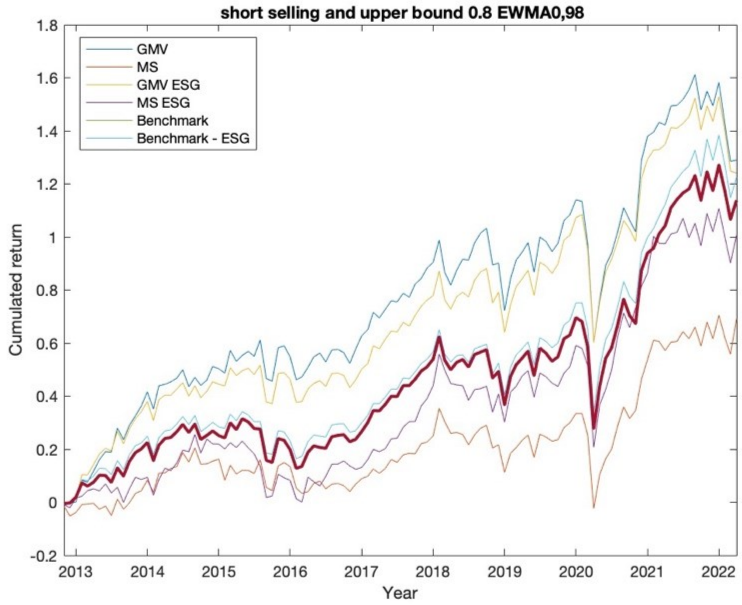
Figure 5.23: Portfolios cumulated returns with upper bound constraint using RW

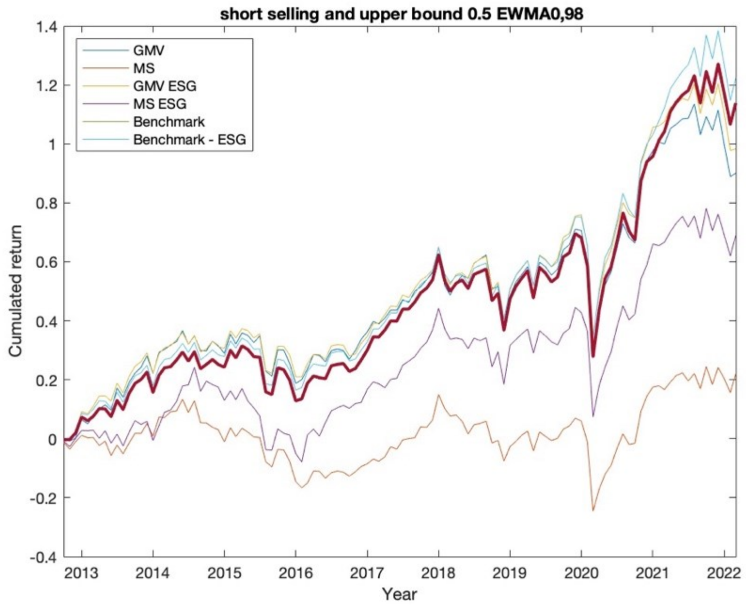


Computing the cumulated returns of the Short Selling strategy, Figure 5.23, what emerges are the same results of No Short selling strategy. The reduction in the upper bound constraint is related to the increase in the overperformance of the ESG portfolios over the traditional ones. The difference of previous case is that the ESG MS portfolios overperformance is higher than the previous case and starts from the 0.8 upper bound strategy. This result is related to the exploitation of the better performance of the EM ESG Index and EAFE ESG Index with respect to their traditional peers, that compensate the reduction on USA Index, the main MS portfolios component. The overperformance of ESG portfolios starts from 0.8 upper bound strategy because comparing ESG portfolios with the base case, the one without upper bound, the base case has almost the entire composition by USA Index therefore even a reduction of 20% has a relevant effect on the performance.

Figure 5.24: Portfolios cumulated returns with upper bound constraint using EWMA0,98



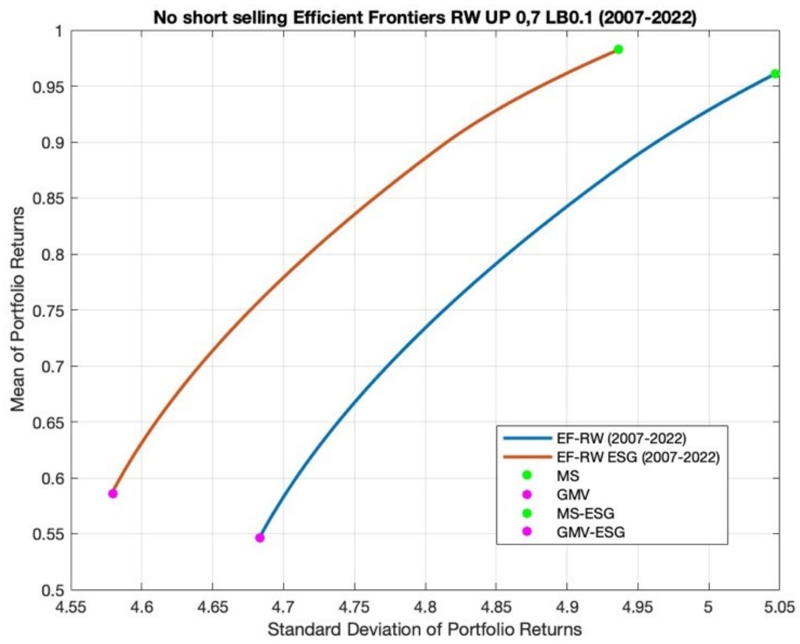

The results in the Figure 5.24, which are related to EWMA0,98 approach, are the same of Rolling Window approach although with some differences. The ESG GMV portfolio starts to overperform the traditional one in the strategy with the 0,7 upper bound. On the contrary, the ESG MS portfolio overperformance starts from the 0,8 upper bound strategy and the overperformance level has a higher intensity than the Rolling Window approach.

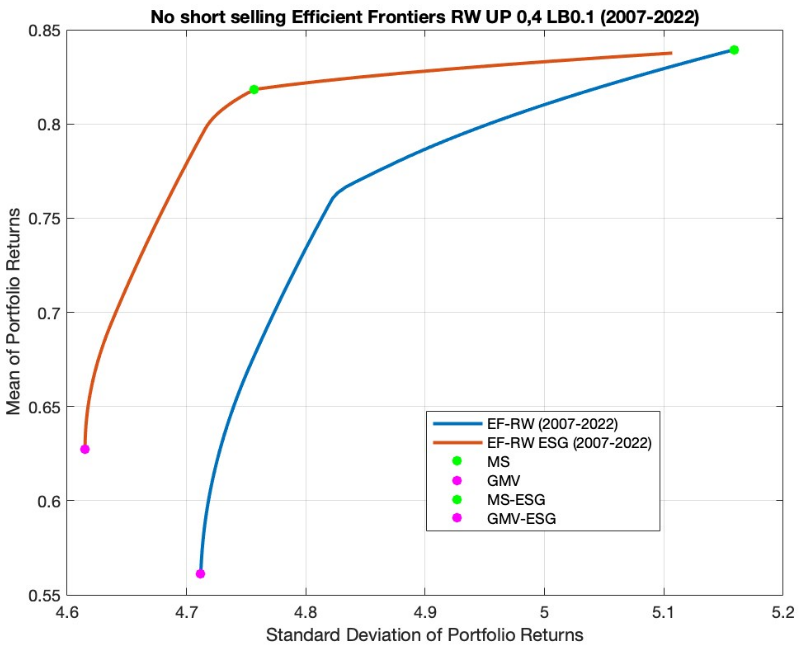
Analyzing lastly the EWMA0,95 results, it's possible to see the same result of EWMA0,98 method for GMV portfolios, while for MS portfolios the magnitude of the MS ESG portfolio overperformance is the lowest one compared to the other methods.

### 5.3.3 Upper Bound, No Short Selling and Minimum Investment strategy

In this section is developed the No Short selling strategy with two constraints: upper bound (0.7 - 0.6 – 0.5 – 0.4) and lower bound (0.1). The results obtained across the three methods share the same key aspects among them. In particular in the Figure 5.25, the results on the EF are the same of previous cases, meaning a shift towards left of the EF, the increase in ESG GMV portfolios dominance and the reduction in both performance and volatility of the MS portfolios.

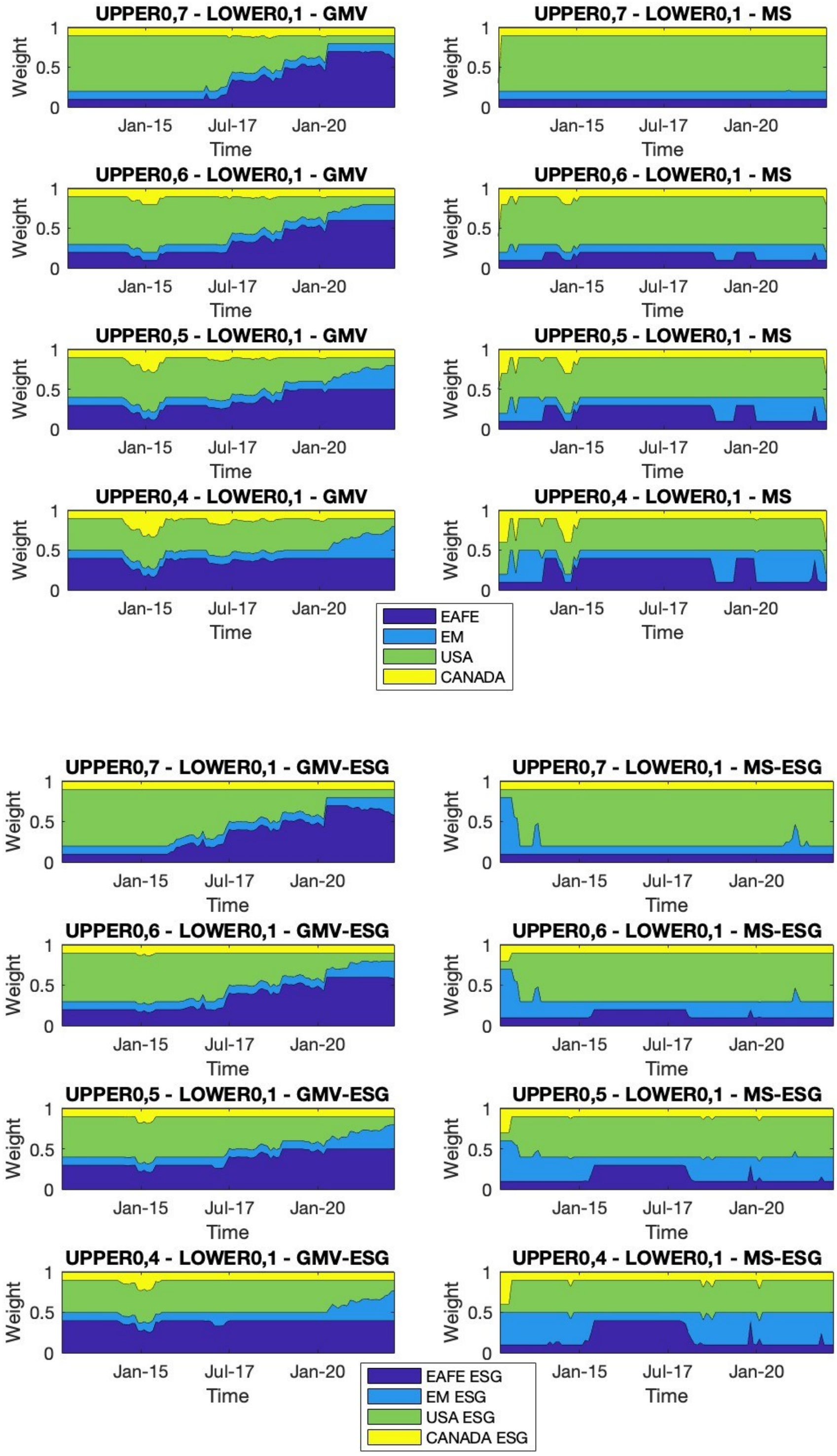
Figure 5.25: No Short Selling EFs with upper bound and lower bound constraints using RW



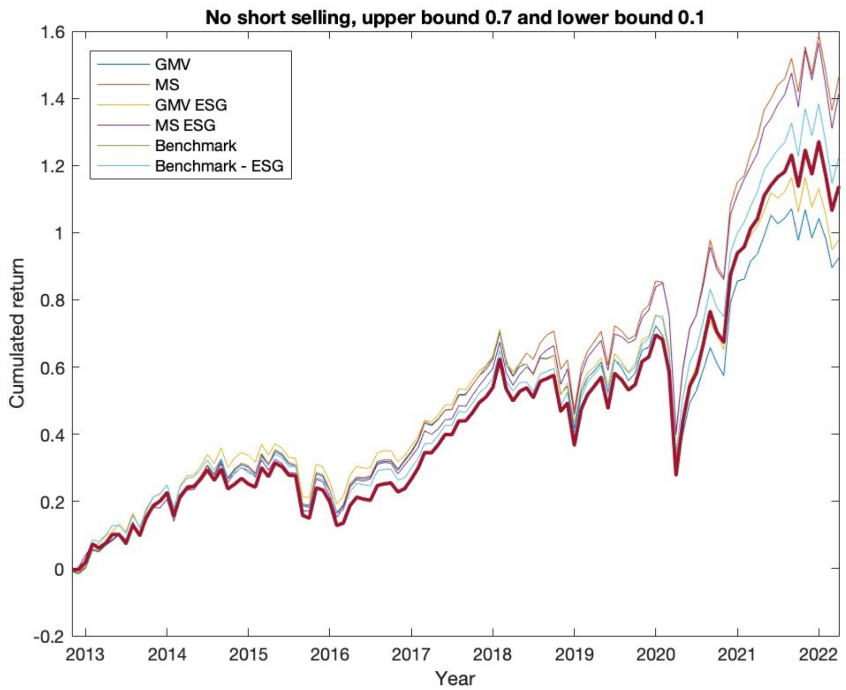
In the portfolio composition, Figure 5.26, is possible to notice the minimum investment in all the indexes and the decrease overtime by the USA Index which is offset by the increase of EAFE Index for traditional portfolios and by both EAFE ESG Index and EM ESG Index for ESG portfolios.

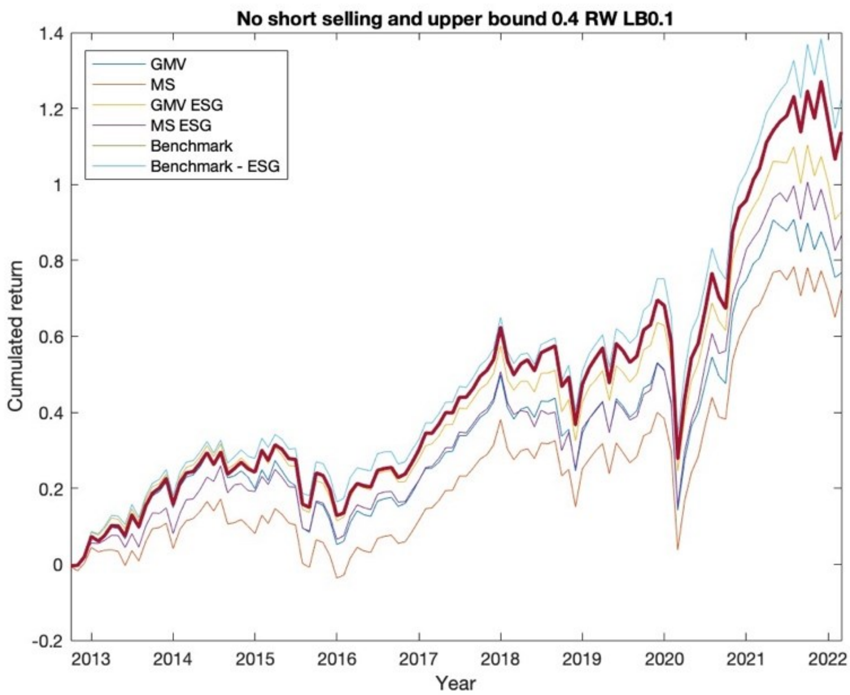
Figure 5.26: Compositions of No Short Selling, upper and lower bound portfolios using RW



What emerges from the Figure 5.27, which is related to the cumulated returns, is the confirmation of EF outcomes. The introduction of lower bounds produces an overall portfolios performance reduction, in particular this reduction has a high intensity for MS portfolios while it has a low magnitude for GMV portfolios. As shown in the previous strategies, the reduction of upper bound leads to an increase in the ESG portfolios overperformance.

Figure 5.27: Cumulated returns of No Short Selling, upper and lower bound portfolios using RW



### 5.4 Out-of-sample analysis

In this paragraph are showed the results related to the out-of-sample test (Tashman 2000). The out-of-sample analysis starts with the division of the historical data series into a fit period, which is used to identify and estimate a model, and test period, in which is assessed the model's forecasting accuracy. The last time in the fit period is the forecasting origin, the point from which the forecasts are generated. In this research has been used the rolling-origin evaluation characterized by the successively updating of the forecasting origin and therefore producing forecasts from each new origin. Specifically, the fit period is used to obtain data on which are computed the mean and variance, then obtained the portfolios inputs, they are applied to the portfolio strategy which last one period. This method tries to replicate what happens in reality, therefore it takes data from the past and it applies the results obtained in the period ahead. Moving forward, the fit period is updated by the new observation, the $61^{st}$ one, and the oldest observation is removed, the $1^{st}$ one, resulting in a constant 60 observations time window. Achieving the new time window, there is the moments computations and the resulting inputs are applied into the new test period. The fit period consists of constant 60 observations, instead the test period lasts one period and it is the period after the forecasting origin. The structure and the operation of the fit period is the same of the Rolling Window method and the difference is in the presence of test period.

The following analysis make a comparison among two evaluations: in-sample and out-of-sample. The in-sample case, the one analyzed in the previous sections, takes the portfolios moments and the portfolios composition considering all the time horizon data, past and present data, therefore obtaining the optimal allocation for each period. In the out-of-sample case, the time horizon data is only related to the past and not the present, therefore if a good or bad event happens the change in the portfolio composition is done the subsequent period. In other words, the difference between the out-of-sample and in-sample evaluations is in the most recent observation of the time window, the actual observation. For the in-sample case the actual observation is part of the time window used for the computation of the moments, instead for the out-of-sample case it is excluded from the time window and the last observation of the time window is the observation one period behind the actual observation. In fact, the out-of-sample evaluation starts one period ahead in comparison to the in-sample evaluation because it needs constant 60 observation for the computation of the moments. The intuition behind the out-of-sample method is that the agent in the real world makes his investment decision only after the events happen and he doesn't know the market movements before it happens. The strategies analyzed are No Short Selling and Short Selling strategies, instead the methods used for the in-sample evaluation and the subsequent computation of the mean and variance are the same of previous analysis: Rolling Window, EWMA0,98 and EWMA0,95.

Figure 5.28: Cumulated returns of GMV portfolios - Short Selling strategy using RW

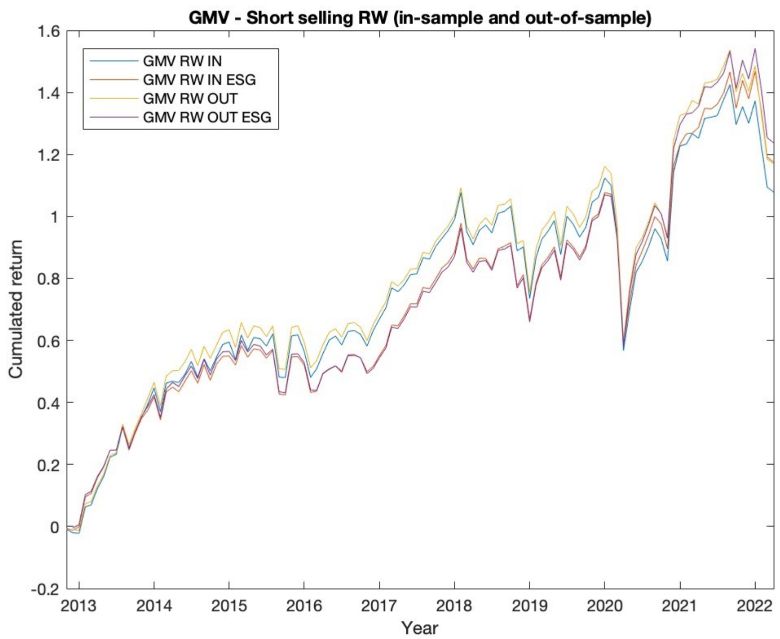
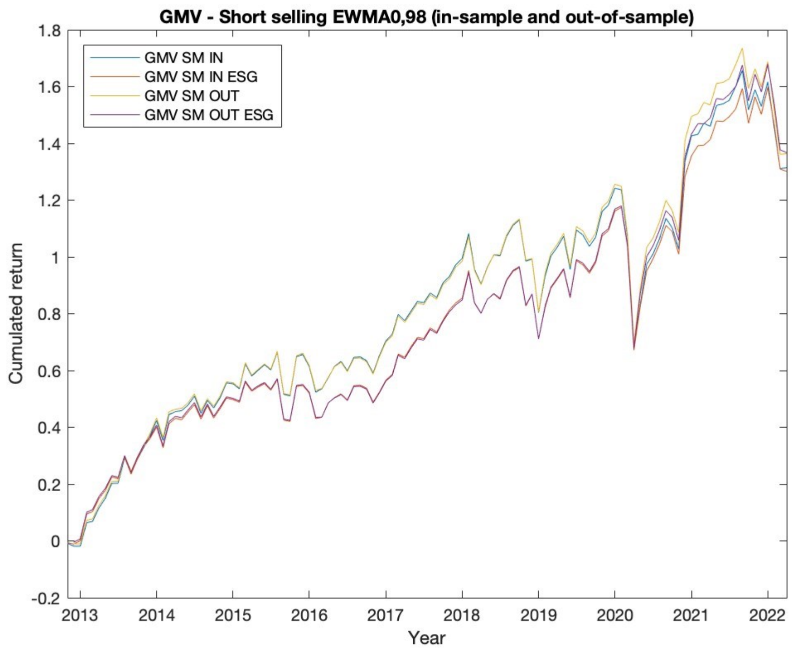



Figure 5.29: Cumulated returns of GMV portfolios - Short Selling strategy using EWMA0.98




Analyzing the Figure 5.28 and Figure 5.29 it's clear as the in-sample and out-of-sample portfolios follow the same path and almost overlap each other's. There is a slight difference in the two paths after the pandemic crisis, because in this period in GMV portfolios there is a difference in the weights of the indexes and it causes a lag of reaction by the out-of-sample portfolios.

The MS portfolios instead have mainly one single stock, the USA Indexes, therefore the pandemic crisis doesn't affect the portfolios composition and doesn't affect the difference across in-sample and out-of-sample evaluation.

Figure 5.30: Cumulated returns of MS portfolios – No Short Selling strategy using EWMA0,95

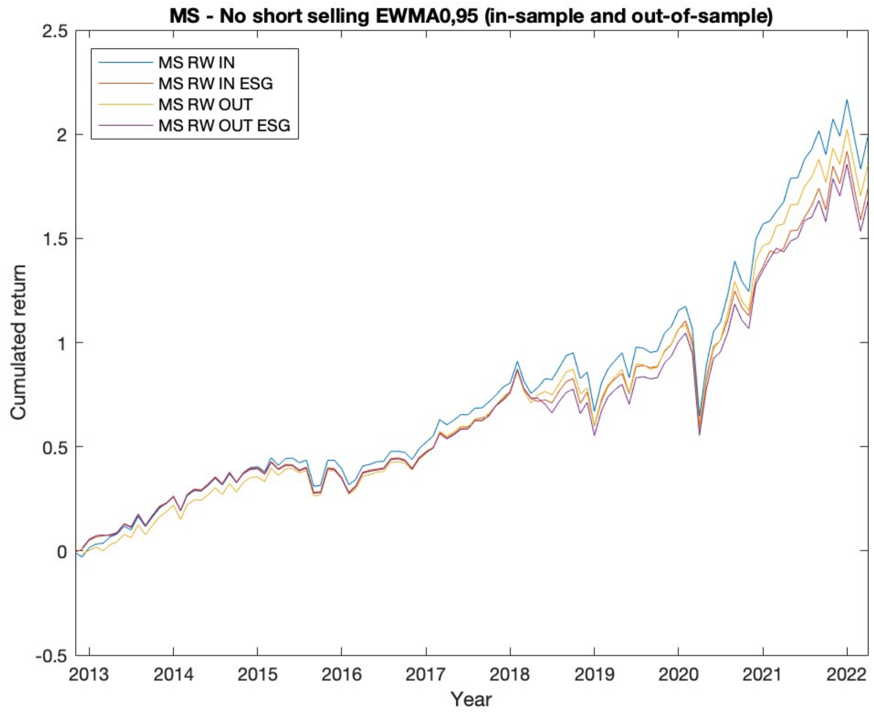
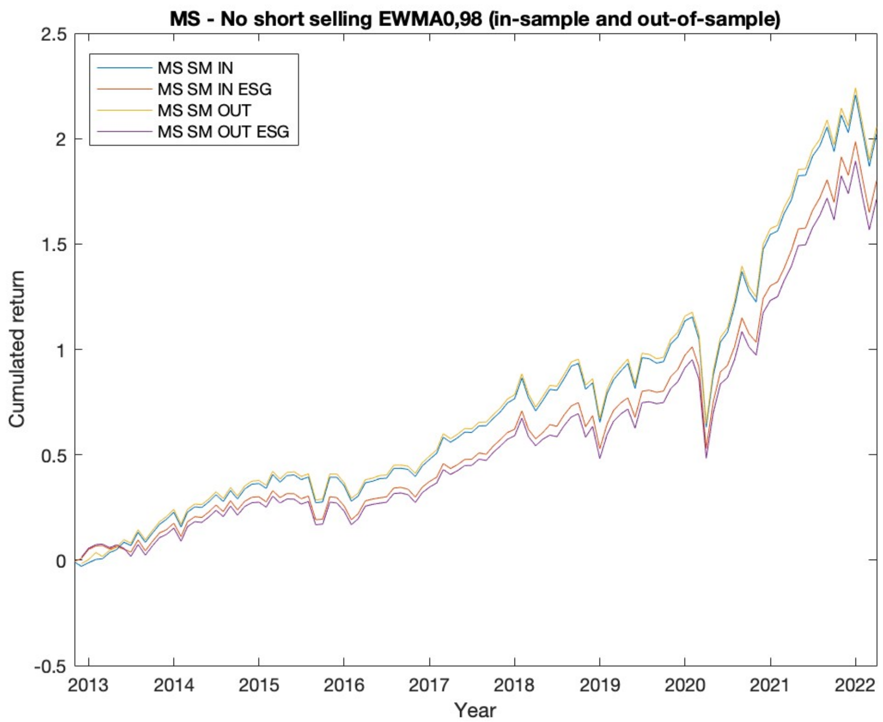



Figure 5.31: Cumulated returns of MS portfolios – No Short Selling strategy using EWMA0,98



What emerges from the comparison among in-sample and out-of-sample evaluation, the Figure 5.30 and Figure 5.31, is their path similarity. This result exhibits the significant positive relation between the theoretical optimal performance and the effective real performance in all the strategies and the methods applied.

# Chapter 6
# Conclusions

In the world of finance sustainable investment is a highly topical and important issue. This new type of investment is considered as a potential solution to ecological and social issues in order to make the financial market more aware of his responsibility in the global economic decisions (Sharma and Talan 2019). The long-term institutional investors incorporate ESG criteria across their portfolio allocation representing trillions of dollars in assets under management (Gibson et al. 2021; USSIF 2020; PRI 2018). The rating agencies for these reasons start to improve their reports on the ESG indicators leading to a development of the ESG score design, which differs among the various rating agencies. In conclusion, the results in this research are in line with the literature results in terms of EFs, period of crisis and overall results.

What emerge in this research regarding the EFs is the shift towards left of the ESG EF with respect to the traditional EF in all the strategies and the methods applied. This particular result is in accordance with the research of Charlo et al. (2015), which explain how the socially responsible investment obtain higher returns in comparison to the traditional investment for the same level of risk. The shift of ESG EFs towards left in comparison to the traditional ones does not necessarily leads to ESG optimal portfolios dominance with respect to the traditional one, but the location of the optimal portfolios varies from case to case.

Moving towards the cumulated percentage returns and performance measure, the results obtained differs across the different methods applied. The traditional MS portfolios overperform the ESG ones in all the strategies and in all the methods, in particular the highest overperformance is for the Sample Moments method, instead it reduces for the RW and both EWMA methods, it reduces also for the Short Selling strategies in comparison to the No Short Selling strategies. The ESG and traditional GMV portfolios have almost the same results, with a slight traditional GMV overperformance, in the Sample Moments case. Analyzing the other methods, RW and both EWMA0.98 and EWMA0.95, there is an ESG GMV portfolios overperformance over the traditional one in all the strategies, with exception of the No Short Selling strategy using EWMA0.98, in particular the overperformance varies in magnitude across the methods and the strategies. The results in terms of GMV portfolios are consistent with what exhibit the research of Melas et al. (2016). The authors explain as many institutional investors investing in ESG assets attempt to lower the risk of their portfolios while keeping to hold equities and their long-term return characteristics. Institutional investors pursuing the minimum volatility strategies in sustainable investment obtain a lower ex-ante portfolio risk, improve the ESG profile of their portfolios while still enjoy an historically significant positive return. The MS portfolios results are in line with the research of the Samanez et al. (2013). They explain how sustainable investments have some interesting characteristics, as increasing in liquidity and reduction in volatility, but they did not achieve a satisfactory financial performance in comparison to the traditional investments.

An important feature that emerges from this research is the comparison on the ESG and traditional portfolios during the downturns and stress periods. In these situations, the ESG portfolios are subjected to a lower downturn in relation to the traditional portfolios. Analyzing the MS portfolios, the traditional portfolio overperformance reduces during the stress periods and higher is the magnitude of the downturn higher is the reduction in the traditional portfolios overperformance. The same concept emerges also for the GMV portfolios, therefore in case of traditional GMV overperformance it reduces during the stress period, instead in case of ESG GMV overperformance it increases during the downturns. In some case, the stress period is the turning point in which the ESG GMV portfolios overperform the traditional one and the overperformance remains constant or continues to increase overtime. For example, the pandemic crisis is the turning point for the ESG GMV portfolios computed with the RW and after this stress period the ESG GMV portfolios overperformance continues to increase slightly over time until the end of the selected period. The results explained are in accordance with the ones obtained by Chen et al. (2021). They exhibit that the SRI portfolio is more robust and prominent than the traditional one during the 2008 and 2015 crisis, in addition they explain that SRI portfolio performs relatively poorly during the recovery period in 2009. According to them the reasons behind these results are related to the assets in the SRI portfolios, that assets have the ability to resist the risk with stable development.

In the section related to the diversification strategy the result that arises is the fact that increasing the portfolio diversification the ESG MS portfolios overperform the traditional one, instead for the GMV portfolios, the ESG GMV portfolios overperformance increase. The result of the MS portfolios is related to the reduction of US indexes weights in the portfolios composition and the increase of the other indexes weights. The other ESG indexes, such as ESG EM Index, ESG EAFE Index and ESG CANADA Index, have a better mean return compared to the other traditional indexes, therefore the increasing of their weights lead to an ESG portfolios performance higher than the traditional one. The results of the GMV portfolios are related to almost the same concepts of the MS portfolios, but in this case the GMV portfolio compositions is already well diversified without one main index, as the US indexes for the MS portfolios, therefore the increase in the portfolio diversification leads to the increase in the ESG GMV portfolios overperformance but with a lower magnitude in comparison to the ESG MS portfolios overperformance. In particular, in the case of minimum investment strategy, the introduction of indexes in the portfolio compositions that were not introduced in the base case, the one without constraints, leads to an increase of the ESG portfolios overperformance more than the case of the upper bound strategy. This result is linked to the mean returns and volatility of the new ESG indexes introduced, which have better moments in comparison to the moments of the same indexes in a traditional form.

However, this study presents some limitations. Future research could aim to examine the portfolios comparison between ESG and traditional portfolios at the country level in order to obtain a different point of view. Other limitations of this study are related to the possible different measure of financial performances and ESG score, which score is subject of debate in the financial literature due to his diversity across different rating providers that use various standards and indicators.

# Appendix

## A. Matlab Code

```
%% 1) SAMPLE MOMENTS METHOD

% loading dataset from the Excel file 'Dati Andrea2'

data = readmatrix('DatiAndrea2','Sheet','Foglio1','Range','B4');
input = readtable('DatiAndrea2','Sheet','Foglio1','Range','A4:A178','ReadVariableNames', false,
'TreatAsEmpty',{'NA'});
input=input(:,1);

% tarnsforming date to datetime format
dM=table2array(input);

% computing monthly returns
rM=((data(2:(size(data,1)),:)./data(1:(size(data,1)-1),:))-1)*100;

% creating labels
lab={'EAFE ESG','EM ESG','USA ESG','CANADA ESG','EAFE','EM','USA','CANADA','ACWI','ACWI ESG'};

% descriptive analysis of returns
Mean=mean(rM)';
Median=median(rM)';
StDev=sqrt(var(rM))';
Min=min(rM)';
Max=max(rM)';
Skew=skewness(rM)';
Kurt=kurtosis(rM)';
TM=table(Mean,Median,StDev,Min,Max,Skew,Kurt,'RowNames',lab);

% storing in Excel the table of the descriptive analyses
writetable(TM,'Dati Andrea2.xlsx','Sheet','Descriptive analysis','Range','C4');


%% 2) STRATEGIC ASSET ALLOCATION
% Evalutation of the Efficient Frontier using SAMPLE MOMENTS METHOD (SM) (Traditional strategy) over the
last t years (2007-2021)
% return of the assets over the last 14 years
r_assets=rM(end-173:end,5:8);
% return of the benchmark over the last 14 years
r_bench=rM(end-173:end,9);
% computing the mean return of the assets (excluding the benchmark) with the sample moments method
MM=mean(r_assets);
figure
bar(1:4,MM) % plotting the returns in a bar chart
set(gca,'Xtick',1:4,'Xticklabel',lab(5:8));
xlabel('Asset');
ylabel('Mean return');
```

```
title('Mean return of assets SM (2007-2022)');


% computing the covariance matrix of the assets with the sample moments method
MV=cov(r_assets);
figure
bar(1:4,sqrt(diag(MV)))
set(gca,'Xtick',1:4,'XtickLabel',lab(5:8));
xlabel('Asset')
ylabel('Standard deviation');
title('Volatilities of assets-SM (2007-2022)')
figure

%% mean and variance of traditional strategy on same figure

% area plots of GMV and MS computed with sample moments
% (No short selling)
subplot(2,1,1)
bar(1:4,MM) % plotting the returns in a bar chart
set(gca,'Xtick',1:4,'Xticklabel',lab(5:8));
xlabel('Asset');
ylabel('Mean return');
title('Mean return of assets SM (2007-2022)');
hold on
subplot(2,1,2)
bar(1:4,sqrt(diag(MV)))
set(gca,'Xtick',1:4,'XtickLabel',lab(5:8));
xlabel('Asset')
ylabel('Standard deviation');
title('Volatilities of assets-SM (2007-2022)')
figure
hold on


%% EFFICIENT FRONTIERS
% computing the 'No short selling' Efficient Frontier
p1=Portfolio;
p1=p1.setAssetList(lab(5:8));
p1=p1.setAssetMoments(MM,MV);

% setting default constraints (no short selling)
p1=p1.setDefaultConstraints;

% plotting the 'No short selling' Efficient Frontier
nport=100;
p1.plotFrontier(nport);
title('No short selling Efficient Frontier-SM (2007-2022)')

% storing risk and return of efficient portfolios
[prisk,pret]=p1.plotFrontier(nport);

% computing the Max Sharpe
pwgtMS = estimateMaxSharpeRatio(p1);
```

```
[prskMS, pretMS] = estimatePortMoments(p1,pwgtMS);
% computing the Minimum Variance Portfolio
pwgtGMV=p1.estimateFrontierLimits('Min');
[prskGMV, pretGMV] = estimatePortMoments(p1,pwgtGMV);
% adding them to the EF
p1.plotFrontier(nport);
hold on
scatter(prskMS,pretMS,'filled','g');
scatter(prskGMV,pretGMV,'filled','m');
legend('EF-SM (2007-2022)','MS','GMV')

% storing weights of the efficient portfolios
pwgt=p1.estimateFrontier(nport);

% drawing weights of the efficient portfolios
figure
area(prisk,pwgt','FaceColor','flat');
ylim([0 1])
xlabel('Risk')
ylabel('Weight')
legend(lab(5:8))
title('Weights of No short selling Efficent Frontier-SM (2007-2022)')

% computing the Unconstrained Efficient Frontier and comparing it with
% the No short selling Efficent Frontier
pUN=Portfolio(p1,'LowerBound',-1);
pUN.plotFrontier(nport);
hold on
p1.plotFrontier(nport)
legend('Unconstrained Efficient Frontier-SM (2007-2022)','No short selling Efficient Frontier-SM (2007-2022)')

% storing risk and return of efficient portfolios
[priskUN,pretUN]=pUN.plotFrontier(nport);
% computing the Max Sharpe
pwgtMSUN = estimateMaxSharpeRatio(pUN);
[prskMSUN, pretMSUN] = estimatePortMoments(pUN,pwgtMSUN);
% computing the Minimum Variance Portfolio
pwgtGMVUN=pUN.estimateFrontierLimits('Min');
[prskGMVUN, pretGMVUN] = estimatePortMoments(pUN,pwgtGMVUN);
% adding them to the EF
pUN.plotFrontier(nport);
hold on
scatter(prskMSUN,pretMSUN,'filled','g');
scatter(prskGMVUN,pretGMVUN,'filled','m');
legend('UN EF-SM (2007-2022)','MS','GMV')

% storing weights of the efficient portfolios
pwgtUN=pUN.estimateFrontier(nport);

% drawing weights of the efficient portfolios
figure
area(priskUN,pwgtUN'.*(pwgtUN'>0),'FaceColor','flat');
hold on
```

```
area(priskUN,pwgtUN'.*(pwgtUN'<0),'FaceColor','flat');
legend(lab(5:8))
xlabel('Risk')
ylabel('Weight')
title('Weights of Unconstrained Efficient Frontier-SM (2007-2022)')

% evaluating the location of the benchmark with respect to the EF
% 'Unconstrained' efficient frontier
return_bench=mean(r_bench);
risk_bench=sqrt(var(r_bench));
pUN.plotFrontier(nport)
hold on
scatter(risk_bench,return_bench,'filled','r')
legend('UN EF-SM (2007-2022)','Benchmark')
figure
% 'No short selling' efficient frontier
p1.plotFrontier(nport);
hold on
scatter(risk_bench,return_bench,'filled','r')
legend('No short selling EF-SM (2007-2022)','Benchmark');
figure

%% Evalutation of the Efficient Frontier  using SAMPLE MOMENTS METHOD (SM) (ESG strategy) over the last
t years (2007-2022)
% return of the assets over the last 14 years
r_assetsESG=rM(end-173:end,1:4);
% return of the benchmark over the last 14 years
r_benchESG=rM(end-173:end,10);
% computing the mean return of the assets (excluding the benchmark) with the sample moments method
MM=mean(r_assetsESG);
figure
bar(1:4,MM) % plotting the returns in a bar chart
set(gca,'Xtick',1:4,'Xticklabel',lab(1:4));
xlabel('AssetESG');
ylabel('Mean return');
title('Mean return of assets ESG-SM (2007-2022)');

% computing the covariance matrix of the assets with the sample moments method
MV=cov(r_assetsESG);
figure
bar(1:4,sqrt(diag(MV)))
set(gca,'Xtick',1:4,'XtickLabel',lab(1:4));
xlabel('AssetESG')
ylabel('Standard deviation');
title('Volatilities of assets ESG-SM (2007-2022)')
figure

%% mean and variance of ESG strategy on same figure

% area plots of GMV and MS computed with sample moments
% S1ESG (No short selling)
subplot(2,1,1)
bar(1:4,MM) % plotting the returns in a bar chart
```

```
set(gca,'Xtick',1:4,'Xticklabel',lab(1:4));
xlabel('Asset');
ylabel('Mean return');
title('Mean return of assets ESG-SM (2007-2022)');
hold on
subplot(2,1,2)
bar(1:4,sqrt(diag(MV)))
set(gca,'Xtick',1:4,'XtickLabel',lab(1:4));
xlabel('Asset')
ylabel('Standard deviation');
title('Volatilities of assets ESG-SM (2007-2022)')
figure
hold on

%% computing the 'No short selling' Efficient Frontier
p1ESG=Portfolio;
p1ESG=p1ESG.setAssetList(lab(1:4));
p1ESG=p1ESG.setAssetMoments(MM,MV);

% setting default constraints (no short selling)
p1ESG=p1ESG.setDefaultConstraints;

% plotting the 'No short selling' Efficient Frontier
nport=100;
p1ESG.plotFrontier(nport);
title('No short selling Efficient Frontier-SM ESG (2007-2022)')

% storing risk and return of efficient portfolios
[priskESG,pretESG]=p1ESG.plotFrontier(nport);

% computing the Max Sharpe
pwgtMSESG = estimateMaxSharpeRatio(p1ESG);
[prskMSESG, pretMSESG] = estimatePortMoments(p1ESG,pwgtMSESG);
% computing the Minimum Variance Portfolio
pwgtGMVESG=p1ESG.estimateFrontierLimits('Min');
[prskGMVESG, pretGMVESG] = estimatePortMoments(p1ESG,pwgtGMVESG);
% adding them to the EF
p1ESG.plotFrontier(nport);
hold on
scatter(prskMSESG,pretMSESG,'filled','g');
scatter(prskGMVESG,pretGMVESG,'filled','m');
legend('EF-SM ESG (2007-2022)','MS-ESG','GMV-ESG')

% storing weights of the efficient portfolios
pwgtESG=p1ESG.estimateFrontier(nport);

% drawing weights of the efficient portfolios
figure
area(priskESG,pwgtESG','FaceColor','flat');
ylim([0 1])
xlabel('Risk')
ylabel('Weight')
legend(lab(1:4))
```

```
title('Weights of No short selling Efficent Frontier-SM ESG (2007-2022)')

% computing the Unconstrained Efficient Frontier and comparing it with
% the No short selling Efficent Frontier
pUNESG=Portfolio(p1ESG,'LowerBound',-1);
pUNESG.plotFrontier(nport);
hold on
p1ESG.plotFrontier(nport)
legend('Unconstrained Efficient Frontier-SM ESG (2007-2022)','No short selling Efficient Frontier-SM ESG (2007-2022)')

% storing risk and return of efficient portfolios
[priskUNESG,pretUNESG]=pUNESG.plotFrontier(nport);
% computing the Max Sharpe
pwgtMSUNESG = estimateMaxSharpeRatio(pUNESG);
[prskMSUNESG, pretMSUNESG] = estimatePortMoments(pUNESG,pwgtMSUNESG);
% computing the Minimum Variance Portfolio
pwgtGMVUNESG=pUNESG.estimateFrontierLimits('Min');
[prskGMVUNESG, pretGMVUNESG] = estimatePortMoments(pUNESG,pwgtGMVUNESG);
% adding them to the EF
pUNESG.plotFrontier(nport);
hold on
scatter(prskMSUNESG,pretMSUNESG,'filled','g');
scatter(prskGMVUNESG,pretGMVUNESG,'filled','m');
legend('UN EF-SM ESG (2007-2022)','MS ESG','GMV ESG')

% storing weights of the efficient portfolios
pwgtUNESG=pUNESG.estimateFrontier(nport);


% drawing weights of the efficient portfolios
figure
area(priskUNESG,pwgtUNESG'.*(pwgtUNESG'>0),'FaceColor','flat');
hold on
area(priskUNESG,pwgtUNESG'.*(pwgtUNESG'<0),'FaceColor','flat');
legend(lab(1:4))
xlabel('Risk')
ylabel('Weight')
title('Weights of Unconstrained Efficient Frontier-SM ESG (2007-2022)')


% evaluating the location of the benchmark with respect to the EF
% 'Unconstrained' efficient frontier
return_benchESG=mean(r_benchESG);
risk_benchESG=sqrt(var(r_benchESG));
pUNESG.plotFrontier(nport)
hold on
scatter(risk_benchESG,return_benchESG,'filled','r')
legend('UN EF-SM ESG (2007-2022)','Benchmark-ESG')
figure
% 'No short selling' efficient frontier
p1ESG.plotFrontier(nport);
hold on
```

```
scatter(risk_benchESG,return_benchESG,'filled','r')
legend('No short selling EF-SM ESG (2007-2022)','Benchmark-ESG')
figure



%% Plot the traditional and ESG EF on same grapth (No short selling EF)
% adding them to the EF
p1.plotFrontier(nport);
hold on
p1ESG.plotFrontier(nport);
hold on
scatter(prskMS,pretMS,'filled','g');
scatter(prskGMV,pretGMV,'filled','m');
scatter(prskMSESG,pretMSESG,'filled','g');
scatter(prskGMVESG,pretGMVESG,'filled','m');
legend('EF-SM (2007-2022)','EF-SM ESG (2007-2022)','MS','GMV','MS-ESG','GMV-ESG');
title('No short selling Efficient Frontiers (2007-2022)')


%% Plot the traditional and ESG EF on same grapth (UN EF)
% adding them to the EF
pUN.plotFrontier(nport);
hold on
pUNESG.plotFrontier(nport);
hold on
scatter(prskMSUN,pretMSUN,'filled','g');
scatter(prskGMVUN,pretGMVUN,'filled','m');
scatter(prskMSUNESG,pretMSUNESG,'filled','g');
scatter(prskGMVUNESG,pretGMVUNESG,'filled','m');
legend('UN EF-SM (2007-2022)','UN EF-SM ESG (2007-2022)','MS','GMV','MS-ESG','GMV-ESG');
title('UN Efficient Frontiers (2007-2022)')




%% 3) MONTHLY TACTICAL CHOICES

% (Traditional Strategy) computing inputs of Markowitz using approaches sample moments approach

rI=rM(:,5:8);      % indexes returns
rB=rM(:,9);         % benchamrk/market return
[r,c]=size(rI);     % row/column dimensions

% window size for estimation
w=60;

% estimation of exptected returns
% loop for sample estimator
% pre-allocation for expected returns computation
```

```
ErS=zeros(w,c);   % sample estimator

   for j=w:r-1    % r-1 as we use data up to r-1 to allocate 1-step-ahead
    % sample estimator
    ErS(j+1-w,:)=mean(rl(1:j,:));

   end

% estimation of covariance
% loop for sample estimator
% pre-allocation for covariance computation
% we have now a three-dimension array!
EvS=zeros(r-w,c,c);     % sample estimator

  for j=w:(r-1)   % r-1 as we use data up to r-1 to allocate 1-step-ahead
    % sample estimator
    EvS(j+1-w,:,:)=cov(rl(1:j,:));
  end

% After having computed the inputs we are going to create 3 different strategies:
% 1) no short selling
% 2) no short selling, transaction costs and turnover constraint
% 3) lower bound
% 3) lower bound, transaction costs and turnover constraint

%% S1: no short selling
% loop for the evaluation of realized returns with sample estimators of
% both expected returns and covariance
% pre-allocation for returns (GMV (columns 1) and Sharpe Ratio (column 2))
PortRetS1=zeros(r-w,2);
% pre-allocation for weights
PortWS1=zeros(2,r-w,c);

% creating portfolio objects
ps1=Portfolio;
ps1=ps1.setAssetList(lab(5:8));
ps1=ps1.setDefaultConstraints; % no short selling constraint

for j=(w+1):r
    ps1=ps1.setAssetMoments(ErS(j-w,:),squeeze(EvS(j-w,:,:)));
    % GMV
    pwgtGMVS1=ps1.estimateFrontierLimits('Min');
    PortWS1(1,j-w,:)=pwgtGMVS1';
    PortRetS1(j-w,1)=rl(j,:)*(pwgtGMVS1);
    % MaxSharpe
    pwgtMS1=estimateMaxSharpeRatio(ps1);
    PortWS1(2,j-w,:)=pwgtMS1';
    PortRetS1(j-w,2)=rl(j,:)*(pwgtMS1);
end

%% S2: No short selling, transactions costs and turnover constraint

% creating portfolio objects
```

```
ps2=Portfolio;
ps2=ps2.setAssetList(lab(5:8));
ps2=ps2.setDefaultConstraints; % no short selling constraint


% adding transaction costs
bc=(0.00125); % buying cost
sc=bc;       % selling cost are equal to buying cost
ps2=setCosts(ps2,bc,sc,1/ps2.NumAssets,4);
% pre-allocation for returns
PortRetS2=zeros(r-w,2);
% pre-allocation for weights
PortWS2=zeros(2,r-w,c);
j=w+1;
ps2=ps2.setAssetMoments(ErS(j-w,:),squeeze(EvS(j-w,:,:)));
% GMV
pwgtGMV=ps2.estimateFrontierLimits('Min');
PortWS2(1,j-w,:)=pwgtGMV';
PortRetS2(j-w,1)=rl(j,:)*(pwgtGMV);
GMV0W=pwgtGMV;
% MaxSharpe
pwgtMS=estimateMaxSharpeRatio(ps2);
PortWS2(2,j-w,:)=pwgtMS';
PortRetS2(j-w,2)=rl(j,:)*(pwgtMS);
MS0W=pwgtMS;
ps2=Portfolio(ps2,'Turnover',0.05);
for j=(w+2):r
  % set moments
  ps2=ps2.setAssetMoments(ErS(j-w,:),squeeze(EvS(j-w,:,:)));
  % GMV
  ps2=Portfolio(ps2,'InitPort',GMV0W);  % set initial portfolio
  pwgtGMV=ps2.estimateFrontierLimits('Min');
  PortWS2(1,j-w,:)=pwgtGMV';
  PortRetS2(j-w,1)=rl(j,:)*(pwgtGMV);
  GMV0W=pwgtGMV;
  % MaxSharpe
  ps2=Portfolio(ps2,'InitPort',MS0W);  % set initial portfolio
  try
    pwgtMS=estimateMaxSharpeRatio(ps2);
    PortWS2(2,j-w,:)=pwgtMS';
    PortRetS2(j-w,2)=rl(j,:)*(pwgtMS);
    MS0W=pwgtMS;
  catch
    p2s=Portfolio(ps2,'Turnover',0.3);
    pwgtMS=estimateMaxSharpeRatio(ps2);
    PortWS2(2,j-w,:)=pwgtMS';
    PortRetS2(j-w,2)=rl(j,:)*(pwgtMS);
    MS0W=pwgtMS;
    ps2=Portfolio(ps2,'Turnover',0.05);
  end
end
```

```
%% S3: Lower bound from second iteration

% adding lower bound to the no short selling portfolio
ps3=Portfolio(ps1,'LowerBound',-0.5);

% pre-allocation for returns
PortRetS3=zeros(r-w,2);
% pre-allocation for weights
PortWS3=zeros(2,r-w,c);
for j=(w+1):r
    % set moments
    ps3=ps3.setAssetMoments(ErS(j-w,:),squeeze(EvS(j-w,:,:)));
    % GMV
    pwgtGMV=ps3.estimateFrontierLimits('Min');
    PortWS3(1,j-w,:)=pwgtGMV';
    PortRetS3(j-w,1)=rl(j,:)*(pwgtGMV);
    % MaxSharpe
    pwgtMS3=estimateMaxSharpeRatio(ps3);
    PortWS3(2,j-w,:)=pwgtMS3';
    PortRetS3(j-w,2)=rl(j,:)*(pwgtMS3);
end

%% S4: Lower bound and turnover constraint from second iteration

% lower bound to the no short selling portfolio
ps4=Portfolio(ps1,'LowerBound',-0.5);

% adding transaction costs
bc=(0.00125); % buying cost
sc=bc;        % selling cost are equal to buying cost
ps4=setCosts(ps4,bc,sc,1/ps4.NumAssets,4);

% pre-allocation for returns
PortRetS4=zeros(r-w,2);
% pre-allocation for weights
PortWS4=zeros(2,r-w,c);
j=w+1;
ps4=ps4.setAssetMoments(ErS(j-w,:),squeeze(EvS(j-w,:,:)));
% GMV
pwgtGMV4=ps4.estimateFrontierLimits('Min');
PortWS4(1,j-w,:)=pwgtGMV4';
PortRetS4(j-w,1)=rl(j,:)*(pwgtGMV4);
GMV0W=pwgtGMV4;
% MaxSharpe
pwgtMS4=estimateMaxSharpeRatio(ps4);
PortWS4(2,j-w,:)=pwgtMS4';
PortRetS4(j-w,2)=rl(j,:)*(pwgtMS4);
MS0W=pwgtMS4; % initial portfolio allocation for period w+2
ps4=Portfolio(ps4,'Turnover',0.1);
for j=(w+2):r
    % set moments
    ps4=ps4.setAssetMoments(ErS(j-w,:),squeeze(EvS(j-w,:,:)));
```

```
  % GMV
  ps4=Portfolio(ps4,'InitPort',GMV0W);  % set initial portfolio
  pwgtGMV4=ps4.estimateFrontierLimits('Min');
  PortWS4(1,j-w,:)=pwgtGMV4';
  PortRetS4(j-w,1)=rI(j,:)*(pwgtGMV4);
  GMV0W=pwgtGMV4;
  % MaxSharpe
  ps4=Portfolio(ps4,'InitPort',MS0W);  % set initial portfolio
  try
     pwgtMS4=estimateMaxSharpeRatio(ps4);
     PortWS4(2,j-w,:)=pwgtMS4';
     PortRetS4(j-w,2)=rI(j,:)*(pwgtMS4);
     MS0W=pwgtMS4;
  catch
     ps4=Portfolio(ps4,'Turnover',0.3);
     pwgtMS4=estimateMaxSharpeRatio(ps4);
     PortWS4(2,j-w,:)=pwgtMS4';
     PortRetS4(j-w,2)=rI(j,:)*(pwgtMS4);
     MS0W=pwgtMS4;
     ps4=Portfolio(ps4,'Turnover',0.1);
  end
end

%% (ESG Strategy) Computing inputs of Markowitz using approaches sample moments approach

rIESG=rM(:,1:4);      % indexes returns
rBESG=rM(:,10);         % benchamrk/market return
[r,c]=size(rIESG);    % row/column dimensions

% window size for estimation
w=60;

% estimation of exptected returns
% loop for sample estimator
% pre-allocation for expected returns computation
ErSESG=zeros(w,c);   % sample estimator

 for j=w:r-1    % r-1 as we use data up to r-1 to allocate 1-step-ahead
  % sample estimator
  ErSESG(j+1-w,:)=mean(rIESG(1:j,:));

 end

% estimation of covariance
% loop for sample estimator
% pre-allocation for covariance computation
% we have now a three-dimension array!
EvSESG=zeros(r-w,c,c);     % sample estimator

 for j=w:(r-1)   % r-1 as we use data up to r-1 to allocate 1-step-ahead
  % sample estimator
  EvSESG(j+1-w,:,:)=cov(rIESG(1:j,:));
 end
```

```
% After having computed the inputs we are going to create 3 different strategies:
% 1) no short selling
% 2) no short selling, transaction costs and turnover constraint
% 3) lower bound
% 3) lower bound, transaction costs and turnover constraint


%% S1ESG: no short selling
% loop for the evaluation of realized returns with sample estimators of
% both expected returns and covariance
% pre-allocation for returns (GMV (columns 1) and Sharpe Ratio (column 2))
PortRetS1ESG=zeros(r-w,2);
% pre-allocation for weights
PortWS1ESG=zeros(2,r-w,c);

% creating portfolio objects
ps1ESG=Portfolio;
ps1ESG=ps1ESG.setAssetList(lab(1:4));
ps1ESG=ps1ESG.setDefaultConstraints; % no short selling constraint

for j=(w+1):r
    ps1ESG=ps1ESG.setAssetMoments(ErSESG(j-w,:),squeeze(EvSESG(j-w,:,:)));
    % GMV
    pwgtGMVS1ESG=ps1ESG.estimateFrontierLimits('Min');
    PortWS1ESG(1,j-w,:)=pwgtGMVS1ESG';
    PortRetS1ESG(j-w,1)=rlESG(j,:)*(pwgtGMVS1ESG);
    % MaxSharpe
    pwgtMS1ESG=estimateMaxSharpeRatio(ps1ESG);
    PortWS1ESG(2,j-w,:)=pwgtMS1ESG';
    PortRetS1ESG(j-w,2)=rlESG(j,:)*(pwgtMS1ESG);
end


%% S2cnb: No short selling, transactions costs and turnover constraint

% creating portfolio objects
ps2ESG=Portfolio;
ps2ESG=ps2ESG.setAssetList(lab(1:4));
ps2ESG=ps2ESG.setDefaultConstraints; % no short selling constraint


% adding transaction costs
bc=(0.00125); % buying cost
sc=bc;        % selling cost are equal to buying cost
ps2ESG=setCosts(ps2ESG,bc,sc,1/ps2ESG.NumAssets,4);
% pre-allocation for returns
PortRetS2ESG=zeros(r-w,2);
% pre-allocation for weights
PortWS2ESG=zeros(2,r-w,c);
j=w+1;
ps2ESG=ps2ESG.setAssetMoments(ErSESG(j-w,:),squeeze(EvSESG(j-w,:,:)));
% GMV
```

```
pwgtGMVESG=ps2ESG.estimateFrontierLimits('Min');
PortWS2ESG(1,j-w,:)=pwgtGMVESG';
PortRetS2ESG(j-w,1)=rIESG(j,:)*(pwgtGMVESG);
GMV0WESG=pwgtGMVESG;
% MaxSharpe
pwgtMSESG=estimateMaxSharpeRatio(ps2ESG);
PortWS2ESG(2,j-w,:)=pwgtMSESG';
PortRetS2ESG(j-w,2)=rIESG(j,:)*(pwgtMSESG);
MS0WESG=pwgtMSESG;
ps2ESG=Portfolio(ps2ESG,'Turnover',0.05);
for j=(w+2):r
   % set moments
   ps2ESG=ps2ESG.setAssetMoments(ErSESG(j-w,:),squeeze(EvSESG(j-w,:,:)));
   % GMV
   ps2ESG=Portfolio(ps2ESG,'InitPort',GMV0WESG);  % set initial portfolio
   pwgtGMVESG=ps2ESG.estimateFrontierLimits('Min');
   PortWS2ESG(1,j-w,:)=pwgtGMVESG';
   PortRetS2ESG(j-w,1)=rIESG(j,:)*(pwgtGMVESG);
   GMV0WESG=pwgtGMVESG;
   % MaxSharpe
   ps2ESG=Portfolio(ps2ESG,'InitPort',MS0WESG);  % set initial portfolio
   try
      pwgtMSESG=estimateMaxSharpeRatio(ps2ESG);
      PortWS2ESG(2,j-w,:)=pwgtMSESG';
      PortRetS2ESG(j-w,2)=rIESG(j,:)*(pwgtMSESG);
      MS0WESG=pwgtMSESG;
   catch
      ps2ESG=Portfolio(ps2ESG,'Turnover',0.3);
      pwgtMSESG=estimateMaxSharpeRatio(ps2ESG);
      PortWS2ESG(2,j-w,:)=pwgtMSESG';
      PortRetS2ESG(j-w,2)=rIESG(j,:)*(pwgtMSESG);
      MS0WESG=pwgtMSESG;
      ps2ESG=Portfolio(ps2ESG,'Turnover',0.05);
   end
end



%% S3cnb: Lower bound from second iteration

% adding lower bound to the no short selling portfolio
ps3ESG=Portfolio(ps1ESG,'LowerBound',-0.5);

% pre-allocation for returns
PortRetS3ESG=zeros(r-w,2);
% pre-allocation for weights
PortWS3ESG=zeros(2,r-w,c);
for j=(w+1):r
   % set moments
   ps3ESG=ps3ESG.setAssetMoments(ErSESG(j-w,:),squeeze(EvSESG(j-w,:,:)));
   % GMV
   pwgtGMVESG=ps3ESG.estimateFrontierLimits('Min');
   PortWS3ESG(1,j-w,:)=pwgtGMVESG';
```

```
    PortRetS3ESG(j-w,1)=rIESG(j,:)*(pwgtGMVESG);
    % MaxSharpe
    pwgtMS3ESG=estimateMaxSharpeRatio(ps3ESG);
    PortWS3ESG(2,j-w,:)=pwgtMS3ESG';
    PortRetS3ESG(j-w,2)=rIESG(j,:)*(pwgtMS3ESG);
end



%% S4cnb: Lower bound, transaction costs and turnover constraint from second iteration

% adding lower bound to the no short selling portfolio
ps4ESG=Portfolio(ps1ESG,'LowerBound',-0.5);

% adding transaction costs
bc=(0.00125); % buying cost
sc=bc;       % selling cost are equal to buying cost
ps4ESG=setCosts(ps4ESG,bc,sc,1/ps4ESG.NumAssets,4);

% pre-allocation for returns
PortRetS4ESG=zeros(r-w,2);
% pre-allocation for weights
PortWS4ESG=zeros(2,r-w,c);
j=w+1;
ps4ESG=ps4ESG.setAssetMoments(ErSESG(j-w,:),squeeze(EvSESG(j-w,:,:)));
% GMV
pwgtGMV4ESG=ps4ESG.estimateFrontierLimits('Min');
PortWS4ESG(1,j-w,:)=pwgtGMV4ESG';
PortRetS4ESG(j-w,1)=rIESG(j,:)*(pwgtGMV4ESG);
GMV0WESG=pwgtGMV4ESG;
% MaxSharpe
pwgtMS4ESG=estimateMaxSharpeRatio(ps4ESG);
PortWS4ESG(2,j-w,:)=pwgtMS4ESG';
PortRetS4ESG(j-w,2)=rIESG(j,:)*(pwgtMS4ESG);
MS0WESG=pwgtMS4ESG; % initial portfolio allocation for period w+2
ps4ESG=Portfolio(ps4ESG,'Turnover',0.1);
for j=(w+2):r
    % set moments
    ps4ESG=ps4ESG.setAssetMoments(ErSESG(j-w,:),squeeze(EvSESG(j-w,:,:)));
    % GMV
    ps4ESG=Portfolio(ps4ESG,'InitPort',GMV0WESG);  % set initial portfolio
    pwgtGMV4ESG=ps4ESG.estimateFrontierLimits('Min');
    PortWS4ESG(1,j-w,:)=pwgtGMV4ESG';
    PortRetS4ESG(j-w,1)=rIESG(j,:)*(pwgtGMV4ESG);
    GMV0WESG=pwgtGMV4ESG;
    % MaxSharpe
    ps4ESG=Portfolio(ps4ESG,'InitPort',MS0WESG);  % set initial portfolio
    try
        pwgtMS4ESG=estimateMaxSharpeRatio(ps4ESG);
        PortWS4ESG(2,j-w,:)=pwgtMS4ESG';
        PortRetS4ESG(j-w,2)=rIESG(j,:)*(pwgtMS4ESG);
        MS0WESG=pwgtMS4ESG;
    catch
```

```
        ps4ESG=Portfolio(ps4ESG,'Turnover',0.3);
        pwgtMS4ESG=estimateMaxSharpeRatio(ps4ESG);
        PortWS4ESG(2,j-w,:)=pwgtMS4ESG';
        PortRetS4ESG(j-w,2)=rIESG(j,:)*(pwgtMS4ESG);
        MS0WESG=pwgtMS4ESG;
        ps4ESG=Portfolio(ps4ESG,'Turnover',0.1);
    end
end


%% TIME EVOLUTION OF THE PORTFOLIO COMPOSITION (Traditional)

% area plots of GMV and MS computed with sample moments
% S1 (No short selling)
subplot(4,2,1)
area(dM(w+1:r),squeeze(PortWS1(1,:,:)),'FaceColor','flat')
datetick('x','mmm-yy')
xlim([dM(w+1) dM(r)])
xlabel('Time')
ylim([0 1])
ylabel('Weight')
title('S1 - GMV')
hold on
subplot(4,2,2)
area(dM(w+1:r),squeeze(PortWS1(2,:,:)),'Facecolor','flat')
datetick('x','mmm-yy')
xlim([dM(w+1) dM(r)])
xlabel('Time')
ylim([0 1])
ylabel('Weight')
title('S1 - MS')
hold on
% S2 (No short selling, transaction cost and turnover constraint)
subplot(4,2,3)
area(dM(w+1:r),squeeze(PortWS2(1,:,:)),'FaceColor','flat')
datetick('x','mmm-yy')
xlim([dM(w+1) dM(r)])
xlabel('Time')
ylim([0 1])
ylabel('Weight')
title('S2 - GMV')
hold on
subplot(4,2,4)
area(dM(w+1:r),squeeze(PortWS2(2,:,:)),'FaceColor','flat')
datetick('x','mmm-yy')
xlim([dM(w+1) dM(r)])
xlabel('Time')
ylim([0 1])
ylabel('Weight')
title('S2 - MS')
hold on
% S3 (Lower bound)
```

```
subplot(4,2,5)
W=squeeze(PortWS3(1,:,:));
area(dM(w+1:r),W.*(W>0),'FaceColor','flat')
hold on
area(dM(w+1:r),W.*(W<0),'FaceColor','flat')
datetick('x','mmm-yy')
xlim([dM(w+1) dM(r)])
xlabel('Time')
ylabel('Weight')
title('S3 - GMV')
hold on
subplot(4,2,6)
W=squeeze(PortWS3(2,:,:));
area(dM(w+1:r),W.*(W>0),'FaceColor','flat')
hold on
area(dM(w+1:r),W.*(W<0),'FaceColor','flat')
datetick('x','mmm-yy')
xlim([dM(w+1) dM(r)])
xlabel('Time')
ylabel('Weight')
title('S3 - MS')
% S4 (Lower bound, transaction cost and turnover constraint)
subplot(4,2,7)
W=squeeze(PortWS4(1,:,:));
area(dM(w+1:r),W.*(W>0),'FaceColor','flat')
hold on
area(dM(w+1:r),W.*(W<0),'FaceColor','flat')
datetick('x','mmm-yy')
xlim([dM(w+1) dM(r)])
xlabel('Time')
ylabel('Weight')
title('S4 - GMV')
hold on
subplot(4,2,8)
W=squeeze(PortWS4(2,:,:));
area(dM(w+1:r),W.*(W>0),'FaceColor','flat')
hold on
area(dM(w+1:r),W.*(W<0),'FaceColor','flat')
datetick('x','mmm-yy')
xlim([dM(w+1) dM(r)])
xlabel('Time')
ylabel('Weight')
title('S4 - MS')
legend(lab(5:8))

%% TIME EVOLUTION OF THE PORTFOLIO COMPOSITION (ESG)

% area plots of GMV and MS computed with sample moments
% S1ESG (No short selling)
subplot(4,2,1)
area(dM(w+1:r),squeeze(PortWS1ESG(1,:,:)),'FaceColor','flat')
datetick('x','mmm-yy')
xlim([dM(w+1) dM(r)])
```

```
xlabel('Time')
ylim([0 1])
ylabel('Weight')
title('S1 - GMV-ESG')
hold on
subplot(4,2,2)
area(dM(w+1:r),squeeze(PortWS1ESG(2,:,:)),'Facecolor','flat')
datetick('x','mmm-yy')
xlim([dM(w+1) dM(r)])
xlabel('Time')
ylim([0 1])
ylabel('Weight')
title('S1 - MS-ESG')
hold on
% S2ESG (No short selling, transaction cost and turnover constraint)
subplot(4,2,3)
area(dM(w+1:r),squeeze(PortWS2ESG(1,:,:)),'FaceColor','flat')
datetick('x','mmm-yy')
xlim([dM(w+1) dM(r)])
xlabel('Time')
ylim([0 1])
ylabel('Weight')
title('S2 - GMV-ESG')
hold on
subplot(4,2,4)
area(dM(w+1:r),squeeze(PortWS2ESG(2,:,:)),'FaceColor','flat')
datetick('x','mmm-yy')
xlim([dM(w+1) dM(r)])
xlabel('Time')
ylim([0 1])
ylabel('Weight')
title('S2 - MS-ESG')
hold on
% S3ESG (Lower bound)
subplot(4,2,5)
W=squeeze(PortWS3ESG(1,:,:));
area(dM(w+1:r),W.*(W>0),'FaceColor','flat')
hold on
area(dM(w+1:r),W.*(W<0),'FaceColor','flat')
datetick('x','mmm-yy')
xlim([dM(w+1) dM(r)])
xlabel('Time')
ylabel('Weight')
title('S3 - GMV-ESG')
hold on
subplot(4,2,6)
W=squeeze(PortWS3ESG(2,:,:));
area(dM(w+1:r),W.*(W>0),'FaceColor','flat')
hold on
area(dM(w+1:r),W.*(W<0),'FaceColor','flat')
datetick('x','mmm-yy')
xlim([dM(w+1) dM(r)])
xlabel('Time')
```

```
ylabel('Weight')
title('S3 - MS-ESG')
% S4ESG (Lower bound, transaction cost and turnover constraint)
subplot(4,2,7)
W=squeeze(PortWS4ESG(1,:,:));
area(dM(w+1:r),W.*(W>0),'FaceColor','flat')
hold on
area(dM(w+1:r),W.*(W<0),'FaceColor','flat')
datetick('x','mmm-yy')
xlim([dM(w+1) dM(r)])
xlabel('Time')
ylabel('Weight')
title('S4 - GMV-ESG')
hold on
subplot(4,2,8)
W=squeeze(PortWS4ESG(2,:,:));
area(dM(w+1:r),W.*(W>0),'FaceColor','flat')
hold on
area(dM(w+1:r),W.*(W<0),'FaceColor','flat')
datetick('x','mmm-yy')
xlim([dM(w+1) dM(r)])
xlabel('Time')
ylabel('Weight')
title('S4 - MS-ESG')
legend(lab(1:4))

%% CUMULATED RETURNS

% w=60;   % window used for estimation

% cumulated returns of the benchmarket
CRrB=cumprod(rB(w+1:end,1)/100+1)-1;
CRrBESG=cumprod(rBESG(w+1:end,1)/100+1)-1;
% cumulated returns of the indexes
CRrI=cumprod(rI(w+1:end,:)/100+1)-1;
% cumulated returns of the strategies (traditional)
CRS1GMV=cumprod(PortRetS1(:,1)/100+1)-1;
CRS2GMV=cumprod(PortRetS2(:,1)/100+1)-1;
CRS3GMV=cumprod(PortRetS3(:,1)/100+1)-1;
CRS4GMV=cumprod(PortRetS4(:,1)/100+1)-1;
CRS1MS=cumprod(PortRetS1(:,2)/100+1)-1;
CRS2MS=cumprod(PortRetS2(:,2)/100+1)-1;
CRS3MS=cumprod(PortRetS3(:,2)/100+1)-1;
CRS4MS=cumprod(PortRetS4(:,2)/100+1)-1;

% cumulated returns of the strategies (conditional)
CRS1GMVESG=cumprod(PortRetS1ESG(:,1)/100+1)-1;
CRS2GMVESG=cumprod(PortRetS2ESG(:,1)/100+1)-1;
CRS3GMVESG=cumprod(PortRetS3ESG(:,1)/100+1)-1;
CRS4GMVESG=cumprod(PortRetS4ESG(:,1)/100+1)-1;
CRS1MSESG=cumprod(PortRetS1ESG(:,2)/100+1)-1;
CRS2MSESG=cumprod(PortRetS2ESG(:,2)/100+1)-1;
CRS3MSESG=cumprod(PortRetS3ESG(:,2)/100+1)-1;
```

```
CRS4MSESG=cumprod(PortRetS4ESG(:,2)/100+1)-1;


% plots
% benchmark
figure
plot(dM(w+2:end),[CRrB CRrBESG])
xlabel('Year')
ylabel('Cumulated return')
hold on
xlabel('Year')
ylabel('Cumulated return')
legend('Benchmark','Benchmark - ESG')

% Strategy 1 (No short selling)
figure
plot(dM(w+2:end),[CRS1GMV CRS1MS CRS1GMVESG CRS1MSESG CRrB CRrBESG])
hold on
plot(dM(w+2:end),CRrB,'LineWidth',2)
hold on
ylabel('Cumulated return')
xlabel('Year')
legend({'GMV ','MS','GMV ESG','MS ESG','Benchmark','Benchmark - ESG'})
title('No short selling')


% Strategy 2 (No short selling, transaction cost and turnover constraint)
figure
plot(dM(w+2:end),[CRS2GMV CRS2MS CRS2GMVESG CRS2MSESG CRrB CRrBESG])
hold on
plot(dM(w+2:end),CRrB,'LineWidth',2)
hold on
ylabel('Cumulated return')
xlabel('Year')
legend({'GMV ','MS','GMV ESG','MS ESG','Benchmark','Benchmark - ESG'})
title('No short selling, transaction cost and turnover constraint')

% Strategy 3 (Lower bound)
figure
plot(dM(w+1:r),[CRS3GMV CRS3MS CRS3GMVESG CRS3MSESG CRrB CRrBESG])
hold on
plot(dM(w+1:r),CRrB,'LineWidth',2)
hold on
legend({'GMV ','MS','GMV ESG','MS ESG','Benchmark','Benchmark - ESG'})
ylabel('Cumulated return')
xlabel('Year')
title('Lower bound')

% Strategy 4 (Lower bound, transaction cost and turnover constraint)
figure
plot(dM(w+1:r),[CRS4GMV CRS4MS CRS4GMVESG CRS4MSESG CRrB CRrBESG])
hold on
plot(dM(w+1:r),CRrB,'LineWidth',2)
```

```matlab
hold on
legend({'GMV ','MS','GMV ESG','MS ESG','Benchmark','Benchmark - ESG'})
ylabel('Cumulated return')
xlabel('Year')
title('Lower bound, transaction cost and turnover constraint')


%% Correlations

% Correlations between returns of traditional benchmark and returns of
% ESG benchmark
corrBench = corrcoef(rB,rBESG)

% Correlations between returns of traditional GMV portfolios and returns of
% ESG GMV portfolios
corrS1GMV = corrcoef(PortRetS1(:,1),PortRetS1ESG(:,1))
corrS2GMV = corrcoef(PortRetS2(:,1),PortRetS2ESG(:,1))
corrS3GMV = corrcoef(PortRetS3(:,1),PortRetS3ESG(:,1))
corrS4GMV = corrcoef(PortRetS4(:,1),PortRetS4ESG(:,1))

% Correlations between returns of traditional MS portfolios and returns of
% ESG MS portfolios
corrS1MS = corrcoef(PortRetS1(:,2),PortRetS1ESG(:,2))
corrS2MS = corrcoef(PortRetS2(:,2),PortRetS2ESG(:,2))
corrS3MS = corrcoef(PortRetS3(:,2),PortRetS3ESG(:,2))
corrS4MS = corrcoef(PortRetS4(:,2),PortRetS4ESG(:,2))


%% PERFORMANCE MEASURES

% returns of the benchmark and of the porfolios
allret=[rB(w+1:end,1) rBESG(w+1:end,1) PortRetS1(:,1) PortRetS2(:,1) PortRetS3(:,1) PortRetS4(:,1)
PortRetS1(:,2) PortRetS2(:,2) PortRetS3(:,2) PortRetS4(:,2)...
    PortRetS1ESG(:,1) PortRetS2ESG(:,1) PortRetS3ESG(:,1) PortRetS4ESG(:,1) PortRetS1ESG(:,2)
PortRetS2ESG(:,2) PortRetS3ESG(:,2) PortRetS4ESG(:,2)];

% Sharpe ratio
pm1=mean(allret)'./sqrt(var(allret))';
% Sortino ratio
s2=zeros(size(allret,2),1);
for j=1:size(allret,2)
    % compute semi-standard deviation
    s2(j)=sqrt(var(allret(allret(:,j)<0,j)));
end
pm2=mean(allret)'./ s2;

% Treynor ration
s3=zeros(size(allret,2),1);
for j=1:size(allret,2)
% compute beta on the Benchmark
%     Y=XB B=Y'/X'=X\Y
%     B=(X'*X)\(X'*Y); B=(Y'*X)/(X'*X);
%     beta=cov(BNCH,Y)/var(BNCH)
```

```
    s3(j)= (((rB(w+1:end,1)-mean(rB(w+1:end,1)))')*(allret(:,j)-mean(allret(:,j))))...
        /((rB(w+1:end,1)-mean(rB(w+1:end,1)))'*(rB(w+1:end,1)-mean(rB(w+1:end,1))));
end
pm3=mean(allret)'./ s3;

% Value-at-Risk
alpha=0.05;
s4=quantile(allret,alpha);
pm4=mean(allret)'./ abs(s4)';

% Expected Shortfall
alpha=0.05;
s5=zeros(size(allret,2),1);
for j=1:size(allret,2)
    % compute conditional mean
    s5(j)=mean(allret(allret(:,j)<quantile(allret(:,j),alpha),j));
end
pm5=mean(allret)'./ abs(s5);

% DrawDown sequence
DD=zeros(size(allret,1),size(allret,2));
for i=1:size(allret,2)
    DD(1,i)=min(allret(1,i)/100,0);
    for j=2:size(allret,1)
        DD(j,i)=min(0,(1+DD(j-1,i))*(1+allret(j,i)/100)-1);
    end
end
s6=max(abs(DD))'*100;
% Calmar ratio
pm6=mean(allret)'./s6;
% Sterling ratio
k=5;
s7=zeros(size(allret,2),1);
for j=1:size(allret,2)
    % average of the largest DD
    [sDDj,~]=sort(abs(DD(:,j)),'descend');
    s7(j)=mean(sDDj(1:k))*100;
end
pm7=mean(allret)'./s7;

% Farinelli-Tibiletti
% settings 1-2 Sortino, 1-3 K3 or Kappa, 1-1 Omega...
p=1;   % upside power
q=2;   % downside power
tau=0;  % threshold
% compute upside and downside partial moments
u8=zeros(size(allret,2),1);
s8=zeros(size(allret,2),1);
for j=1:size(allret,2)
    % compute partial moments
    u8(j)=(mean((abs(allret(:,j)-tau).*(allret(:,j)>=tau)).^p)).^(1/p);
    s8(j)=(mean((abs(allret(:,j)-tau).*(allret(:,j)<tau)).^q)).^(1/q);
end
```

```
pm8=u8./s8;

% summarizing results
allPM=[pm1 pm2 pm3 pm4 pm5 pm6 pm7 pm8];
Tab1=table({'Benchmark';'Benchmark-ESG';'GMV SM-no short selling';'GMV SM-no short selling, trans costs and turnover';'GMV SM-lower bound';'GMV SM-lower bound, transaction cost and turnover';...
    'MS SM-no short selling';'MS SM-no short selling, trans costs and turnover';'MS SM-lower bound';'MS SM-lower bound, transaction cost and turnover'; ...
    'GMV-ESG SM-no short selling';'GMV-ESG SM-no short selling, trans costs and turnover';'GMV-ESG SM-lower bound';'GMV-ESG SM-lower bound, transaction cost and turnover';...
    'MS-ESG SM-no short selling';'MS-ESG SM-no short selling, trans costs and turnover';'MS-ESG SM-lower bound';'MS-ESG SM-lower bound, transaction cost and turnover'},...
    allPM(:,1),allPM(:,2),allPM(:,3),allPM(:,4),allPM(:,5),allPM(:,6),allPM(:,7),allPM(:,8),...
    'VariableNames',{'Strategy' 'Sh' 'So' 'Tr' 'VaR' 'ES' 'Cal' 'Ste' 'FT'});


% storing in Excel the summary table
writetable(Tab1,'DatiAndrea2.xlsx','Sheet','Perfromance measures','Range','C4');
```

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