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Master Thesis

Empirical analysis of ESG score momentum on stock performance

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Abstract

Institutional investors are increasingly implementing non-financial performance into their investment decisions, often referred to as socially responsible investing. This thesis will therefore investigate whether institutional investors can yield a positive alpha by applying an ESG score momentum-based strategy, as such contributing with empirical findings to the inconsistent literature regarding the correlation between ESG score momentum and stock performance.

The authors investigates this relationship by testing two ESG- and pillar-specific score momentum-based strategies, for both the US- and European markets. As such, two portfolios are constructed: a High portfolio for companies with the strongest score momentum, and a Low portfolio for the companies with the poorest score momentum. OLS regressions are applied on the CAPM-, Fama & French three-factor- and Carhart four-factor models, in order to evaluate if parts of the excess return could be assigned to other factors. The findings provide evidence of positive and negative correlation for both a strong and a poor score momentum, respectively, as the strategies yield a significant positive alpha at the 1% statistical level for both the CAPM single-index and the Fama & French multifactor models. A too high degree of uncertainty was associated with the results of the Carhart model regression, which ultimately led the authors to exclude the model from the analysis. Further, the alpha is not particularly contingent to geography, although the magnitude of alpha is greater in Europe compared to that of the US market.

Consequently, the findings both support and contradicts present literature. As such, this thesis contributes to the field of investigation with an additional tool to implement in an institutional investor's investment decision. Furthermore, the empirical findings facilitate a discussion regarding ESG implementation which ultimately might enhance the market efficiency.

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1. Introduction

1.1 Motivation

Today’s capital markets are characterized by an increased focus on companies’ non-financial performance, emphasizing enhanced attention towards environmental, social and governance (ESG) impacts. Socially responsible investing (SRI) includes the impact of an investment on matters such as sustainability and ethicality, to name a few (Corporatefinanceinstitute.com, 2021). SRI has therefore become an essential part of the financial universe, as it has shown that the market capitalization of a company no longer consists solely of financial performance, but also of other non-financial factors driven by ESG.

The increased research and media-attention has enhanced both stakeholders’ knowledge of and attention towards such matters, hence their expectation of ESG-related operations and investments have increased. Governments worldwide have further developed regulations in this regard, increasing companies’ incentives towards a more sustainable path of conducting business.

As such, the investment policies of institutional investors have changed in line with the ESG-focus. The European market is considered the world leader on ESG-mandated assets, illustrated by 45% of total assets under management is operating under ESG-mandate, making up USD 12.89 trillion (EFAMA, 2021). Deloitte Center for Financial Services (DCFS) believe that the ESG-mandated assets in the US market consist of 25%, making up USD 12 trillion, and will increase by more than three times than non-ESG-mandated assets by 2025 (Deloitte, 2020). The development within ESG-mandated assets emphasizes the increased focus on SRI. The abovementioned impact was exemplified as Larry Fink, the CEO of one of the world’s largest asset managers Blackrock, who in his annual CEO letter in 2021 stated that the company would avoid investments characterized by a “high sustainability risk”, and referred to companies with a high ESG-profile to be enjoying a “sustainability premium”, indicating that their sustainable investment strategy is economically motivated (Fink, 2021).

ESG-scores have developed into a generally accepted criteria in the process of evaluating the non-financial performance of a company, as they serve as a proxy of a company's environmental, social, and governance performance. The scores are calculated on numerous parameters which describe both the qualitative and quantitative impact of ESG-related risks. However, as there is no universal standard for non-financial reporting or one sole score provider for every company, there is a certain degree of subjectiveness related to ESG scores. Even though there has been a considerable increase in sustainable investments and research within this field, scholars provide ambiguous results, as some findings indicate a clear positive correlation, while others suggest either a neutral or negative correlation (Friede, Busch, & Bassen, 2015) (McWilliams & Siegel, 2001) (Hong & Kacperczyk, 2007).

The motivation for researching the ESG score momentum-effect on stock returns is that it might provide investors with useful insight into equity market reactions in relation to new ESG information, rather than solely financial characteristics, as it might be a correlation present. Further, the potential findings will have an applied influence as trillions of USD are under asset management incorporating ESG strategies, as it might assist investors with their investment decision process (Baker, 2020).

Ambiguine literature on the subject of ESG and lack of non-financial reporting transparency adds further complexity to the future investment strategies for investors and stakeholders, as evaluating the materiality of future ESG-related risks of a company becomes difficult. As such, this thesis' aim is to obtain clarity in whether there is a relationship between ESG score momentum and stock return performance. Further, such literature in relation to specific pillar scores is scarce, hence this thesis will include each specific ESG pillar in the analysis.

In addition, the authors will investigate whether these effects materialize differently based on geography. As Europe has been at the forefront of the global overall ESG development (Pham & Msika, 2019), the authors find it interesting to evaluate how the investors react to non-financial company information, such as ESG scores provided by the rating agencies. Further, the US market is the preferable comparison as it is the world leading financial market and has experienced a strong overall ESG development throughout the last 10-15 years (Nason, 2020). As such, the authors can compare effects between two of the worlds most well-developed and important financial markets.

1.2 Problem statement

The objective of this thesis is to evaluate the hypothesis that investors can predict stock price behavior by analyzing company-specific ESG performance. As such, this thesis will study the impact of ESG score-momentum on the stock price and evaluate if it carries a significant alpha within the stock returns. This will be done by constructing portfolios with the strongest and poorest performers in terms of change in ESG- and pillar-specific scores for the US- and European market and analyze their returns. In addition, we examine whether the returns are attributable to other factors such as size- and value factors of (Fama & French, 1992) and momentum of (Carhart, 1997).

For that reason, this thesis will research the following problem statement:

"Can an investor yield positive alpha by applying an ESG score momentum-based trading strategy, and is this strategy applicable for the underlying pillar scores?"

In order to accurately answer the problem statement, this thesis will answer the following four research questions:

Q1. "Is there a positive alpha associated with companies holding strong or poor score momentum?"

Q2. "Is the momentum-effect on alpha more notable for any particular pillar scores?"

Q3. "Is the alpha more notable in Europe than in the US?"

Q4. "Does the momentum strategy yield an alpha, beyond the Fama & French and Carhart multifactor models?"

1.3 Research perspective

This thesis will make use of a critical rationalistic and an objective epistemological approach in order to answer the abovementioned problem statement. Such a rationalistic method builds on classical rationalism where knowledge and scientific recognition is achieved through empirical tests of theoretical hypothesis´.

The objective epistemological approach is based upon validity, as both the problem statement and analysis are conducted on objective results from the observable field of investigation. Therefore, ensuring that the authors will obtain an objective perspective by solely being confined with the collected observable data. Further, the authors will make use of the deductive approach as the problem statement will investigate the relationship between company stock return performance and non-financial ESG data. This thesis is conducted upon thoroughly explained data, which increase the reliability of the thesis in order to facilitate further research based on this thesis' findings (Presskorn-Thygesen, 2021).

1.4 Structure

This thesis is divided into five parts. The first part will both introduce the area of investigation and formulate a problem statement on the basis of the hypothesis stated above (section one). To give the reader a good understanding of the relationship between the financial- and stock return performance and ESG, the second part consists of literature review of the most prominent research conducted on this field of investigation (section two). Part three describes the relevant theory as well as the methods applied for the analysis of our results (section three to five). The fourth part will address and discuss the empirical results from the analysis (section six and seven). In the last part, this thesis will conclude on the findings (section eight) as well as reflect on potential fields for future research (section nine).

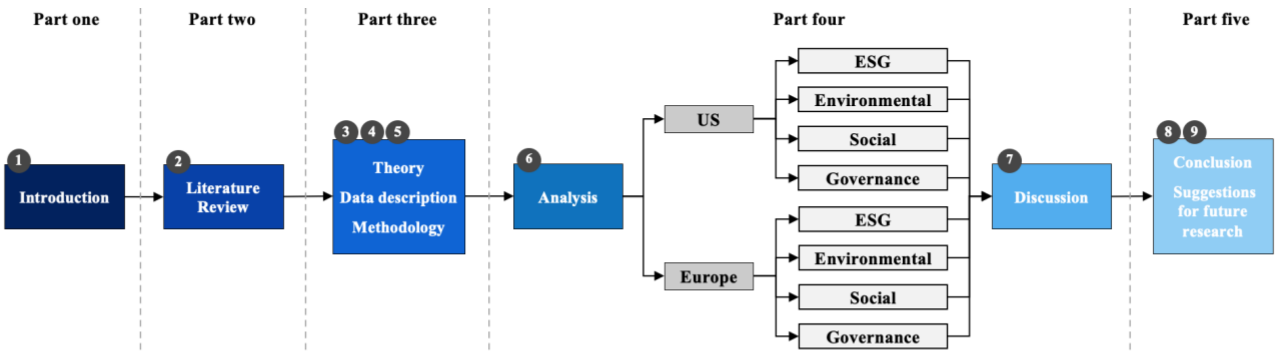

Illustration 1 - Structure. Source: Own construction

2. Literature review

2.1 Environmental, Social and Governance

For the last couple of decades, the focus towards socially responsible investing (SRI), also known as sustainable investment, has gained popularity as investors now incorporate non-financial performance to their set of criteria's within their investment decision process. The non-financial investment decisions are based on an ESG framework which is divided into environmental-, social- and governmental pillars and is used by stakeholders to evaluate the sustainability of their investment as well as the materiality of the future risks and opportunities related to it.

The UN Principles for Responsible Investment (PRI) is the world's leading organization of responsible investing. From 2010 to 2020 the number of investors who have implemented their principles has grown from 740 to 3,000, which includes USD 103 trillion under management (PRI, 2020). PRI helps institutional investors to implement six voluntary principles to facilitate socially responsible investing. As such, companies have to improve their transparency on disclosing their ESG-profiles in order to enhance their attractiveness, as many institutional investors operate under PRI and other strict ESG-mandates.

Most investors rely on ESG-related research from third party providers such as MSCI, Bloomberg, Thomson Reuters and Refinitiv, where the former is considered the leading provider within this area (Phillips, 2020, p. 6). The number of such providers is an indication of the growing demand for non-financial information related to companies' environmental, social and governmental measures.

Despite the increased focus on ESG-related measures, the results from Russell Investments ESG survey for 2020 found that only 22% of their respondents have portfolio performance measures with direct ties to ESG – scores. This survey study 400 asset managers from around the globe, varying from hedge fund managers to private market strategists where 75% of the participants are PRI signatories. The survey finds that despite today's ESG-hype, the main focus is financial performance. By incorporating ESG-related performance, investors can to some degree hedge against future risks as well as partake in opportunities of this kind. As such, ESG scores can be utilized for both positive and negative screening of companies (Phillips, 2020).

This survey implies that ESG-measures has been implemented into investors' risk-return equation, as environmental, social and governance factors might become material. It is noted that there is a considerable difference between the US- and the European market, as the survey finds that US investors don't operate with SRI to the same degree as European investors (Phillips, 2020).

Another survey published by the CFA Institute on socially responsible investing finds that 82% of their participants view ESG information material for financial performance, where there is a distinct difference between US- and European investors. 22% of US investors view ESG information as non-material, compared to 4% of European investors (Amel-Zadeh & Serafeim, 2018, p. 92). According to the research paper, most investors implement ESG information in valuation models[1] and negative portfolio screening[2], rather than positive[3]. The research found that US investors are less likely to implement ESG information in their investment strategies other than in screening, which is consistent with their concern regarding data reliability, as a screening strategy would need the least substantial amount of ESG data (Amel-Zadeh & Serafeim, 2018, p. 94).

Investors have a rather bilateral perception of ESG investments, as they await a clear correlation between ESG- and financial performance. Fundamental economic theory implies that the management's main responsibility is to maximize a firm's value, and therefore the benefit of SRI implementation must exceed the cost to become compliant to the shareholders (Friedman, 1970). The more resent SRI research implies improved financial performance as a result of SRI implementation, which forms the basis of this thesis (Friede, Busch, & Bassen, 2015).

[1] Integration of ESG information in valuation models implies that ESG factors are implemented into a traditional financial valuation of equities (Amel-Zadeh & Serafeim, 2018, p. 94).
[2] Negative screening implies the exclusion of certain equities that are below a pre-determined ESG criteria (Amel-Zadeh & Serafeim, 2018, p. 94).
[3] Positive screening implies the inclusion of certain equities that are above or contain a pre-determined ESG criteria (Amel-Zadeh & Serafeim, 2018, p. 94).

2.2 ESG momentum

The proposed momentum-based trading strategy is rooted in the research on the financial impact of a company's ESG-related measures. As the following literature on ESG scoring presents, a higher ESG score is an indication of a better ability to face future ESG-related risks as well as enhanced financial performance, which in turn should be reflected in the stock price after new ESG-related information is absorbed by market participants.

In 2015 (Nagy, Kassam, & Lee, 2015) found that an ESG momentum-based trading strategy outperformed their benchmark (MSCI World Index) by 2.2% annually from 2007 to 2015. Furthermore, the research found that a large part of the excess risk was due to idiosyncratic risk, i.e. could be attributable to ESG signals. In addition, the researchers found that the ESG momentum-based strategy outperformed the ESG tilt strategy, which instead based its portfolio constituents on score level rather than change in score (i.e. momentum).

(Tsai & Wu, 2021) found that improvement in overall Corporate Social Responsibility is value enhancing. Further, during a crisis, improvement in the CSR dimension such as environmental, human rights and product characteristics were particularly determinantal drivers of higher financial returns.

A study by (Chen & Yang, 2020) demonstrates a pattern of investor exaggeration to corporate ESG information resulting in ESG momentum effects. The research found optimistic responses to higher ESG scores and negative when the scores were lower. Moreover, the researchers found the most significant overreaction to environmental factors rather than social and governance. As such, these overreactions showed to facilitate significant short-term profits by implementing an ESG momentum-based strategy.

In relation to companies' ESG disclosure, (Fatemi, Glaum, & Kaiser, 2017) found that ESG disclosure itself decreases firm value, but also "*(...) that disclosure plays a crucial moderating role by mitigating the negative effect of weaknesses and attenuating the positive effect of strengths."* (Fatemi, Glaum, & Kaiser, 2017, p. 45). Further, the authors continue to address reporting as a tool that can be used to achieve a positive company related ESG bias. The voluntary disclosure theory by Verrecchia (1983) and Dye (1985), amongst others, argues that companies with enhanced ESG performance chooses to a greater extent report on their initiatives. When the ESG performance is decreasing, the company chooses to minimize the reporting on its activities. As such, it's inferred that companies seek to distance themselves from bad ESG performers.

Empirical evidence on whether ESG disclose enhances or decreases firm value is contradicting. Research from de (de Villiers & van Staden, 2011) and (Ho & Taylor, 2007) suggests a negative relationship while others such as (Clarkson, Fang, Li, & Richardson, 2013) found it to be positive.

2.3 ESG and financial performance

There has been conducted empirical research on the correlation between ESG investments and corporate financial performance based on the overall ESG- and individual pillar scores. These findings show contradicting evidence of whether the correlation is positive, neutral or negative (Halbritter & Dorfleitner, 2015).

2.3.1 Positive correlation

Several recent studies argue that there is a positive correlation between ESG related measures and corporate financial performance. Strategies that have shown positive correlation is both portfolio and non-portfolio studies, where ESG investments outperform the market. Friede et al. (2015) conducted a research on 2,200 empirical studies, and the results show that there is a positive correlation between ESG measures and corporate financial performance, which have been stable since mid 1990s. The results indicate that investors should consider including ESG investments in their risk-return equation as empirical studies argue that the measures have a substantial positive financial effect (Friede, Busch, & Bassen, 2015). Further, a study conducted by (De & Clayman, 2015) identified a significant negative correlation between ESG ratings and stock volatility, indicating that investors could increase their risk-adjusted return by implement best-in class ESG stocks.

2.3.2 Neutral correlation

Other studies are yet to find either a positive or negative correlation between ESG investing and financial performance. This is in line with the efficient market theory, where companies' expected return is based on their risk profile, hence companies investing in ESG measures should not yield a higher expected return compared to other companies with the same risk profile. An empirical study conducted by (McWilliams & Siegel, 2001) found that companies who invest in ESG measures will equalize their additional revenue with the related cost, hence the equilibrium will remain neutral. The results are substantiated by the study conducted by (Utz & Wimmer, 2014) who studied the financial performance of sustainable investment funds and regular mutual funds and found that SRI funds neither under- or overperformed, hence they concluded the study with a neutral correlation.

2.3.3 Negative correlation

Neo-classic theory suggests that investing in ESG measures would lead to an additional cost, which would have a negative impact on the financial performance (Aguilera-Carcuel & Duque-Grisales, 2019). A research conducted by Hong et. al (2007) highlights this through a study on sin-stocks, which are defined as *"publicly traded companies involved in the production of alcohol, tobacco and gaming"* (Hong & Kacperczyk, 2007, p. 16). The research found that investors who followed social norms that avoid sin-stocks would be affected by an additional cost. The sin-stocks would be traded at a discount, whereas non-sin-stocks would be traded at a premium, which implies that the stocks are under- and overvalued, respectively, indicating a negative correlation between ESG and financial performance (Hong & Kacperczyk, 2007).

2.4 Impact of individual ESG pillars

As mentioned, the neoclassic economic approach suggests that investing in ESG will generate an additional cost for a company, although resent research is yet to reach a consensus on how ESG and its pillars respectively affect a company's financial performance (Aguilera-Carcuel & Duque-Grisales, 2019, p. 319). A company's non-financial performance is hard to determine, hence it is challenging to assess their impact on the financial performance, which is why the ESG-scores are used as proxies.

2.4.1 Environmental

The evaluation of a firm's business measures towards environmental responsibility and its effect on financial performance has been covered by earlier research through case studies observing how the stock price of a company has been affected by environmental-related company news. (Aguilera-Carcuel & Duque-Grisales, 2019, p. 321). Naturally, positive environmental-related news has affected the stock price positively, and consequently a negative announcement has affected the stock price negatively (Grand Conte & D´Elia, 2005). Although today's view is that high environmental performance will increase the corporate financial performance, modern research has presented evidence of the contrary, which underlines comprehensiveness of the environmental aspect of corporate operations (Klassen & Corbett, 2006).

Non-financial proxies related to the environmental pillar follow a framework which can be hard to separate from other corporate metrics. The financial performance may be caused by both external factors and corporate measures other than what is included in the environmental pillar, such as low efficiency or bad internal processes. In the case of the latter, efficient internal processes aiming at higher profitability can consequently affect environmental factors such as pollution and dumping of toxic waste. A case study by (Klassen & Mclaughlin, 1996) observed that the first-time announcement of positive environmental achievements has the strongest positive impact on stock price, whereas a negative announcement consequently led to an opposite effect.

Another case-study of the effects of the environmental pillar was conducted by (Derwall, 2004) which consisted of eco-efficient portfolios from the US market extending from 1997-2003. The portfolio consisting of the most eco-friendly companies outperformed the poorest-performing portfolio with approximately 6% per annum, implying that environmental considerations can be significant. (Galema, Plantiga, & Scholtens, 2008) further argues that most investors use the Fama & French regression model to analyze the risk involved in the return of an investment. The study argue that an outperformance can be hard to detect, as a high environmental performance will decrease the book-to-market value, which consequently leads to that the model alpha might not detect the SRI measures.

2.4.2 Social

(Capon, Farley, & Hoenig, 1990) conducted a research of more than 300 studies, which include the correlation between social governance- and financial performance. As the research found a positive correlation between strong social governance- and financial performance, other individual studies contradict the results, as some indicate negative or no correlation (Arlow & Gannon, 1982) and (Klassen & Mclaughlin, 1996).

Friedman presented his view that the social pillar is an unnecessary measure which he considered as a donation from the shareholders to their stakeholders which would decrease the financial performance of a company (Friedman, 1970). More recent literature suggests that the social impact of a company can create potential future value, further arguing that companies should implement all stakeholders into their business decisions (Freeman, 1984). (McWilliams & Siegel, 2001) on the other hand argued that there is a neutral relationship between SRI and the financial performance of a company.

Another study regarding the social pillar is (Edmans, 2011), who conducted a research on (Levering, Moskowitz, and Katz, 1984; Levering and Moskowitz, 1993) who studied the link between stock performance and employee satisfaction. Edmans' results indicate a positive correlation creating a significant alpha between the employee satisfaction and historical stock return, which emphasizes the advantage of a positive social pillar screening.

Research conducted by (Dumitrescu & Zakriya, 2021) investigated the implication of corporate social responsibility initiatives on stock price crash risk. In relation to CSR, the research aimed at initiatives towards stakeholders such as employees, customers, suppliers and the community. The paper lays forward the view that risk measures such as volatility and market covariance does not capture the true downside risk to which a shareholder is exposed, hence the paper derives its crash risk from its outliers. As such, the findings were that the impact from firm-specific bad news mainly is determined by the social dimension. The inconsistent empirical results from the social impact on financial performance might be caused by a lack of theory which connects SRI to financial performance.

2.4.3 Governance

Throughout the last couple of decades, numerous corporate scandals have resulted in increased the corporate governance focus of investors, as transparency and responsibility has become essential when assessing whether to invest in a company (Renneborg, Horst, & Zhang, 2007). In terms of data reliability, the extent of governmental data collection as well as the degree of classification- and criteria acceptance of such surpasses that of the environmental and social dimension (Tang, 2019). As such, suggesting greater transparency and stronger reliance on company information on governance measures.

Empirical studies show that there is a positive correlation between corporate governance and firm value (La Porta, Lopez-De-Silanses, Shleifer, & Vishny, 2002). Research presented by (Gompers, Ishii, & Metrick, 2003) suggests a positive relationship between strong corporate governance and corporate financial performance. The research, which studied 1,500 companies during the 1990s, found that a long-term strategy involving going long in companies with strong shareholder rights and short companies with weak shareholder rights would earn a return of 8.5% per annum.

(Cremers & Nair, 2005) further develops (Gompers, Ishii, & Metrick, 2003)'s theory by analyzing the connection between governance mechanisms and stock returns. They found that a similar long-short strategy on equities with strong corporate governance generates an abnormal return of 10-15% pa. ranging from 1990-2001. As such, further emphasizing a positive correlation between governance pillar scores and corporate financial performance (Renneborg, Horst, & Zhang, 2007).

(Bauer, Gunster, & Otten, 2003) study finds that corporate governance increases investor trust as well as resulting in higher expected future cash-flow. Bauer further identifies that governance standards stay persistent across time, sectors and varies strongly depending on country law. Investor trust can be related to a company's reputational cost, which (Klein & Leffler, 1981) investigated through an empirical study, arguing that reputational costs are substantial for companies which lack safety and proper financial representation. Other empirical studies argue that the reputational costs exceed the potential fees that governments can impose as a response to company wrongdoings by more than seven times (Karpoff, Lott Jr., & Wehrly, 2005).

On the other hand, (Parigi, Pelizzon, & von Thadden, 2014) studied the impact of corporate governance matters on stock price returns and found that the strictness of corporate governance had a negative impact on company earnings (Parigi, Pelizzon, & von Thadden, 2014, p. 1). As such, suggesting higher stock returns for companies with looser corporate governance policies. Further, the researchers found a positive relationship between the level of strictness and stock systematic risk.

2.5 Geographical dependent ESG effect

Recent literature suggests that there are different geographical differences regarding the effect of ESG measures and corporate financial performance, although these show ambiguous and at times contradicting results (Schröder, 2007). As mentioned, (Friede, Busch, & Bassen, 2015) conducted a research of more than 2.000 empirical studies which identified inconsistent sub-effects in different regions from the correlation between ESG measures and corporate financial performance. The study finds that North America show a positive correlation share of 42,7%, compared to developed markets in Europe who had a positive share of 26,1%.

The study conducted by (Cunha, et al., 2019) finds that there is a substantial difference between the impact of ESG measures on stock return in US compared to Europe. The research compares sustainable indices to the market, and both regions experienced excess risk-adjusted returns by investing in a particular sustainable index, and found that the US market experience a greater alpha.

2.6 ESG disclosure

Although regulators have begun enacting measures to increase transparency of ESG disclosures, no mandatory requirements of this sort are yet carried out. As such, in terms of non-financial reporting, there are indications of differences in level of ESG disclosure between the US and Europe.

For instance, there are no mandatory disclosure requirements for US listed companies as of today. A proposal for ESG disclosure requirements has been approved by the House of Representatives, but has yet to reach the floor of the House (Clarkin, Sawyer, & Levin, 2020). As a result of this, several independent standard-makers have emerged in order to meet investor demands. Two of the most accepted frameworks are Sustainability Accounting Standards Board ("SASB") and Task Force on Climate-Related Financial Disclosures ("TCFD"), although they do not address the same cross-sections or weights of material matters. As a result of the lack of transparency, the market practice in the US has shown to be defined by these independent standard-makers.

Up until 2015, this was also the case for the European market. EU's directive on disclosure of non-financial information first introduced in late 2014 lays down rules on non-financial disclosure for certain companies of larger market capitalization (Camilleri, 2015). These rules are set in order to assist investors to better evaluate risks and materiality of environmental, social and governance matters.

In relation to the level of ESG disclosure, (Grewal, Riedl, & Serafeima, 2018) conducted a study on the market reaction to events associated with the passage of the abovementioned EU directive for non-financial disclosure. The study found (1) a negative reaction to these events, (2) a less negative reaction to companies with high "predirective" ESG performance and (3) a less negative reaction from investors to companies with high "predirective" level of disclosure (Grewal, Riedl, & Serafeima, 2018, s. 1). As such, laying forward investor's perception of the net costs associated with companies with weak non-financial performance, and vice versa.

Further, (Yu, Van Luu, & Chen, 2020) studied the lack of ESG disclosure, which they found could facilitate companies to reduce their risk related to low ESG scores by influencing the institutional investors and the public narrative through greenwashing. Greenwashing involves disclosing a great amount of ESG data which underlines the positive impacts and therefore distract underlying poor ESG performance, which eventually will lead to misleading reporting.

2.7 Divergence of ESG scores

As earlier mentioned, ESG rating providers utilize different sets of criteria when scoring. As a result of this, company scores can diverge between the different providers. (Berg, Koelbel, & Rigobon, 2020) conducted a study on these divergences and found the average score correlation amongst six of the most prominent providers to be 0.54, suggesting a low level of consistency between different scoring issuers. Further, the researchers found that these issuers differ more in scope and measurement than weighting, which emphasizes the lack of transparency.

Further, research conducted by (Doyle, 2018) found an inherent bias in ESG scoring to companies with higher market capitalization, area and industry/sector, hence undermining disclosure transparency. In addition, the research found the limitations of disclosure and lack of standardization of non-financial performance to be a determinant for scoring divergencies as providers are left with making assumptions which further adds to the subjectiveness of ESG scoring.

2.8 Market capitalization effects

Both the S&P 500 and S&P Europe 350 consist of companies with a high market capitalization. Literature on this subject suggests that companies with a large market capitalization (>USD 10 bn) tends to receive a greater media attention, naturally enhancing the companies' focus on both positive and negative ESG-related measures. The attained media attention might affect the ESG scores for companies with higher market capitalization compared to companies with a mid (USD 2 – 10 bn)- and small (<USD 2 bn) market capitalization (Fang & Peress, 2009)**.** That said, scholars found that ESG has a higher explanatory degree for small- and mid-cap companies compared to large (De & Clayman, 2010).

Media attention has a high influence on investors ESG perception, which might affect the return of the stock greater than the actual change in ESG scores, such as the ones provided by Refinitiv (Refinitiv, 2020, s. 14). Further, Refinitiv conducted a research which found that there is a high positive correlation between ESG scores and market capitalization, as companies with high market capitalization typically have the financial opportunity to address ESG related measures (Borokova, 2020).

3. Theory

3.1 Financial market theory

By presenting some of the most fundamental frameworks and concepts of financial market theory the reader is provided with insights into the mechanics and behavior of equity markets. As conceptual frameworks such as Modern Portfolio Theory (MPT) and the Capital Asset Pricing Model (CAPM) are heavily imbedded in the most traditional investment strategies of today, a brief presentation is provided to assist in the understanding of this paper's analysis and findings. In addition, the multifactor models introduced by (Fama & French, 1992) and (Carhart, 1997) are included to add further debt to the analysis.

3.2 Modern portfolio theory

Modern portfolio theory (MPT) is a conceptual framework that describes a method of allocating assets in order to maximize a portfolio's expected return given the investors level of risk preferences.

Markowitz' normative theory was built on a set of assumptions that today's modern portfolio theory has adapted even though they have been widely challenged. Two of the most significant key assumptions are that 1) Investors are rational, meaning that they seek to maximize returns while minimizing risk (mean-variance optimizing) (Munk, 2019, p. 197) and 2) the expected utility maxim (the investor makes choices based on what gives the highest expected value of utility) (Munk, 2019, p. 230). This concept of risk and return trade-off refers to the perception that investors require higher expected return for a higher level of risk. By using statistical properties such as return standard deviation and variance to define financial risks of an isolated security or a portfolio, the concepts of systematic and unsystematic risk was introduced – both assumed in MPT to be inherent in all portfolios (Markowitz, 1959). As systematic risk is considered as the market risk (and therefore undiversifiable), the unsystematic risk is company-specific risk and can, according to Markowitz, be eliminated through diversification. The term diversification refers to the relationship between correlation of a portfolio's securities and the risk of the portfolio itself, where the idea is that by investing in several different securities with low degree of correlation the investor can expect higher returns and minimize risk (Markowitz, 1959).

The Efficient Frontier is another key concept by Markowitz which describes the relationship between the expected return and risk of a portfolio. It is typically illustrated by plotting each portfolio by expected return and level of risk where all mean-variance efficient portfolios (portfolios with maximum expected return for a specific level of risk) forms what is called a hyperbola that is the Efficient Frontier of risky assets. This shows how an investor can by looking at the securities' correlation maximize their portfolio's expected return given their risk preferences.

3.3 Market efficiency

The Efficient Market Hypothesis (EMH) states that all available information is fully reflected in the market prices and that no investor can therefore generate alpha through stock picking or market timing (Malkiel & Fama, 1970). Only through accepting higher risk can the investor expect higher returns. This in turn implies that future stock prices cannot be predicted by looking at historical returns – stock prices follow a random walk (Kendall & Hill, 1953). As prices always reflect all available information which investors instantly act upon, market price movements are therefore due to new information – which is defined as unpredictable.

Despite its extensive adoption to financial models and studies, the EMH has been subject to great controversy. This has led to the introduction of the concept of three levels of market efficiency – the weak-, semi-strong- and the strong form of efficiency. The weak form of market efficiency is described by market prices reflecting all historical trading data which implies that no above-market-average returns can be obtained by utilizing techniques such as technical analysis. Semi-efficient markets are considered to reflect both past stock prices as well as all public information regarding the asset. Thus, advocates of this theory believe that trading strategies based on fundamental analysis of publicly available information will not provide returns above that of the general market either. Lastly, the authors have the strong form of market efficiency which suggests that all information, both private and public, is accounted for in the stock price and therefore not even inside investors could perform better than the general market average (Bodie, Kane, & Marcus, 2010).

There has been empirical evidence of anomalies with regard to the concept of market efficiency. These include the price/earnings- and company size effects which has shown evidence of yielding above-market-average returns although these have been counter-argued to not account for the aspect of risk. This aspect of the mechanisms of financial markets has provided the authors with sufficient grounds for including additional model testing in this paper such as the Fama & French and Carhart multifactor model, which will be revisited under section 3.5 and 3.6. As the presence of these anomalies have proven to be of such a considerable magnitude, although the markets have shown to be relatively efficient, investors are still seeking to outperform the market through stock picking. It should also be noted that not all markets share the same level of market efficiency for reasons such as transaction costs and taxes (Bodie, Kane, & Marcus, 2010).

3.3.1 Discussion on market efficiency

In relation to this paper, a statistically significant alpha based on an ESG momentum strategy, if detected, would suggest a violation of the assumption of an efficient market in the semi-strong form. As the ESG scores used in this thesis' proposed trading strategy is based on public information such as annual- and sustainability reports, an efficient market in its semi-strong form should reflect this in the current market prices. Empirical studies on momentum investment strategies criticize the EMH, as there has been discovered short-term correlations unequal zero, which indicates that investors might trade on a momentum strategy. If the market would absorb the momentum effect, the abnormal return would become zero (Malkiel B. G., 2003). Some practitioners believe that the stock behavior can be explained through a psychological aspect, such as (Gupta, Preetibedi, & Poonamlakra, 2014), who suggests that behavioral finance can explain stock behavior. This view is based on their findings on how past stock performance can predict future stock behavior through human biases on their own investing history, which ultimately questions the random walk theory.

3.4 Capital Market Theory

The Capital Asset Pricing Model (CAPM) is arguably the most established model for equilibrium prices of financial assets and describes the relationship between systematic risk and expected return. The model is based on Markowitz' mean variance portfolio theory and was developed by Treynor (1961), Sharpe (1964), Lintner (1965) and Mossin (1966) (Munk, 2019).

For CAPM to hold, the model builds on the following assumptions (Tourre, 2019, s. 5):

1. Investors can borrow and lend at the risk-free rate
2. Investors have mean-variance preferences and the same investment horizon
3. Homogenous beliefs. All investors agree on the probability distribution of future returns
4. Investors cannot affect prices by their own trades. They are price takers.
5. All assets are tradeable without frictions, i.e. no transaction costs, taxes etc.

Also referred to as the single-index model, CAPM states that a stock only yields above-risk-free-returns because of its systematic risk for which the investor should be compensated. The logic behind CAPM is that all investors agree on the risk-free rate and the efficient frontier as well as the composition of the tangency portfolio and therefore only invest in a combination of the two (Munk, 2019, p. 295). It follows that its assumed that all investors share the same investing universe. Further, in equilibrium, asset prices and returns have to be set such that an investor demand for assets has to equal supply which implies that the tangency portfolio must consist of all risky assets in the economy. Thus, the tangency portfolio equals the market portfolio (Munk, 2019, p. 296).

In order to match their individual risk preferences, the investors will weight their portfolios between the tangency portfolio of the efficient frontier and the risk-free asset creating an upward-sloping line called the Capital Market Line (CML). The slope of the CML is called the Sharpe ratio (Munk, 2019, p. 296). It follows that investors can increase their risk beyond that of the market portfolio along the CML by leveraging their investment by borrowing at the risk-free rate.

The basic CAPM model states that for any risky asset, the following equation holds (Munk, 2019, p. 297):

$$E[r_i] - r_f = \beta_i\big(E[r_m] - r_f\big) \tag{1}$$

Where the risk-free rate of return on asset i is given by r_f, the market portfolio return is given by r_m and the market beta for asset i is noted as β_i. As equation 1 indicates, the expected excess return of an asset is directly determined by the market beta and the risk-free rate.

The asset beta is further defined as:

$$\beta_i = \frac{Cov[r_i, r_m]}{Var[r_m]} \tag{2}$$

As such, the beta is determined by the covariance between the asset return and that of the market portfolio divided by the variance of the market portfolio return, which makes it a sensitivity factor of systematic risk. A common approach to determine the beta is to look at time series of historical returns. This is due to CAPM being a one-period model which can result in a varying beta over time (Munk, 2019).

The abovementioned relations also hold for any portfolio. The portfolio return is given by (Munk, 2019, p. 300):

$$r_p = \sum_{i=1}^{N} \pi_i r_i, \tag{3}$$

where π denotes the vector of portfolio weights of the risky assets.

The covariance between the portfolio returns and that of the market is:

$$Cov[r_p, r_m] = Cov\left[\sum_{i=1}^{N} \pi_i r_i, r_m\right] = \sum_{i=1}^{N} \pi_i Cov[r_i, r_m], \tag{4}$$

which leads to the market beta of a portfolio to be given by:

$$\beta_p = \frac{Cov[r_p, r_m]}{Var[r_m]} = \sum_{i=1}^{N} \pi_i \beta_i. \tag{5}$$

3.4.1 Shortcomings CAPM

Though CAPM is one the most established financial theories, it suffers from limitations as many of the assumptions are viewed as unrealistic to the real world. The model is subject to criticism as the systematic risk is calculated upon historical data, which do not necessarily reflect the true future volatility of returns. In addition, the model assumes that all investors strive to achieve a mean-variance portfolio as well as they all are supposed to share an equal investment horizon. This assumption does not hold, as there are market forces such as tax and interest rates that effects an investor's portfolio composition and investing horizon. Further, the risk-free rate will always carry a default-risk, as there are no risk-free investments. The risk-free rate, often a government bond, is also realistically impossible to lend at for investors in general, as they cannot lend at the same rate as the government. Hence the investors' risk-free rate is higher in reality. As the CAPM model has shown to not be particularly accurate in explaining expected excess returns, most researchers have implemented multifactor models in their studies. Hence, this thesis will implement the Fama & French size- and value factors in order to evaluate whether the portfolio returns can be attributable to these effects. Further, the Carhart momentum factor will be added in order to check if the portfolio returns can be assigned to their past performances.

3.5 Fama & French three-factor model

Fama & French introduced the three-factor model which is an extension of the abovementioned CAPM model. This model was constructed in order to explain the stock return anomalies detected by implementing two additional risk factors (Fama & French, 1992). Fama & French found that the two variables size, in terms of market capitalization, and book-to-market equity ratio had strong explanatory power over the cross-sectional variation in stock returns (Fama & French, 1992, p. 429). Through their research, they found that (1) the relation between beta and average return is flat when allowing for variation in beta, (2) value stocks (high book-to-market equity ratios) tends to outperform growth stocks and (3) that small-cap stocks outperform large-cap stocks over the time period of 1963-1990 (Fama & French, 1992). Therefore, the model has three factors: (1) SMB (small minus big), (2) HML (high minus low) and (3) the market risk premium (market portfolio return less risk-free rate).

In order to determine these factors, Fama & French ranked the stocks according to their size and value metrics and grouping them into six portfolios: small/value, small/neutral, small/growth, big/value, big/neutral and big/growth. The SMB factor is effectively the average return of the three *small*-portfolios minus that of the *big*-portfolios, while the HML factor is calculated by subtracting the average return of the two growth-portfolios from that of the two value-portfolios (Fama & French, 1992).

The Fama-French three factor model:

$$r_i - r_f = \alpha_i + \beta_{i,m}(r_m - r_f) + \beta_{i,SMB}SMB + \beta_{i,HML}HML + \epsilon_i \qquad (6)$$

Where $r_i - r_f$ is the excess return of a stock i. α_i implies the excess return. $r_m - r_f$ is the excess return of the market portfolio and β_i ‘s are the factor sensitivities. SMB is the difference between the return of small- and big companies in the portfolio and HML is the difference between the return of growth- and value companies in the portfolio. ϵ_i is the residual error.

Fama & French further suggest that if assets are priced rationally, the *risk* associated with stocks are multidimensional, namely by size and value as mentioned above, and that beta alone does not capture the cross-sectional stock return variation. The value risk factor is considered to capture the relative distress factor of (Chan & Chen, 1991), that stocks with lower stock prices and higher book-to-market equity ratios (with poor prospects) are subject to higher cost of capital and/or suffer from irrational market behavior about these firms. The findings suggest that these firms tend to have higher expected returns than those with stronger prospects (Fama & French, 1992, pp. 428-429).

It's worth noting that the findings of Fama & French were conducted between 1963 and 1990, and there have been observed cases which contradicts the results from that period. The size effect has experienced periods where large caps have outperformed small cap equities, hence critics have questioned the generalization of their findings. The same applies to the HML-factor, where there have been periods where growth companies have outperformed value companies. It is important to note that these results often occurred during recessions, where investors were likely to invest in "pro-cyclical" value companies, hence the strategy looks attractive in the long run, with periods of negative return (Munk, 2019). Further, the sample specific selection was criticized as it likely would affect the generalization of the value premium, as it would not be likely to reoccur in future samples (Bhatt & Rajaram, 2014).

3.6 Carhart four-factor model

Mark Carhart published in 1997 a research paper aiming to demonstrate the explanatory factors of the persistence in mutual funds' mean- and risk-adjusted returns (Carhart, 1997, p. 57). By supplementing the (Jegadeesh & Titman, 1993) one-year momentum anomaly to the (Fama & French, 1992) three-factor model, Carhart constructed what is known as the *Carhart four factor model* (Carhart, 1997, p. 61). The implementation of the momentum factor increases the explanatory degree of the model considerably, which is why the authors have included it in this thesis. By investigating the efficiency of the stock market, the (Jegadeesh & Titman, 1993) paper suggests that profitable trading strategies can be applied by utilizing market over- and underreactions to information. This implies that the four-factor model assumes market inefficiency (Munk, 2019). Further, they found that significant returns can be achieved by buying stocks which has historically performed well and sell stocks that has performed poorly over holding periods of 3-12 months during their research period from 1965 to 1989 (Jegadeesh & Titman, 1993, p. 65). Carhart's implementation of this momentum factor to his four-factor model showed significant improvement in the average pricing errors of the CAPM and three-factor model alone (Carhart, 1997, p. 62).

The momentum-based factor of this model does not require any data beyond that of historical stock prices. This momentum factor is represented by *winners-minus-losers (WML)* which is the difference in return between the portfolio of the past top-performing stocks (*winners*) and that of the past bottom-performing stocks (*losers*) (Munk, 2019).

As a measure of risk, the momentum factor is argued to capture both liquidity- and credit risk as pricing of such are economically intuitive. Further, (Liu & Zhang, 2008) suggest that the momentum factor is much attributable to the industrial production growth rate, which is a key indicator for the economic cyclical development. As such, Daniel and Moskowitz (2016) show that the WML-strategy yields significant negative returns during volatile periods and following market declines (Munk, 2019, p. 359).

The Carhart four factor model is given by:

$$r_i - r_f = \alpha_i + \beta_{i,m}(r_m - r_f) + \beta_{i,SMB}SMB + \beta_{i,HML}HML + \beta_{i,WML}WML + \epsilon_i \quad (7)$$

3.7 Ordinary Least Squares Regression

The ordinary least squares (OLS) regression model is considered one of the most acknowledged regression methods which estimates the relationship between one or more independent variables and a dependent variable. In short, the OLS chooses the regression coefficients that estimates the regression line as close to the observed data where the accuracy is measured by the sum of the squared errors of the prediction of Y given X (Stock & Watson, 2015, p. 114). This method holds several desirable theoretical properties, such as being unbiased and consistent, which has made it widely adapted as a “common language” for regression analysis throughout economics and finance (Stock & Watson, 2015). As such, the OLS regression model is considered ideal for the purpose of this thesis.

The OLS value prediction function is given by (Stock & Watson, 2015, p. 191):

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_{1i} + \cdots + \hat{\beta}_k X_{ki}, i = 1, \dots, n, and \quad (8)$$

$$\hat{u}_i = Y_i - \hat{Y}_i, i = 1, \dots, n \quad (9)$$

Where $\hat{Y}$ is the predicted value of the dependent variable based on the OLS estimators $\hat{\beta}_0, \dots, \hat{\beta}_k$ and an error term $\widehat{\mu_i}$ estimated from n observations on the dependent- and independent variables $(X_{1i}, \dots, X_{ki})$ from a sample. As such, these are mere estimators of the *true* value of Y and the population coefficients and error terms (Stock & Watson, 2015). $\hat{\beta}_0$ is the intercept, meaning that this determines the level of the regression line and that the expected value $\hat{Y}_i$ equals $\hat{\beta}_0$ given that all regressors equals zero. As such, the coefficient $\hat{\beta}_1$ represents the expected change in the dependent variable, $\hat{Y}_i$, given a one-unit change in X_{1i} holding the other independent variables constant. This concept applies to the other coefficients as well.

Underlying this multiple regression model are the following assumptions (Severgnini, 2019, s. 5):

1. The relationship is linear in parameters
2. The Xs are nonstochastic variables whose values are fixed or the X values are independent of the error term: $cov(u_i, X_{2i}) = cov(u_i, X_{3i}) = \cdots = cov(u_i, X_{ki}) = 0$
3. The error term has zero expected value: $\mathrm{E}(\mathrm{u_i}|\mathrm{X_{2i}}, X_{3i}, \dots, X_{ki}) = 0$
4. The error term has constant variance for all observations (homoscedasticity)
5. The random variables u_i are statistically independent (no autocorrelation): $cov\left(u_i, u_j\right) = 0\ for\ i \neq j$
6. The number of observations *(n)* must be greater than the number of parameters to be estimated
7. The nature of X: Variability in X values $(var(X\ different\ from\ 0))$. No outliers.
8. No exact collinearity between the X variables
9. No specification bias

A small sample size, relatively speaking, can result in a complicated sampling distribution of $\hat{Y}$. Yet, certain statements about it can be made that hold for all n such as that the mean of the sample distribution, μ_Y, is an unbiased estimator of $\hat{Y}$ as it is given by $E\left(\hat{Y}\right) = \mu_Y$. As such, the larger the sample size the more can be said about the sampling distribution, e.g. as the central limit theorem states, that this distribution is approximately normal (Stock & Watson, 2015, p. 128). Furthermore, as the sample size gets larger, the regression estimates are more likely to approach the true values of β_i as their variance decreases.

These OLS regression estimates are given by (Stock & Watson, 2015, p. 115):

$$\hat{\beta}_k = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sum_{i=1}^{n}(X_i - \bar{X})^2} = \frac{s_{XY}}{s_X^2} \tag{10}$$

R^2 is included to measure how well the regression line describes the observed data. The R^2 measures the fraction of the variance of Y_I predicted by X_I given by the explained sum of squares (ESS), which is the sum of squared deviations of $\hat{Y}$ from their average, and the total sum of squares (TSS), which is the sum of all deviations from Y_I from its average squared (Stock & Watson, 2015, pp. 119-120):

$$R^2 = \frac{ESS}{TSS} = \frac{\sum\left(\hat{Y} - \bar{Y}\right)^2}{\sum\left(Y_i - \bar{Y}\right)^2} = 1 - \frac{SSR}{TSS} \tag{11}$$

Further, R^2 can be rewritten as the variance of the dependent variable not explained by X_I, but by the sum of squared residuals (SSR), which is the sum of the OLS residuals squared $\sum_{i=1}^{n} \hat{u}_i^2$, and TSS.

Ranging from 0 to 1, a higher R^2 indicates a higher explanatory power of the regressors in the variance of Y_I. It is not typical for the R^2 to land on extreme values such as 0 or 1, but generally fall somewhere in between. As the number of independent variables increase so does the R^2, although a higher R^2 does not necessarily mean a better model fit. As such, the authors include the adjusted R^2 ($\bar{R}^2$) which is the goodness of fit deflated by a factor derived from the number of regressors in the model (Stock & Watson, 2015):

$$\bar{R}^2 = 1 - \frac{1-n}{n-k-1} * \frac{SSR}{TSS} = 1 - \frac{s_{\hat{u}}^2}{s_Y^2} \tag{12}$$

This factor, $\frac{n-1}{n-k-1}$, is always greater than one showing that the adjusted R^2 is always less than R^2. In addition, adding a regressor has two effects on the adjusted R^2, namely (1) that the SSR falls (which increases adjusted R^2) and (2) the factor increases (which decreases adjusted R^2). Whether adding another variable to the model increases or decreases the adjusted R^2 depends on which of the two effects is stronger (Stock & Watson, 2015, p. 194).

In addition, the standard error of the regression (SER) is included which is an estimator of the standard deviation of the error u_I, i.e. the observation spread around the regression line measured in units of the dependent variable (Stock & Watson, 2015). This means that if the unit notation of Y_I is in USD, then the SER assesses the magnitude of the typical regression errors *in USD:*

$$SER = \sqrt{S_{\hat{u}}^2,\ S_{\hat{u}}^2 = \frac{1}{n-k-1}\sum_{t=1}^{n}\widehat{u_t^2} = \frac{SSR}{n-k-1}} \tag{13}$$

As the equation indicates, the $\frac{1}{n-k-1}$ factor corrects for the downward bias introduced by the estimation of $k+1$ coefficients and is called "the degrees of freedom" correction (Stock & Watson, 2015, p. 193).

In order to assess whether the estimated coefficients are statistically significant, i.e. whether the true coefficients in fact do take some specific value, the authors will perform t-tests. These t-tests are typically rooted by stating the hypothesis that these coefficients are zero, which is why they are called null hypothesis (or *the null*) (Stock & Watson, 2015, p. 215). The alternative hypotheses', which are tested, are two sided:

$$H_0: \beta_j = \beta_{j,0}\ vs.\ H_1: \beta_j \neq \beta_{j,0}\ (Two-sided\ alternative) \tag{14}$$

The t-test is performed by calculating the *t-statistic* which is based on the standard deviation of $\widehat{\beta_J}, (SE(\hat{\beta}_j))$:

$$t = \frac{\hat{\beta}_j - \beta_{j,0}}{SE(\hat{\beta}_j)} \tag{15}$$

If one would to test the significance of the coefficient at the 5% confidence level, the critical value of 1.96 is used. This means that if the t-statistic exceeds the absolute value of 1.96, the authors reject the null and stand by the alternative hypothesis. Further, the same approach would be used to test for significance at the 10% and 1% level as well, although with their belonging critical values. Alternatively, computing the *p-value* also functions as a method of determining the significance of the coefficients. The p-value is essentially the probability of obtaining the same estimations as in the null, assuming the null is true, which means that if the p-value is less than or equal to the desired level of significance, e.g. 0.1, 0.05 or 0.01, the authors reject the null hypothesis (Stock & Watson, 2015, pp. 215-216).

A mean for capturing the true value of β_j is by constructing a 95% two-sided confidence interval. As such, this interval is set to contain the values of β_j that is not subject to rejection by a 5% two-sided hypothesis test (Stock & Watson, 2015, p. 217).

The 95% confidence interval is given by:

$$95\% \; confidence \; interval \; for \; \beta_j = \widehat{\beta_j} \pm 1.96SE(\hat{\beta}_j) \tag{16}$$

3.8 Estimation considerations

3.8.1 Omitted variable bias

If the OLS leaves out one or more relevant independent variables which are determents of the dependent variable and which are correlated with the included independent variables in the model, the model will have *omitted variable bias (OVB)*. The true effect of a unit change in the independent variables on the dependent variable may therefore not be reflected in the OLS estimators. Furthermore, if the omitted variable is a determinant of Y, the error term u_I is also correlated with X_i and the conditional mean of u_i given X_i is nonzero (Stock & Watson, 2015, p. 182). This is a violation of the first assumption of the least squares model which results in a biased OLS estimator where the larger the correlation between the regressor and the error term the larger the bias.

The degree of OVB can be measured through the following equation where the OLS estimator has the limit of:

$$\widehat{\beta_1} \xrightarrow{P} \beta_1 + \rho_{Xu}\frac{\sigma_u}{\sigma_X} \tag{17}$$

Where the direction of the OLS estimator bias is conditional on whether $\hat{\beta}_1$ and u are positively or negatively correlated (Stock & Watson, 2015, p. 183).

3.8.2 Multicollinearity

Perfect multicollinearity occurs when one regressor is a perfect linear function of the other regressors (Stock & Watson, 2015, p. 768). As such, if the model suffers from perfect multicollinearity, one will prefer to exclude one or more of the regressors. Imperfect multicollinearity occurs when two or more regressors are strongly correlated. In that case the OLS will estimate at least one of the regressors imprecisely. Even though there is a presence of multicollinearity, the model will still have unbiased estimates with minimum variance in addition to being correctly specified (Stock & Watson, 2015).

3.8.3 Heteroskedasticity

As mentioned in the assumptions in section 3.7, the OLS assumes homoscedasticity, meaning that the variance of a conditional distribution of a predicted variable is consistent over time. Otherwise, heteroskedasticity emerges if the variance of a conditional distribution of a predicted variable is non-constant. The OLS regression will remain unbiased and consistent, whether homo- or heteroskedasticity occurs, though the t-statistic is dependent on heteroskedasticity, which implies that homoskedasticity will interfere with the regression (Stock & Watson, 2015, pp. 157-159).

3.8.4 Autocorrelation

The assumption of no autocorrelation states that the covariances and correlation between the residuals in the model are all zero and that the residuals therefore are independently distributed, i.e. serial independence. If they in fact are correlated, the error in one period might be carried over to the next period, causing the OLS to be biased and inconsistent (Stock & Watson, 2015, p. 523).

3.8.5 Sample selection bias

The sample selection bias might occur when the data-collection process contains flaws which affects the availability of data, hence the estimation from the OLS regression will be inconclusive. The sample selection bias does not occur if there is missing data at random, though the results will consequently be less conclusive, but without any bias (Stock & Watson, 2015, p. 323).

3.8.5.1 *Survivorship bias*

Survivorship biases often occurs from sample selection bias, as the data collected for a back-testing implements equities that exist throughout the whole period of the study, hence companies who have stopped trading or left the market are excluded, creating a biased data panel (Stock & Watson, 2015, p. 324).

3.8.6 Simultaneous causality bias

A simultaneous causality bias occurs when there is a causal link between the independent- and the dependent variable, and vice versa. The bias occurs in an OLS as a consequence of the correlation between the independent variable and the error term (Stock & Watson, 2015, p. 326).

4. Data description

Data description will describe the data selected for this thesis, which consists of non-financial ESG- and financial data. The ESG score matrix will be described in detail, as well as the ESG provider will be presented. Further, the choice of risk-free rate will be elaborated upon, which is used to determine the market risk premia. Lastly, the choice of benchmark will also be described, as it contains the portfolio constituents and as well as it will determine the relative portfolio performance.

4.1 ESG Scores

ESG scores contributes to convey a transparent and unbiased assessment of a company's ESG performance in relation to environmental-, social-, and governance matters. ESG data, which the ESG scores are derived from, are gathered from annual-, sustainable-, NGO-, CSR-, and media reports (Refinitiv, 2020, s. 4). ESG scores are divided into the three abovementioned pillars, and are weighted differently in the overall ESG scores depending on which industry the company is operating in. The degree of industry-specific weighing differs between score issuers. Such scores are used by stakeholders to assess a company's ability to act sustainable, in addition to other financial tools, in order to estimate the future risk and performance of the company. ESG scores are also commonly used by investors as a criterion to evaluate if an equity should be included in a portfolio, i.e. negative screening. In addition, companies use these scores for internal purposes, in order to evaluate their own ESG performance.

Providers such as MSCI, Bloomberg, Thomson Reuters and Refinitiv are all well-known and established as credible providers, although the accessibility is limited. As Copenhagen Business School only offers Bloomberg and Refinitiv data, this research will be based upon data from Refinitiv, as it is considered the most reliable source of the two.

4.2 Refinitiv ESG Scores

Refinitiv covers more than 80% of the global market capitalization and rates more than 10,000 companies worldwide. It offers one of the most comprehensive ESG score databases on the market, with over 450,000 ESG measures manually treated by over 150 individual research analysts. The database is one of the largest in the world and is continuously updated throughout the year in line with corporate reporting practices. In more exceptional cases, the ESG data is updated on a weekly basis, especially in cases where there is a change in reporting practices or the corporate structure throughout the year.

4.2.1 Scoring system

Refinitiv's scoring system facilitates a framework that quantifies firm characteristics which is difficult to observe and assess for the investor. The Refinitiv ESG scores are computed trough Refinitiv ESG scoring framework, which consists of a transparent assessment-system consisting of 450 + data points, compiled into 186 sub-set of measures which are industry-specific as the data considers impact- and industry relevance. Further, the measures are gathered into 10 categories, which define the company's ESG performance, commitment and effectiveness, based on publicly available information (Refinitiv, 2020, s. 6). Refinitiv's scores ranges in value from 0-100, where a high (low) value indicates a strong (poor) ESG performance. ESG scores are a combination of the environmental, social and governance pillars and their weight respectively, where the weights are determined by the materiality, varying between industries. The overall ESG score is a relative sum as the pillars are industry-specific weighted for the environmental and social pillars. Moreover, the governance pillar is equally weighted for all industries, as Refinitiv believe that corporate governance is equally important independent of industry (Refinitiv, 2020, s. 11).

The ESG scoring framework of Refinitiv is illustrated by illustration 2 below:

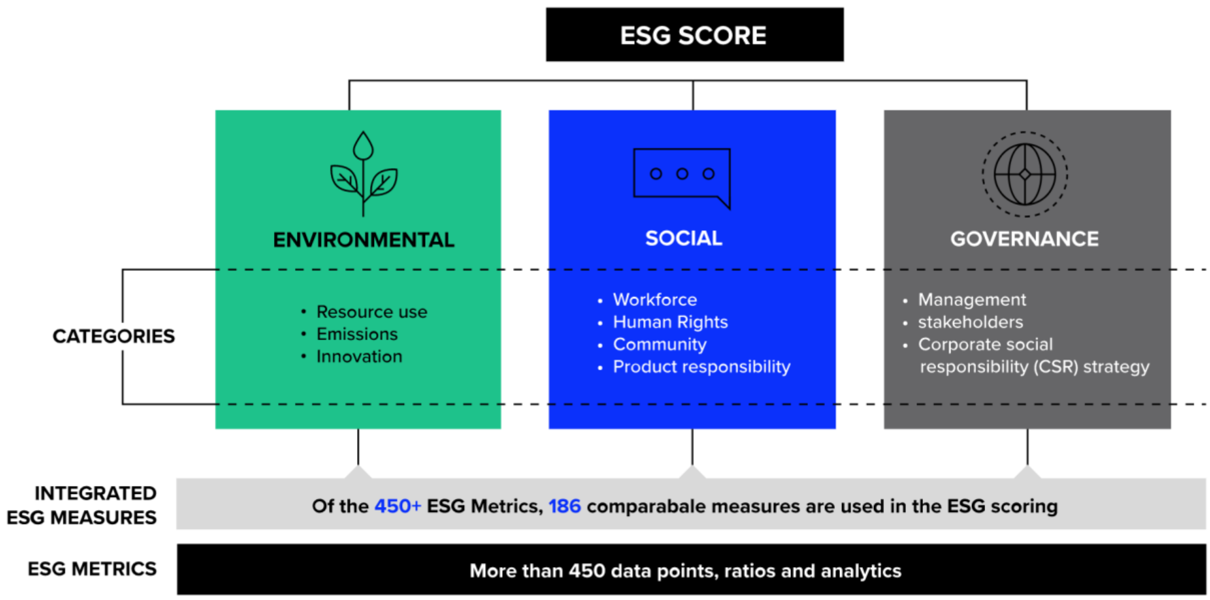

Illustration 2 – ESG Score matrix. Source: (Refinitiv.com, 2020)

The environmental pillar score is evaluated upon a company's resource use, emissions and innovation. Refinitiv evaluates a company's resource use by examining its efforts to reduce the use of materials, energy or water, in combination with the implementation of eco-efficient solution through their supply chain management. Emission reduction score is defined by how a company reduces their environmental emissions in both its production and overall operations. Lastly, the innovation score evaluates how a company reduces the environmental costs for its customers through new environmental-friendly technology (Refinitiv, 2020, s. 22).

Further, the social pillar is composed of four categories, which score a company upon its workforce, emphasis on human rights, relation to community and its product responsibility. Refinitiv measure a company's workforce on their effectiveness with regard to employee satisfaction and safety, as well as measuring the diversity and the level of equal opportunities in the workforce. Human rights scores are further measured on the effectiveness of a company's ability to emphasize and maintain fundamental human rights. The community score is evaluated upon how a company interact and respect the local community. Product responsibility is the last category included in the social pillar and is measured upon the quality of a company's supplied product or service, while taking the consumers health and safety into consideration (Refinitiv, 2020, s. 22).

Lastly, the governance pillar is divided into three categories, and score companies upon their management, shareholders and corporate social responsibility strategy. The management score is measured on how a company follows its best practice regarding corporate governance principles. Shareholder score is defined as how a company treats its shareholders, as well as its implemented measures to avoid hostile takeovers. Lastly, the CSR strategy measures a company's transparency regarding the implementation of ESG measures in day-to-day operations (Refinitiv, 2020, s. 22).

Refinitiv's ESG score rating system takes the risk exposure into account and evaluates whether a company's risk management is sufficient. Hence companies with high-risk exposures are required to have strong risk management compared to companies with a lower risk exposure. As such, highlighting these kinds of strengths and weaknesses. Further, strong risk management increases overall scores. Key issues will vary on a company-specific level and are calculated through an extensive analysis focusing on company-specific metrics related to risk exposure. The analysis focuses on whether or not a company has achieved a strong track record between their risk- and opportunity exposure and how the management has performed in this regard (Refinitiv, 2020, s. 7).

The retrieved data contains the overall ESG scores, as well as the score for each individual pillar. It is further noted that the data do not contain any industry-specific pillar weights, nor any score information regarding the ten key issues.

4.3 Risk-free rate

The risk-free rate is important for an investor's investment decision, as it is used as a proxy for what an investor should expect to earn on a risk-free investment, i.e. the minimal required return. It should be determined by the currency of the returns, as different currencies don't necessarily share the same risk measures (Damodaran, 2008). For the purpose of this thesis, the 1-year US treasury bond is used as a proxy for the risk-free rate, for both the S&P 500 and S&P Europe 350, as the portfolios change dynamically and are rebalanced each year.

Constituents of the S&P Europe 350 operate in multiple geographical markets, hence their returns are denominated in different currencies. Some currencies have the potential of bearing higher default risk, which should be reflected in their respective risk-free rate of return. With regard to the companies within this thesis' sample, the authors do not assess such default risk to be materially different between the two markets as the interest rate parity is assumed to be efficient. As such, implying that the chosen risk-free rate is presumed to be a suitable proxy for the institutional investors operating in both markets. The 1-year US treasury bond is divided into a constant monthly fixture, as the returns are given on a monthly basis, as shown in equation 18:

$$r_f^m = \frac{r_f^y}{12} \tag{18}$$

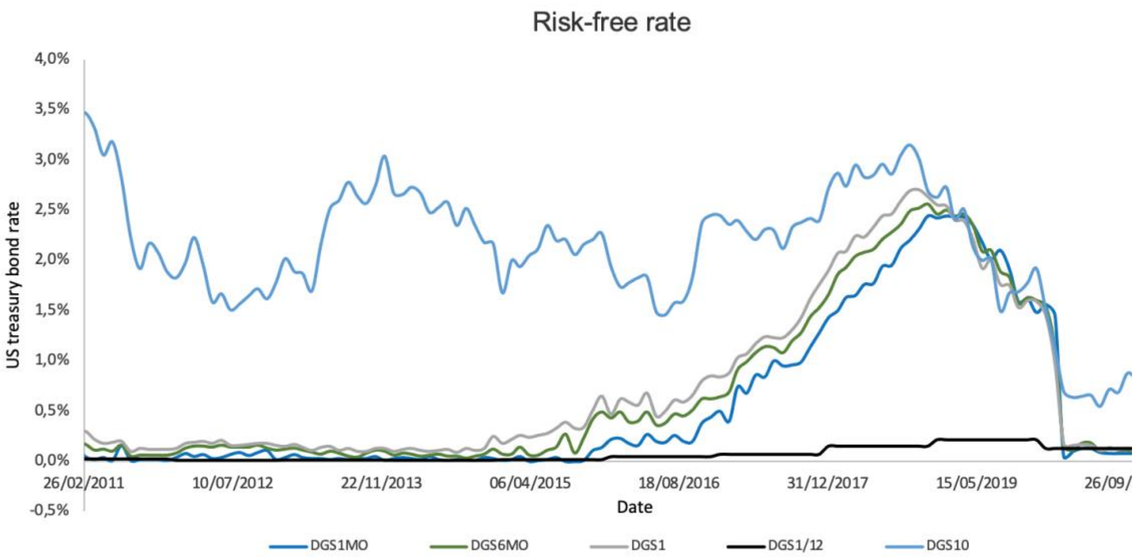

Illustration 3 – Risk-free rates. Source: (U.S. Department of the treasury, 2021)

The authors have selected a one-year duration on the bond, as the alternative 1- and 6-months constant maturity rate bonds have shown to be lower, and the 10-year constant maturity bond have shown to be very conservative, resulting in a more aggressive or defensive excess return. The more suitable 1-year treasury bond will provide a sufficient result, facilitating a credible analysis.

4.4 Benchmark comparison

It is difficult to find portfolios that represent the whole US- and European market, hence the authors have used indices as proxies. The market risk premia, as well as the portfolios, are constructed upon two indices which represents the large capitalization segment in each respective market. The chosen S&P indices have been used for other prior research, which have shown to work satisfactory, such as (Alareeni & Hamdan, 2020). This thesis could have used other proxies, such as MSCI or STOXX, though the authors have had limited access to it, hence S&P indices appear as adequate benchmarks.

4.4.1 S&P benchmark indices

As mentioned, this thesis has a market capitalization requirement to ensure credible ESG-data, as there are higher ESG reporting demands on companies with a large market capitalization. Further, a turnover requirement is present to mitigate liquidity risk, which is considered fulfilled as both indices consists of highly liquid stocks with a public float of at least 10% of its shares outstanding (S&P Dow Jones Indices - 500, 2021).

The S&P 500 index is considered applicable as the benchmark for the US market as it fulfils the market capitalization- and turnover requirements, which the authors have set to be of mid- and large cap companies that are highly liquid. The index contains 505 constituents of the large market capitalization segment, selected from a diverse set of industries. It is noted that it is not the 500 largest companies in the market measured in market capitalization, but a representation of the largest companies in a selected group of industries in the US market. Further, the S&P Europe 350 Index is considered an appropriate benchmark for the European market, as it contains 350 blue-chip[4] constituents, in addition to being managed equally as the S&P 500. The S&P Europe 350 constituents represent 16 European developed markets (S&P Dow Jones Indices - 350, 2021).

The two indices are ideal as benchmarks for the two markets of investigation, as they both are constructed on a standardized S&P framework, as well as their constituents aims to represent the whole market.

[4] A blue-chip stock is considered a company of large size and exceptional reputation.

4.4.2 Regions

The indices used in this thesis represent the US- and European markets which share several characteristics as well as some distinct differences. The focus on ESG has increased rapidly over the last couple of decades in developed markets, however, with varying degrees. The US market is experiencing a record growth in sustainable funds with an increase of USD 50 billion by the end of the year 2020. In contrast, the European market's sustainable funds increased by USD 61.6 billion in the third quarter of 2020 alone (Bloomberg, 2020).

The European market has experienced a strong focus towards SRI over the last couple of decades, where attention towards the more prominent environmental pillar was enhanced as a result of the introduction of the Paris agreement in 2015. As such, this pillar has since become implemented by most companies driven by the demand from different stakeholders. In the US market, the discussion around the Environmental pillar is more disputed, which can be illustrated by the event where the Trump administration pulled out of the Paris agreement in 2020. This did not only remove some of the focus on environmental issues, but the administration also discouraged environmental investing (McGrath, 2020).

In addition to an already high environmental incentive, the European Comity introduced the European Green Deal Investment Plan in January 2020, as it will facilitate EUR 1 trillion to environmental investments in the next decades in order for Europe to become climate-neutral (European Commission, 2020). This incentive, in addition to a favorable European taxation system for environmentally focused companies, has and will increase the environmental focus across industries in Europe. The new taxation system which was published in 2020 and takes force in 2022, is favorable for environmentally sustainable companies (European Comission, 2021). The US don't have the same degree of environmental incentives, which weakened the development throughout the period of investigation.

Both the American- and European markets have had an increased focus on the social pillar, as a result of sustainable accounting and a shift in focus from stakeholders. The social pillar is mostly a case-to-case issue as well as it depends widely on industrial sectors, as it usually only becomes a forefront issue after there has been an issue or accident. There has been an increased focus on especially workforce and social and economic inequalities, and both markets have taken this into account by implementing an industry standard. Non-financial issues have become more prominent, as more institutional investors implement these factors into their assessment of a company’s performance (Nelson, 2020).

The governance pillar has been a focus area long before the environmental- and social pillars became relevant. Corporate governance matters are important in the US, as it is no longer enough to only generate profit. This is emphasized by the US Sentencing commission guidelines which is a framework developed for companies to operate with a clear CSR strategy. Since the establishment of EU, it has put forward a more prominent strategy on corporate social responsibility through EUs view that social solidarity, environmental preservation and economic growth should coexist, which was determined by a sustainable strategy implemented in EU in 2001 (Forte, 2013).

Further, governmental subsidies are present in both markets to different degrees, somewhat depending on industry-specifics and geography, which reduces the risk related to ESG development costs. The fact that companies receive subsidies in regard of tax reduction or cash subsidies will ultimately increase their financial performance (Buhr, 2016).

4.4.3 Index sector composition

This section will present and compare the sector weighting of the S&P 500 with that of the S&P Europe 350 in order to evaluate whether there are any major differences which might impact the comparability of the two markets. Further, in terms of portfolio performance comparison with the benchmark, sector composition might be explanatory of the portfolio returns.

As indicated by Illustration 4, the S&P 500 of the US market looks fairly differentiated with somewhat dominating sectors such as consumer discretionary and information technology, which combined constitute 45% of the index. Illustration 5 of the S&P Europe 350 of the European market is also considered to be fairly representative for every sector. Most prominent are the consumer discretionary and financials sector, which combined constitute c. 41% of the index.

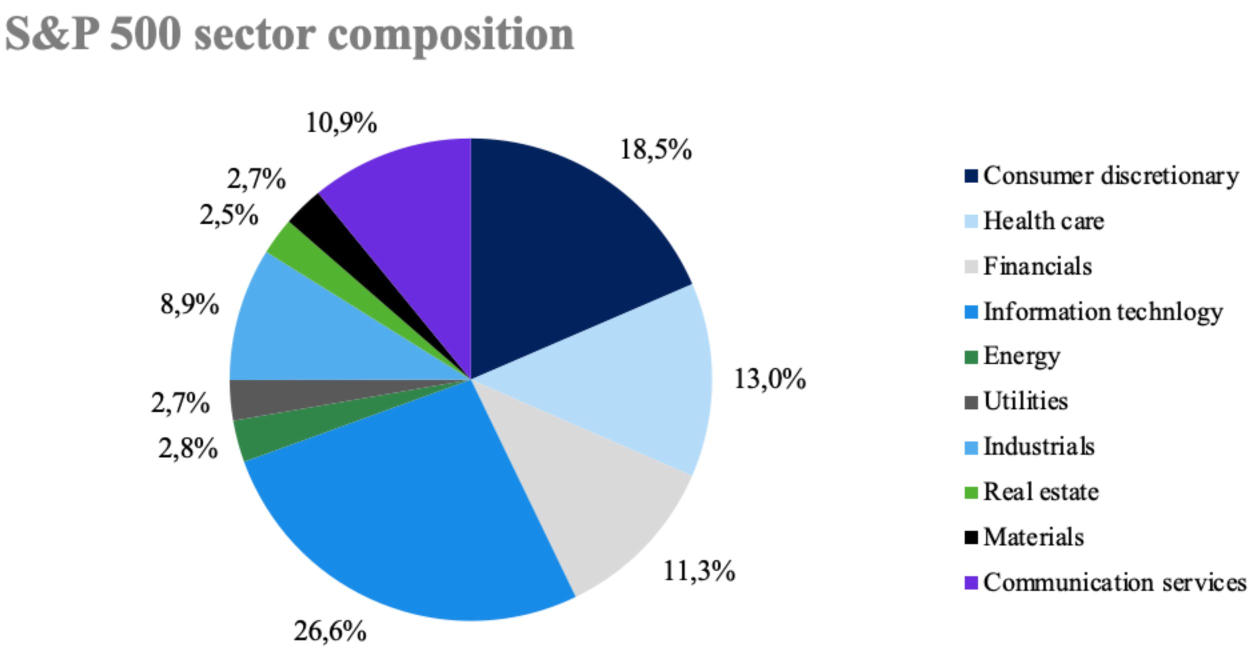

Illustration 4 - S&P 500 Sector composition. Source: (S&P Dow Jones Indices - 500, 2021)

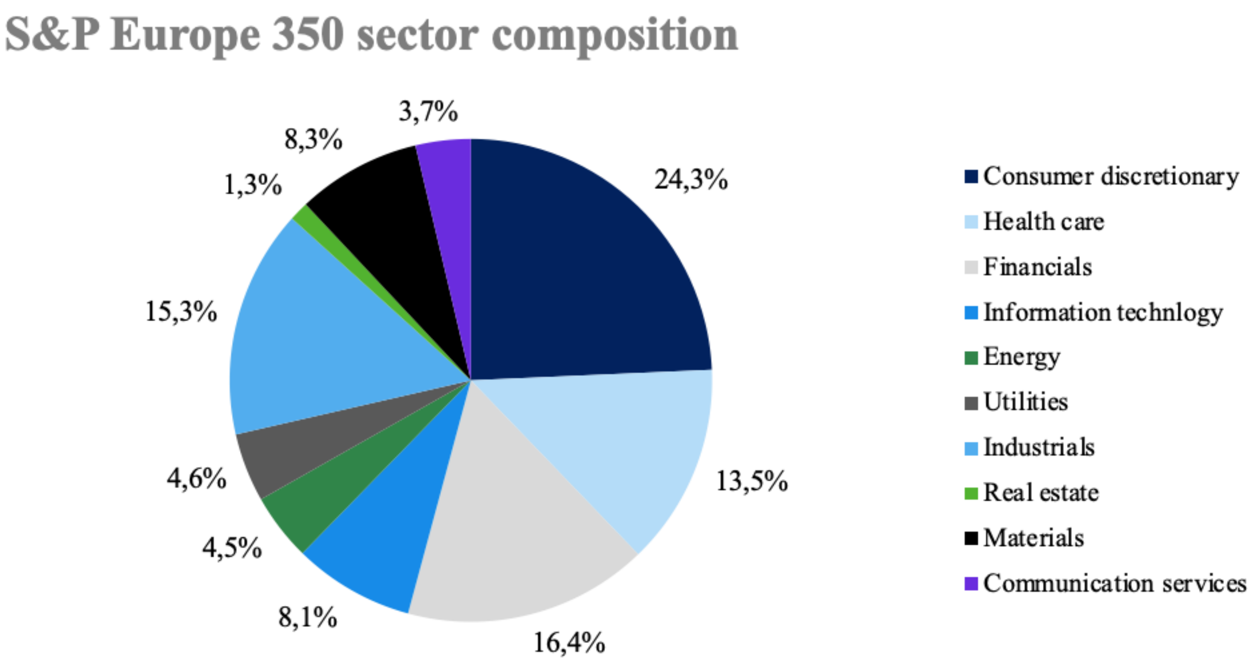

Illustration 5 - S&P Europe 350 Sector composition. Source: (S&P Dow Jones Indices - 350, 2021)

Most notably, the two markets do not share the same representation of the IT sector and communication services, which makes up c. three times more of the index in the S&P 500 than in the S&P Europe 350. On the other hand, the opposite is the case for the industrials sector which makes up almost twice as much of the index in Europe than in the US.

The sector composition might influence the reliability and interpretation of the results as less diversified portfolios might be exposed to industry-specific value drivers, which again will impact the findings on portfolio alpha.

4.4.4 General metrics

In order to further assess the results from our study the below general metrics for the benchmarks are presented. However, the reader should note that the general metrics below are based on the screened data set of the S&P 500 and S&P Europe 350 as the required financial data were not available for every constituent in the indices, ref. section 5.1 Data preparation and cleaning.

The index general metrics will function as a benchmark when assessing the features of the constructed portfolios in the following analysis. Table 1 highlights the general metrics of the two indices, where the difference in ESG scores are illustrated as S&P Europe 350 scores 20% above that of the S&P 500 on average throughout the period under investigation. The high score level in Europe compared to the US is somewhat consistent for all pillars. The historical score development can be found in appendix 11.6.1.5.2 and 11.6.2.5.2.

General metrics

	S&P Europe 350		**S&P 500**	
	Average	Median	Average	Median
ESG score	68.1	68.0	56.8	57.3
Environmental score	67.2	66.7	49.3	48.7
Social score	70.5	71.2	58.6	58.8
Governance score	62.2	60.6	59.2	60.9
Market capitalisation (USD bn)	25.9	26.7	38.5	38.3
Price/Earnings	26.3	26.0	48.6	37.8
Return on equity	16.2%	16.0%	23.6%	20.7%
Debt/equity	1.12	1.16	0.91	0.89
Book-to-market	0.55	0.52	0.43	0.40
Current ratio	1.5	1.4	1.5	1.5

Table 1- Benchmark General metrics. Source: Own construction

In terms of market capitalization, the average constituent of the S&P 500 has 49% larger market capitalization than that of the S&P Europe 350. This is also the case for the indices’ P/E ratio, where the S&P 500 is priced considerably higher relative to its earning than the S&P Europe 350. Although, for the former, the average P/E ratio is considerably higher than the median, suggesting that the high average might be due to a few single companies with considerably higher pricing. Return on equity (ROE) is also higher for companies constituting the S&P 500, which is indicated to be 7.4 ppts. above that of the S&P Europe 350.

Further, the table suggests a higher level of debt-to-equity- and book-to-market equity ratio for the European companies. The lower book-to-market ratio of the S&P Europe 350 constituents suggests a larger share of value companies in the European market. No difference in default risk is observed between the two indices, as indicated by their similar average current ratio, which on average is considered to be satisfactory with a value of 1.5, just below the rule of thumb of a satisfactory level of 2 (Plenborg, Petersen, & Kinserdal, 2017, p. 231).

5. Methodology

This section will describe the methods used to construct and analyze the momentum-based portfolios. Further, this thesis will make use of the portfolio approach to determine whether there is a correlation between ESG- and stock performance as it is the most commonly used strategy, though the authors could have chosen to investigate the correlation on an individual stock level. The authors have chosen to use the portfolio approach as it is less affected by company-specific factors. As such, our research will construct and analyze the strong- and poor ESG score momentum-performing portfolios based on the two proposed strategies.

5.1 Data preparation and cleaning

After retrieving the monthly ESG- and company-specific market data, the authors screened for duplicates and errors such as "NA" values. Duplicated company data arise from companies being subsidiaries or type A, B or C stocks, all of which were removed. Companies which displayed "NA" were either removed due to missing data or supplemented by company-specific financial data retrieved from Yahoo Finance (Yahoo Finance, 2020). S&P 500 had 505 constituents in the raw data material, whereas the sample were down to 427 companies post screening. For S&P Europe 350, the number of investable stocks went from 363 in the raw data down to 326 after the screening process.

Further, both the ESG- and stock price data were examined in order to ensure the credibility of the dataset for the model. Through examining the time series, several missing values were detected on multiple occasions. By investigating additional sources for the missing information, most of the instances were due to companies not being publicly listed which raised the question of whether to emphasize the number of investible companies or the length of the data history in line with the general scholar opinion (Fitzgeorge-Parker, 2020). As the ESG data is derived from publicly available information, these missing ESG data for certain companies at specific dates where consistent with that of the missing price data, which could be caused as both sets of data are computed on the basis of reporting practices, which might not have been made publicly available. In order to avoid removing too many companies from the data set, the authors set the cut-off to be at 01.01.2009, based on the scope of the data. Given that the scores from Refinitiv is reliant on the company's annual reports, little ESG data for 2020 were available. As such, the analysis will be performed up to 01.01.2020.

In addition, the financial data sets were screened for outliers whereas the ESG datasets were smoothened. In order to trim the stock return data set for outliers the method of *winsorizing* was applied, which is a procedure that moderates the impact of outliers on the mean and variance by reassigning values to observations beyond the top and bottom decile. As such, outliers above the upper (below the lower) given decile is replaced with the next highest (lowest) value**,** which minimizes the effect of these sporadic outliers on the analysis (Blaine, 2018).

The authors look at the development in ESG related scores over the time period of the research, and in order to avoid noise that would interfere with the results, the ESG scores are adjusted by a twelve-month simple moving average (SMA) technique. The SMA allows the authors to highlight the trend in the ESG scores, facilitating for a reliable momentum, avoiding a disproportionate result. The process involves smoothening out fluctuating data, by applying a mean of the datapoints from the last 12 months. The formula is given by:

$$SMA(12)_i^m = \frac{1}{12}\sum_{t=1}^{12} ESGS_i^{m-12+t} \tag{19}$$

Where $SMA(12)_i^m$ represents the twelve-month simple moving average and is computed by a twelve-month average of a company's (i) respective ESG scores, $ESGS_i^m$.

The simple moving average method minimizes the impact of ESG scores outliers which would cause an abnormal big (small) momentum, hence the method is applied as a conservative measure to maintain a credible basis for our research. The SMA is conducted on a twelve-month basis to smoothen the fluctuations within the year, as the authors have identified that there might occur changes in scores within a year.

The authors have conducted two different trimming techniques on stock return and ESG scores respectively. The reason why there are two distinct different methods, is due to different applications. Winsorizing removes extreme outliers, as stock price data might exhibit short-term noise, whereas the SMA highlights the trend of ESG scores which facilitates for the momentum calculation.

5.2 Portfolio construction

As mentioned previously in the thesis, the research will conduct a portfolio construction approach to investigate the relationship between ESG- and pillar score and stock performance. The authors construct equally weighted portfolios consisting of the top and bottom performing decile on ESG- and pillar score momentum. As such, the authors can assess the ESG score momentum-based effect on both ends of the performance spectrum. The portfolio construction method, compared to single stocks, facilitates the authors with a more credible result as the idiosyncratic risks are reduced, hence the factor loadings become more reliable creating lower standard errors for their risk premia (Ang, Liu, & Schwarz, 2020).

5.2.1 ESG score momentum

The ESG momentum has been computed by a twelve-month change in the twelve-month simple moving average ESG, Environmental-, Social- and Governance- pillar score for the screened dataset of the S&P 500 and S&P Europe 350 constituents, respectively.

$$ESG\ momentum_i^m = SMA(12)_i^m - SMA(12)_i^{m-12} \qquad (20)$$

After the momentum calculation, each company is ranked in descending order based on their respective score momentum. There has been conducted research with various holding periods, both long and short periods, with somewhat inconclusive results. This thesis will conduct an ESG momentum strategy based upon a twelve-month holding period, as most ESG scores practically are updated on a yearly basis, in line with academic research such as (Jegadeesh & Titman, 1993).

Although the cleaned data stretches back to 2009, the twelve-month simple moving average-momentum strategy require a twelve-month data prior to the period, hence the first portfolio composition is constructed at 01.01.2011, and rebalanced each year until 01.01.2020. The High- and Low portfolios are constructed through assigning companies to the strongest- and poorest performing portfolios, respectively, based on their ranking. Momentum score cut-off has been discussed by academics, though this thesis will obtain portfolios consisting of the top- and bottom decile companies for High and Low, respectively, in line with academia such as (Kempf & Osthoff, 2007).

As such, the strategy further constructs portfolios where the companies with the top- and bottom decile score-momentum performance are assigned to their respective portfolios at each rebalance date. The method will ensure the authors that the analysis will obtain portfolios continuously consisting of the top- and bottom ESG score momentum-performing constituents.

As the constituents are grouped, an equally weighted investment is conducted on each of the portfolios of USD 1000. The value of the initial investment will grow with each respective stock return of the constituents in the portfolios throughout the holding period and is then equally reinvested in the new portfolio at the yearly rebalance date. The monthly return (r_p^m) of the portfolio is therefore computed on the monthly value change of the investment (V_p^m). The new constituents are selected on the same decile assumptions throughout the analysis.

$$V_p^m = \sum_{i=1}^{N} r_i^m * I_i^{m-1} \tag{21}$$

$$r_p^m = \frac{V_p^m}{V_p^{m-1}} - 1 = \sum_{i=1}^{N} w_i^{m-1} * r_i^m \tag{22}$$

The equally weighted investment strategy emphasizes the homogeneity, as the portfolio return therefore become unaffected by size-differences. The authors further emphasize the assumption that no transaction costs or slippage are accounted for when rebalancing.

5.3 Factor construction

In order conduct the OLS regression, the risk factors of the Fama-French and Carhart theory are computed as SMB^m, HML^m and WML^m for each of the markets, respectively.

First step in the factor construction process is to group companies by market capitalization into Big (companies with the 50% highest market capitalization) and Small (50% lowest) on a monthly basis.

Second, within both groups, each company is again grouped based on their book-to-market ratio into three different groups: Growth (Low B/M), Neutral (Neutral B/M) and Value (High B/M) by a 30%-40%-30% split, respectively. The book-to-market ratio was calculated within the size groups, based on the book-price per share divided by share price:

$$\frac{B}{M_i}^m = \frac{BPS_i^m}{PS_i^m} \tag{23}$$

As such, the process generates six groups of companies: “Small/Growth”, “Small/Neutral”, “Small/Value”, “Big/Growth”, “Big/Neutral” and “Big/Value”.

In order to calculate the SMB^m factor, the analysis subtract the monthly return of “Big” companies from the monthly return of the “Small” companies:

$$SMB^m = \frac{r_{SG}^m + r_{SN}^m + r_{SV}^m}{3} - \frac{r_{BG}^m + r_{BN}^m + r_{BV}^m}{3} \tag{24}$$

Further, the HML^m factor is calculated by subtracting the monthly return of the “Growth” companies from the “Value” companies:

$$HML^m = \frac{r_{SV}^m + r_{BV}^m}{2} - \frac{r_{SG}^m + r_{BG}^m}{2} \tag{25}$$

The additional factor from Carhart (1997) is calculated by observing the eleven-month return, lagged one-month, and grouping the companies after performance into Winners (high) and Losers (low) with a 30% - 30% split, respectively. The factor is computed by:

$$Return_i^m = \frac{P_i^{m-1}}{P_i^{m-12}} - 1 \tag{26}$$

Where $Return$ represent the eleven-month return, lagged one-month. P represent a one- and eleven-month lagged stock price, respectively.

The Carhart process divides the stocks into a group of four. “Small-High”, “Small-Low”, “Big-High” and “Big-Low”.

Finally, the Carhart multifactor WML^m is computed to create the factor for Winners minus Losers:

$$WML^m = \frac{r_{SH}^m + r_{BH}^m}{2} - \frac{r_{SL}^m + r_{BL}^m}{2} \tag{27}$$

The factor models are computed based on the data for each respective market, which means that the factors for US does not equal those of Europe. This is done in order to achieve a greater explanatory degree of the return of the portfolios, which consequently might complement the conclusion on the problem statement. In addition to the self-constructed factors, Fama & French provide factors for SMB and HML, respectively. The provided factors are retrieved from the Dartmouth database (Fama & French, 2020). In order to evaluate the research's self-constructed factors, the thesis will implement the factors as a robustness test, constructed by Fama & French for both the US- and the European market.

5.4 Regression

In the following section, the authors will present the OLS method used to determine the risk component of CAPM as well as the explanatory effects of the multifactor models in order to answer the research questions. The authors perform each regression model separately to better isolate the effect from each input factor on portfolio return as well as their effects relative to each other. Lastly, the alpha will determine the excess return that cannot be explained by systematic risk or other factors.

5.4.1 CAPM single-index model

The CAPM regression model, or the single-index model, is implemented in order to answer the research questions 1 to 3 as the alpha determines the performance of the proposed score momentum-based strategies compared to that of the benchmark. The market excess return is computed by the monthly return on both benchmarks respectively, and the abovementioned 1-year US T-bond.

To determine the alpha by the intercept, the authors have restated the CAPM as:

$$r_p^m - r_f^m = \alpha_p^m + \beta_p^m\left(r_m^m - r_f^m\right) + \epsilon_p^m \tag{28}$$

The OLS model carries out a t-test which determines the significance of the alpha (intercept), and β_p^m indicates the portfolio exposure to the general market portfolio. The OLS uses 10%-, 5%- and 1% significance levels to further evaluate if the alpha is unequal to zero. Lastly, adjusted R^2 and confidence intervals are computed based on the HAC standard errors for reliability assessments.

5.4.2 Multifactor model

The multifactor models allow the authors to examine whether there are other variables that explains the abnormal returns of the portfolios. These factors will investigate the performance of each portfolio by their exposure to size-, value and momentum risk factors. By gradually including the factors, it is easier to determine whether the return is explained by alpha, or other factors. The multifactor model is explained by:

$$r_p^m - r_f^m = \alpha_p^m + \beta_m\left(r_m^m - r_f^m\right) + \beta_{SMB}SMB^m + \beta_{HML}HML^m + \beta_{WML}WML^m + \epsilon_p^m \quad (29)$$

The multifactor model is further included to complement the CAPM model in order to answer the problem statement, as well as research question 4, on whether there are other factors outside of the scope of the four-factor model that can explain the alpha.

5.5 Performance metrics

In order to evaluate each portfolio derived from the proposed trading strategy beyond the generated alpha, this thesis will compute a number of performance- and risk metrics. As such, providing solid ground for comparing each portfolio against each other and the benchmark, with regard to certain performance measures and risk properties. These tools will contribute to the analysis as they assist the authors in assessing results from the strategies.

5.5.1 Expected return

Expected return indicates the expected profit or loss an investor can expect from the investment of a given portfolio. The expected return is calculated on a monthly basis by using the historical monthly stock returns throughout the dataset. The expected return is calculated by:

$$E[r_p^m] = \frac{1}{M}\left(\sum\nolimits_{m=1}^{M} r_p^m\right), \qquad m = 1, \dots, 109, \tag{30}$$

where 109 represents the number of observations in the data set.

In order to annualize the expected returns, the monthly expected portfolio return is compounded each month. Further, the authors take the arithmetic mean of the annualized monthly expected returns to get the expected annual return:

$$E[r_p^y] = \frac{1}{M}\left(\sum\nolimits_{m=1}^{M} \left(1 + r_p^m\right)^{12} - 1\right), \qquad m = 1, \dots, 109, \tag{31}$$

5.5.2 Volatility

The volatility of the portfolio shows the risk involved in the investment of the portfolio. Volatility is computed on a monthly basis based on the below presented equation 32, and further annualized as shown in equation 33:

$$\sigma_p^m = \sqrt{\frac{1}{M-1}\left(\sum_{m=1}^{M} \left(1 + r_p^m - E[r_p^m]\right)^2\right)}, \qquad m = 1, \dots, 109 \tag{32}$$

$$\sigma_p^y = \sigma_p^m * \sqrt{12} \tag{33}$$

5.5.3 Sharpe ratio

To orderly compare excess return to the total volatility of the different portfolios, the authors use the Sharpe ratio, as it is risk-adjusted. The Sharpe ratio express the excess return of a portfolio over its risk-free rate, relative to the portfolio's standard deviation (volatility). The Sharpe ratio is computed on a monthly basis through the following equation (Munk, 2019, p. 53):

$$Sharpe\ ratio_p^m = \frac{E\left[r_p^m\right] - r_f^m}{\sigma_p^m} \tag{34}$$

Further, the authors are interested in the Sharpe ratio on an annual basis. As expected returns and volatility are subjects to estimation errors, such as those mentioned in section 3.8, annualizing by multiplying the monthly Sharpe ratio by the square root of 12 does not provide the most accurate result (Lo, 2014). As such, the annualized Sharpe ratio is determined by the following equation:

$$Sharpe\ ratio_p^y = \frac{\frac{1}{M}\sum_{m=1}^{M}\left(\left(1+\left(r_p^m - r_f^m\right)\right)^{12} - 1\right)}{\sigma_p^y}, m = 1, \dots, 109 \tag{35}$$

As the investors are assumed to maximize their expected return to the lowest possible risk, the higher the Sharpe ratio the better.

5.5.4 Information ratio

As the portfolios constructed by this thesis' proposed trading strategies move away from the benchmark due to its own stock selection, they naturally take on portfolio-specific risk (Munk, 2019, p. 361). The information ratio (IR) allows for comparison between the portfolio returns and their benchmark by determining how much of the portfolio returns are assigned to their abnormal return rather than the return of the benchmark. As such, the information ratio states the portfolio's *active* return to its portfolio-specific risk.

The ratio is computed by subtracting the return of the benchmark to the return of the portfolio and dividing by the tracking error which is the standard deviation of the non-systematic return of the two investments (Munk, 2019):

$$IR_i^m = \frac{E\left[r_p^m - r_b^m\right]}{\sigma(r_p^m - r_b^m)} \tag{36}$$

Where a portfolio's active return is given by $E\left[r_p^m - r_b^m\right]$ and the tracking error by $\sigma(r_p^m - r_b^m)$. In order to compute the annualized information ratio, the annualized excess return will be computed through equation 31, while the annualized tracking error will utilize equation 33. The higher the value of the ratio, the better the portfolio is performing compared to its benchmark. An IR between 0.4 and 0.6 is considered a good investment, and an information ratio between 0.6 and 1 is considered a great investment.

5.5.5 Benchmark correlation

In order to determine the portfolio correlation with their respective benchmark, the authors makes use of the following equation (Bodie, Kane, & Marcus, 2010, p. 75):

$$\rho(p,b) = \frac{\sum_{m=1}^{M}(r_p^m - \overline{r_p^m})(r_b^m - \overline{r_b^m})}{\sqrt{\sum_{m=1}^{M}(r_p^m - \overline{r_p^m})}\sqrt{\sum_{m=1}^{M}(r_b^m - \overline{r_b^m})}} \tag{37}$$

5.5.6 Total return index

The authors will apply an indexation of the benchmark and each portfolio in order to better visualize the historical monthly returns throughout the time period. The portfolios are indexed to 100 from 01.01.2011 up until 01.01.2020, which is the end of this thesis' period of investigation. The TRI is computed as follows:

$$TRI_m = TRI_{m-1} * \left(1 + r_p^m\right) \tag{38}$$

In addition to the TRI, the high watermark (HWM) will be used as a proxy to determine the highest value each respective TRI has experienced throughout the time period. The high water mark functions as a measure for the investors to assess the performance of the portfolio as of late, as well as it facilitate for the risk measure maximum drawdown:

$$HWM_m = max[TRI_{01.02.2011}, \dots, TRI_{01.01.2020}] \tag{39}$$

5.6 Risk metrics

5.6.1 Maximum drawdown

In order to determine the downside risk of the portfolios, the authors include maximum drawdown (MDD) which represents the largest peak-to-trough drop throughout the period of investigation. The trough value (TV) represents the lowest level of TRI after the high watermark. Equal to the high water mark, the investors can assess the current level of the portfolio and determine the downside of the investment. The MDD is computed as follows:

$$MDD_m = \frac{TV_m - HWM_m}{HWM_m} \tag{40}$$

5.6.2 Skewness

The calculation of skewness is conducted as a risk measure as it quantifies to what extent the return distribution deviate from the normal distribution. Investors often use skewness in addition to volatility to predict future performance, as it gives an indication of the weight of the tails of the distribution. A positive (negative) skewness shows longer tails over the positive (negative) return. As such, investors seek to avoid negative skewness. The skewness is computed through the equation below (Munk, 2019, p. 75) :

$$Skewness = \frac{\frac{1}{M}\sum_{m=1}^{M}\left(r_p^m - \overline{r_p^m}\right)^3}{\left(\frac{1}{M}\sum_{m=1}^{M}\left(r_p^m - \overline{r_p^m}\right)^2\right)^{\frac{3}{2}}} \tag{41}$$

5.6.3 Kurtosis

The kurtosis is calculated as a measure to evaluate the shape of the distribution, i.e. the thickness of the tails. A normal kurtosis is considered to lie close to zero. If the value of the kurtosis exceeds zero, it is considered high, which implies that there is a higher possibility of large positive and negative return realizations. A kurtosis below zero implies the opposite (Munk, 2019, p. 75). The kurtosis is computed as follows:

$$Kurtosis = \frac{\frac{1}{M}\sum_{m=1}^{M}\left(r_p^m - \overline{r_p^m}\right)^4}{\left(\frac{1}{M}\sum_{m=1}^{M}\left(r_p^m - \overline{r_p^m}\right)^2\right)^2} - 3 \tag{42}$$

5.6.4 Value at risk

The value-at-risk tail risk measure (VaR) measures the maximum loss of an asset over a certain time period with a certain probability, i.e. the potential loss only exceeds the VaR with a determined probability p (Munk, 2019, p. 61). For our research, the VaR represents the maximum negative return in percentage during one month, based on historical returns for each portfolio as well as the benchmarks. For this thesis' research, the 5% value at risk will be calculated by the equation presented below:

$$VaR_p = q_{95} \tag{43}$$

5.6.5 Expected Shortfall

As the VaR do not take into account the magnitude of the extreme losses which exceeds the 5% VaR, the authors supplement the VaR by calculating the Expected shortfall (ES). The expected shortfall indicates the expected loss when the return exceeds the VaR by taking the average return for those 5% most extreme losses. As such, the expected shortfall should exceed the VaR:

$$Expected\ shortfall_p = E\left[Return \middle| Return < VaR_p\right] \tag{44}$$

5.7 Model testing

The models that have been included in this thesis possess multiple underlying econometric assumptions. This section will therefore test and discuss whether the models contradict any of these, as the analysis is dependent on its credibility. If any assumptions are found to be contradicted, the authors will take action. Even though the OLS is blue, i.e. best linear unbiased estimator, large variances and covariances within the model can make accurate estimations difficult. Furthermore, the authors wish to examine whether the underlying OLS assumptions are violated.

Common signs of unprecise models are that they have wider confidence intervals, insignificant t-ratios, and for some instances, a high R^2's as well as error terms that are sensitive to small changes in the data (Stock & Watson, 2015).

5.7.1 Econometric considerations

5.7.1.1 Multicollinearity

As the aim of this thesis is to examine whether there is an alpha within the returns of the portfolios constructed upon the ESG- and pillar score momentum-based trading strategies, our main focus is the intercept of the OLS. Furthermore, the factors applied are considered well-established and independent as such.

In order to determine the degree of multicollinearity the authors check for correlation among the independent variables within the model. This is done through the correlation matrices and the variance inflation factor (VIF) found in Appendix 11.5.1-4. The VIF indicates the correlation between the independent variables through regressing a variable against the other independent variables in the model, where the VIF factor represents the explanatory power of the remaining independent variables have on one specific independent variable (Woolridge, J.M., 2016). As equation 45 illustrates, the VIF score is a function of the R^2 of the regression, which means that the higher explanatory power of the other independent variables, the higher the score:

$$\mathrm{VIF_j} = \frac{1}{1 - \mathrm{R_j^2}} \tag{45}$$

Determining a specific cut-off value for an acceptable score is not particularly helpful. As with the adjusted R^2, its more an indicator for multicollinearity although a score of 1 means no correlation. A score that exceeds 5 means a high multicollinearity. Both the correlation matrix and VIF score output suggests that no multicollinearity is detected.

5.7.1.2 Heteroscedasticity

In order to assess the level of homoscedasticity in the regression models, a Breusch-Pagan (BP)-test is conducted. It is performed by constructing a linear regression on the squared error term through the independent variables as inputs:

$$\hat{u}^2 = \delta_0 + \delta_1 x_1 + \delta_2 x_2 + \ldots + \delta_k x_k + \text{error} \tag{46}$$

The BP-test assumes homoscedasticity, i.e. constant variation in the error term, where the null hypothesis of homoscedasticity is rejected if the explanatory variables has too much explanatory power over the error term. Through the Lagrange multiplier test statistic (LM test) the p-value can be computed in order to evaluate whether the models are homo- or heteroscedastic:

$$\text{LM} = n * R^2_{\hat{u}^2} \tag{47}$$

Where $R^2_{\hat{u}^2}$ is the level of fit for the squared error model with a sample size of n and (k-1) degrees of freedom. If the p-value is below the significance level, the null of homoscedasticity is rejected (Woolridge, J.M., 2016).

By looking at the test results in Appendix 11.5.5, heteroscedasticity is particularly detected in every Fama & French and CAPM models for the European market, as the BP-test generates high scores and p-values below the 1% level of significance. For US, this is only the case for the CAPM ESG score-based model and at the 5% level for that of the environmental score-based model. As such, indicating stronger model predictions for the US market.

5.7.1.3 Autocorrelation

The authors check the models for autocorrelation through a Breusch-Godfrey test, which allows testing for both positive- and negative correlation. The test is performed through the Lagrange multiplier (LM) form of statistic with one-period lag (Woolridge, J.M., 2016). If the p-value is below the significance level, the null of no autocorrelation amongst residuals is rejected.

As the test results in Appendix 11.5.6 illustrates, all but three models shows indication of autocorrelation at the 5% significance level. When raising the level of significance to 10%, the number of models which exhibit signs of autocorrelation rises to six. All of the abovementioned models with indications of such are for the European market, again indicating stronger model predictions for the US market.

5.7.1.4 Heteroscedastic- and autocorrelation consistent standard errors

As previously mentioned, there has been indications of heteroscedasticity and autocorrelation within the models, which means that the homoscedastic-only and autocorrelated standard errors won't be valid as they are derived under the false assumption of homoscedasticity and un-autocorrelated errors, respectively (Stock & Watson, 2015, p. 364). It is therefore typical to compute HAC standard errors that allow for both in order to stay consistent with the fourth and fifth OLS assumptions. The method for computing HAC standard errors is derived from the methodology of Newey-West and can be found in Appendix 11.5.7 (Stock & Watson, 2015, pp. 598-599). Note that the HAC standard errors are valid even if the models don't suffer from heteroscedasticity, autocorrelation or both (Stock & Watson, 2015, p. 364).

5.7.2 Selection biases

As a part of the methodology, the investment universe has been subject to a screening process based on company size, ESG- and financial data history as well as survivorship of the individual company.

Both S&P 500 and S&P Europe 350 are, as mentioned in the methodology, constituted of the biggest and most well-established companies in the U.S. and Europe, respectively. As such, the models' investment universes are biased towards these types of stocks with a certain level of market capitalization and liquidity. This entails on the other side a somewhat homogenous selection of potential investments for the investor.

Given the restrictions that the data availability imposed on our research, the time horizon of eleven years stretches from 01.01.2009 to 01.01.2020 and therefore excludes the implications that any financial crisis has on the proposed trading strategy, such as the financial crisis in 2008, or covid-19 in march 2020. As such, the impact from any national- or international financial- or other structural shocks are therefore uncertain when assessing the findings of this thesis.

Lastly, there is an obvious survivorship bias within the models as the average financial- and non-financial metrics of the sample does not account for companies which left the indices throughout the period under investigation.

5.7.3 Multifactor model evaluation

Evaluating the multifactor models is an important step in model testing in order to confirm their accuracy and reliability. Both the CAPM and Fama & French multifactor models exhibit a satisfactory level of significance which substantiates the authors' application of them. With regard to the Carhart four-factor model, its significance is not considered as such.

As the Carhart four-factor model output in Appendix 11.4 illustrates, the portfolio alphas become insignificant for all portfolios in the European market. The same is the case for the High social- and governance score-based portfolio models for the US market. Further, these uncertainties are reflected in the wide confidence intervals of both the factor coefficients and alpha for both the European and US market. As such, the authors cannot with a satisfactory level of certainty preclude that the true value of the alpha is not zero. For the CAPM single-index- and Fama & French multifactor models, the confidence intervals are considerably narrower. As such, in order to provide the highest degree of accuracy in our findings, the authors conclude to disregard the Carhart four-factor regression model in the following analysis.

6. Analysis

The following section will analyze the findings from the research based on the abovementioned methodology by comparing the strong momentum-based portfolio strategy (High) to that of the poor score momentum-based strategy (Low) as well as the benchmark. Further, this section is divided by the two markets of investigation and will analyze the momentum-based portfolios for overall ESG- and each pillar score separately. The analysis addresses the portfolios' general metrics, -performance measures', and a following OLS single-index- and multifactor regression analysis. Lastly, a sector composition comparison between the portfolios in all pillars will be conducted.

6.1 Portfolio analysis

6.1.1 US market

The portfolios under investigation are the constructed High- and Low portfolios based upon the ESG score momentum strategy, created of the constituents from the S&P 500. Both portfolios will be assessed in relation to each other as well as their benchmark.

6.1.1.1 ESG scores

6.1.1.1.1 General metrics

KPI overview - ESG	**High**		**Low**		**S&P 500**	
	Average	Median	Average	Median	Average	Median
ESG score	59.3	59.2	53.6	53.8	56.8	57.3
Market capitalization (USD bn)	31.7	33.6	40.5	35.8	38.5	38.3
Price/Earnings	30.5	31.5	28.2	28.4	48.6	37.8
Return on equity	19.0%	17.7%	18.8%	18.6%	23.6%	20.7%
Debt/equity	0.88	0.89	0.88	0.92	0.91	0.89
Book-to-market	0.43	0.39	0.42	0.39	0.43	0.40
Current ratio	1.9	1.8	1.8	1.8	1.5	1.5

Table 2 – ESG General metrics. Source: Own construction

The average ESG score for High and Low throughout the time period are observed to be marginally above and below that of the benchmark, respectively, which lies somewhat in the middle of Refinitiv's scale of 0-100. Further, the authors note that the ESG momentums are created in each direction on relatively equal ESG scores. Average market capitalization for High is considerably lower than that of the Low, both lying above and below that of the benchmark, respectively. Debt-to equity (D/E) ratios are similar between the two, which could be explained by a relative equal industry-composition (see sector composition below). Further, the average P/E ratio indicates that both portfolios are notably undervalued compared to the benchmark. The current ratio implies that both portfolios have a close-to satisfying short-term liquidity as they score just below 2, which indicate a satisfying short-term liquidity risk. As such, the general metrics of the portfolios are considered relatively similar which is somewhat emphasized by the following performance measures.

6.1.1.1.2 Performance measures

ESG - portfolio descriptive statistics	High		Low		S&P 500	
	Monthly	Yearly	Monthly	Yearly	Monthly	Yearly
Performance measures						
Expected return	0.01	0.14	0.01	0.17	0.01	0.12
Volatility	0.03	0.10	0.03	0.10	0.04	0.13
Sharpe ratio	0.36	1.23	0.41	1.43	0.24	0.83
Information ratio	0.12	0.42	0.24	0.82	-	-
Total return index	313.96		385.43		254.02	
Risk measures						
Benchmark correlation	0.94		0.92		-	
High watermark	313.96		385.43		254.02	
Max. drawdown	-0.14		-0.12		-0.19	
Skewness	-0.41		-0.12		-0.58	
Kurtosis	0.14		0.51		1.04	
5% Empirical VaR	-0.05		-0.04		-0.06	
Expected shortfall	-0.05		-0.05		-0.08	

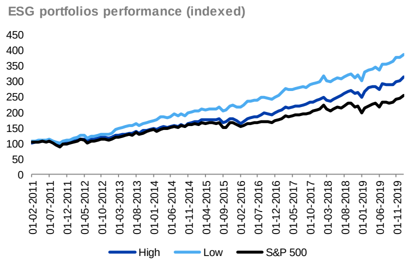

Table 3 – ESG Performance measures. Source: Own construction

As indicated by Table 3 above, the expected return of High and Low are 2 ppts. and 5 ppts. above that of the benchmark on an annual basis, respectively. The adjusted risk measure, Sharpe ratio, shows a greater yearly risk-adjusted return for both portfolios compared to the benchmark. This is also the case with regard to the information ratio, suggesting that both portfolios are rewarded by their additional tracking error. Low scores above High on both the Sharpe ratio and the information ratio. Both portfolios clearly outperform the index as illustrated by the TRI, where the Low portfolio notably outperform the High portfolio with 71.47 ppts. and the benchmark with 131.41 ppts.

6.1.1.1.3 Risk measures

Both portfolios indicate a high degree of benchmark correlation, where the High has a marginally higher correlation than the Low. The high watermark of Low is also above that of High as well as the benchmark, which was achieved at period-end. This is the case for both portfolios and the benchmark.

The Low portfolio has the least severe maximum drawdown, as it is 2- and 7 ppts. less extreme than that of High and the benchmark, respectively. As such, emphasizing the portfolios less severe downside risk. Both portfolios' return distributions exhibit negative skewness, indicating that both portfolios have a lower mean than median, although higher than the benchmark. Portfolio return distribution kurtosis is also lower than the benchmark for both portfolios, indicating that the portfolio returns consist of fewer extreme outliers. The risk measures empirical value at risk and expected shortfall are close to equal for both portfolios, which are relatively low compared to the benchmark.

6.1.1.1.4 Alpha detection

	Dependent variable:			
	Highr		Lowr	
	(1)	(2)	(3)	(4)
MRP	0.7492^{***}	0.7252^{***}	0.7493^{***}	0.7302^{***}
	(0.6870, 0.8114)	(0.6663, 0.7841)	(0.6794, 0.8193)	(0.6595, 0.8008)
SMB		0.5471^{***}		0.3560^{**}
		(0.2994, 0.7949)		(0.0107, 0.7012)
HML		-0.1920^{**}		-0.0453
		(-0.3552, -0.0289)		(-0.2490, 0.1584)
Constant	0.0045^{***}	0.0046^{***}	0.0065^{***}	0.0071^{***}
	(0.0028, 0.0063)	(0.0022, 0.0069)	(0.0041, 0.0089)	(0.0041, 0.0100)
Observations	108	108	108	108
R^2	0.8800	0.8968	0.8404	0.8474
Adjusted R^2	0.8788	0.8939	0.8389	0.8430
Residual Std. Error	0.0105 (df = 106)	0.0098 (df = 104)	0.0124 (df = 106)	0.0122 (df = 104)
F Statistic	776.9720^{***} (df = 1; 106)	301.3875^{***} (df = 3; 104)	558.3102^{***} (df = 1; 106)	192.4953^{***} (df = 3; 104)

Note: The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.

Table 4 – ESG OLS. Source: Own construction

The CAPM OLS regression model exhibits relatively high goodness of fit for both portfolios. Market beta (MRP) for High and Low are close to indicial and below one, which indicates that the portfolios possess less systematic risk than the market. The market risk premium-coefficients for both portfolio models are highly statistical significant at a 1% level. The single-index model shows that the High- and Low portfolios yield a positive annualized alpha of 5.54% and 8.08%, respectively, both significant at a 1% significance level. This implies that both portfolios achieve a higher return than the market portfolio.

When applying the factors of Fama & French, the alphas of both portfolios increase. The Fama & French model generates annualized alphas for High and Low of 5.66% and 8.86%, respectively. Both significant at the 1% level. The Fama & French model show a roughly equally high explanatory degree as the CAPM model in terms of adjusted R^2, as well as both portfolios obtain a significant market beta at a 1% level. Further, the model indicates notable positive exposure to size effects for both portfolios significant at the 1% level, where the magnitude is greater for High than Low. The exposure towards the value effect is negative for both portfolios, where the magnitude is more severe for High which is significant at the 5% level. For Low, the factor exposure is insignificant. As such, indicating that the portfolio returns are negatively affected by the value premium effect.

All F-statistics show overall model significance at the 1% significance level across all models.

6.1.1.1.5 Sector composition

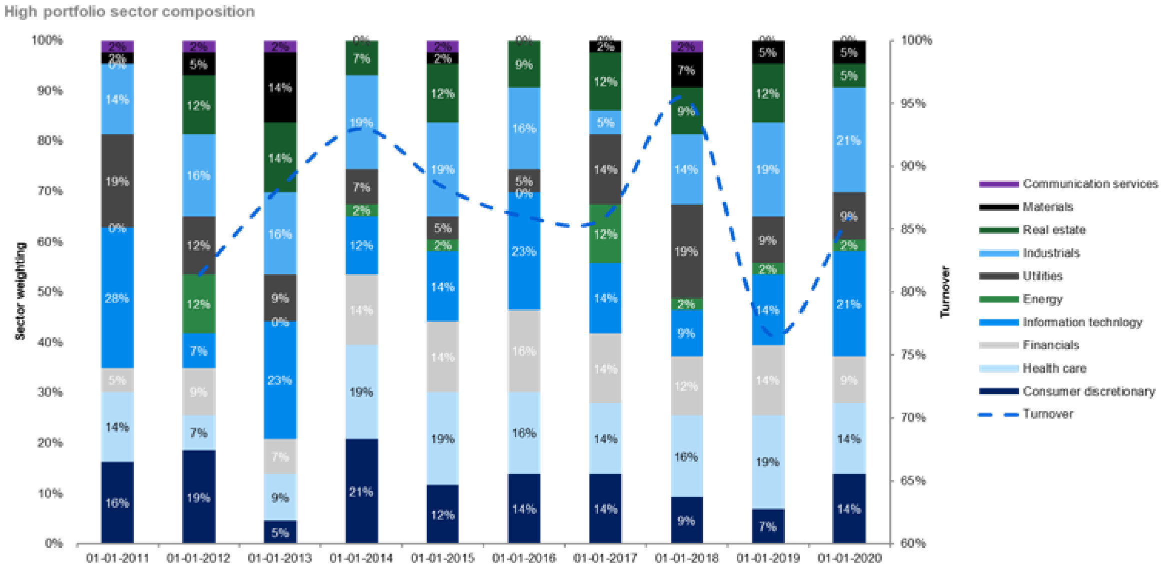

Illustration 6 – ESG Sector composition (High portfolio). Source: Own construction

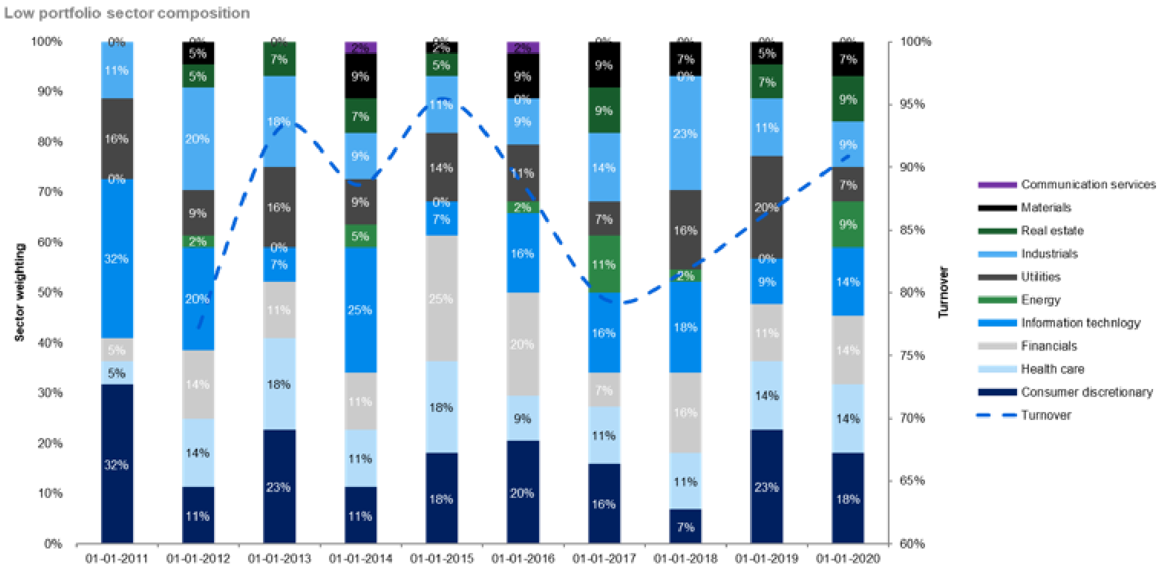

Illustration 7 – ESG Sector composition (Low portfolio). Source: Own construction

The sector composition chart above illustrates the high degree of turnover, with an average turnover of 87% for both portfolios. Despite high turnover, the sector composition of both portfolios remained stable throughout the time period. As such, suggesting a stable overall ESG score-momentum across sectors. Further, the sector representation within the portfolios is also similar to that of the benchmark, indicating no particular sector-specific value driver within the portfolios that potentially could affect our results. The high turnover further highlights the vast number of companies who introduces short term overall ESG-related strategies to improve their scores, which in turn creates short-term momentums. This is further emphasized as the authors has noted multiple companies has shifted between the two performance portfolios throughout the period under investigation.

6.1.1.1.6 Sub-conclusion

The effect from both strong and poor ESG score momentum on portfolio alpha in the US market has become evident. In terms of absolute return, the Low outperforms both High and the benchmark. The general metrics show clear similarities between the High- and Low performance portfolios, where the latter has exhibited outperformance on an overall basis in terms of performance and risk. Both the CAPM and Fama & French OLS regression models suggests highly significant positive alphas in both portfolios. This suggests no clear difference between a strong and poor momentum in terms of alpha generation, although the magnitude of alpha is greater within the returns of the Low portfolios. All factor coefficients were significant at different levels for the High portfolio in addition to allocating a greater explanation of the alpha after implementing the size- and value premium factor of Fama & French. This is also the case for Low, with the exception of the value premium-effects which is suggested by the OLS to be insignificant. Both portfolios exhibit high turnover rate, which can be described through companies' short-term ESG-related strategies.

6.1.1.2 Environmental pillar

6.1.1.2.1 General metrics

KPI overview - Environmental pillar

	High		**Low**		**S&P 500**	
	Average	Median	Average	Median	Average	Median
Environmental score	55.9	56.8	49.4	49.7	49.3	48.7
Market capitalisation (USD bn)	31.3	33.7	32.9	32.2	38.5	38.3
Price/Earnings	45.0	36.3	26.8	25.8	47.4	34.9
Return on equity	20.9%	19.8%	20.1%	19.9%	23.6%	20.7%
Debt/equity	1.08	1.06	1.04	1.03	0.91	0.89
Book-to-market	0.42	0.38	0.43	0.42	0.43	0.40
Current ratio	1.8	1.8	1.6	1.5	1.5	1.5

Table 5 – Environmental General metrics. Source: Own construction

The High portfolio exhibits an average environmental score above that of the Low and the benchmark. In terms of pillar score, the environmental score of the benchmark is the lowest of all pillars in the US market. Further, the average market capitalization for both portfolios are below that of the S&P 500 average, which indicates that the extreme momentums are generated from companies of similar size.

Low portfolio average Price/Earnings ratio is considerably lower than both High and the benchmark, implying that companies with a low environmental momentum is undervalued compared to earnings in the US market. As such, suggesting a notable focus from investors towards the environmental pillar score. Further, both portfolios show a strong degree of short-term liquidity which is somewhat similar to that of the benchmark. Debt-to-equity ratio is higher than the benchmark average for both portfolios, which might be due to their sector composition, which is constituted by predominant asset heavy industries such as industrials and utilities.

6.1.1.2.2 Performance measures

Environmental pillar - portfolio descriptive statistics

	High		Low		S&P 500	
	Monthly	Yearly	Monthly	Yearly	Monthly	Yearly
Performance measures						
Expected return	0.01	0.15	0.01	0.16	0.01	0.12
Volatility	0.03	0.10	0.03	0.10	0.04	0.13
Sharpe ratio	0.37	1.28	0.39	1.34	0.24	0.83
Information ratio	0.16	0.56	0.18	0.63	-	-
Total return index	326.89		352.65		254.02	
Risk measures						
Benchmark correlation	0.95		0.92		-	
High watermark	326.89		352.65		254.02	
Max. drawdown	-0.12		-0.15		-0.19	
Skewness	-0.32		-0.05		-0.58	
Kurtosis	0.11		0.37		1.04	
5% Empirical VaR	-0.03		-0.04		-0.06	
Expected shortfall	-0.06		-0.05		-0.08	

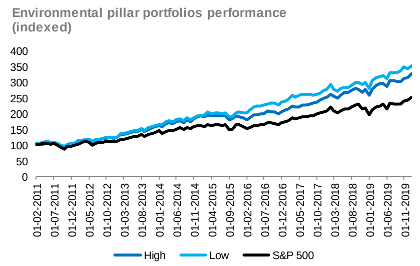

Table 6 – Environmental Performance measures. Source: Own construction

As with the abovementioned ESG score momentum-based portfolios, the Low portfolio outperformed both High and the benchmark throughout the period under investigation. In terms of annual expected return, Low is expected to yield 1 ppts. and 4 ppts. above High and the benchmark, respectively. The risk-adjusted measures of Sharpe ratio indicates that both portfolios generate better risk-adjusted returns than the benchmark by a margin. Further, the positive information ratio of both portfolios indicates that they are rewarded by their additional tracking error with regard to the benchmark. This is especially the case for Low which has the highest IR. In terms of their total return index, table 6 also indicates their notable outperformance of the benchmark throughout the period under investigation, where Low outperformed High and the benchmark by 25.8- and 98.6 ppts., respectively.

6.1.1.2.3 Risk measures

The high watermark is equal to the total return index at period end as all portfolios including the benchmark achieved their all-time high TRI at that period of time. Both portfolios exhibit a high degree of benchmark correlation. Maximum drawdown is the least severe for the Low portfolio, which is 3 ppts. less than that of High. Further, the S&P 500 exhibited a 7 ppts. and 4 ppts. more severe MDD than High and Low, respectively. As such, indicating less downside risk than the benchmark. The skewness is fairly symmetrical for both portfolios, as they lie within the interval of -0.32 to -0.05. In addition, their skewness is less negative than that of the benchmark, indicating that the benchmark will experience a somewhat larger portion of negative returns.

6.1.1.2.4 Alpha detection

	Dependent variable:			
	Highr		Lowr	
	(1)	(2)	(3)	(4)
MRP	0.7606^{***}	0.7433^{***}	0.7468^{***}	0.7239^{***}
	(0.7085, 0.8127)	(0.6909, 0.7958)	(0.6809, 0.8128)	(0.6570, 0.7908)
SMB		0.3757^{***}		0.3422^{**}
		(0.1239, 0.6275)		(0.0320, 0.6525)
HML		-0.1141		0.0567
		(-0.2784, 0.0501)		(-0.1794, 0.2929)
Constant	0.0048^{***}	0.0050^{***}	0.0057^{***}	0.0070^{***}
	(0.0032, 0.0064)	(0.0029, 0.0070)	(0.0032, 0.0081)	(0.0041, 0.0099)
Observations	108	108	108	108
R^2	0.9066	0.9144	0.8425	0.8514
Adjusted R^2	0.9057	0.9120	0.8410	0.8471
Residual Std. Error	0.0092 (df = 106)	0.0089 (df = 104)	0.0122 (df = 106)	0.0120 (df = 104)
F Statistic	$1{,}028.8050^{***}$ (df = 1; 106)	370.4680^{***} (df = 3; 104)	566.9892^{***} (df = 1; 106)	198.6046^{***} (df = 3; 104)

Note: The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.

Table 7 – Environmental OLS. Source: Own construction

The adjusted R^2 is relatively high in the CAPM OLS model for both portfolios and ranges between 0.841-0.906, emphasizing a somewhat lower benchmark correlation. Similar to the findings for the ESG momentum model, the market beta (MRP) for both the High and Low model are significant at a 1% level, with a value short of 0.8. As such, indicating that the portfolios have a lower systematic risk. Further, the OLS suggests annualized alphas of 5.91% and 7.06% for High and Low, respectively, both significant at the 1% level.

The Fama & French multifactor model share the same explanatory degree as the CAPM single-index in terms of adjusted R^2. Market betas are significant at a 1% level and below 1 for both portfolios, which indicates a lower systematic risk than the market, emphasized by the descriptive statistics above. Further, highly significant annualized alphas of 6.17% and 8.73% for High and Low, respectively, are detected. Both portfolios exhibit indications of being moderate positively exposed to size effects, where the effects are significant at the 1% and 5% level for High and Low, respectively. The value premium effects are indicated to be contradicting for the two portfolios where the effect is negative for High and positive for Low. In terms of magnitude, the effect is considered weak in addition to being insignificant for both.

All F-statistics show overall model significance at the 1% significance level across all models.

6.1.1.2.5 Sector composition

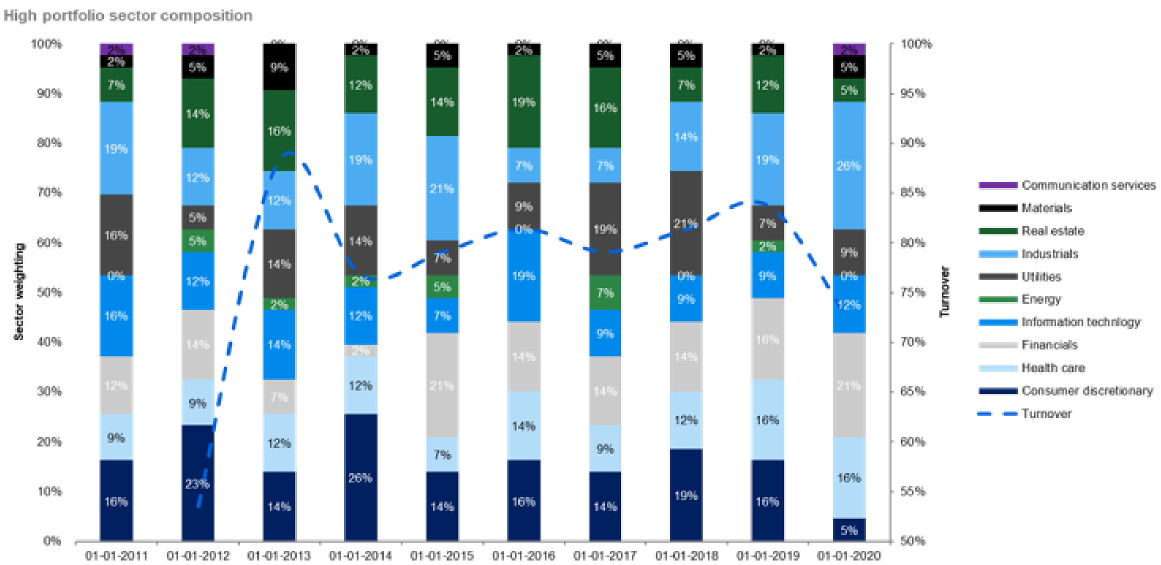

Illustration 8 – Environmental General metrics (High portfolio). Source: Own construction

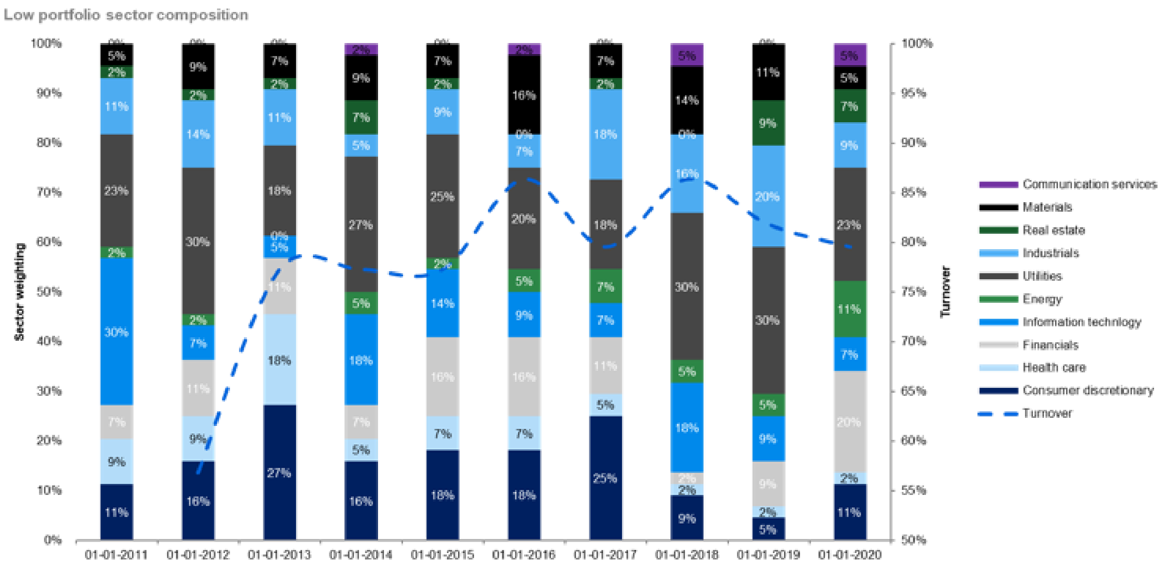

Illustration 9 – Environmental General metrics (Low portfolio). Source: Own construction

Average turnover of 77% and 78% for the High and Low portfolio, respectively, throughout the time period, which is the lowest of all pillar portfolios in the US market. As such, suggesting a low US environmental focus as a high focus would presumably lead to an increased turnover, especially in the High portfolio, as there would have been more companies that would increase their environmental scores. The sector composition for the High portfolio is considered diversified, although with a notable weight towards the industrials and healthcare sectors, which combined make up on average 27% of the portfolio.

6.1.1.2.6 Sub-conclusion

Both strong and poor environmental score momentum effects on portfolio alphas are detected for the US market. In terms of absolute return, both portfolios outperform the benchmark, where Low also outperforms High. The general metrics show, like the abovementioned ESG momentum-based portfolios, clear similarities between the High- and Low performance measures, where the latter has exhibited greater performance in terms of performance and risk.

The environmental score average, and turnover, is the lowest average of all benchmark portfolios which emphasizes that the US market does not facilitate an environmental change, as companies are less incentivized to implement new measures to increase their scores. Both the single-index model and the Fama & French models detect significant positive alphas for both portfolios, where some explanation can be assigned to the size effect for both portfolios, although with different statistical significance.

6.1.1.3 Social pillar

6.1.1.3.1 General metrics

KPI overview - Social pillar

	High		Low		S&P 500	
	Average	Median	Average	Median	Average	Median
Social score	63.9	63.0	53.2	52.8	58.6	58.8
Market capitalization (USD bn)	35.3	35.7	36.2	36.5	38.5	38.3
Price/Earnings	29.7	29.8	28.0	27.7	47.4	34.9
Return on equity	22.3%	20.2%	22.2%	20.8%	23.6%	20.7%
Debt/equity	0.90	0.87	1.17	1.05	0.91	0.89
Book-to-market	0.41	0.37	0.42	0.43	0.43	0.40
Current ratio	1.9	1.9	1.8	1.8	1.5	1.5

Table 8 – Social General metrics. Source: Own construction

Average social score differs between the High- and Low portfolio, indicating that a high (low) social momentum is created upon companies with a high (low) social pillar score. The average market capitalization is similar between both portfolios and the benchmark, but the P/E is remarkably lower for both the High- and Low portfolio compared to the market. This indicates that companies with high social focus, as well as companies with a low social focus, tend to be undervalued, compared to their earnings. Their D/E differ somewhat, which likely is a result of the industry composition, as the Low portfolio is heavily affected by asset heavy industries, such as industrials (see sector composition below).

6.1.1.3.2 Performance measures

Social pillar - portfolio descriptive statistics

	High		Low		S&P 500	
	Monthly	Yearly	Monthly	Yearly	Monthly	Yearly
Performance measures						
Expected return	0.01	0.16	0.01	0.16	0.01	0.12
Volatility	0.03	0.10	0.03	0.11	0.04	0.13
Sharpe ratio	0.39	1.36	0.37	1.29	0.24	0.83
Information ratio	0.21	0.73	0.23	0.81	-	-
Total return index	355.42		362.60		254.02	
Risk measures						
Benchmark correlation	0.94		0.94		-	
High watermark	355.42		362.60		254.02	
Max. drawdown	-0.12		-0.17		-0.19	
Skewness	-0.42		-0.23		-0.58	
Kurtosis	0.10		0.28		1.04	
5% Empirical VaR	-0.04		-0.05		-0.06	
Expected shortfall	-0.05		-0.06		-0.08	

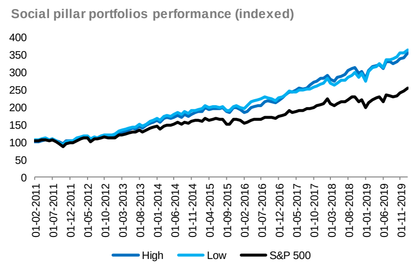

Table 9 – Social Performance measures. Source: Own construction

Table 9 above, demonstrates the significant outperformance of both portfolios with regard to their benchmark. Both portfolios yield approximately the same expected return and volatility, notably more satisfying than the benchmark. Above-benchmark risk-adjusted returns are suggested by considerably higher Sharpe ratio for both portfolios, where High exhibits the greatest. As indicated by their positive information ratios, both portfolios are rewarded by their respective idiosyncratic risks. This is to a greater extent the case for Low.

6.1.1.3.3 Risk measures

Total return index equals the high watermark for both portfolios as well as the benchmark, as they all hit their peak total return index at period end. In terms of downside risk, High and Low experienced 7 ppts. and 2 ppts. less severe maximum drawdown than the benchmark, respectively, during the period under investigation. As such, indicating a considerably lower downside risk for the High-momentum portfolio. Both portfolios experience a negative skewness with a significantly lower kurtosis than the benchmark, implying that both portfolios experience fewer negative and less extreme returns.

6.1.1.3.4 Alpha detection

	Dependent variable:			
	Highr		Lowr	
	(1)	(2)	(3)	(4)
MRP	0.7547***	0.7351***	0.8153***	0.7978***
	(0.7001, 0.8094)	(0.6797, 0.7905)	(0.7451, 0.8855)	(0.7294, 0.8661)
SMB		0.4830***		0.2954*
		(0.2840, 0.6819)		(-0.0534, 0.6442)
HML		-0.2026**		-0.0009
		(-0.3730, -0.0323)		(-0.2057, 0.2039)
Constant	0.0056***	0.0054***	0.0054***	0.0062***
	(0.0037, 0.0076)	(0.0032, 0.0076)	(0.0032, 0.0076)	(0.0035, 0.0088)
Observations	108	108	108	108
R^2	0.8877	0.9013	0.8769	0.8816
Adjusted R^2	0.8866	0.8984	0.8758	0.8782
Residual Std. Error	0.0102 (df = 106)	0.0096 (df = 104)	0.0116 (df = 106)	0.0115 (df = 104)
F Statistic	837.5370*** (df = 1; 106)	316.4796*** (df = 3; 104)	755.3730*** (df = 1; 106)	258.1855*** (df = 3; 104)
Note:	The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.			

Table 10 – Social OLS. Source: Own construction

The single-index model achieves a high explanatory level, for both the High- and Low portfolios with an adjusted R^2 score of 0.887 and 0.876, respectively. Market risk premium coefficients for both portfolios lies around 0.8, which implies less systematic risk than the market. This is to a greater extent the case for High, which exhibits the lowest MRP coefficient. In addition, both coefficients are significant at the 1% level. Highly significant alphas at the 1% level are detected in both portfolios, which corresponds to 6.93% and 6.68% for High and Low, respectively, on an annual basis.

The Fama & French multifactor models for the social pillar share characteristics with the CAPM model, as both the High- and Low portfolio have a strong goodness of fit, as well as highly significant market risk premium-coefficients of similar magnitude. Highly significant and positive size effect exposure of considerable magnitude is suggested by the multifactor model for High. This is also the case for Low, although less so as the coefficient magnitude is smaller, in addition to a significance level of 10%. Value premium exposure is considered negative for both portfolios. In terms of magnitude, the exposure is considered moderate for High and almost non-existing for Low. For High the effect is indicated to be significant at the 5% level, while insignificant for Low. Portfolio alphas are highly significant at the 1% level and corresponds to an annualized excess return of 6.7% and 7.7% for High and Low, respectively.

All F-statistics show overall model significance at the 1% significance level across all models.

6.1.1.3.5 Sector composition

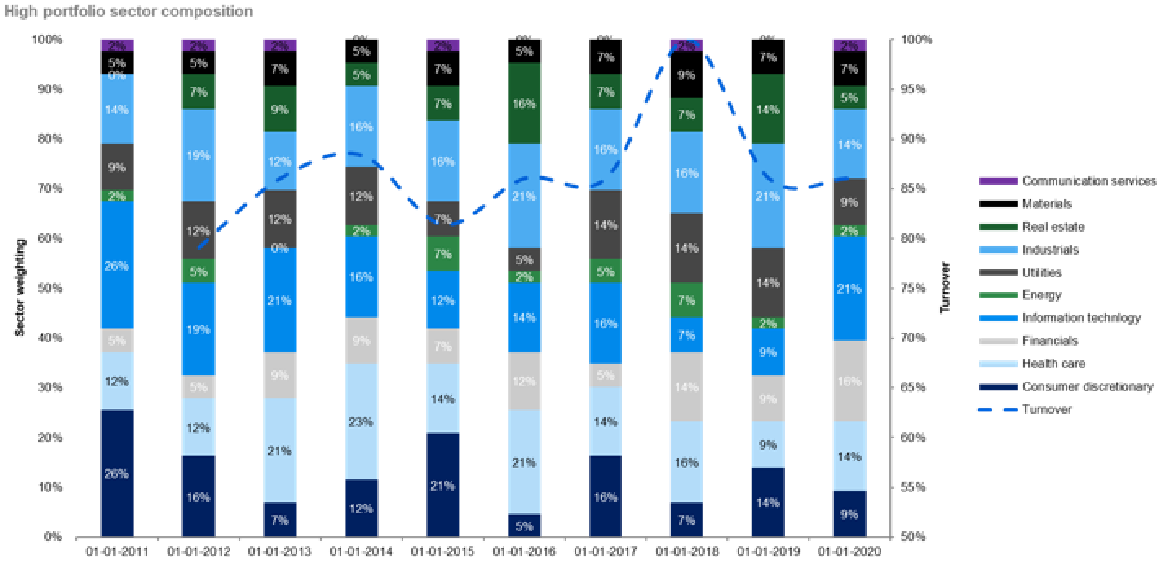

Illustration 10 – Social General metrics (High portfolio). Source: Own construction

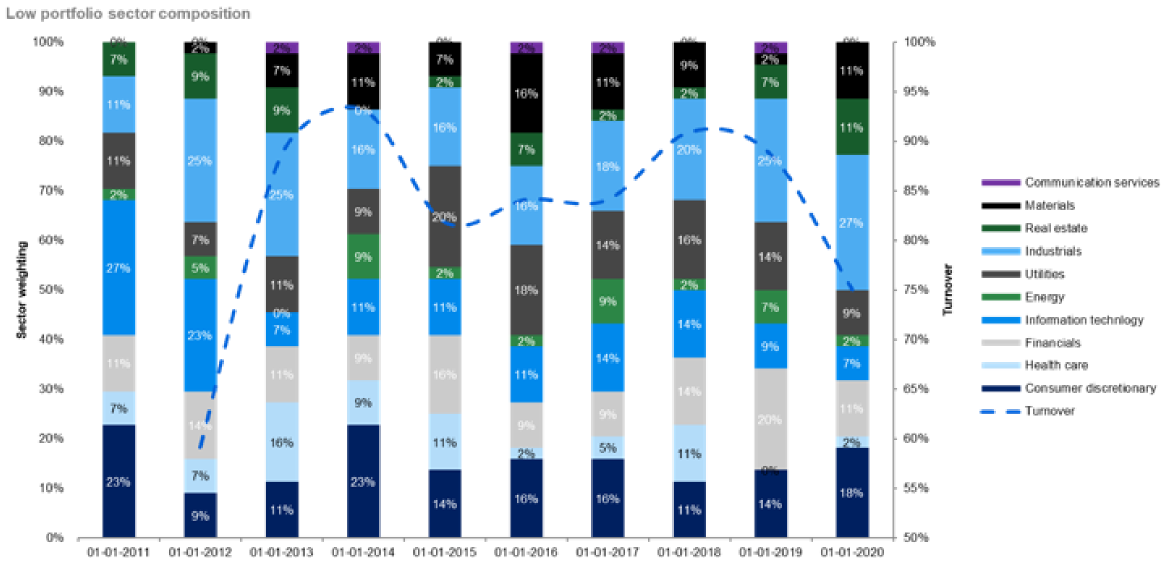

Illustration 11 – Social General metrics (Low portfolio). Source: Own construction

Average turnover is 87% and 83% for the High and Low portfolio, respectively, throughout the time period. Despite relative high turnover, the sector representation within both portfolios is considered fairly stable for both portfolios. The High portfolio experienced a peak in turnover at 100% in 2018, indicating a great number of companies which are improving their social scores during this time. The sector composition of High is considered more diversified than that of Low throughout the time period as the latter to a greater extent consists of fewer and heavier weighted sectors such as industrials and consumer discretionary.

6.1.1.3.6 Sub-conclusion

Significant positive alphas are detected for both the High- and Low social pillar score momentum-based portfolios in both the single-index- and Fama & French models. Also similar for both portfolios, significant market risk premium-coefficients below one indicates low systematic risk. In addition, the implementation of size- and value premium factors of Fama & French impacted portfolio alphas differently for the two portfolios. While High experienced a decrease in portfolio alpha, the effect was positive for Low. As such, suggesting that Low to generates an alpha beyond the Fama & French model to a greater extent than High. In terms of risk and return, the two performance portfolios exhibit similar properties outperforming the benchmark considerably on both metrics. Further, the portfolios display a satisfactory degree of diversification throughout the period, which both enhances the comparability between the portfolios as well as emphasizes the use of S&P 500 as a suitable benchmark.

6.1.1.4 Governance pillar

6.1.1.4.1 General metrics

KPI overview - Governance pillar

	High		Low		S&P 500	
	Average	Median	Average	Median	Average	Median
Governance score	64.5	64.3	49.5	50.7	59.2	60.9
Market capitalization (USD bn)	33.4	30.9	38.1	34.4	38.5	38.3
Price/Earnings	29.3	28.1	27.2	25.2	47.4	34.9
Return on equity	20.4%	20.5%	21.0%	20.9%	23.6%	20.7%
Debt/equity	0.92	0.92	0.99	1.04	0.91	0.89
Book-to-market	0.43	0.44	0.41	0.40	0.43	0.40
Current ratio	1.9	1.9	1.8	1.7	1.5	1.5

Table 11 – Governance General metrics. Source: Own construction

The High governance portfolio has the highest score average of all US portfolios, indicating that US companies view governance as an important measure. High portfolio average market capitalization across the time period is notably below both that of Low and the benchmark. Average P/E for both portfolios are considerably lower than the benchmark, indicating a relative company undervaluation to their earnings compared to the market. Both portfolios exhibit similar capital structures as the benchmark in terms of debt-to-equity. Further, both portfolios displays above-benchmark average current ratios, which are close-to the satisfying level of 2.

6.1.1.4.2 Performance measures

Governance - portfolio descriptive statistics

	High		Low		S&P 500	
	Monthly	Yearly	Monthly	Yearly	Monthly	Yearly
Performance measures						
Expected return	0.01	0.14	0.01	0.17	0.01	0.12
Volatility	0.03	0.10	0.03	0.11	0.04	0.13
Sharpe ratio	0.36	1.23	0.42	1.44	0.24	0.83
Information ratio	0.18	0.61	0.24	0.84	-	-
Total return index	319.42		397.11		254.02	
Risk measures						
Benchmark correlation	0.97		0.91		-	
High watermark	319.42		397.11		254.02	
Max. drawdown	-0.15		-0.11		-0.19	
Skewness	-0.45		0.03		-0.58	
Kurtosis	0.12		0.52		1.04	
5% Empirical VaR	-0.04		-0.04		-0.06	
Expected shortfall	-0.05		-0.05		-0.08	

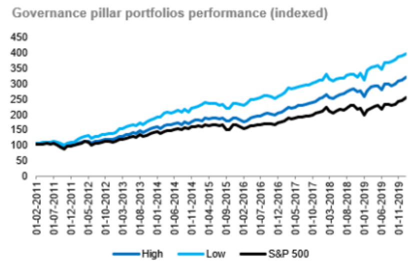

Table 12 – Governance Performance measures. Source: Own construction

The High and Low portfolios are expected to yield an excess return of 2 ppts. and 5 ppts. above the S&P 500, respectively, based on their historical returns throughout the period of investigation. In addition, portfolio volatility is below that of the benchmark for both portfolios, resulting in notably greater Sharpe ratios. This is also reflected in their positive information ratios, which suggests that both portfolios are rewarded by their tracking error in terms of return.

As with the other pillar-specific portfolios the total return index equals their high watermarks as both hit their peak total return index at period end. In terms of such outperformance, High and Low outperformed the benchmark by 65.4 ppts. and 143.09 ppts., respectively, throughout the time period.

6.1.1.4.3 Risk measures

The High portfolio have the highest benchmark correlation of all US portfolios of 0.97, emphasizing it's comparable characteristics as the benchmark. Maximum drawdown for High and Low were 4 ppts. and 8 ppts. less severe than that of the benchmark at -19%. As such, the return downside risk is less severe than the benchmark for both portfolios. This is further substantiated by their less extensive value at risk and expected shortfall than that of the benchmark. The skewness and kurtosis of the two portfolios does not indicate any particular issues with the return distributions as they indicate light tails and few outliers.

6.1.1.4.4 Alpha detection

	Dependent variable:			
	Highr		Lowr	
	(1)	(2)	(3)	(4)
MRP	0.7774^{***}	0.7409^{***}	0.7518^{***}	0.7335^{***}
	(0.7168, 0.8380)	(0.6796, 0.8022)	(0.6747, 0.8289)	(0.6573, 0.8097)
SMB		0.6314^{***}		0.4199^{**}
		(0.3930, 0.8698)		(0.0286, 0.8111)
HML		-0.0245		-0.1499
		(-0.2245, 0.1756)		(-0.3756, 0.0759)
Constant	0.0050^{***}	0.0065^{***}	0.0067^{***}	0.0067^{***}
	(0.0030, 0.0070)	(0.0038, 0.0091)	(0.0042, 0.0093)	(0.0039, 0.0096)
Observations	108	108	108	108
R^2	0.8785	0.9012	0.8218	0.8310
Adjusted R^2	0.8773	0.8984	0.8201	0.8261
Residual Std. Error	0.0109 (df = 106)	0.0100 (df = 104)	0.0133 (df = 106)	0.0130 (df = 104)
F Statistic	766.1386^{***} (df = 1; 106)	316.2585^{***} (df = 3; 104)	488.6737^{***} (df = 1; 106)	170.4608^{***} (df = 3; 104)
Note:	The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.			

Table 13 – Governance OLS. Source: Own construction

The single-index model's adjusted R^2 indicates a high explanatory degree as it ranges from 0.8201 – 0.8773. Further, the market risk premium-coefficients are statistically significant at the 1% level and lies below 1. As such, indicating that both High and Low exhibit a moderate exposure to the market. In terms of alpha, the single-index model indicates positive alphas significant at the 1% level for both portfolios. On an annualized basis, High and Low are suggested by the OLS to yield alphas of 6.17% and 8.34%, respectively.

The OLS indicates no particular increase in adjusted R^2 after implementation of the size- and value premium-factors. Further, the Fama & French multifactor model assigns less explanatory power to the market risk premium for both portfolios, although they are still significant at the 1% level. Significant positive exposure to size effects at the 1% and 5% level of significance for High and Low, respectively, where the exposure is of greater magnitude in the returns of the High portfolio. In terms of the value premium effect, the OLS regression suggests the exposure to be moderately negative, although insignificant for High as well as Low. Both portfolio returns are suggested to yield highly significant alphas of material magnitude, where their annualized expected excess return is indicated to be 8.1% and 8.3% for High and Low, respectively. Furthermore, the multifactor model for High assigns a greater amount of the expected excess return to the alpha compared to the single-index. This is not the case for Low.

All models show a highly significant F statistic at 1%, indicating that the model provide a better fit for the data in the regression than a model without the independent variables.

6.1.1.4.5 Sector composition

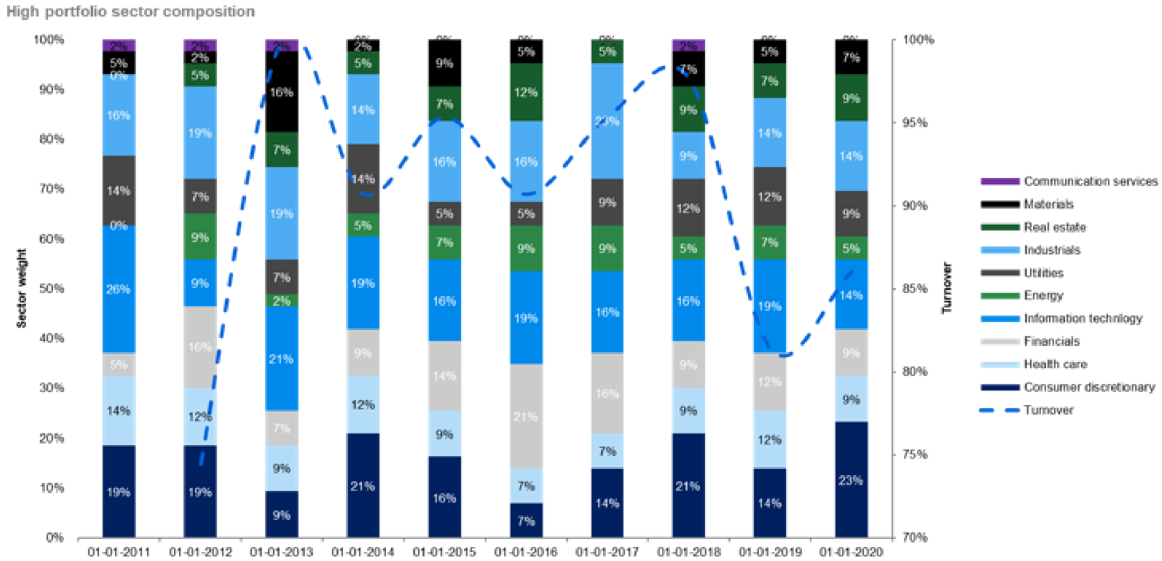

Illustration 12 – Governance Sector composition (High portfolio). Source: Own construction

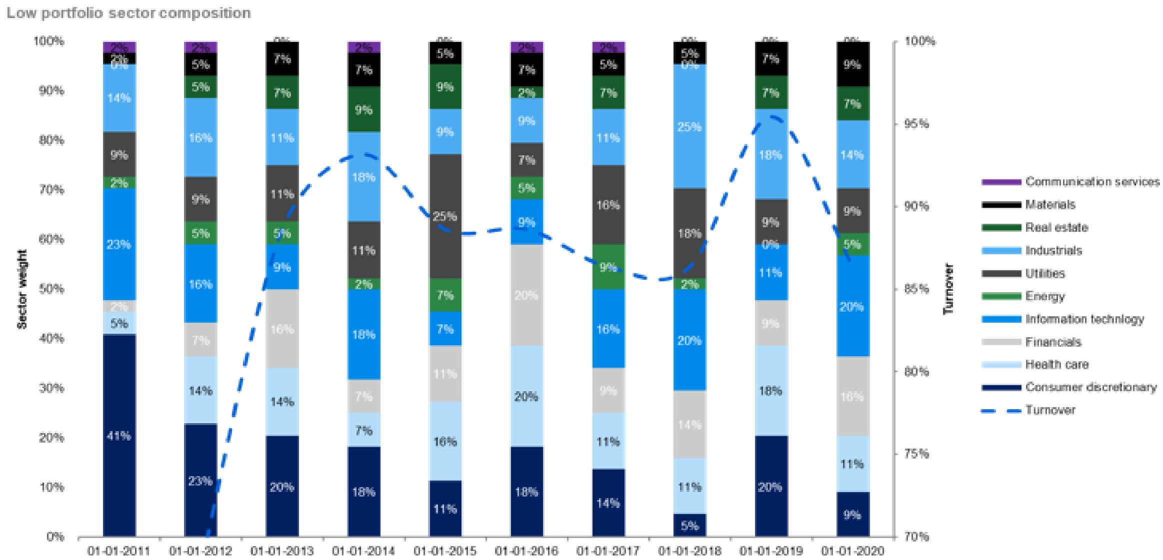

Illustration 13 – Governance Sector composition (Low portfolio). Source: Own construction

As the governance pillar score is equally weighted in the overall ESG scores independent of company sector, its importance should be close to similar across the market. 90% average portfolio turnover for the High portfolio throughout the period, which is 3 ppts. above that of Low and the highest amongst all pillar-specific portfolios of the US market, emphasizes the focus towards the pillar. In terms of sector representation, both portfolios are considered fairly diversified. High portfolio displays stable sector weights throughout the time period, whereas the weight of the consumer discretionary sector weight of the Low portfolio has decreased significantly. As such, suggesting that companies within this sector have increased their focus on corporate governance measures.

6.1.1.4.6 Sub-conclusion

Highly significant positive alphas of similar material magnitude are detected in the returns for both the High and Low portfolio, indicated by both the single-index- and the Fama & French multifactor model. As indicated in the other pillar-specific portfolios of the US market, significant market risk premium-coefficients below one suggests low systematic risk. In terms of overall performance, both portfolios outperformed the benchmark considerably throughout the period under investigation, where the total return of the Low portfolio was notably above that of High. After implementing the Fama & French size- and value premium factors, the alpha of the High portfolio increased to a level similar to that of Low. As such, providing evidence of positive alpha generation from trading on both strong and poor ESG momentum. The exposure to size effects is suggested by the multifactor model to be positive and significant, although this is not the case for the value premium-effect. In terms of risk, both portfolios exhibit similar risk profiles with higher Sharpe ratios and less severe downside risk than the benchmark. Both portfolios exhibit an adequately degree of diversification throughout the time period, which strengthens the comparability between the portfolios in addition to emphasize the use of the S&P 500 as a benchmark.

6.1.1.5 Sub-conclusion US market

The above presented findings provide strong evidence of positive alpha of material magnitude in the returns of portfolios constructed on both strong and poor ESG score momentum in the US market. This momentum effect on portfolio returns is consistent across all pillars. As such, suggesting no particular proof of whether the effect is entirely positive or negative. However, the findings do suggest that the magnitude itself, independent of direction, of the momentum do in fact have a positive effect on stock returns. In terms of portfolio performance, the authors find that both portfolios outperform the benchmark considerably in terms of return and risk. This is especially the case for Low which performed better than High, although their performances are notably similar throughout the period under investigation.

Further, the two portfolios display significant exposure to the Fama & French size effects across all pillars, although insignificant exposure to that of the value premium. In terms of alpha, all portfolios exhibit highly significant alphas beyond the Fama & French multifactor model. Most notable is the momentum effect on the overall ESG scores where High and Low generates the lowest and highest annualized alphas, respectively, of all portfolios on the US market. As such, emphasizing the investor focus on overall environmental, social and governance matters. In terms of average pillar score level, the US market scored lowest on the environmental pillar, which suggests that environmental issues are the least important focus area amongst US companies.

6.1.2 European market

The portfolios under investigation are the constructed High and Low portfolios based upon the strong- and poor ESG momentum created upon S&P Europe 350. which consists of the overall ESG-, Environmental-, Social-, and Governance pillar scores.

6.1.2.1 ESG scores

6.1.2.1.1 General metrics

KPI overview - ESG	**High**		**Low**		**S&P Europe 350**	
	Average	Median	Average	Median	Average	Median
ESG score	66.2	64.9	61.4	63.0	68.1	68.0
Market capitalization (USD bn	19.9	19.3	21.7	22.4	25.9	26.7
Price/Earnings	19.8	20.5	19.3	18.5	26.3	26.0
Return on equity	14.3%	13.9%	16.9%	16.3%	16.2%	16.0%
Debt/equity	0.98	0.91	1.18	1.26	1.12	1.16
Book-to-market	0.46	0.48	0.58	0.62	0.55	0.52
Current ratio	0.7	0.7	0.7	0.7	1.5	1.4

Table 14 – ESG General metrics. Source: Own construction

Average ESG scores for the High and Low portfolio are below that of the benchmark in the European market. Further, the authors note that the S&P Europe 350 average ESG score is c. 20 ppts. above that of the S&P 500, which may indicate a stronger European focus on SRI. The same is the case for the portfolios' market capitalization where High and Low are 23% and 16% below benchmark, respectively. In terms of P/E ratio, High and Low are 25% and 27% below benchmark average, respectively. These findings are consistent with the literature regarding the higher ESG focus in the European market.

Lastly, the authors observe a significantly lower current ratio for both portfolios, which indicates a notably weaker ability to meet its short-term obligations and is therefore associated with higher financial risk.

6.1.2.1.2 Performance measures

ESG - portfolio descriptive statistics	High		Low		S&P Europe 350	
	Monthly	Yearly	Monthly	Yearly	Monthly	Yearly
Performance measures						
Expected return	0.01	0.13	0.01	0.15	0.01	0.07
Volatility	0.03	0.10	0.03	0.11	0.04	0.13
Sharpe ratio	0.34	1.19	0.35	1.21	0.13	0.86
Information ratio	0.18	0.64	0.23	0.79	-	-
Total return index	284.08		323.88		169.47	
Risk measures						
Benchmark correlation	0.79		0.76		-	
High watermark	284.08		323.88		169.47	
Max. drawdown	-0.15		-0.14		-0.21	
Skewness	-0.49		0.01		0.03	
Kurtosis	0.02		0.51		2.38	
5% Empirical VaR	-0.05		-0.04		-0.06	
Expected shortfall	-0.05		-0.05		-0.08	

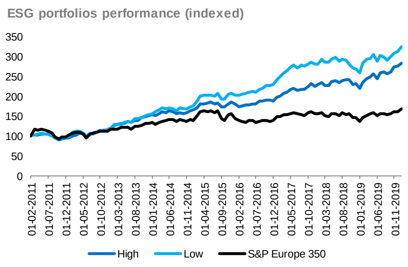

Table 15 – ESG Performance measures. Source: Own construction

High and Low yields an excess annual expected return to the benchmark of 6 ppts. and 8 ppts., respectively, with a corresponding lower volatility which is reflected in their high Sharpe- and information ratio. As such, both portfolios provide higher risk-adjusted return than S&P Europe 350, where Low does so to a greater extent. This is also reflected in the total return index which indicates a nine-year outperformance of 114.6 ppts. and 154.4 ppts. by High and Low, respectively.

6.1.2.1.3 Risk measures

The benchmark correlation is 0.79 and 0.76 for High and Low throughout the time period which is lower than all portfolios constructed in the US market previously presented. This despite the relatively less extensive investment universe in Europe compared to that of the US market. Both High and Low’s maximum drawdowns are also less extreme than that of the benchmark indicating a less severe downside risk. This is also illustrated by their lower VaR and expected shortfall compared to the benchmark. Lastly, the kurtosis for both portfolios reflects return distributions with relative flat tales, which is especially the case for the High portfolio. This is further substantiated by the level of skewness.

6.1.2.1.4 Alpha detection

	Dependent variable:			
	Highr		Lowr	
	(1)	(2)	(3)	(4)
MRP	0.5667***	0.5582***	0.6161***	0.5496***
	(0.3774, 0.7559)	(0.3247, 0.7917)	(0.4026, 0.8296)	(0.3036, 0.7956)
SMB		0.6026***		0.8049***
		(0.3548, 0.8504)		(0.3984, 1.2113)
HML		0.0944		0.3381***
		(-0.1161, 0.3048)		(0.0990, 0.5771)
Constant	0.0073***	0.0059***	0.0083***	0.0078***
	(0.0043, 0.0102)	(0.0031, 0.0087)	(0.0049, 0.0118)	(0.0045, 0.0111)
Observations	108	108	108	108
R^2	0.6211	0.6585	0.5802	0.6469
Adjusted R^2	0.6175	0.6487	0.5763	0.6367
Residual Std. Error	0.0174 (df = 106)	0.0166 (df = 104)	0.0206 (df = 106)	0.0190 (df = 104)
F Statistic	173.7515*** (df = 1; 106)	66.8604*** (df = 3; 104)	146.5282*** (df = 1; 106)	63.5033*** (df = 3; 104)

Note: The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.

Table 16 – ESG OLS. Source: Own construction

The CAPM OLS adjusted R^2 ranges from 0.5763 to 0.6175, which is notably lower than the regression models constructed for the US market. The beta coefficients and alphas are highly significant for both portfolios at a 1% level of significance. As such, the CAPM model clearly indicates positive and highly significant alphas detected in both portfolio returns. Further, the beta coefficients lies below one for both, emphasizing the relative low exposure to the general market.

By incorporating the self-constructed factors of Fama & French, the OLS' goodness of fit rises slightly. When looking at the significance of each coefficient, all but one (HML for High) show significance at the 1% level. Both portfolio's returns show a notable exposure to the size premium of SMB, where that of Low is notably more material. The exposure is less predominant in the value premium of HML, and even less so for the insignificant High coefficient. As such, indicated by the decrease in portfolio alpha for both, some of the portfolio excess returns are attributable to the size- and value premium effects.

All F-statistics show overall model significance at the 1% significance level across all models.

6.1.2.1.5 Sector composition

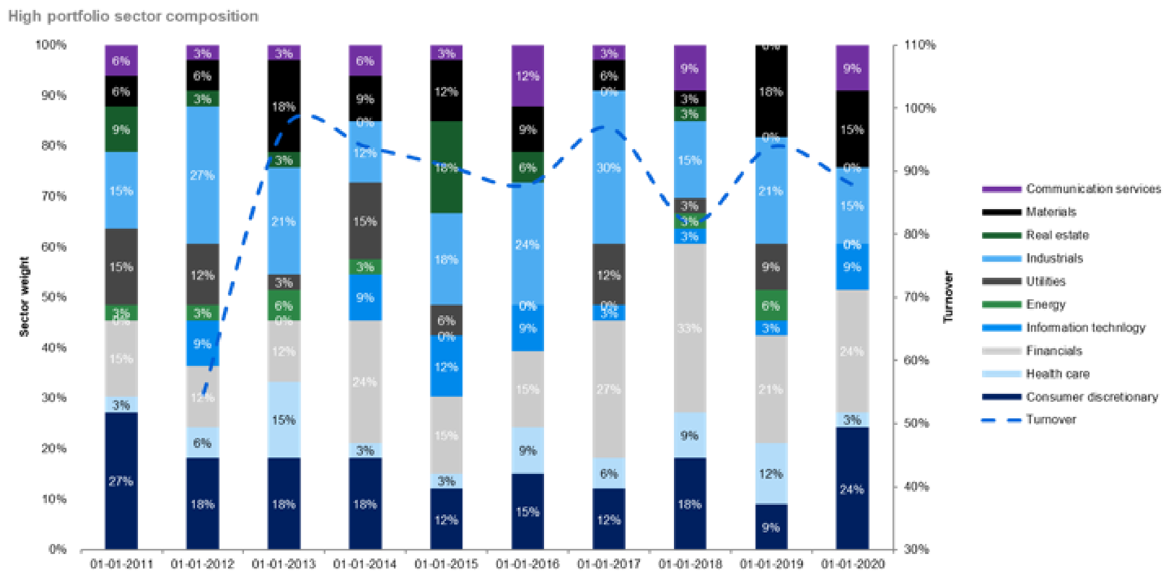

Illustration 14 – ESG General metrics (High portfolio). Source: Own construction

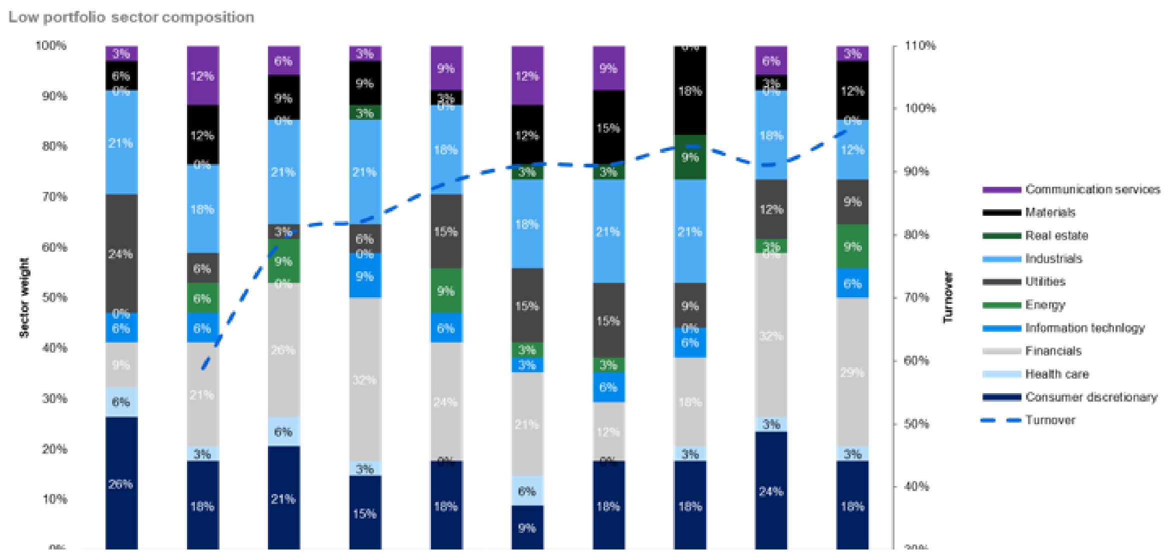

Illustration 15 – ESG General metrics (Low portfolio). Source: Own construction

As presented by illustration 14 and 15, the sector composition of each portfolio is considered fairly diversified throughout the period under investigation. Most predominant are the sectors consumer discretionary, financials and industrials, which constituted on average 57% and 60% of the portfolio constituents throughout the period under investigation for High and Low, respectively. The authors also note the growing portion of the financial sector in both portfolios throughout the period. Portfolio turnover is relatively high for both portfolios with an average of 87% and 86% for High and Low, respectively, where the former experienced peak turnovers at 01.01.2013 and 01.01.2017 of 97%.

6.1.2.1.6 Sub-conclusion

Average ESG scores of the European market are significantly higher than in the US, which is consistent with the literature. Significant alphas of material size from the proposed ESG score momentum-based strategy has been detected in both the single-index and multifactor model. It follows that the implementation of the Fama & French factors shifts a portion of the alpha to these factors which means that the OLS assigns explanatory power of the expected returns to size- and value premium effects. A significant size effect from SMB of considerable magnitude is uncovered in the Fama & French models, reflected in the average market capitalization of both portfolios which are notably less than that of the benchmark. This is the case for the value premium effect on the Low portfolio, although more moderate than that of size effects.

6.1.2.2 Environmental pillar

6.1.2.2.1 General metrics

KPI overview - Environmental pillar

	High		**Low**		**S&P Europe 350**	
	Average	Median	Average	Median	Average	Median
Environmental score	64.1	64.8	60.0	59.2	67.2	66.7
Market capitalization (USD bn)	18.7	17.7	23.1	22.4	25.9	26.7
Price/Earnings	24.6	20.9	19.5	18.0	24.6	24.8
Return on equity	14.3%	14.6%	15.2%	16.7%	15.9%	16.0%
Debt/equity	1.09	1.08	1.07	1.02	1.19	1.18
Book-to-market	0.46	0.49	0.53	0.51	0.55	0.52
Current ratio	0.7	0.6	0.8	0.7	1.5	1.4

Table 17 – Environmental General metrics. Source: Own construction

As suggested by the aforementioned literature, average environmental score is significantly higher for both portfolios as well as the benchmark compared to those of the US market. High, Low and benchmark environmental score is 15%, 22% and 36% above that of the US, respectively. As such, the authors note that both portfolios build their momentum from fairly high scores.

High portfolio average market capitalization is notably lower than both Low and benchmark, e.g. 19% and 28% below the former and latter, respectively. Low portfolio average P/E ratio is significantly below that of both High and the benchmark by 20%, which might be an indication of the effect negative environmental score momentum has on company valuation. As with the ESG-momentum constructed portfolios above, both portfolios exhibit significantly poorer ability to meet their short-term liabilities, indicated by their low current ratios.

6.1.2.2.2 Performance measures

Environmental - portfolio descriptive statistics

	High		Low		S&P Europe 350	
	Monthly	Yearly	Monthly	Yearly	Monthly	Yearly
Performance measures						
Expected return	0.01	0.14	0.01	0.14	0.01	0.07
Volatility	0.03	0.10	0.03	0.10	0.04	0.13
Sharpe ratio	0.36	1.24	0.35	1.20	0.13	0.86
Information ratio	0.22	0.74	0.22	0.76	-	-
Total return index	302.85		307.57		169.47	
Risk measures						
Benchmark correlation	0.80		0.79		-	
High watermark	302.85		307.57		169.47	
Max. drawdown	-0.16		-0.16		-0.21	
Skewness	-0.50		0.08		0.03	
Kurtosis	-0.11		0.54		2.38	
5% Empirical VaR	-0.04		-0.04		-0.06	
Expected shortfall	-0.05		-0.05		-0.08	

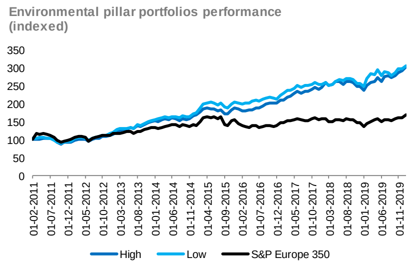

Table 18 – Environmental Performance measures. Source: Own construction

Both High and Low yields extensively higher annual expected returns than the benchmark together with a lower annual volatility of 0.3 ppts. below the benchmark. This is also reflected in their higher Sharpe- and positive information ratio. As with the ESG score momentum-based portfolios above, the two portfolios track each other closely in addition to outperform the benchmark. TRI for High and Low outperforms the benchmark over the nine-year period by 133 ppts. and 138 ppts., respectively.

6.1.2.2.3 Risk measures

Both portfolios exhibit a notable positive correlation of c. 0.8 with the benchmark, indicating a notable exposure to the general market. Maximum drawdown together with the VaR and expected shortfall for both portfolios over the time period indicates less downside risk than the benchmark. The skewness for both portfolios indicates that their returns are close to normally distributed, as well as their low kurtosis show long and thin tails, which emphasize the low volatility of the portfolios.

6.1.2.2.4 Alpha detection

	Dependent variable:			
	Highr		Lowr	
	(1)	(2)	(3)	(4)
MRP	0.5884^{***}	0.5647^{***}	0.6120^{***}	0.5791^{***}
	(0.3973, 0.7795)	(0.3338, 0.7956)	(0.4193, 0.8047)	(0.3505, 0.8078)
SMB		0.5887^{***}		0.6233^{***}
		(0.3258, 0.8515)		(0.3421, 0.9046)
HML		0.1515		0.1901^{*}
		(-0.0603, 0.3634)		(-0.0199, 0.4000)
Constant	0.0078^{***}	0.0068^{***}	0.0078^{***}	0.0070^{***}
	(0.0048, 0.0108)	(0.0038, 0.0098)	(0.0047, 0.0110)	(0.0040, 0.0100)
Observations	108	108	108	108
R^2	0.6382	0.6730	0.6234	0.6600
Adjusted R^2	0.6348	0.6635	0.6198	0.6502
Residual Std. Error	0.0174 (df = 106)	0.0167 (df = 104)	0.0187 (df = 106)	0.0179 (df = 104)
F Statistic	187.0073^{***} (df = 1; 106)	71.3404^{***} (df = 3; 104)	175.4300^{***} (df = 1; 106)	67.3062^{***} (df = 3; 104)

Note: The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.

Table 19 – Environmental OLS. Source: Own construction

The CAPM OLS adjusted R^2 ranges from 0.6198 to 0.6348. The beta coefficients and alphas are highly significant for both portfolios at the 1% level of significance. As such, the CAPM model clearly indicates identical, positive and highly significant alphas detected in both portfolios. Further, the market risk premium beta coefficients lie below one for both, emphasizing the low level of systematic risk to the general market. The single-index model annualized alphas for both portfolios are notably 0.65 ppts. higher than that of the ESG-momentum based models.

As with the CAPM above, the Fama & French model generates highly significant coefficients of the monthly excess market return for both portfolios, although assigning less explanatory power of the excess return to it, therefore emphasizing the CAPM results. In addition, by adding the two factors adjusted R^2 elevates marginally. SMB factor is highly significant at the 1% level for both portfolios. In contrast, only the multifactor model for Low shows significant exposure to the HML factor, which is positive at the 10% level.

F-statistics show overall model significance at the 1% significance level across all models.

6.1.2.2.5 Sector composition

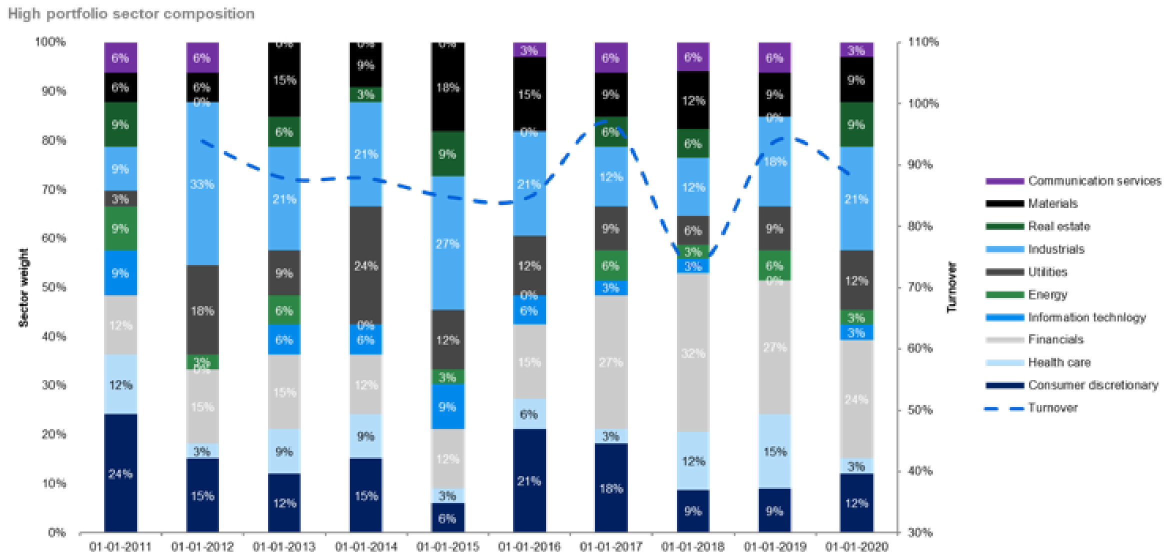

Illustration 16 – Environmental General metrics (High portfolio). Source: Own construction

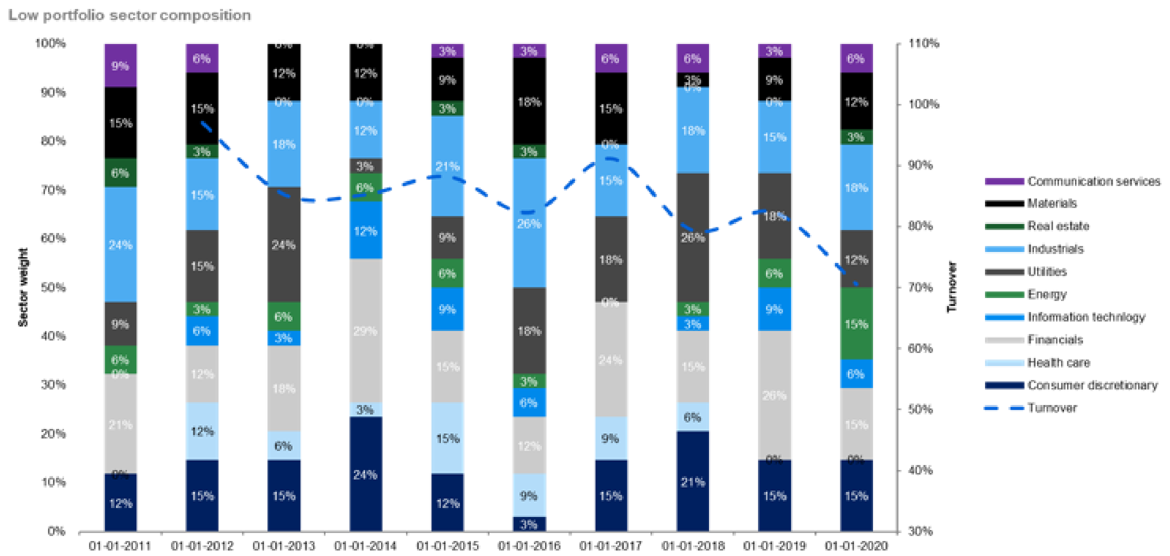

Illustration 17 – Environmental General metrics (Low portfolio). Source: Own construction

Illustration 16 and 17 show each portfolio's historical sector composition indicates portfolio diversification throughout the period under investigation. As with the ESG-momentum based portfolios, the financial, industrial and consumer discretionary sectors are the most predominant sectors for High and Low with an average combined portfolio weight of 53% and 51%, respectively. Throughout the period under investigation the financial sector increases its weight in the High portfolio by 100%, which might suggest an increasing focus on SRI within this sector. Finally, as with the ESG score momentum-based portfolios, there is a considerable turnover throughout the period with an average of 88% and 85% for High and Low, respectively.

6.1.2.2.6 Sub-conclusion

Average environmental scores of the European market are significantly higher than in the US, which is consistent with the literature presented. It follows that the Low is valued less in relation to its earnings than High and the benchmark, which might indicate a negative valuation effect from the poorer environmental scores and low score momentum. However, this is not the case when looking at the portfolio return performance, where Low outperforms the High. Significant alphas of material size from the presented environmental pillar score momentum-based strategies have been detected in both the single-index and multifactor model, although the latter assigns a slight portion of the generated alpha to size- and value premium effects for both the High- and Low portfolio.

6.1.2.3 Social pillar

6.1.2.3.1 General metrics

KPI overview - Social pillar

	High		**Low**		**S&P Europe 350**	
	Average	Median	Average	Median	Average	Median
Social score	67.1	68.6	62.5	63.9	70.5	71.2
Market capitalization (USD bn)	19.4	20.4	21.1	20.4	25.9	26.7
Price/Earnings	19.4	18.8	22.8	19.4	31.6	26.2
Return on equity	14.9%	16.1%	13.2%	12.7%	16.2%	16.0%
Debt/equity	0.97	0.99	1.23	1.26	1.19	1.16
Book-to-market	0.49	0.49	0.51	0.48	0.55	0.52
Current ratio	0.8	0.8	0.7	0.7	1.5	1.4

Table 20 – Social General metrics. Source: Own construction

Average social pillar score of the European market is notably higher than that of the US, in addition to be the highest pillar-specific score across all pillars in Europe. The portfolio characteristics share similarities to the environmental portfolios, as both portfolios are characterized by lower average market capitalization and P/E than the benchmark. Low portfolio average market capitalization is above that of the High on social score by 8.8%. Further, the P/E ratio of Low is above High’s, which indicates an opposite effect than that of the Environmental pillar mentioned earlier, namely that a poor Social score momentum suggests no particular negative effect on company valuation in relation to its earnings.

The authors note that the average ROE for High and Low are 1.3 ppts. and 3 ppts. below that of the benchmark, respectively. The current ratio is, as for the other European portfolios, significantly lower than the 2, which is the rule of thumb for a satisfying short-term liquidity.

6.1.2.3.2 Performance measures

Social - portfolio descriptive statistics

	High		Low		S&P Europe 350	
	Monthly	Yearly	Monthly	Yearly	Monthly	Yearly
Performance measures						
Expected return	0.01	0.12	0.01	0.13	0.01	0.07
Volatility	0.03	0.09	0.03	0.10	0.04	0.13
Sharpe ratio	0.34	1.17	0.31	1.07	0.13	0.86
Information ratio	0.19	0.67	0.18	0.61	-	-
Total return index	276.51		276.70		169.47	
Risk measures						
Benchmark correlation	0.84		0.78		-	
High watermark	276.51		276.70		169.47	
Max. drawdown	-0.14		-0.14		-0.21	
Skewness	-0.44		-0.01		0.03	
Kurtosis	-0.21		0.38		2.38	
5% Empirical VaR	-0.05		-0.05		-0.06	
Expected shortfall	-0.05		-0.05		-0.08	

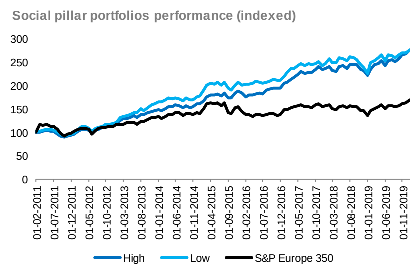

Table 21 – Social Performance measures. Source: Own construction

High and Low yields considerably higher expected returns than the benchmark together with a lower volatility, e.g. 0.4 ppts. and 0.3 ppts. below the benchmark, respectively. This is also reflected in their higher Sharpe- and positive information ratio. As with the aforementioned ESG- and environmental pillar score-based portfolios, the two portfolios track each other in addition to outperform the benchmark by a sizeable amount. Both portfolios outperformed the benchmark over the nine-year period by 107 ppts. on the TRI chart presented above.

6.1.2.3.3 Risk measures

The High portfolio has a benchmark correlation of 0.84, which is the highest of all the European portfolios. Maximum drawdown together with the VaR and expected shortfall for both High and Low over the time period are identical and indicates less severe downside risk than the benchmark. Skewness for both portfolios indicate returns are normally distributed, as well as their low kurtosis exhibits long and thin tails which emphasize the low volatility relative to the benchmark.

6.1.2.3.4 Alpha detection

	Dependent variable:			
	Highr		Lowr	
	(1)	(2)	(3)	(4)
MRP	0.6004^{***}	0.5719^{***}	0.6157^{***}	0.5820^{***}
	(0.4141, 0.7867)	(0.3473, 0.7966)	(0.4137, 0.8176)	(0.3424, 0.8217)
SMB		0.5261^{***}		0.6111^{***}
		(0.3121, 0.7402)		(0.2393, 0.9830)
HML		0.1632^{*}		0.1920
		(-0.0294, 0.3558)		(-0.0373, 0.4212)
Constant	0.0068^{***}	0.0061^{***}	0.0068^{***}	0.0060^{***}
	(0.0044, 0.0092)	(0.0041, 0.0082)	(0.0036, 0.0101)	(0.0028, 0.0093)
Observations	108	108	108	108
R^2	0.7089	0.7400	0.6081	0.6425
Adjusted R^2	0.7062	0.7325	0.6045	0.6322
Residual Std. Error	0.0151 (df = 106)	0.0144 (df = 104)	0.0194 (df = 106)	0.0187 (df = 104)
F Statistic	258.1986^{***} (df = 1; 106)	98.6755^{***} (df = 3; 104)	164.5105^{***} (df = 1; 106)	62.3018^{***} (df = 3; 104)
Note:	The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.			

Table 22 – Social OLS. Source: Own construction

CAPM OLS adjusted R^2 for the two portfolios ranges from 0.6045 to 0.7062. The beta coefficients and alphas are significant for both portfolios at the 1% significance level. As such, the single-index model clearly suggests a positive and highly significant alpha detected in the portfolios' returns. Further, the beta coefficient lies below one for both, emphasizing the low benchmark correlation and therefore low exposure to the general market. The annualized alpha for both portfolios are identical at 8.5%.

When incorporating the Fama & French factors the adjusted R^2 rises for both portfolio models. The OLS models suggest a significant and material exposure to the size effect, where the exposure is more notable for Low. With regards to the value premium effect, only the model for High shows significant exposure which is at the 10% level of significance. Further, the authors note this exposure to be less than that of SMB. As such, indicated by the decrease in portfolio alpha for both, some of the portfolios excess returns are attributable to size- and value premium effects. This is the case for the market risk premium as well.

F-statistics show overall model significance at the 1% significance level across all models.

6.1.2.3.5 Sector composition

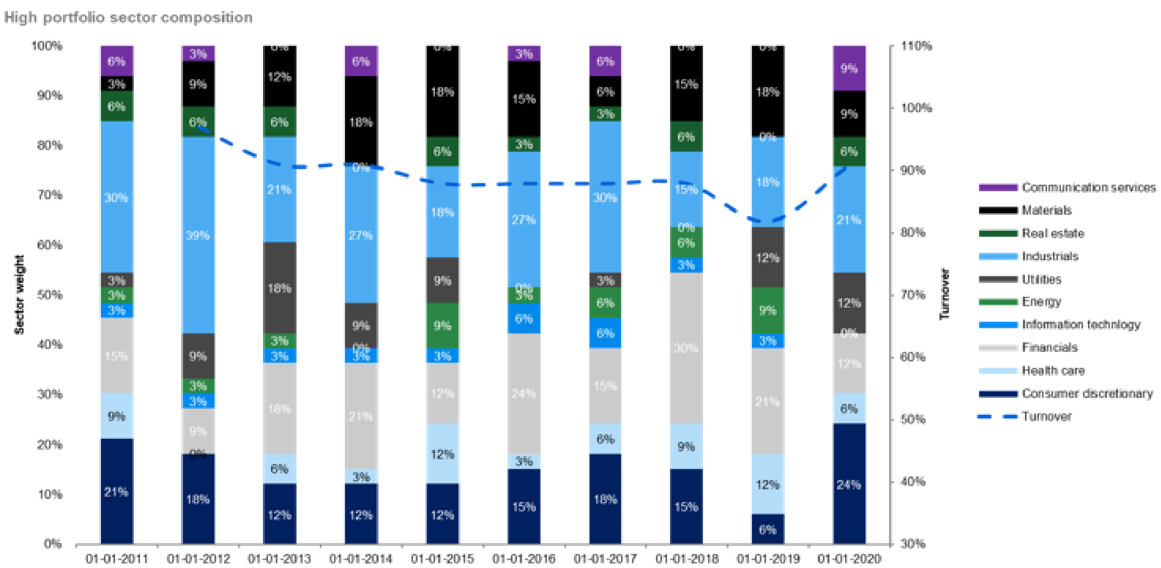

Illustration 18 – Social General metrics (High portfolio). Source: Own construction

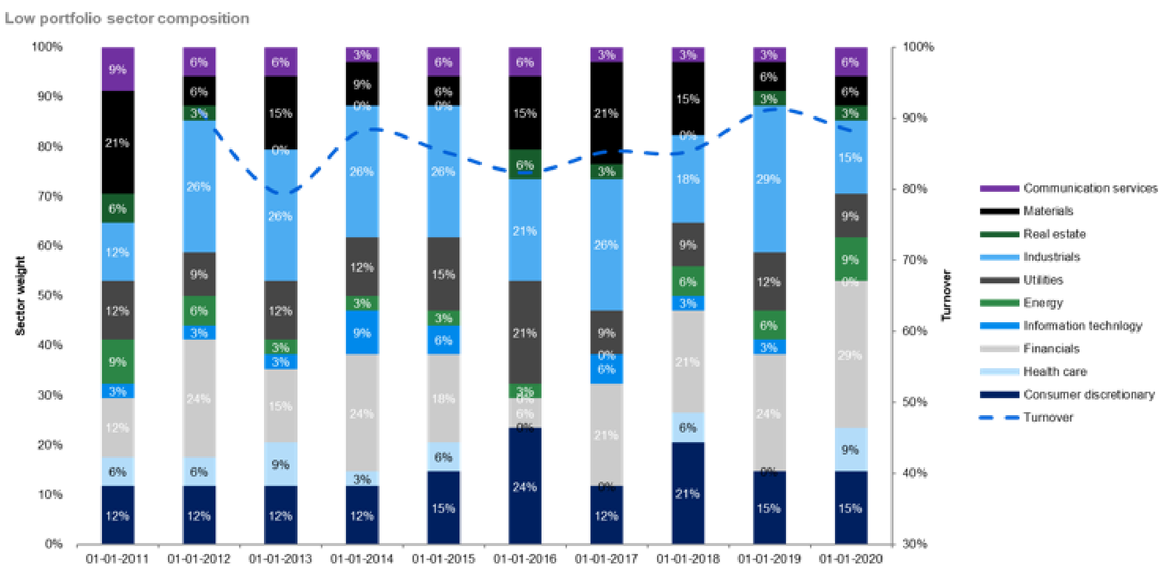

Illustration 19 – Social General metrics (Low portfolio). Source: Own construction

As indicated by illustration 18 and 19 above, both portfolios are considered fairly diversified where the most predominant sectors are consumer discretionary, financials and industry, which has shown to be consistent throughout the other pillar-based portfolios covered so far. These sectors have, on average, constituted 58% and 56% of High and Low throughout the period under investigation, respectively. Industrials' share has trended downwards throughout the period for High, while the share of financial companies has increased for Low. In the case of industrials, this might indicate a peak in social scores for the sector, whereas for Low the increasing share of financial companies might indicate a more extensively downward trend in social scores for this sector. On an end note, the turnover is considerably high for the two portfolios with an average of 89% and 85% for High and Low, respectively.

6.1.2.3.6 Sub-conclusion

Average social pillar scores of the European market are significantly higher than in the US, which also is consistent with the literature. Significant alphas of material size from the proposed social pillar score momentum-based strategy have been detected in both the single-index and multifactor models, although the latter assigns a slight portion of the generated alpha to size- and value premium for both the High and Low portfolio. As indicated by the portfolio sector composition chart for the nine-year period under investigation, the increase in financial companies in the Low portfolio suggests a weaker trend in social scoring in this sector. The same chart for High illustrates a decrease in industrials, suggesting a peak in social scoring within this sector.

6.1.2.4 Governance pillar

6.1.2.4.1 General metrics

KPI overview - Governance pillar

	High		**Low**		**S&P Europe 350**	
	Average	Median	Average	Median	Average	Median
Governance score	64.5	64.0	51.1	49.0	62.2	60.6
Market capitalization (USD bn)	20.5	19.8	22.3	22.6	25.9	26.7
Price/Earnings	21.2	20.6	22.5	19.4	31.6	26.2
Return on equity	14.9%	15.2%	16.0%	16.1%	16.2%	16.0%
Debt/equity	1.09	1.10	1.07	1.07	1.19	1.16
Book-to-market	0.46	0.48	0.51	0.51	0.55	0.52
Current ratio	0.7	0.8	0.9	0.9	1.5	1.4

Table 23 – Governance General metrics. Source: Own construction

As previously mentioned for the US governance pillar, Refinitiv has a constant weight on the governance scores in regard of the overall ESG scores, hence governance score should be of interest to all constituents regardless of their sector. The governance scores have the lowest benchmark average pillar-specific score in Europe. Average score for High is 26% greater than that of Low, which is the greatest score difference of the portfolios in the European market. Despite this, the Low portfolio is valued greater relative to its earnings compared to High, which indicates a lesser focus on governance measure amongst European investors. Further, this is contradicting results compared to the US market where the average P/E ratio was greater for the High portfolio. Current ratio is also below benchmark for both portfolios, which has been consistent throughout every portfolio across all pillars in Europe.

6.1.2.4.2 Performance measures

Governance - portfolio descriptive statistics

	High		Low		S&P Europe 350	
	Monthly	Yearly	Monthly	Yearly	Monthly	Yearly
Performance measures						
Expected return	0.01	0.11	0.01	0.15	0.01	0.07
Volatility	0.03	0.09	0.03	0.10	0.04	0.13
Sharpe ratio	0.31	1.09	0.38	1.30	0.13	0.86
Information ratio	0.14	0.49	0.26	0.90	-	-
Total return index	253.08		334.96		169.47	
Risk measures						
Benchmark correlation	0.80		0.80		-	
High watermark	253.08		334.96		169.47	
Max. drawdown	-0.14		-0.16		-0.21	
Skewness	-0.36		-0.13		0.03	
Kurtosis	0.04		0.61		2.38	
5% Empirical VaR	-0.04		-0.04		-0.06	
Expected shortfall	-0.04		-0.05		-0.08	

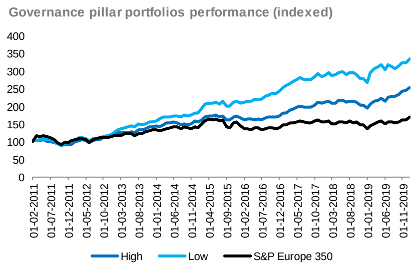

Table 24 – Governance Performance measures. Source: Own construction

Both High and Low yields considerably higher expected returns than the benchmark. This is especially the case for Low with an 165.5 ppts. outperformance in terms of TRI, which corresponds to almost twice the total return of the S&P Europe 350 over the nine-year period. This is reflected in their higher Sharpe- and positive information ratio, which is also considerably higher for Low than High.

6.1.2.4.3 Risk measures

Both portfolios have a benchmark correlation of 0.8, which might occur as the benchmark itself makes up the investment universe. The maximum drawdown, VaR and expected shortfall for both portfolios indicates less downside risk than the benchmark, which is more predominant for Low. Skewness and kurtosis for both portfolios indicate that the returns are normally distributed, which also is the case for the benchmark.

6.1.2.4.4 Alpha detection

	Dependent variable:			
	Highr		Lowr	
	(1)	(2)	(3)	(4)
MRP	0.5567***	0.5177***	0.6199***	0.5919***
	(0.3854, 0.7280)	(0.3135, 0.7218)	(0.4237, 0.8161)	(0.3579, 0.8258)
SMB		0.5785***		0.5358***
		(0.3311, 0.8259)		(0.2143, 0.8573)
HML		0.2092**		0.1625
		(0.0199, 0.3985)		(-0.0611, 0.3861)
Constant	0.0062***	0.0056***	0.0086***	0.0079***
	(0.0035, 0.0089)	(0.0030, 0.0083)	(0.0055, 0.0116)	(0.0050, 0.0107)
Observations	108	108	108	108
R^2	0.6429	0.6853	0.6464	0.6737
Adjusted R^2	0.6395	0.6762	0.6431	0.6643
Residual Std. Error	0.0163 (df = 106)	0.0154 (df = 104)	0.0180 (df = 106)	0.0175 (df = 104)
F Statistic	190.8074*** (df = 1; 106)	75.4789*** (df = 3; 104)	193.7699*** (df = 1; 106)	71.5879*** (df = 3; 104)
Note:	The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.			

Table 25 – Governance OLS. Source: Own construction

The CAPM OLS adjusted R^2 for the two portfolios ranges from 0.6395 to 0.6431. The beta coefficients and alphas are significant for both models at the 1% significance level. As such, the CAPM model clearly indicates a positive and highly significant alpha detected in the portfolio returns. When comparing the governance score momentum-based portfolios to those of the other pillars, Low portfolio yields the highest annualized alpha of 10.8%. Further, the market risk premium coefficient lies below one for both, which indicate a low exposure to the general market, which is consistent with the finding in performance measures above.

When incorporating the Fama & French factors, the adjusted R^2 rises for both portfolio models. For High, every coefficient is significant at the 1% level with the exception of HML, which is significant at the 5% level. However, the authors are under the impression that the Fama & French multifactor model for High is strong. For Low, all coefficients but HML are significant at the 1% level. HML is insignificant, suggesting no significant relationship between the portfolios' excess return and the value premium effect. Generally, neither High or Low are suggested by the OLS to have exposure of considerable magnitude to the value premium effect. Both multifactor models gives less explanatory power to the market risk premium after implementing Fama & French factors compared to the single-index model, although both are significant at the 1% level. High portfolio excess return is suggested by the OLS coefficients to have an apparent size effect. When looking at the general metrics, this is substantiated as both portfolios in fact do contain companies with lower market capitalization than the benchmark.

F-statistics show overall model significance at the 1% significance level across all models.

6.1.2.4.5 Sector composition

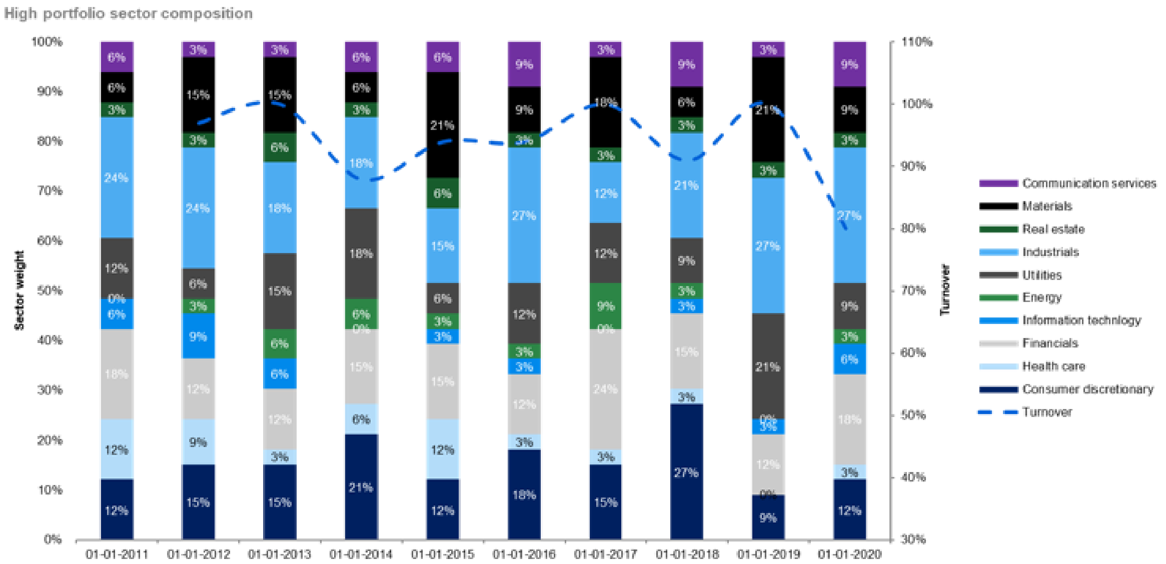

Illustration 20 – Governance General metrics (High portfolio). Source: Own construction

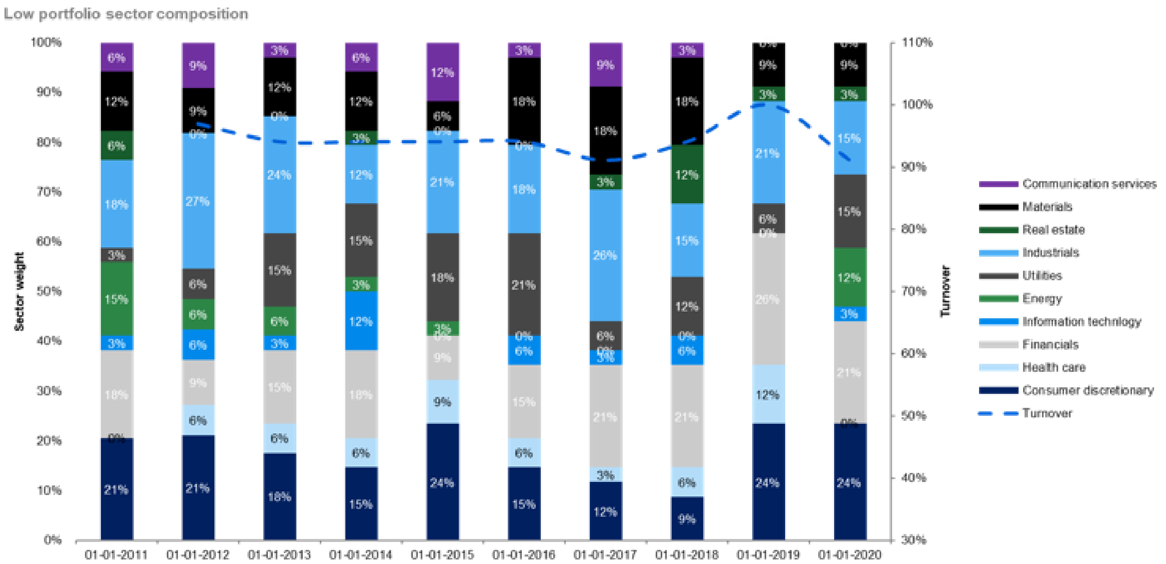

Illustration 21 – Governance General metrics (Low portfolio). Source: Own construction

Illustration 20 and 21 indicates a fair degree of diversification throughout the period. As with the ESG momentum-based portfolios, the financial, industrial and consumer discretionary sectors are the most predominant sectors for High and Low portfolios with an average combined portfolio share of 53% and 55%, respectively. Portfolio turnover is on average the highest of all other pillar-based portfolios at 94% for both.

6.1.2.4.6 Sub-conclusion

Average government pillar scores of the European market are significantly higher than in the US. Further, the average governance score for High is considerably higher than that of Low, which also is the case in the US market. Significant alphas of material size from the proposed government pillar score momentum-based strategy have been detected in both the CAPM and Fama & French model. The authors note that the Low portfolio yields the highest alpha amongst the other pillar-specific portfolios in the European market. Further, the multifactor model assigns a slight portion of the generated alpha to size- and value premium effects for High.

6.1.2.5 Sub-conclusion European market

Ultimately, the discoveries bring forward strong evidence of considerable positive alpha in the excess returns of the ESG score momentum-based portfolios on the European market. These results are consistent across all pillars, suggesting no notable difference in the momentum effect on any specific pillar. As the High and Low portfolios display several similar properties, no conclusion on whether the effect is solely positive or negative can be made based on the research. On the other hand, as with the US market, a positive momentum effect on stock return appears to be attributed to the magnitude of the momentum itself rather than a specific direction, i.e. positive or negative.

Performance-wise, we find that both portfolios outperform the benchmark considerably in terms of return and risk during the period under investigation. Similar to the US market, the two performance portfolios display similar properties in terms of return and risk measures where both High and Low generated higher Sharpe ratio and positive information ratio in addition to less severe downside risk. In terms of the relative performance between the two, Low outperformed High consistently across all pillars. This was most notable in the governance score-based portfolios.

Both portfolios exhibit significant positive exposure to the Fama & French size effects across all pillars. The exposure to value premium effects is further suggested to be moderately positive, although these effects lack consistency in terms of significance levels. In terms of alpha, all portfolios are suggested to yield highly significant alphas both by the single-index model and the Fama & French multifactor model. Most notable is the momentum effect on the governance pillar portfolios, where the Low portfolio generated the highest alpha amongst all pillars. As a consequence, the portfolio alpha difference of the governance pillar is the largest across all pillars in both Europe. As such, suggesting a lower level of focus on strong corporate governance amongst European investors than the other pillars. Lastly, all portfolios are considered diversified despite an overall high turnover, which makes the S&P Europe 350 a well-suited benchmark for comparison.

6.2 Robustness checks

The authors present the following robustness checks in order to validate the above presented findings. By constructing new High and Low portfolios based on the 30% top and bottom performing companies based on overall ESG- and pillar score momentum, the authors aim to investigate the impact of this change in methodology on the OLS results. As such, by incorporating companies with weaker (higher) momentum performance a decrease in portfolio alphas will substantiate the proposed trading strategies. Further, the authors can compare the portfolio relationship with the factors of CAPM and Fama & French.

By looking at the OLS coefficient's significance (Appendix 11.7.1), no particular impact from the change in methodology on the regression results is observed as no major difference is detected in either market. However, in the European market, an increased significance in HML factor is detected in the social and governance portfolios. In terms of factor exposure the impact on both Fama & French factors and the exposure to the market risk premium is moderate. This is the case for both markets. Therefore, the robustness checks add no particular additional insight into the factor relationships. Further, adjusted R^2 increase is detected across all models for both markets.

Portfolio alphas decrease as a result of the change in methodology, which provides evidence of a positive relationship between the level of score momentum and portfolio alpha. Although the impact is moderate for High, the decrease is substantial for the Low portfolio in both markets. Indicating that a poor ESG score momentum-based strategy generates a more substantial effect than that of the High.

The robustness checks have also been performed on the Carhart four-factor model in order to evaluate whether the WML factor gains explanatory power after including more companies in the portfolios. As the OLS output in the appendix 11.7.1 suggests, this is not the case as the coefficients still show an overall insignificance, supporting the authors' prior choice of excluding the factor from the model.

Lastly, the authors performed a robustness check on the multifactor model of Fama & French by running the OLS regression on factors retrieved from Kenneth Frenchs Data library, see appendix 11.7.2. As the OLS output in the suggests, none of the factors are significant in either markets emphasizing the authors' choice of constructing the factors themselves.

7. Discussion

7.1 ESG score momentum-based strategy

The results from the above presented analysis contributes with findings to the area of investigation by investigating the ESG- and individual pillar score momentum-based strategies as tools for alpha generation on the US and European market. Throughout this discussion, the authors seek to drill down our findings with reference to each respective research question. As such, this discussion will begin by focusing solely on the difference between the strong and the poor score momentum-based strategies, i.e. regardless of pillar-specificity or market. Further, the authors will discuss differences in momentum effects on portfolio returns by each specific pillar. Next, any momentum effect differences between the US and the European market will be discussed in order to reflect on these variations. Lastly, the discussion will reflect around the findings with regard to the implementation of the Fama & French risk factors.

7.1.1 ESG score momentum-based strategy – Portfolio level

In the following section, the authors will discuss the findings on strong- and poor ESG score momentum-based strategies in relation to the empirical research on this field. Below is a summary of the annualized portfolio alphas generated by the single-index and multifactor model OLS regressions:

	Annualized alpha Fama & French				Annualized alpha CAPM			
	Alpha		Significance		Alpha		Significance	
Portfolio	High	Low	High	Low	High	Low	High	Low
US ESG	5,66%	8,86%	1%	1%	5,54%	8,08%	1%	1%
US Environmental	6,17%	8,73%	1%	1%	5,91%	7,06%	1%	1%
US Social	6,68%	7,70%	1%	1%	6,93%	6,68%	1%	1%
US Governance	8,08%	8,34%	1%	1%	6,17%	8,34%	1%	1%
EU ESG	7,31%	9,77%	1%	1%	9,12%	10,43%	1%	1%
EU Environmental	8,47%	8,73%	1%	1%	9,77%	9,77%	1%	1%
EU Social	7,57%	7,44%	1%	1%	8,47%	8,47%	1%	1%
EU Governance	6,93%	9,90%	1%	1%	7,70%	10,82%	1%	1%

Table 26 – Annualized alpha. Source: Own construction

The above presented positive alphas suggest that both the strong and poor score momentum-based strategies are attractive to implement into an investment decision. As all alphas are significant at the 1% level of significance, the strategy assessments will to a higher degree be based upon the magnitude of alpha and portfolio performance metrics.

Surprisingly, the Low portfolios generates an average alpha which is 1.58 ppts. above that of the High. This clearly indicates that a poor score momentum strategy is preferable, which is somewhat contradicting to the majority of literature on the topic, as scholars argue that investors would increase their discount rates for companies with a poor ESG score momentum as a result of future risk of reputational- and possible legal costs.

An explanation for the performance of the Low portfolios might be due to the portfolio composition. Firstly, it might contain both sin- and other ESG controversial companies. These companies could yield a strong financial performance, as they might focus solely on financial performance, rather than ESG development. Secondly, the portfolio might also contain ESG-friendly companies that struggle to achieve a momentum, as they already have a score close to 100. This implies that both sin-stocks and ESG controversial firms, as well as ESG-friendly firms can attribute and yield a higher return than the benchmark. Another factor that might drive the Low portfolio's return, could be that constituents might implement a greenwashing strategy, with the aim to change the investors perception of the companies' ESG related measures. However, these public narratives imposed by the companies might not necessarily be reflected in their ESG scores. As such, the companies become more attractive to investors which ultimately could drive their stock returns. This might also be applicable to the High portfolio constituents. Despite the outperformance of the Low portfolio, the strong score momentum strategy is still attractive as it too outperforms the benchmark, and is further in line with the findings of (Friede, Busch, & Bassen, 2015), on a positive relationship between ESG- and stock performance.

(Phillips, 2020) found that investors implement ESG measures to hedge against future risks, which is in line with this thesis' findings. This is indicated by the overall improved ESG scores, which likely is a result of companies mitigating against the risks associated with strict ESG mandates e.g. negative ESG screening. (Friede, Busch, & Bassen, 2015) further implies that there is a positive correlation between ESG- and financial performance, and this thesis both substantiates and contradict the claim. Even though the average ESG score has increased overall throughout the period under investigation, the Low portfolios have yielded the highest alpha. As such, suggesting that the portfolios with poor score momentum are within the ESG mandates, hence they are not punished by negative screening.

The authors further note that there might be factors outside the scope of this thesis that can influence the results from the investment strategies. One of which might be score level. Score level is clearly interesting to evaluate, and it is not unlikely that investors use score level, instead of or in addition to, score momentum in their investment decisions, as well as it might be included in investment mandates. The results from this thesis might therefore be affected, as companies with a strong or poor momentum can have different score levels. Further, (Fang & Peress, 2009) suggest that companies with a high market capitalization will affect their scores through attained media attention, indicating that companies with high market capitalization might achieve a greater momentum, which again might affect the results.

The authors find the lack of consistency of ESG scoring amongst different providers impairing for the reliability of this thesis' findings, as presented in the research provided by (Berg, Koelbel, & Rigobon, 2020). Rooted in the shortage of industry non-financial reporting transparency, as suggested by (Doyle, 2018), the Refinitiv scoring on which this research is built upon, might not represent the *true* scores of which the market as a whole would have provided if there were complete scoring consistency. As such, the same is the case for the score momentum on which the portfolios are constructed upon. As a consequence, the momentum effects suggested by our findings might not represent the true momentum effects which might explain our contradicting empirical findings.

The previously mentioned literature regarding the findings of (Grewal, Riedl, & Serafeima, 2018) on market reactions to non-financial disclosure also imposes some uncertainties to whether the alphas detected in this thesis' findings are fully attributable to momentum effects from the proposed trading strategies. As a consequence of today's voluntary non-financial reporting, companies' ESG-related disclosures tend to be biased in order to maximize shareholder value. As such, indicated by literature, markets react different not only to the reporting itself, but also on the level of company disclosure as some investors react negatively to an increase in level of disclosure, which ultimately will decrease the return. This might interfere with the results of this thesis, as our method does not take into account the level of disclosure in our sample. As such, these interferences might explain the similarities observed between the two performance portfolios.

7.1.2 ESG score momentum-based strategy – Pillar level

By incorporating the presented literature to the empirical findings of this thesis, the authors seek to reflect on the observed similarities and differences of the pillar-specific momentum effects on portfolio returns.

There is no particular pillar that yield a notable greater alpha than the others, hence this thesis do not suggest that any particular pillar score are exclusively attributable to yield a greater positive alpha. Even though there is no considerable difference in alpha magnitude and significance level assigned to any pillars, the governance pillar does have the most notable difference between its two portfolios as the relative outperformance of the Low compared to the High is bigger than any other pillar.

By arguing that governance is the most quantifiable pillar, earlier literature suggests a higher ability for investors to assess the materiality of governance measures on financial performance. Although similar results are detected in both markets, the authors find the degree of outperformance of the Low portfolio noteworthy. These findings are therefore both contradicting and in line with the literature claiming a positive correlation between strong corporate governance and financial performance by (La Porta, Lopez-De-Silanses, Shleifer, & Vishny, 2002), (Gompers, Ishii, & Metrick, 2003) and (Cremers & Nair, 2005).

Assuming stricter corporate governance is reflected by higher governance scores, the findings on the Low portfolio outperformance are in line with the literature of (Parigi, Pelizzon, & von Thadden, 2014) on the negative relationship between the strictness of corporate governance and the investors' expectations of company earnings. As such, indicating an additional effect from the poor governance score momentum on stock performance: First, the impact from poorer ESG momentum on governance matters on financial performance, and second, which is the positive effect from lax governance on company cash flows. The net effect is not fully determined by this research, but the indications of such conflicting effects might explain the similarities observed in the High and Low portfolios. As such, indicated by the Low outperformance of High, suggest that the lax governance on company cash flows might be stronger.

Further, regarding the social pillar, (McWilliams & Siegel, 2001) argued for a neutral relationship between SRI measures and financial performance, but this is countered by the outperformance of both portfolios in relation to the momentum effect. If the relationship was really neutral, then their performance should also be neutral – or due to some other factors not observed in the model. Further, the findings, which are consistent across both markets, are both in line with and contradicting to the findings of (Arlow & Gannon, 1982) on the negative correlation between social- and financial performance.

With regard to the findings of (Dumitrescu & Zakriya, 2021) on the positive impact of strong stakeholder relations on stock price crash risk, the High social pillar momentum score-based portfolio results exhibit lower downside risk than both the benchmark and Low portfolios. This is especially the case when comparing with that of the benchmark, which is consistent across both the US- and European markets. These findings from the social pillar are indicated by their less extreme maximum drawdown, VaR and expected shortfall for both High portfolios, which are considered metrics more directed towards the portfolios' downside risk rather than volatility alone. As such, the findings are consistent with the findings of (Dumitrescu & Zakriya, 2021).

As the environmental pillar has become the forefront of the ESG-hype by the increased focus on global warming and the companies' environmental footprint, the authors find it surprising that the poor score momentum strategy outperform the strong throughout the time period of investigation. Findings from this thesis regarding the relationship between pillar score momentum and stock performance are somewhat contradicting with that of (Chen & Yang, 2020), who found that companies with a high environmental score outperformed those with a low score base. As the results deals with momentum, the signal effect would suggest that the High portfolio would outperform the Low, though this is not the case.

7.1.3 ESG score momentum-based strategy – Geographical level

Several differences between the two markets have been detected throughout the analysis. By pulling on the previous presented literature, this section will discuss and reflect upon these findings in order to explain these differences.

The development of the ESG scores in the US market has been marginally higher than that of the European throughout the time period of investigation as it had a lower score base. The opposite is the case for Europe (Appendix 11.6.1.5.2 & 11.6.2.5.2). The different score base might ultimately affect the comparison of the two markets, although it's outside of the scope of investigation. Despite positive alphas in both markets as illustrated in table 26, the European market had a notably higher alpha for close to all portfolios, indicating a higher degree of market inefficacy in that particular market.

Environmental scores have improved in both markets over the period under investigation. The screened S&P 500 has experienced a score improvement of 41%, only to reach the lowest pillar benchmark average, whereas the screened S&P Europe 350 has had a 10% improvement, to their highest pillar benchmark average (Appendix 11.6.2.5.4 & 11.6.1.5.4). The different score base level might again lower the basis of comparison between the two markets.

As the European market has been encouraged to improve their environmental scores through attractive governmental incentives, and further with a new taxation system and green bonds, the US market has experienced a fraction of it, and even discouraged it under the Trump administration (McGrath, 2020). Despite geographical differences in incentives, both portfolios in both markets outperform their benchmark, hence the findings provide no evidence to suggest that the environmental momentum effect is contingent on geography. Further, subsidies might explain the performance of the High portfolios. As stated above, Europe has increased their tax-subsidies over the time period of investigation, which might have had a positive impact on company earnings. Therefore, the financial performance of companies with a strong ESG profile might increase, which further could improve the correlation between ESG momentum and stock performance. The authors note the possibility of subsidies risk, as governments might decrease certain subsidies, which ultimately might weaken the financial performance of companies with strong ESG momentum.

That said, the environmental Low portfolio in the US is outperforming High to a greater extent than in Europe, emphasizing that investors in US assess environmental momentum less material. The findings from the analysis does not apply with (Derwall, 2004), as the High- and Low portfolios share approximately the same risk-adjusted returns.

Further, the findings are in line with literature from (Capon, Farley, & Hoenig, 1990) on a positive relationship between social- and financial performance, although also contradicting as the performance of Low is similar to that of High on almost all metrics. This is the case for both the US- and the European market, suggesting that the momentum effect is not contingent on geography. When looking at the average social pillar scores for Europe, the gap between High and Low are not that significant as both score relatively high, but that of the US is more significant where High and Low are above and below the benchmark average, respectively. Yet their performances across both markets are similar in nature, suggesting a presence of geographical difference with regard to a score level effect. One explanation for this may be structural differences, as recent findings from (EFAMA, 2021) indicates that the focus on social governance measures is more enhanced in the European markets as regulations are more prominent. When the materiality of social governance measures are lower in the US, it becomes less important to investors.

In relation to (Bauer, Gunster, & Otten, 2003)'s findings on corporate governance standard contingency on country law, the authors identify a higher level of governance pillar scoring in Europe than in the US. This is in line with Bauer et al. (2003)'s findings. On the other hand, similarities in terms of investor reaction to corporate governance score momentum are observed across both markets, i.e. both High and Low portfolio yields considerable excess returns beyond the benchmark in addition to produce significant alphas of material size. As such, both supporting and contradicting the literature of (Cremers & Nair, 2005) on the positive relationship between governance mechanisms and stock return.

Further, in terms of difference in risk between the two portfolios, the authors note some variations. As the level of corporate governance regulations are higher in Europe, one would assume the impact from weakening governance scores would be more severe in Europe than in the US. This is not the case performance-wise as the degree of Low outperformance to High is greater in Europe. In terms of downside risk, the authors note some variations. High experienced a -15% drawdown while Low showed -11% in the US, whereas that of Europe were -14% and -16%, respectively, which suggests a more notable downside risk in Europe. As the Low governance portfolio in Europe exhibits poorer governance scores, our findings on the impact of poorer performance on governance matters on downside risk is in line with the research of (Grewal, Riedl, & Serafeima, 2018) on the stronger negative market reactions to companies with weaker ESG-related performance.

Our findings suggest no notable geographical differences with regard to the momentum effect as both markets display similar portfolio results in terms of performance and alpha generation. The fact that the portfolios perform close to equal on both markets indicates that there are factors outside the scope of this thesis that might affect the results.

7.1.4 Alpha beyond the Fama & French multifactor model

Although significant positive alphas of considerable magnitude are detected in the Fama & French multifactor models, our findings do exhibit some variations. As such, the following section will reflect upon these inconsistencies.

The European market exhibits lower alphas for all Fama & French models compared to the CAPM single-index, which indicates that parts of the excess return to a greater extent is explained by size- and value premium effects. This is not the case for the US market. As such, the authors note that there might be additional explanatory factors absent in the model which might shed light on the determination of the portfolio's excess returns.

There are different considerations that investors in both markets should take into account as a result of the regression models' findings. Size premium is positive and highly significant for all portfolios, in line with the theory of (Fama & French, 1992). This positive relationship seems reasonable, as the data is selected upon companies with a large market capitalization, which indicate that they all should have the financial ability to increase their scores. It appears that bigger companies might be more negatively affected by obstructive media attention with regard to a poor ESG performance than companies of smaller size, consequently reducing the stock return for bigger companies (Fang & Peress, 2009).

Value premium reacts different in the two markets, as the US market is negatively affected by the value premium effect, whereas the European portfolios react positively to it. The value premium could ultimately indicate that the alpha might be assigned to other factors, as the book-to-market ratio decreases with pillar specific measures on socially responsible investing, which ultimately could lead to that the Fama & French model might not detect SRI measures within the alpha (Galema, Plantiga, & Scholtens, 2008).

7.2 Critique of own methods

The retrieved data has a high influence on the empirical research, as it contains certain limitations and biases. Survivorship- and selection bias has influenced the data, as it has been selected upon high market capitalization- and turnover requirements. Data consisting of companies with these characteristics might affect the empirical results, as literature suggest that a ESG score momentum-based strategy has a greater explanatory degree on companies with a lower market capitalization. The trade-off is that a somewhat biased dataset will determine whether there is a correlation between ESG score-momentum and stock performance for companies with a large market capitalization (De & Clayman, 2010). Further, the analysis' lack of data, in terms of length, challenged the reliability of the future application of this research's findings. Lack of ESG data is a well addressed issue in today's literature, as it has made a long-term ESG score momentum-based research difficult to conduct (Fitzgeorge-Parker, 2020).

As the Refinitiv industry-specific weighting data is unavailable, the authors have not been able to correct for this particular bias. In terms of reliability, the authors question whether the results can be repeated. The methods used in this thesis are well-implemented in the ESG-research and is regarded as highly reliable. Even though the methods can be repeated, it doesn't imply that the results will be equal, as the interpretation of non-financial data differ between providers, as well as the inconsistent level of disclosure might influence scores. This is emphasized by the contradicting research presented in the literature review.

The OLS models might be influenced by the currency delimitation. Damodaran believe that the risk-free rate should be denominated in the same currency as the return. Even though this thesis addresses two international markets, the authors assume that the US 1-year T-bond is sufficient as the hurdle rate for institutional investors. Further, both transaction cost and slippage are excluded from this paper as the materiality of such factors are hard to measure.

Our findings are based upon data consisting of historical stock prices. Consequently, the authors underline that future stock price performance might deviate from the past which an investor should take into consideration. The validity of the results is solely dependent on the data retrieved from Refinitiv and Yahoo Finance which are generally viewed as reliable sources. This thesis might have increased its validity by implementing ESG- and financial data from other well-known data providers, namely MSCI and Thomson Reuters, although such access have been limited.

7.3 Market efficiency

As addressed under the market efficiency theory, a statistically significant alpha based upon an ESG score momentum-based strategy would imply that there is a violation of the market efficiency in the semi-strong form. This inefficiency implies that not all public information is included in the stock price at the time the information becomes public. The authors underline that the thesis' objective is not to evaluate the market efficiency, as the method don't emphasize it, although the authors would like to point out certain findings. As the regression models from this thesis find statistically significant alphas that are unequal to zero, the semi-strong market efficiency is violated (Malkiel B. G., 2003).

Under section 3. Theory, the CAPM and multifactor model is used to determine whether the market is efficient or not. The findings from CAPM in both markets indicate that there is an inefficient market, as both a strong- and poor ESG score-momentum yield a statistically significant alpha at the 1% level. Further, the market inefficiency is consistent throughout the Fama & French models, as the alphas remain significant in both markets. A violation of the market efficiency in a semi-strong form, allows investors to implement an overall ESG, environmental, social and governance momentum-based strategy, as they can exploit the inefficient market.

One could argue that the inefficient market is a result of the lack of ESG framework, hence investors react differently to the same information. In addition to this, the ESG providers might interpret ESG information differently, providing the investors with somewhat inconsistent information, giving them investment incentives on different grounds.

8. Conclusion

In order to answer the problem statement and its subsequent research questions, this thesis has put forward the theoretical basis, methodology and analysis in order to evaluate the relationship between both a company's ESG- and pillar score-momentum and company stock performance through a proposed score momentum-based trading strategy. Through the back-testing and evaluation of the strategy, which is the core of this thesis, the end goal is to provide further empirical findings to the existing literature as well as for investors for implementation into their investment decision process.

Through the proposed long-only trading strategy, the authors aim to construct positive alpha-generating portfolios based on their change in score, which would serve as an indicator of future materiality of ESG-related risks and opportunities. Based on the proposed score momentum-based trading strategy, the authors constructed two portfolios consisting of companies from both ends of the score momentum spectrum and evaluated their performance against each other as well as the benchmark. In order to assess whether the strategy is applicable to any of the specific ESG pillars, the strategy was applied to each pillar for comparison. Lastly, the portfolio performances are examined in relation to the Fama & French and Carhart four-factor models to evaluate whether the strategy yields alpha beyond that of these multifactor models. In the following paragraphs the authors will address each research question in order to conclude on the problem statement this thesis has put forward.

With regard to research question one, the empirical findings suggests that there is a significant positive alpha associated with companies holding both a strong- and poor ESG score-momentum. In terms of alpha magnitude, the poor score momentum-based trading strategy, with two exceptions, yielded the highest alpha across all pillars for both markets. As such, suggesting a stronger effect from the poor score momentum on stock performance. As a consequence, this thesis adds ambiguity to the existing literature on this subject. However, the results of this thesis do suggest that a trading strategy based upon momentum itself, independent of direction, yields significant positive alpha.

The findings detect highly significant positive alpha of relatively similar magnitude in the environmental, social and governance pillars. As such, the authors do not find any evidence on whether the momentum effect is more notable on alpha for any particular pillar through both the single-index- and Fama & French multifactor models. There is although a slight difference in the magnitude of the alphas between the two markets. For Europe, the annualized alpha is on average 0.9- and 0.6 ppts. above that of the US for High and Low, respectively. To conclude, the alpha is therefore slightly more notable in Europe, than in the US.

The multifactor regression analysis provides evidence of positive alpha generation beyond that of the Fama & French three-factor model for both markets. As previously mentioned, too much uncertainty is associated with the results from the Carhart four-factor model which led the authors to discard it from the analysis, although it should be mentioned that this model did show indications of positive alphas as well.

Findings from this thesis further adds to the scarce and somewhat contradicting literature on the subject of the relationship between company ESG score momentum and stock return performance as there is a complex set of factors determining the portfolio performance which our research does not uncover. However, the proposed strategy does provide significant material alphas across both markets which brings the authors to emphasize that the deductions from this thesis are that the proposed strategy should be assessed merely as a supplementary tool to the investment decision process. As the findings of this thesis further suggests that the portfolio alphas are not entirely attributed to the momentum effect, our result does provide solid grounds for future research.

9. Suggestions for future research

On an end note, this thesis' research is providing somewhat ambiguous results in relation to the current empirical research within this field, as both ends of the momentum spectrum yields significant alphas. However, the authors find the magnitude of benchmark outperformance and alphas intriguing, and raises questions surrounding the nature of the alphas.

The abovementioned empirical results also indicate consistent low betas for all portfolios across every pillar for both the US- and European market. As such, further analysis of the relationship between low beta and positive alpha could provide additional insight into the nature of the portfolio alphas. A paper published in 2013 by Andrea Frazzini and Lasse Pedersen found that high-beta assets are associated with low alphas. By constructing a betting-against-beta (BAB) factor model which is long assets with low beta and short assets with high beta, the model yielded significant positive risk-adjusted returns. Their model is grounded upon their assumption that the Capital Asset Pricing Model does not hold as investors have constrains in terms of availability of risk-free leverage. Hence, they bid up high-beta assets to meet their desired expected return. These findings are in line with this thesis' findings of portfolio betas below one with relative high alphas. As such, the empirical evidence from (Frazzini & Pedersen, 2013) could assist in explaining these alphas by implementing a BAB factor.

The momentum strategy presented in this thesis, is based on a 12 month holding period, and is therefore considered to be a short-term trading strategy. A suggestion for future research would be to test for longer holding periods, e.g. 18-24 months to see if the strategy yields significant alphas for longer holding periods as well. Lastly, the authors built the portfolios to be equally weighted as opposed to value-weighted, which may produce different results. Future research could determine the effects of a different portfolio construction method.

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11. Appendix

11.1 S&P Benchmark

11.1.1 S&P 500

Country Breakdown

COUNTRY	NUMBER OF CONSTITUENTS	TOTAL MARKET CAP [USD MILLION]	INDEX WEIGHT [%]
United States	505	35,385,262.16	100

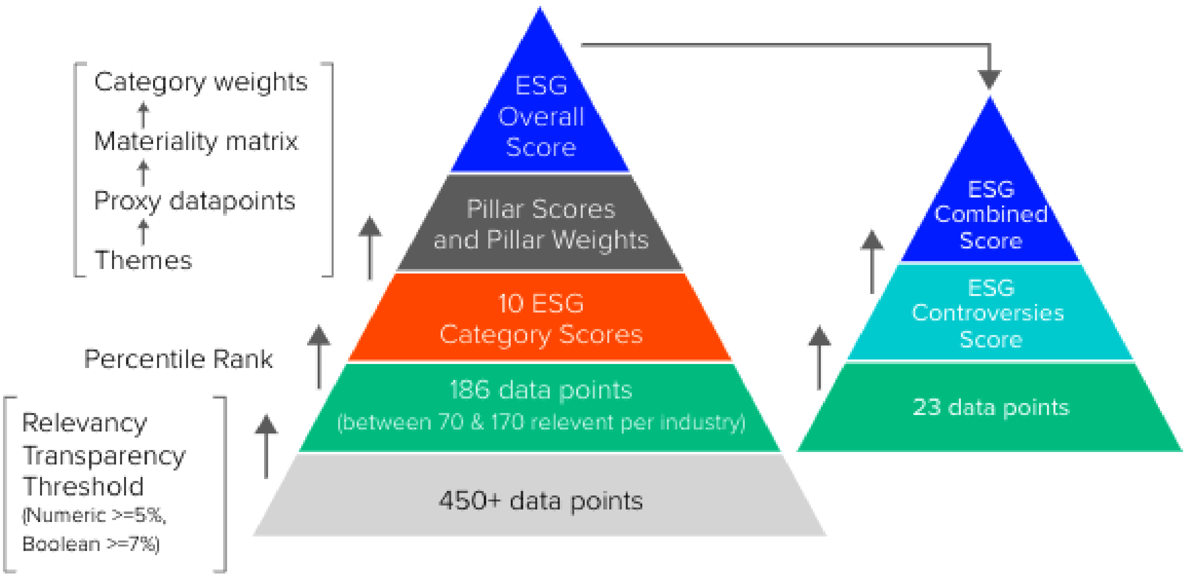
11.1.2 S&P Europe 350

Country Breakdown

COUNTRY	NUMBER OF CONSTITUENTS	TOTAL MARKET CAP [USD MILLION]	INDEX WEIGHT [%]
United Kingdom	87	2,485,214.19	23.4
France	52	2,421,523.08	17
Switzerland	37	1,650,872.37	15
Germany	50	1,885,416.97	14.9
Netherlands	19	901,306.97	6.9
Sweden	30	616,327.51	5.2
Italy	19	530,442.55	4
Spain	17	540,642.16	3.9
Denmark	14	456,688	3.6
Finland	11	245,495.18	2
Belgium	8	215,605.9	1.4
Ireland	7	155,012.06	1.3
Norway	7	171,553	0.9
Portugal	2	31,661.17	0.2
Luxembourg	1	31,895.23	0.2
Austria	2	31,220.54	0.2

11.2 Refinitiv

11.2.1 Score calculation methodology

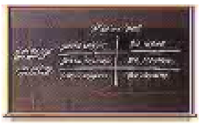


11.2.2 ESG materiality matrix

Pillars	Catagories	Themes	Data points	Weight method
Environmental	Emmission	Emissions	TR.AnalyticCO2	Quant industry median
		Waste	TR.AnalyticTotalWaste	Quant industry median
		Biodiversity *		
		Environmental management systems *		
	Innovation	Product innovation	TR.EnvProducts	Transparency weights
		Green revenues/R&D/capex	TR.AnalyticEnvRD	Quant industry median
	Resource use	Water	TR.AnalyticWaterUse	Quant industry median
		Energy	TR.AnalyticEnergyUse	Quant industry median
		Sustainable packaging *		
		Environmental supply chain *		
Governance	CSR strategy	CSR strategy	Data points in governance category/data points in governance pillar	Count of data points in each governance category/All data points in governance pillar
		ESG reporting and transparency		
	Management	Structure (independence, diversity, committees)	Data points in governance category/data points in governance pillar	Count of data points in each governance category/All data points in governance pillar
		Compensation		
	Shareholders	Shareholder rights	Data points in governance category/data points in governance pillar	Count of data points in each governance category/All data points in governance pillar
		Takeover defenses		
Social	Community	Equally important to all industry groups, hence a median weight of 5 is assigned to all industry groups		Equally important to all industry groups
	Human rights	Human rights	TR.PolicyHumanRights	Transparency weights
	Product responsibility	Responsible marketing	TR.PolicyResponsibleMarketing	Transparency weights
		Product quality	TR.ProductQualityMonitoring	Transparency weights
		Data privacy	TR.PolicyDataPrivacy	Transparency weights
	Workforce	Diversity and inclusion	TR.WomenEmployees	Quant industry median
		Career development and training	TR.AvgTrainingHours	Transparency weights
		Working conditions	TR.TradeUnionRep	Quant industry median
		Health and safety	TR.AnalyticLostDays	Transparency weights

11.3 Fama and French

11.3.1 Multifactor



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Description of Fama/French 3 Factors for Developed Markets

Daily Returns: July 1, 1990 – March 31, 2021

Monthly Returns: July 1990 – March 2021

Annual Returns: 1991–2020

Construction: All returns are in U.S. dollars, include dividends and capital gains, and are not continuously compounded. Market is the return on a region's value-weight market portfolio minus the U.S. one month T-bill rate.

To construct the SMB and HML factors, we sort stocks in a region into two market cap and three book-to-market equity (B/M) groups at the end of each June. Big stocks are those in the top 90% of June market cap for the region, and small stocks are those in the bottom 10%. The B/M breakpoints for a region are the 30th and 70th percentiles of B/M for the big stocks of the region.

The developed portfolios use developed size breaks, but we use the B/M breakpoints for the four regions to allocate the stocks of these regions to the developed portfolios. Similarly, the developed ex us portfolios use developed ex us size breaks and regional B/M breakpoints. The independent 2x3 sorts on size and B/M produce six value-weight portfolios, SG, SN, SV, BG, BN, and BV, where S and B indicate small or big and G, N, and V indicate growth (low B/M), neutral, and value (high B/M).

SMB is the equal-weight average of the returns on the three small stock portfolios for the region minus the average of the returns on the three big stock portfolios,

SMB = 1/3 (Small Value + Small Neutral + Small Growth)
– 1/3 (Big Value + Big Neutral + Big Growth).

HML is the equal-weight average of the returns for the two high B/M portfolios for a region minus the average of the returns for the two low B/M portfolios,

HML = 1/2 (Small Value + Big Value)
– 1/2 (Small Growth + Big Growth).

Stocks: Rm–Rf for July of year t to June of t+1 include all stocks for which we have market equity data for June of t. SMB and HML for July of year t to June of t+1 include all stocks for which we have market equity data for December of t–1 and June of t, and (positive) book equity data for t–1.

Country	Developed	Developed ex US	Europe	Japan	Asia Pacific ex Japan	North America
Australia	✔	✔			✔	
Austria	✔	✔	✔			
Belgium	✔	✔	✔			
Canada	✔	✔				✔
Switzerland	✔	✔	✔			
Germany	✔	✔	✔			
Denmark	✔	✔	✔			
Spain	✔	✔	✔			
Finland	✔	✔	✔			
France	✔	✔	✔			
Great Britain	✔	✔	✔			
Greece	✔	✔	✔			
Hong Kong	✔	✔			✔	
Ireland	✔	✔	✔			
Italy	✔	✔	✔			
Japan	✔	✔		✔		
Netherlands	✔	✔	✔			
Norway	✔	✔	✔			
New Zealand	✔	✔			✔	
Portugal	✔	✔	✔			
Sweden	✔	✔	✔			
Singapore	✔	✔			✔	
United States	✔					✔

11.4 Carhart OLS

11.4.1 US market

11.4.1.1 ESG

	Dependent variable:					
	Highr			Lowr		
	(1)	(2)	(3)	(4)	(5)	(6)
MRP	0.7492*** (0.6870, 0.8114)	0.7252*** (0.6663, 0.7841)	0.7272*** (0.6717, 0.7826)	0.7493*** (0.6794, 0.8193)	0.7302*** (0.6595, 0.8008)	0.7188*** (0.6354, 0.8022)
SMB		0.5471*** (0.2994, 0.7949)	0.6444*** (0.3704, 0.9184)		0.3560** (0.0107, 0.7012)	0.4724** (0.0710, 0.8738)
HML		-0.1920** (-0.3552, -0.0289)	-0.2006** (-0.3798, -0.0213)		-0.0453 (-0.2490, 0.1584)	-0.0854 (-0.3108, 0.1400)
WML			-0.0419* (-0.0880, 0.0042)			-0.0728** (-0.1369, -0.0087)
Constant	0.0045*** (0.0028, 0.0063)	0.0046*** (0.0022, 0.0069)	0.0234** (0.0031, 0.0437)	0.0065*** (0.0041, 0.0089)	0.0071*** (0.0041, 0.0100)	0.0385*** (0.0105, 0.0666)
Observations	108	108	97	108	108	97
R^2	0.8800	0.8968	0.9018	0.8404	0.8474	0.8443
Adjusted R^2	0.8788	0.8939	0.8976	0.8389	0.8430	0.8375
Residual Std. Error	0.0105 (df = 106)	0.0098 (df = 104)	0.0093 (df = 92)	0.0124 (df = 106)	0.0122 (df = 104)	0.0120 (df = 92)
F Statistic	776.9720*** (df = 1; 106)	301.3875*** (df = 3; 104)	211.3160*** (df = 4; 92)	558.3102*** (df = 1; 106)	192.4953*** (df = 3; 104)	124.6804*** (df = 4; 92)

Note: The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.

11.4.1.2 Environmental

	Dependent variable:					
		Highr			Lowr	
	(1)	(2)	(3)	(4)	(5)	(6)
MRP	0.7606***	0.7433***	0.7432***	0.7468***	0.7239***	0.7047***
	(0.7085, 0.8127)	(0.6909, 0.7958)	(0.6927, 0.7937)	(0.6809, 0.8128)	(0.6570, 0.7908)	(0.6266, 0.7829)
SMB		0.3757***	0.5046***		0.3422**	0.4795***
		(0.1239, 0.6275)	(0.2426, 0.7666)		(0.0320, 0.6525)	(0.1447, 0.8142)
HML		-0.1141	-0.1332		0.0567	-0.0246
		(-0.2784, 0.0501)	(-0.2992, 0.0327)		(-0.1794, 0.2929)	(-0.2523, 0.2032)
WML			-0.0282			-0.0620**
			(-0.0755, 0.0191)			(-0.1223, -0.0017)
Constant	0.0048***	0.0050***	0.0177*	0.0057***	0.0070***	0.0337**
	(0.0032, 0.0064)	(0.0029, 0.0070)	(-0.0033, 0.0387)	(0.0032, 0.0081)	(0.0041, 0.0099)	(0.0066, 0.0609)
Observations	108	108	97	108	108	97
R^2	0.9066	0.9144	0.9144	0.8425	0.8514	0.8539
Adjusted R^2	0.9057	0.9120	0.9107	0.8410	0.8471	0.8475
Residual Std. Error	0.0092 (df = 106)	0.0089 (df = 104)	0.0087 (df = 92)	0.0122 (df = 106)	0.0120 (df = 104)	0.0113 (df = 92)
F Statistic	1,028.8050*** (df = 1; 106)	370.4680*** (df = 3; 104)	245.7045*** (df = 4; 92)	566.9892*** (df = 1; 106)	198.6046*** (df = 3; 104)	134.4009*** (df = 4; 92)

Note: The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.

11.4.1.3 Social

	Dependent variable:					
		Highr			Lowr	
	(1)	(2)	(3)	(4)	(5)	(6)
MRP	0.7547***	0.7351***	0.7509***	0.8153***	0.7978***	0.7822***
	(0.7001, 0.8094)	(0.6797, 0.7905)	(0.6935, 0.8083)	(0.7451, 0.8855)	(0.7294, 0.8661)	(0.7058, 0.8586)
SMB		0.4830***	0.5593***		0.2954*	0.4768***
		(0.2840, 0.6819)	(0.3427, 0.7758)		(-0.0534, 0.6442)	(0.1186, 0.8351)
HML		-0.2026**	-0.1796*		-0.0009	-0.0814
		(-0.3730, -0.0323)	(-0.3614, 0.0021)		(-0.2057, 0.2039)	(-0.2997, 0.1369)
WML			-0.0064			-0.0534
			(-0.0585, 0.0456)			(-0.1178, 0.0111)
Constant	0.0056***	0.0054***	0.0088	0.0054***	0.0062***	0.0297**
	(0.0037, 0.0076)	(0.0032, 0.0076)	(-0.0136, 0.0312)	(0.0032, 0.0076)	(0.0035, 0.0088)	(0.0004, 0.0589)
Observations	108	108	97	108	108	97
R^2	0.8877	0.9013	0.9025	0.8769	0.8816	0.8841
Adjusted R^2	0.8866	0.8984	0.8982	0.8758	0.8782	0.8790
Residual Std. Error	0.0102 (df = 106)	0.0096 (df = 104)	0.0094 (df = 92)	0.0116 (df = 106)	0.0115 (df = 104)	0.0109 (df = 92)
F Statistic	837.5370*** (df = 1; 106)	316.4796*** (df = 3; 104)	212.8456*** (df = 4; 92)	755.3730*** (df = 1; 106)	258.1855*** (df = 3; 104)	175.3833*** (df = 4; 92)

Note: The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.

11.4.1.4 Governmental

	Dependent variable:					
	Highr			Lowr		
	(1)	(2)	(3)	(4)	(5)	(6)
MRP	0.7774***	0.7409***	0.7457***	0.7518***	0.7335***	0.7303***
	(0.7168, 0.8380)	(0.6796, 0.8022)	(0.6805, 0.8108)	(0.6747, 0.8289)	(0.6573, 0.8097)	(0.6389, 0.8217)
SMB		0.6314***	0.7225***		0.4199**	0.5280**
		(0.3930, 0.8698)	(0.4724, 0.9726)		(0.0286, 0.8111)	(0.0480, 1.0080)
HML		-0.0245	-0.0343		-0.1499	-0.1763
		(-0.2245, 0.1756)	(-0.2554, 0.1869)		(-0.3756, 0.0759)	(-0.4323, 0.0797)
WML			-0.0205			-0.0558
			(-0.0674, 0.0263)			(-0.1250, 0.0134)
Constant	0.0050***	0.0065***	0.0161	0.0067***	0.0067***	0.0308**
	(0.0030, 0.0070)	(0.0038, 0.0091)	(-0.0046, 0.0367)	(0.0042, 0.0093)	(0.0039, 0.0096)	(0.0001, 0.0615)
Observations	108	108	97	108	108	97
R^2	0.8785	0.9012	0.8990	0.8218	0.8310	0.8232
Adjusted R^2	0.8773	0.8984	0.8946	0.8201	0.8261	0.8155
Residual Std. Error	0.0109 (df = 106)	0.0100 (df = 104)	0.0098 (df = 92)	0.0133 (df = 106)	0.0130 (df = 104)	0.0131 (df = 92)
F Statistic	766.1386*** (df = 1; 106)	316.2585*** (df = 3; 104)	204.7722*** (df = 4; 92)	488.6737*** (df = 1; 106)	170.4608*** (df = 3; 104)	107.1128*** (df = 4; 92)

Note: The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.

11.4.2 European market

11.4.2.1 ESG

	Dependent variable:					
	Highr			Lowr		
	(1)	(2)	(3)	(4)	(5)	(6)
MRP	0.5667***	0.5582***	0.6965***	0.6161***	0.5496***	0.7207***
	(0.3774, 0.7559)	(0.3247, 0.7917)	(0.6205, 0.7725)	(0.4026, 0.8296)	(0.3036, 0.7956)	(0.6302, 0.8112)
SMB		0.6026***	0.5984***		0.8049***	0.8344***
		(0.3548, 0.8504)	(0.3774, 0.8194)		(0.3984, 1.2113)	(0.4248, 1.2440)
HML		0.0944	-0.0321		0.3381***	0.2078**
		(-0.1161, 0.3048)	(-0.1518, 0.0875)		(0.0990, 0.5771)	(0.0186, 0.3970)
WML			0.0087			0.0223
			(-0.0316, 0.0490)			(-0.0584, 0.1029)
Constant	0.0073***	0.0059***	0.0021	0.0083***	0.0078***	-0.0028
	(0.0043, 0.0102)	(0.0031, 0.0087)	(-0.0167, 0.0208)	(0.0049, 0.0118)	(0.0045, 0.0111)	(-0.0386, 0.0330)
Observations	108	108	96	108	108	96
R^2	0.6211	0.6585	0.7924	0.5802	0.6469	0.7650
Adjusted R^2	0.6175	0.6487	0.7833	0.5763	0.6367	0.7547
Residual Std. Error	0.0174 (df = 106)	0.0166 (df = 104)	0.0127 (df = 91)	0.0206 (df = 106)	0.0190 (df = 104)	0.0157 (df = 91)
F Statistic	173.7515*** (df = 1; 106)	66.8604*** (df = 3; 104)	86.8567*** (df = 4; 91)	146.5282*** (df = 1; 106)	63.5033*** (df = 3; 104)	74.0600*** (df = 4; 91)

Note: The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.

11.4.2.2 Environmental

	Dependent variable:					
		Highr			Lowr	
	(1)	(2)	(3)	(4)	(5)	(6)
MRP	0.5884^{***}	0.5647^{***}	0.6901^{***}	0.6120^{***}	0.5791^{***}	0.7210^{***}
	(0.3973, 0.7795)	(0.3338, 0.7956)	(0.6132, 0.7671)	(0.4193, 0.8047)	(0.3505, 0.8078)	(0.6185, 0.8235)
SMB		0.5887^{***}	0.5622^{***}		0.6233^{***}	0.6370^{***}
		(0.3258, 0.8515)	(0.2918, 0.8326)		(0.3421, 0.9046)	(0.3511, 0.9229)
HML		0.1515	0.0340		0.1901^{*}	0.0508
		(-0.0603, 0.3634)	(-0.1170, 0.1851)		(-0.0199, 0.4000)	(-0.1017, 0.2034)
WML			-0.0020			0.0086
			(-0.0603, 0.0563)			(-0.0596, 0.0767)
Constant	0.0078^{***}	0.0068^{***}	0.0082	0.0078^{***}	0.0070^{***}	0.0030
	(0.0048, 0.0108)	(0.0038, 0.0098)	(-0.0186, 0.0351)	(0.0047, 0.0110)	(0.0040, 0.0100)	(-0.0273, 0.0333)
Observations	108	108	96	108	108	96
R^2	0.6382	0.6730	0.7868	0.6234	0.6600	0.7662
Adjusted R^2	0.6348	0.6635	0.7775	0.6198	0.6502	0.7559
Residual Std. Error	0.0174 (df = 106)	0.0167 (df = 104)	0.0131 (df = 91)	0.0187 (df = 106)	0.0179 (df = 104)	0.0146 (df = 91)
F Statistic	187.0073^{***} (df = 1; 106)	71.3404^{***} (df = 3; 104)	83.9771^{***} (df = 4; 91)	175.4300^{***} (df = 1; 106)	67.3062^{***} (df = 3; 104)	74.5589^{***} (df = 4; 91)
Note:	The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.					

11.4.2.3 Social

	Dependent variable:					
		Highr			Lowr	
	(1)	(2)	(3)	(4)	(5)	(6)
MRP	0.6004^{***}	0.5719^{***}	0.7197^{***}	0.6157^{***}	0.5820^{***}	0.7412^{***}
	(0.4141, 0.7867)	(0.3473, 0.7966)	(0.6451, 0.7943)	(0.4137, 0.8176)	(0.3424, 0.8217)	(0.6474, 0.8350)
SMB		0.5261^{***}	0.5125^{***}		0.6111^{***}	0.6392^{***}
		(0.3121, 0.7402)	(0.3093, 0.7157)		(0.2393, 0.9830)	(0.2813, 0.9972)
HML		0.1632^{*}	0.0365		0.1920	0.0557
		(-0.0294, 0.3558)	(-0.0680, 0.1409)		(-0.0373, 0.4212)	(-0.1193, 0.2307)
WML			0.0231			0.0193
			(-0.0133, 0.0595)			(-0.0574, 0.0960)
Constant	0.0068^{***}	0.0061^{***}	-0.0042	0.0068^{***}	0.0060^{***}	-0.0032
	(0.0044, 0.0092)	(0.0041, 0.0082)	(-0.0207, 0.0123)	(0.0036, 0.0101)	(0.0028, 0.0093)	(-0.0375, 0.0311)
Observations	108	108	96	108	108	96
R^2	0.7089	0.7400	0.8654	0.6081	0.6425	0.7493
Adjusted R^2	0.7062	0.7325	0.8595	0.6045	0.6322	0.7383
Residual Std. Error	0.0151 (df = 106)	0.0144 (df = 104)	0.0103 (df = 91)	0.0194 (df = 106)	0.0187 (df = 104)	0.0158 (df = 91)
F Statistic	258.1986^{***} (df = 1; 106)	98.6755^{***} (df = 3; 104)	146.2657^{***} (df = 4; 91)	164.5105^{***} (df = 1; 106)	62.3018^{***} (df = 3; 104)	68.0075^{***} (df = 4; 91)
Note:	The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.					

11.4.2.4 Governmental

	Dependent variable:					
		Highr			Lowr	
	(1)	(2)	(3)	(4)	(5)	(6)
MRP	0.5567^{***}	0.5177^{***}	0.6636^{***}	0.6199^{***}	0.5919^{***}	0.7279^{***}
	(0.3854, 0.7280)	(0.3135, 0.7218)	(0.5838, 0.7435)	(0.4237, 0.8161)	(0.3579, 0.8258)	(0.6452, 0.8106)
SMB		0.5785^{***}	0.5729^{***}		0.5358^{***}	0.5584^{***}
		(0.3311, 0.8259)	(0.3130, 0.8327)		(0.2143, 0.8573)	(0.2313, 0.8854)
HML		0.2092^{**}	0.0768		0.1625	0.0299
		(0.0199, 0.3985)	(-0.0582, 0.2118)		(-0.0611, 0.3861)	(-0.1308, 0.1906)
WML			0.0052			0.0089
			(-0.0535, 0.0640)			(-0.0634, 0.0812)
Constant	0.0062^{***}	0.0056^{***}	0.0033	0.0086^{***}	0.0079^{***}	0.0036
	(0.0035, 0.0089)	(0.0030, 0.0083)	(-0.0230, 0.0297)	(0.0055, 0.0116)	(0.0050, 0.0107)	(-0.0280, 0.0353)
Observations	108	108	96	108	108	96
R^2	0.6429	0.6853	0.7974	0.6464	0.6737	0.7776
Adjusted R^2	0.6395	0.6762	0.7885	0.6431	0.6643	0.7678
Residual Std. Error	0.0163 (df = 106)	0.0154 (df = 104)	0.0124 (df = 91)	0.0180 (df = 106)	0.0175 (df = 104)	0.0142 (df = 91)
F Statistic	190.8074^{***} (df = 1; 106)	75.4789^{***} (df = 3; 104)	89.5640^{***} (df = 4; 91)	193.7699^{***} (df = 1; 106)	71.5879^{***} (df = 3; 104)	79.5272^{***} (df = 4; 91)

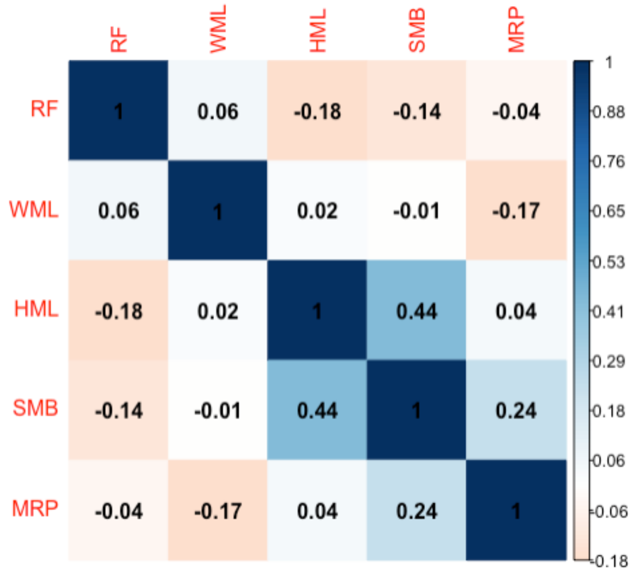
Note: The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.

11.4.3 Annualized alpha

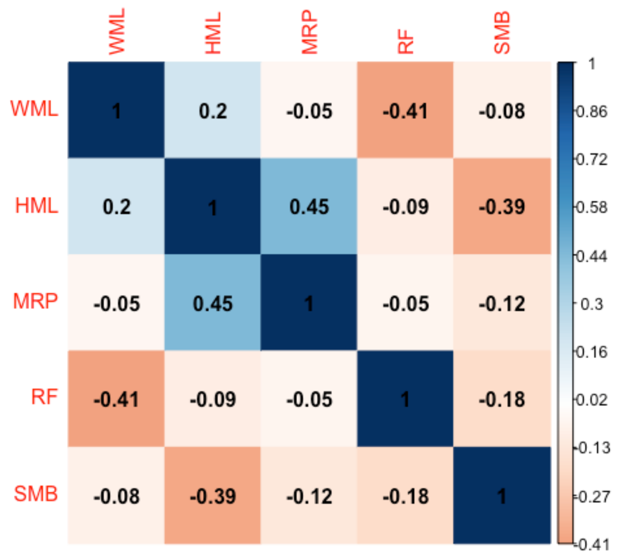
	Annualized alpha Multifactor				**Annualized alpha Fama & French**				**Annualized alpha CAPM**			
	Alpha		**Significance**		**Alpha**		**Significance**		**Alpha**		**Significance**	
Portfolio	**High**	**Low**	**High**	**Low**	**High**	**Low**	**High**	**Low**	**High**	**Low**	**High**	**Low**
US ESG	31,99%	61,59%	5%	1%	5,66%	8,86%	1%	1%	5,54%	8,08%	1%	1%
US Environmental	23,43%	71,74%	10%	1%	6,17%	8,73%	1%	1%	5,91%	7,06%	1%	1%
US Social	11,09%	23,58%	Insignificant	Insignificant	6,68%	7,70%	1%	1%	6,93%	6,68%	1%	1%
US Governance	21,13%	45,93%	Insignificant	Insignificant	8,08%	8,34%	1%	1%	6,17%	8,34%	1%	1%
EU ESG	2,55%	11,09%	Insignificant	Insignificant	7,31%	9,77%	1%	1%	9,12%	10,43%	1%	1%
EU Environmental	10,30%	10,82%	Insignificant	Insignificant	8,47%	8,73%	1%	1%	9,77%	9,77%	1%	1%
EU Social	-4,93%	5,91%	Insignificant	Insignificant	7,57%	7,44%	1%	1%	8,47%	8,47%	1%	1%
EU Governance	4,03%	7,57%	Insignificant	Insignificant	6,93%	9,90%	1%	1%	7,70%	10,82%	1%	1%

11.5 Econometric considerations

11.5.1 Correlation matrix for multifactor models – S&P 500



11.5.2 Correlation matrix for multifactor models – S&P 350



11.5.3 VIF score output – S&P 500

```
     MRP      SMB      HML      WML 
1.096639 1.294132 1.224313 1.032474 
```

11.5.4 VIF score output – S&P 500

MRP	SMB	HML	WML
1.289541	1.180339	1.537589	1.066066

11.5.5 Breusch-Pagan Test - S&P 500 and S&P 350

S&P 500

	Multifactor model				**Fama-French**				**CAPM**			
	High		Low		High		Low		High		Low	
Pillar	Score	P-value	Score	P-value	Score	P-value	Score	P-value	Score	P-value	Score	P-value
ESG	3.097	0.542	1.150	0.886	2.015	0.569	1.329	0.722	1.969	0.161	0.000	0.989
E	4.620	0.329	7.465	0.113	0.526	0.913	1.171	0.760	0.684	0.408	0.028	0.867
S	2.724	0.605	5.919	0.205	1.357	0.716	0.602	0.896	1.883	0.170	0.344	0.558
G	1.719	0.787	4.293	0.368	1.203	0.752	1.372	0.712	0.134	0.714	0.323	0.570

S&P 350

	Multifactor model				**Fama-French**				**CAPM**			
	High		Low		High		Low		High		Low	
Pillar	Score	P-value	Score	P-value	Score	P-value	Score	P-value	Score	P-value	Score	P-value
ESG	0.314	0.989	0.637	0.755	15.268	0.002	17.723	0.001	11.629	0.001	15.222	0.000
E	2.708	0.608	2.155	0.707	14.626	0.002	18.765	0.000	11.895	0.001	15.352	0.000
S	2.150	0.708	0.472	0.976	17.918	0.001	16.068	0.001	13.605	0.000	13.841	0.000
G	2.591	0.629	1.330	0.856	18.025	0.000	16.815	0.001	14.649	0.000	14.031	0.000

11.5.6 Breusch-Godfrey Test for S&P 500 and S&P 350

S&P 500

	Multifactor model				**Fama-French**				**CAPM**			
	High		Low		High		Low		High		Low	
Pillar	Score	P-value	Score	P-value	Score	P-value	Score	P-value	Score	P-value	Score	P-value
ESG	1.195	0.274	0.188	0.665	1.137	0.286	0.307	0.579	1.215	0.270	0.076	0.783
E	0.011	0.916	0.014	0.906	0.257	0.612	0.000	0.989	0.435	0.509	0.013	0.908
S	0.595	0.441	1.031	0.310	0.639	0.424	0.196	0.658	0.220	0.639	0.339	0.560
G	0.372	0.542	0.034	0.853	0.132	0.716	0.063	0.802	0.659	0.417	0.049	0.824

S&P 350

	Multifactor model				**Fama-French**				**CAPM**			
	High		Low		High		Low		High		Low	
Pillar	Score	P-value	Score	P-value	Score	P-value	Score	P-value	Score	P-value	Score	P-value
ESG	3.532	0.060	0.063	0.802	3.954	0.047	2.622	0.105	2.720	0.099	1.256	0.262
E	0.264	0.607	0.828	0.363	0.012	0.914	3.986	0.046	0.044	0.833	2.113	0.146
S	4.039	0.045	0.011	0.915	3.383	0.066	2.234	0.135	1.261	0.262	0.556	0.456
G	0.001	0.981	0.834	0.361	1.385	0.239	1.276	0.259	0.272	0.602	0.121	0.728

11.5.7 HAC standard errors (Newey-West) formulas (Stock & Watson, 2015, p. 598-599)

The HAC variance formula. The heteroskedasticity- and autocorrelation-consistent estimator of the variance of $\hat{\beta}_1$ is

$$\widetilde{\sigma}^2_{\hat{\beta}_1} = \hat{\sigma}^2_{\hat{\beta}_1} \hat{f}_T, \tag{15.15}$$

where $\hat{\sigma}^2_{\hat{\beta}_1}$ is the estimator of the variance of $\hat{\beta}_1$ in the absence of serial correlation, given in Equation (5.4), and where $\hat{f}_T$ is an estimator of the factor f_T in Equation (15.13).

Estimators of f_T used in practice strike a balance between these two extreme cases by choosing the number of autocorrelations to include in a way that depends on the sample size T. If the sample size is small, only a few autocorrelations are used, but if the sample size is large, more autocorrelations are included (but still far fewer than T). Specifically, let $\hat{f}_T$ be given by

$$\hat{f}_T = 1 + 2\sum_{j=1}^{m-1}\left(\frac{m-j}{m}\right)\widetilde{\rho}_j, \tag{15.16}$$

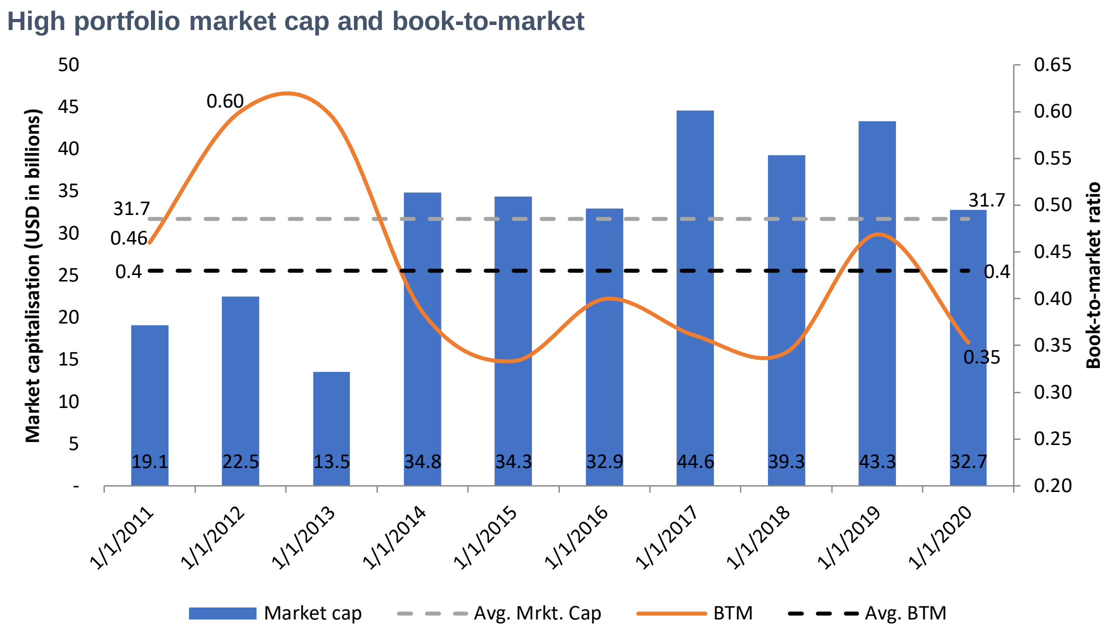
where $\widetilde{\rho}_j = \sum_{t=j+1}^{T}\hat{v}_t\hat{v}_{t-j}/\sum_{t=1}^{T}\hat{v}_t^2$, where $\hat{v}_t = (X_t - \overline{X})\hat{u}_t$ (as in the definition of $\hat{\sigma}^2_{\hat{\beta}_1}$). The parameter m in Equation (15.16) is called the **truncation parameter** of the HAC estimator because the sum of autocorrelations is shortened, or truncated, to include only $m - 1$ autocorrelations instead of the $T - 1$ autocorrelations appearing in the population formula in Equation (15.13).

11.6 Historical general portfolio properties

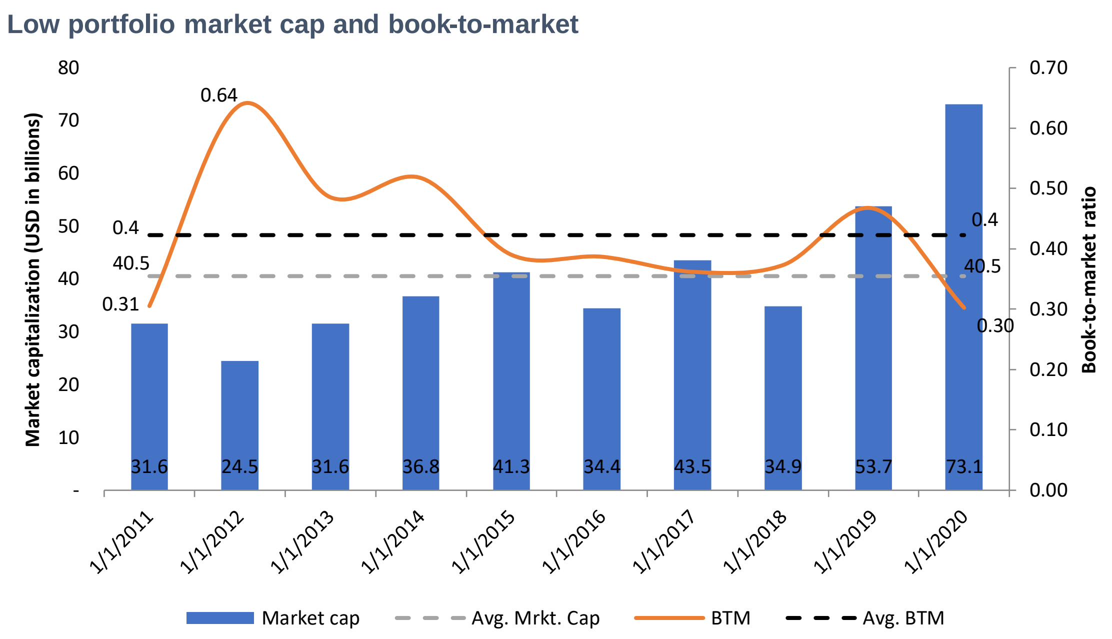
11.6.1 US market

11.6.1.1 ESG portfolios

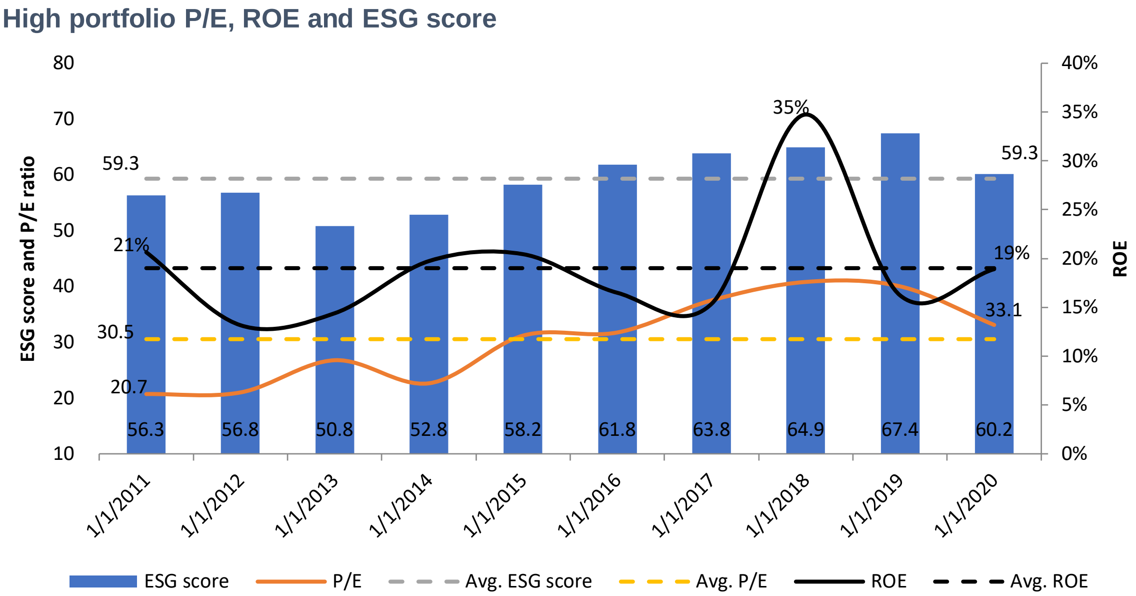
11.6.1.1.1.a Market capitalization and book-to-market - High



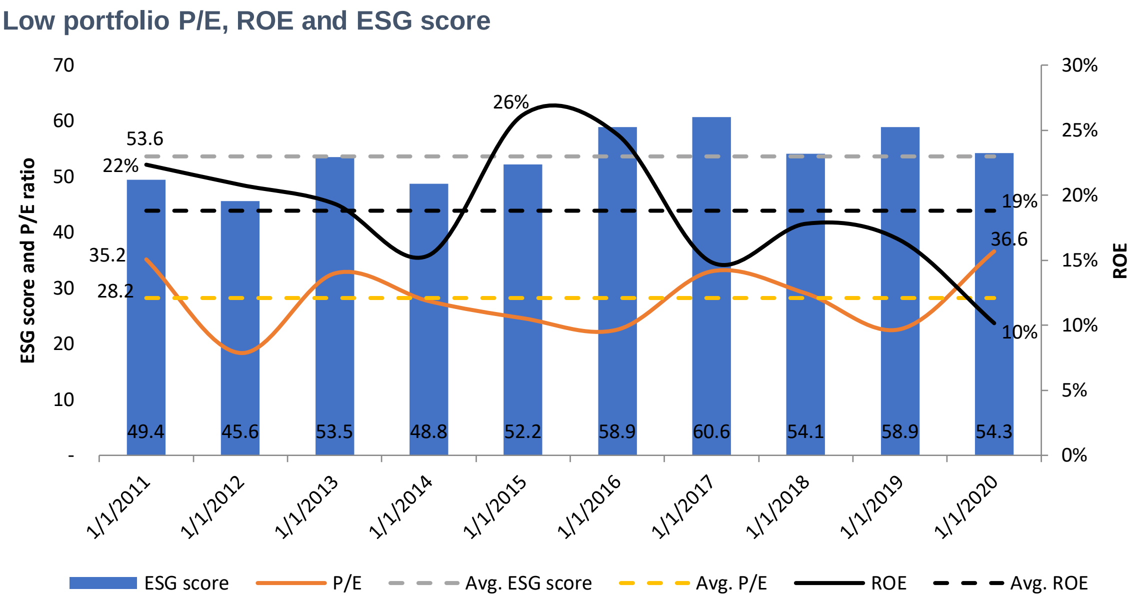
11.6.1.1.1.b Market capitalization and book-to-market - Low



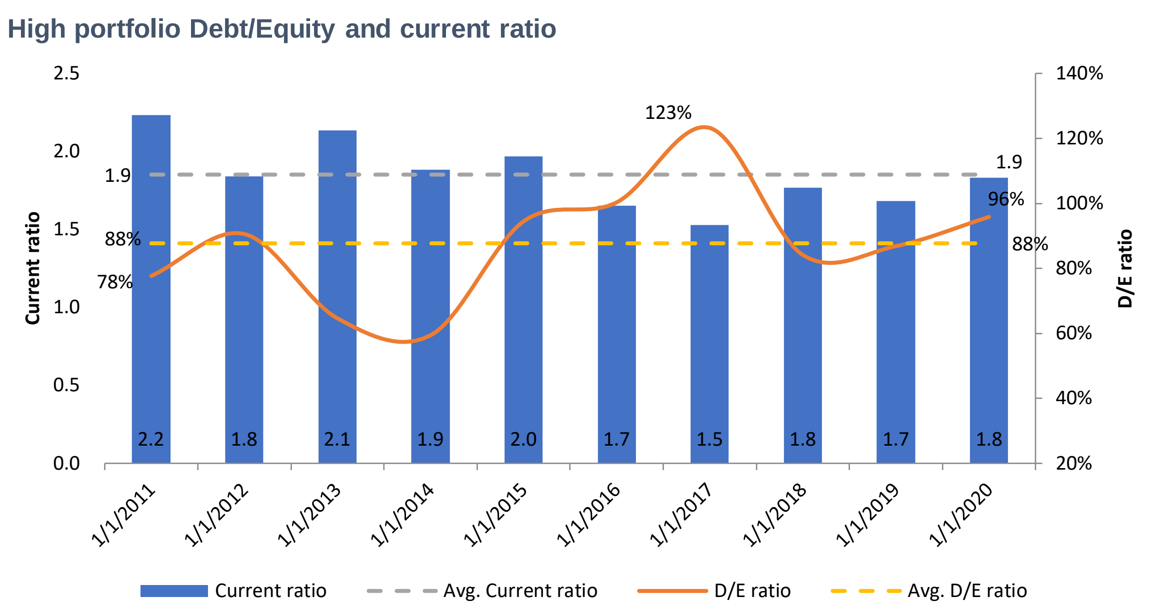
11.6.1.1.2.a Price/earnings, ROE and ESG score - High



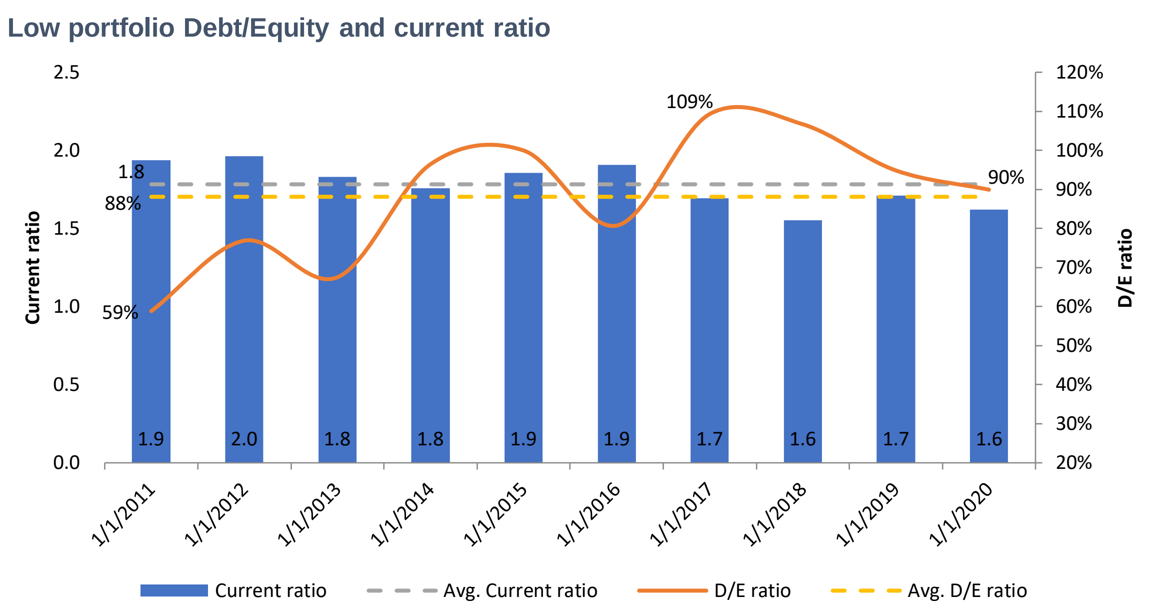
11.6.1.1.2.b Price/earnings, ROE and ESG score - Low



11.6.1.1.3.a Debt-to-equity- and current ratio - High

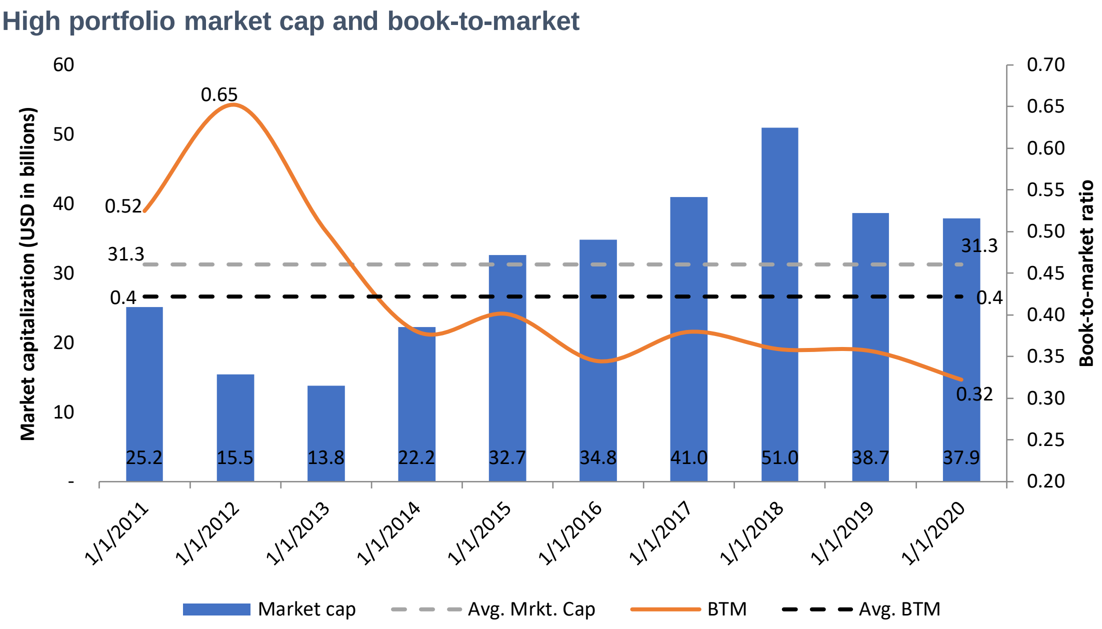


11.6.1.1.3.b Debt-to-equity- and current ratio – Low

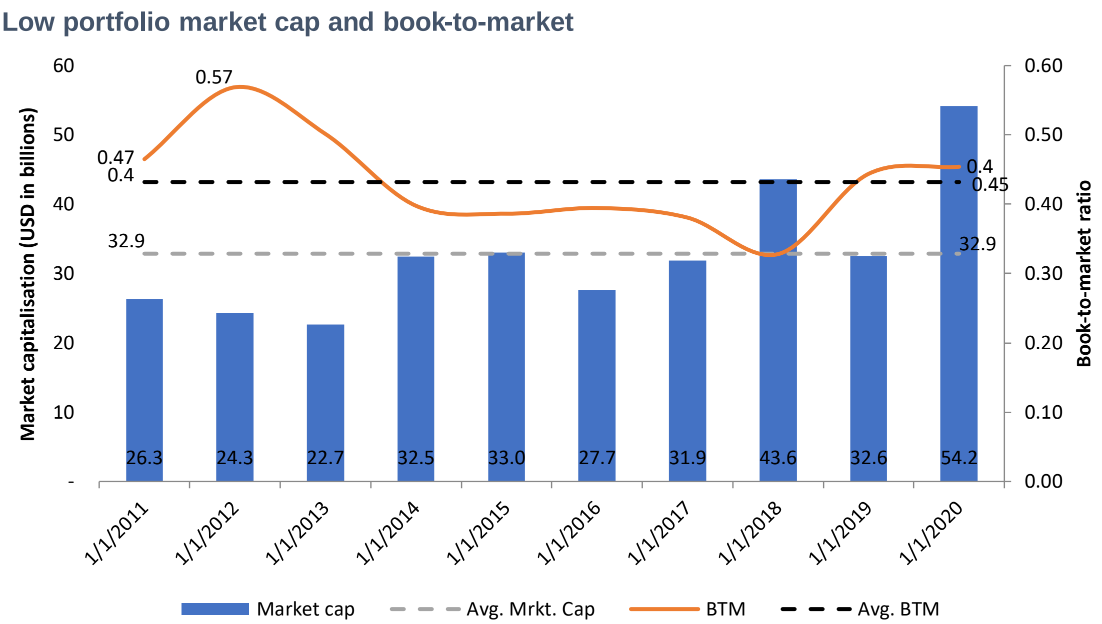


11.6.1.2 Environmental pillar portfolios

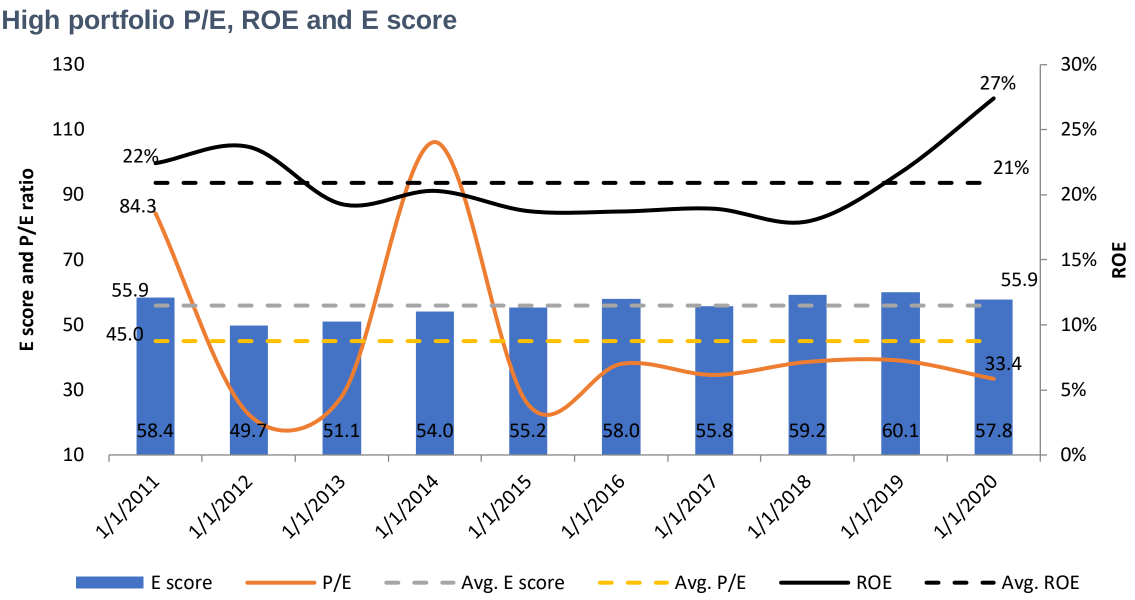
11.6.1.2.1.a Market capitalization and book-to-market - High



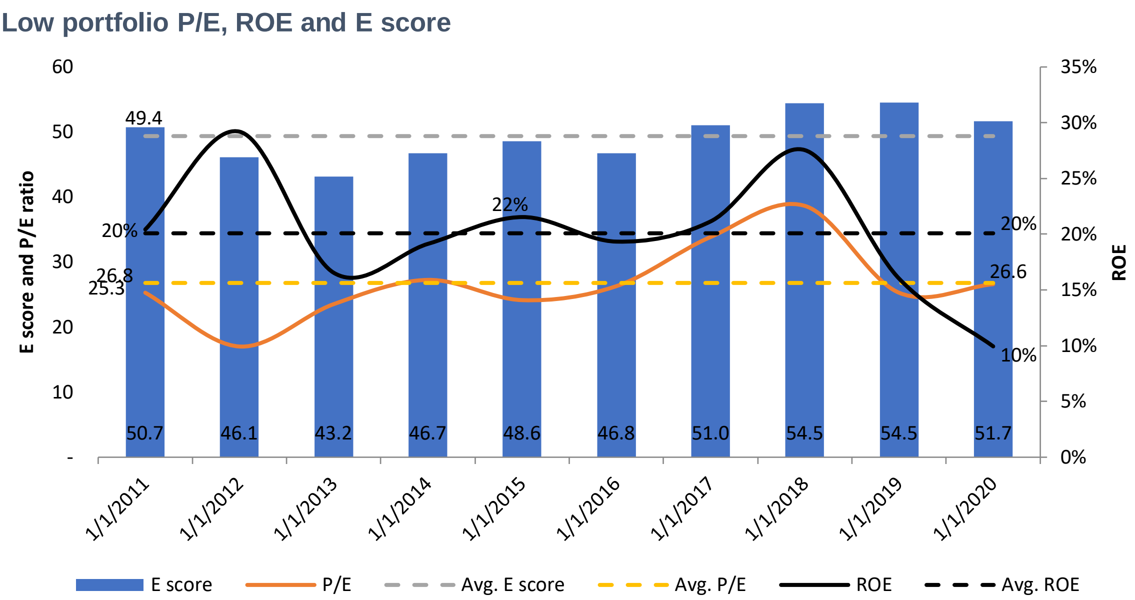
11.6.1.2.1.b Market capitalization and book-to-market – Low



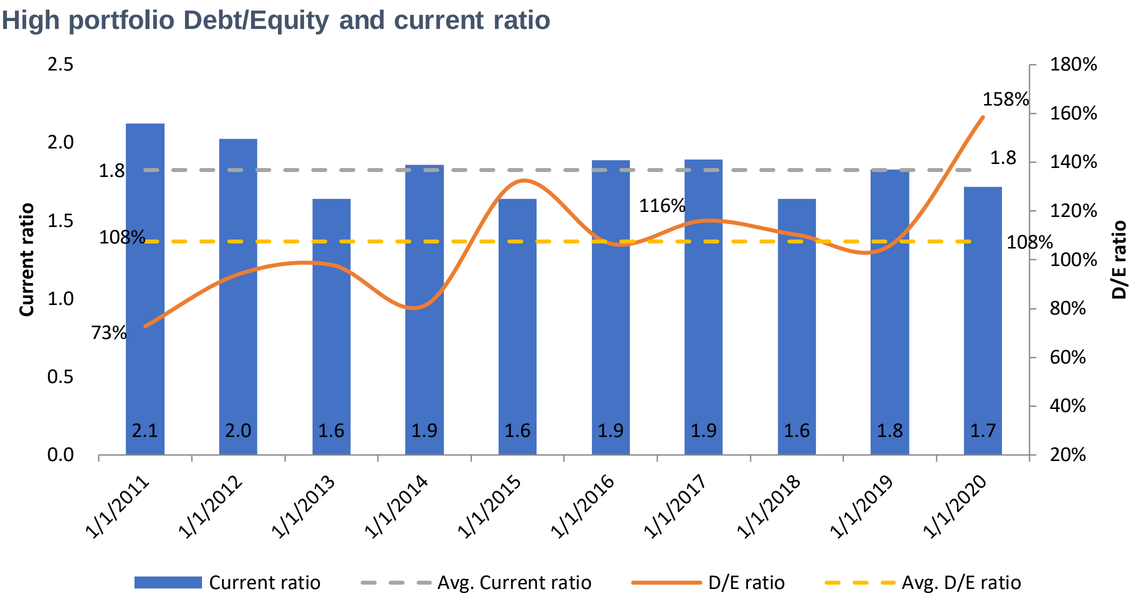
11.6.1.2.2.a Price/earnings, ROE and Environmental pillar score - High



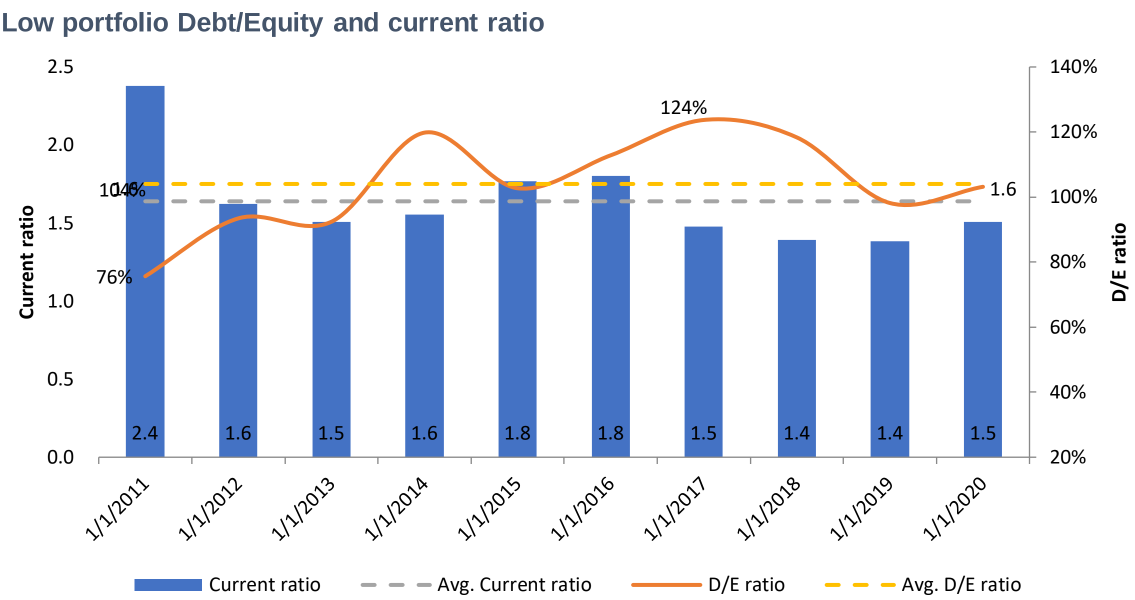
11.6.1.2.2.b Price/earnings, ROE and Environmental pillar score - Low



11.6.1.2.3.a Debt-to-equity- and current ratio - High

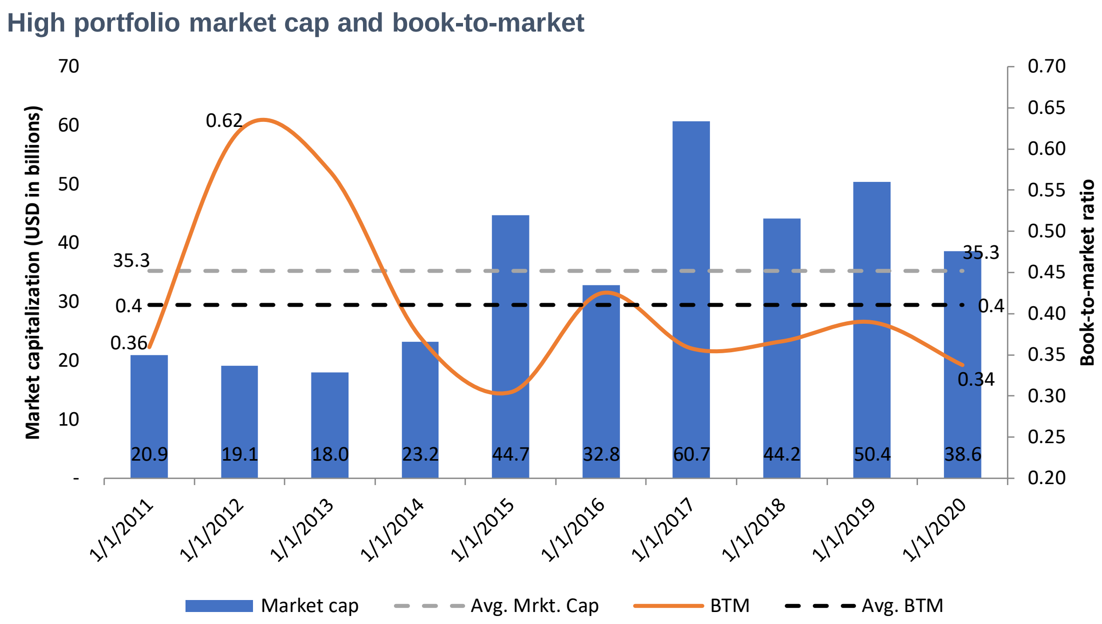


11.6.1.2.3.b Debt-to-equity- and current ratio - Low

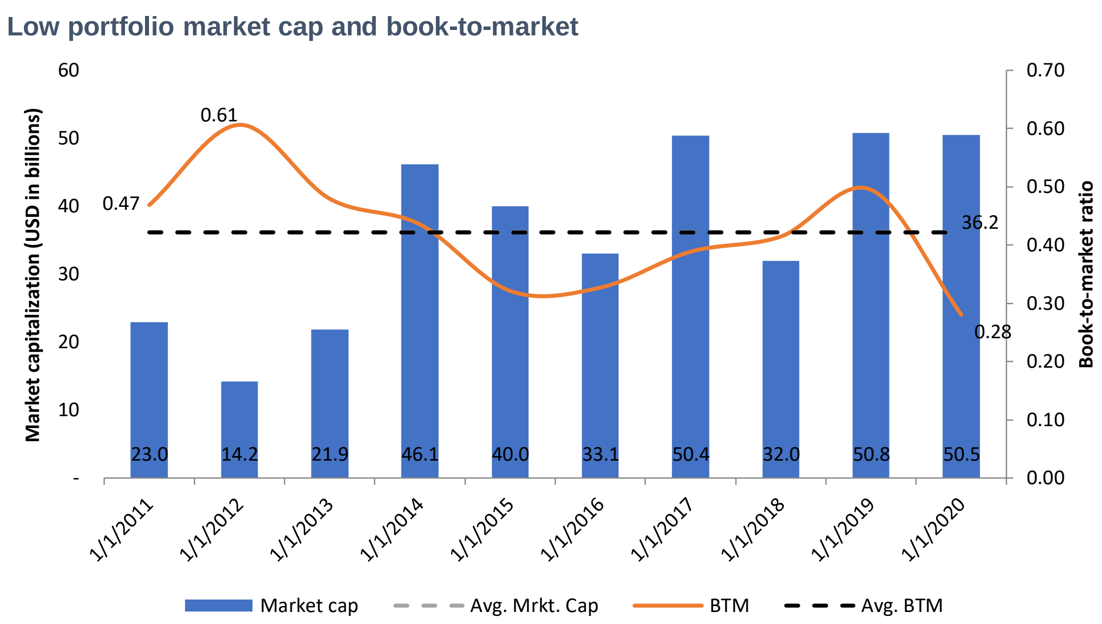


11.6.1.3 Social pillar portfolios

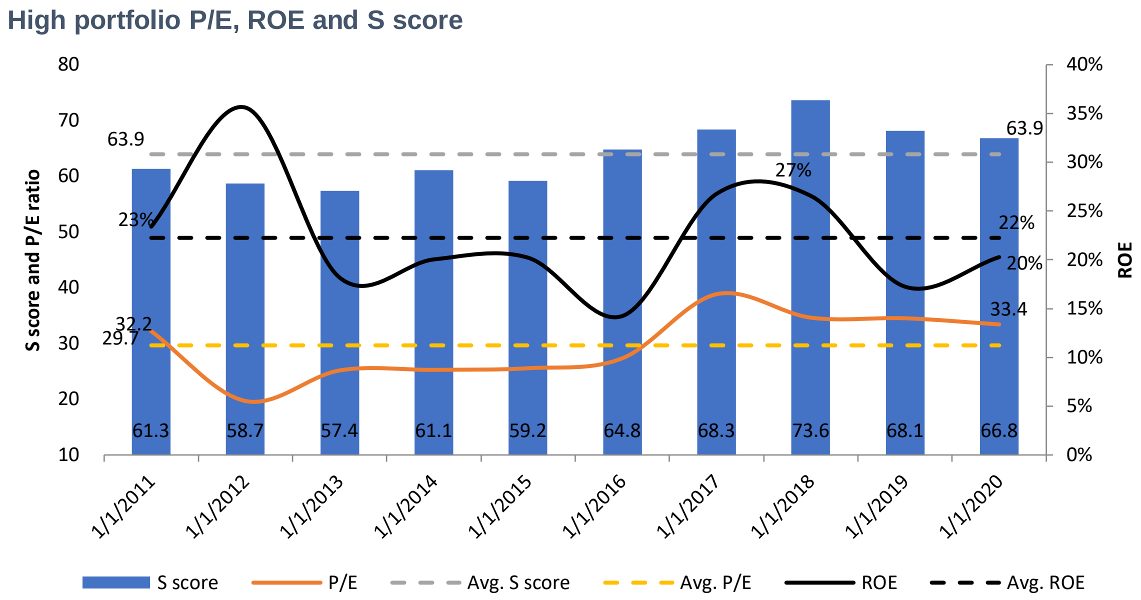
11.6.1.3.1.a Market capitalization and book-to-market - High



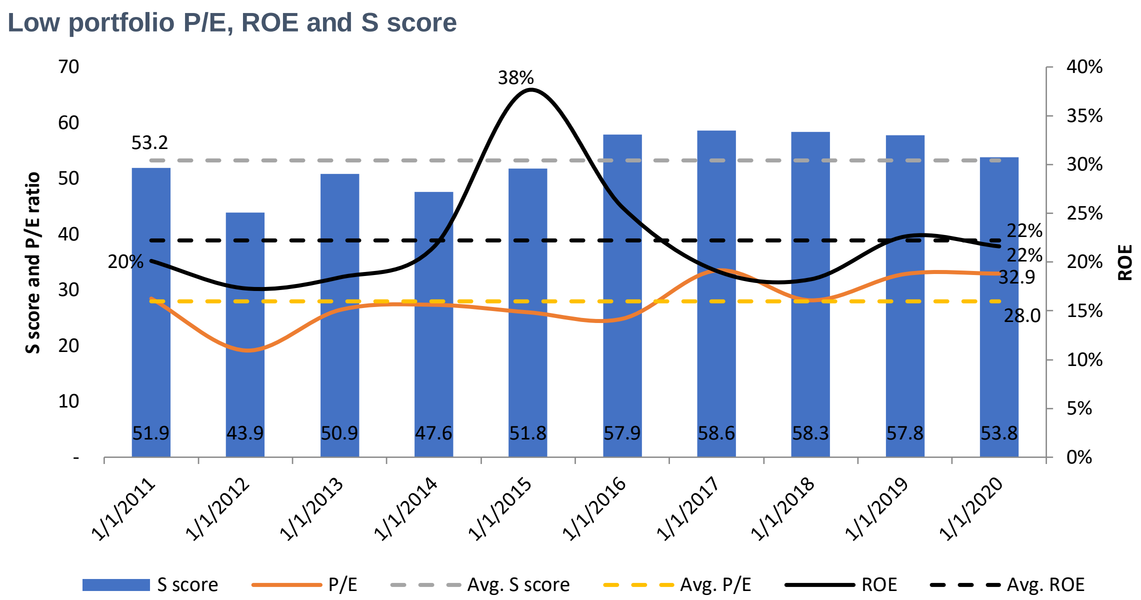
11.6.1.3.1.b Market capitalization and book-to-market - Low



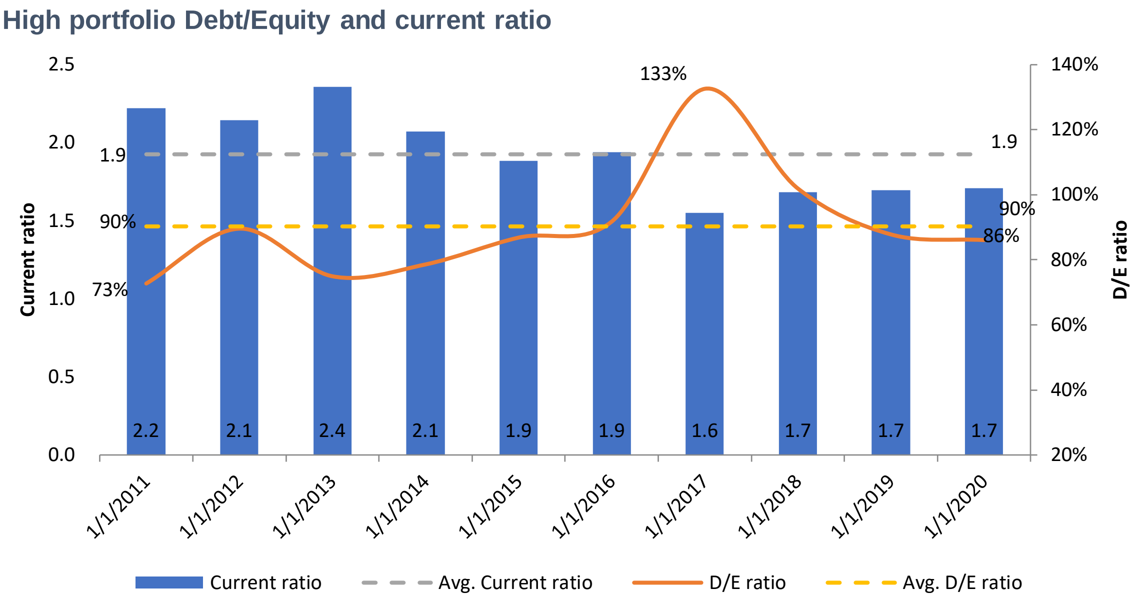
11.6.1.3.2.a Price/earnings, ROE and Social pillar score - High



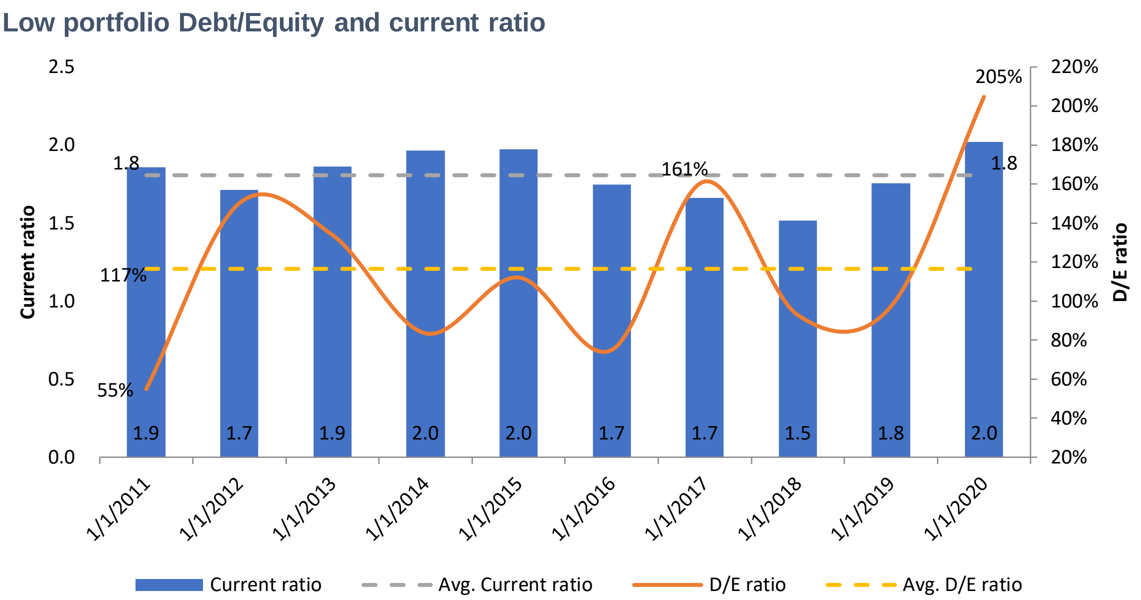
11.6.1.3.2.b Price/earnings, ROE and Social pillar score - Low



11.6.1.3.3.a Debt-to-equity- and current ratio - High

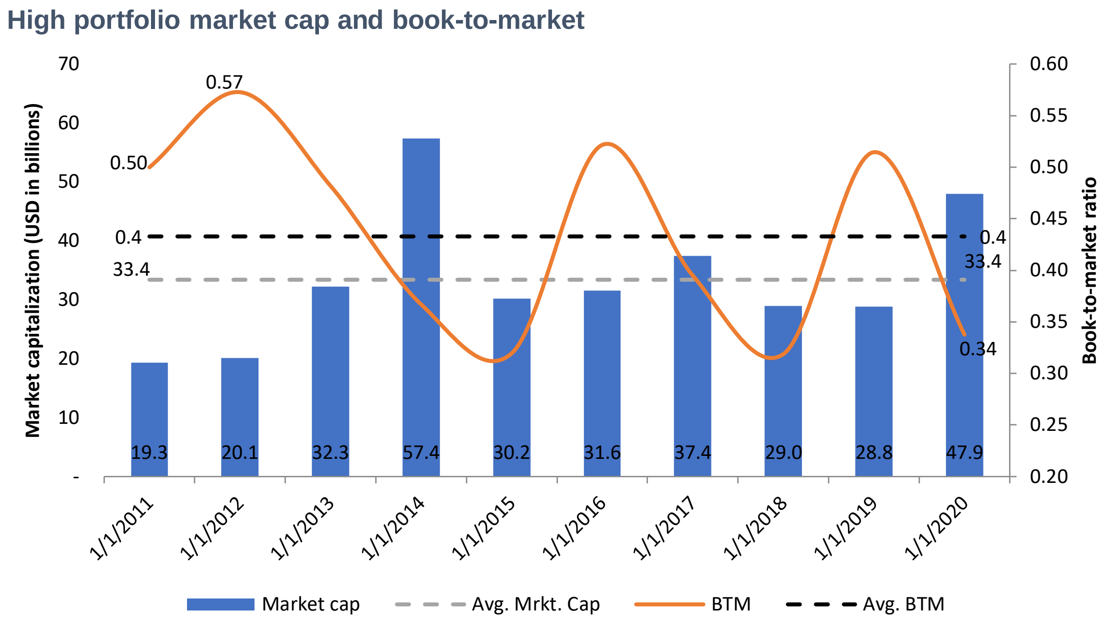


11.6.1.3.3.b Debt-to-equity- and current ratio - Low

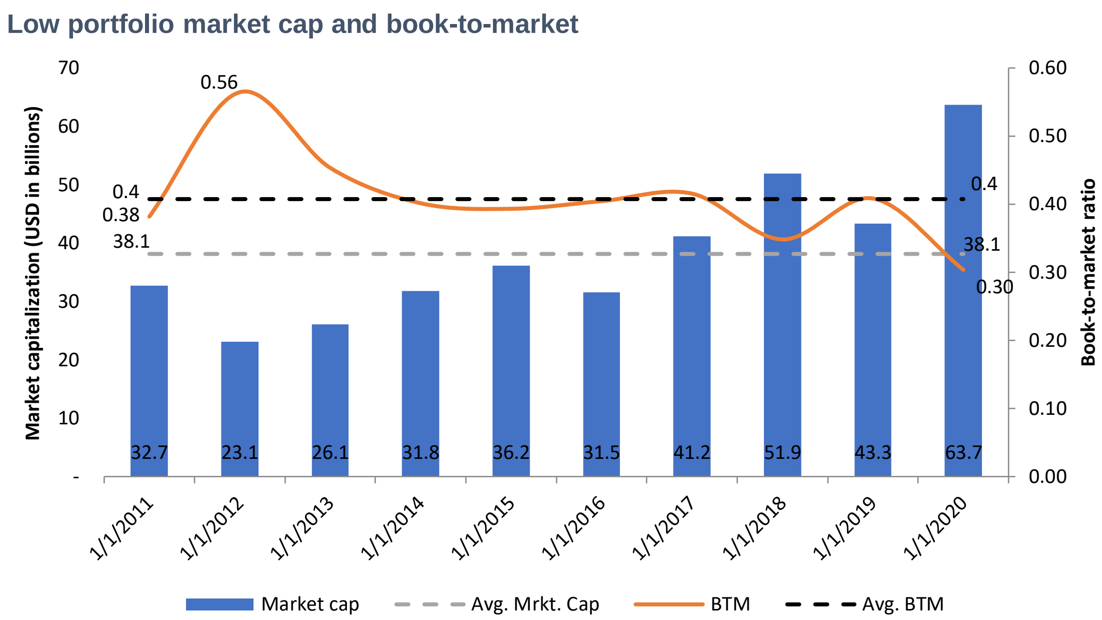


11.6.1.4 Governance pillar portfolios

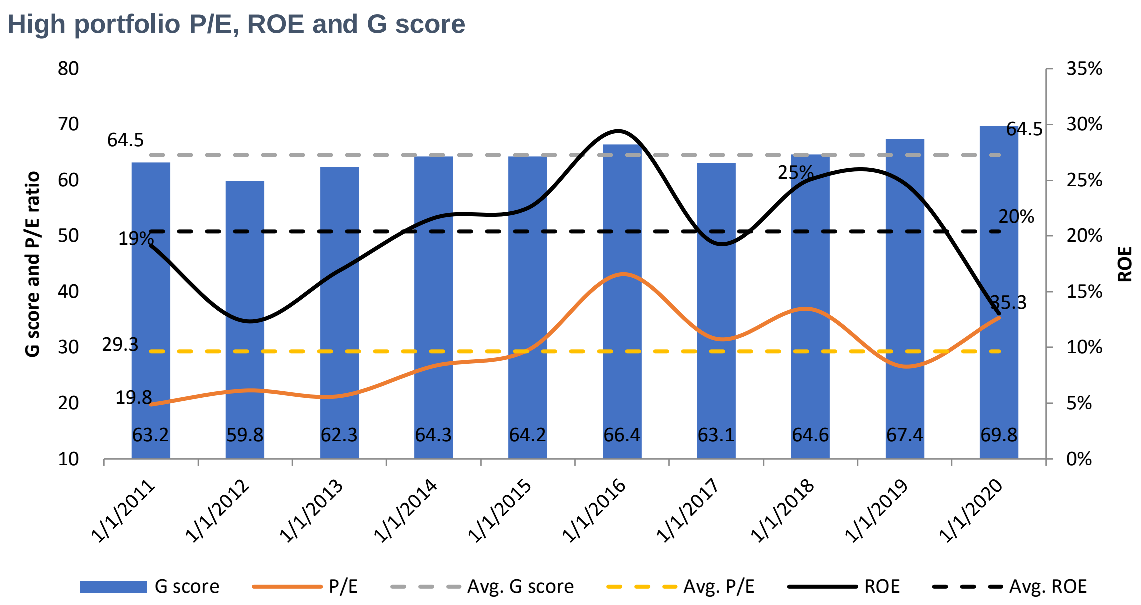
11.6.1.4.1.a Market capitalization and book-to-market – High



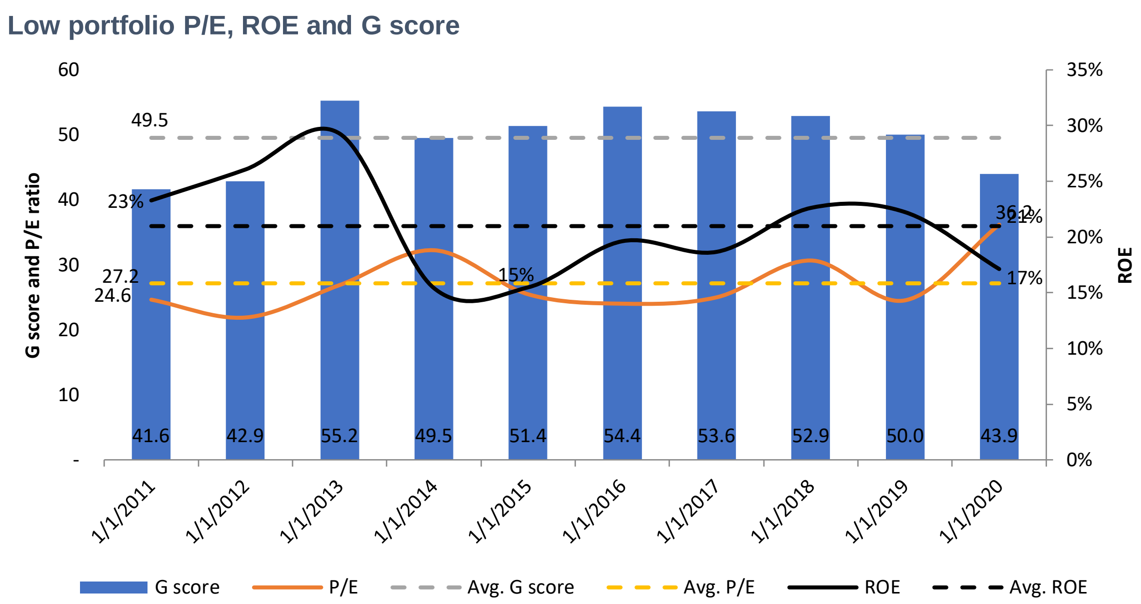
11.6.1.4.1.b Market capitalization and book-to-market – Low



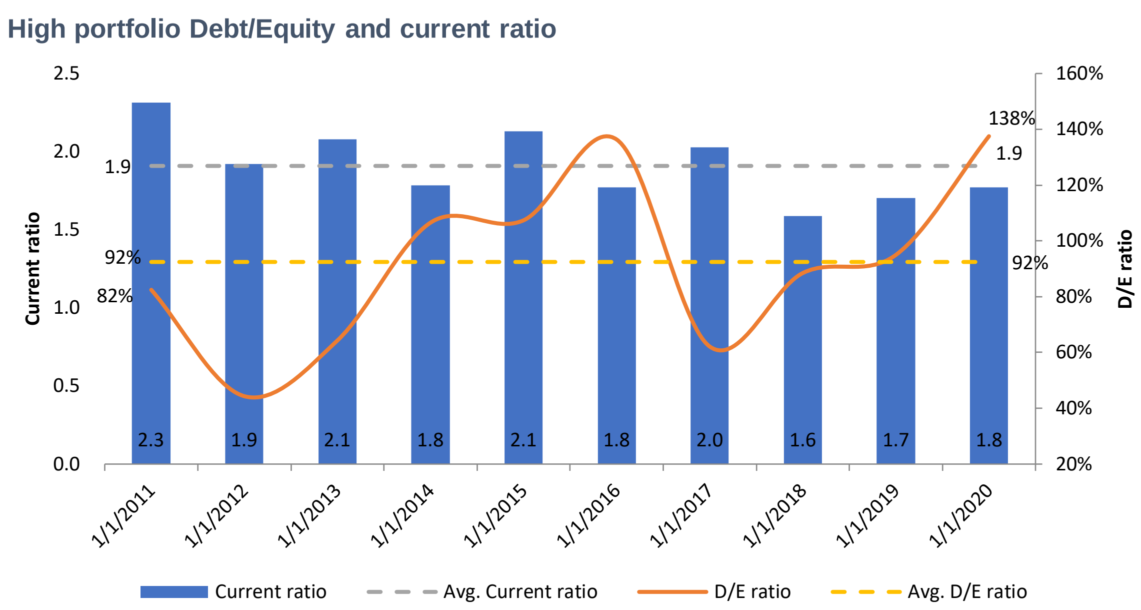
11.6.1.4.2.a Price/earnings, ROE and Governance score – High



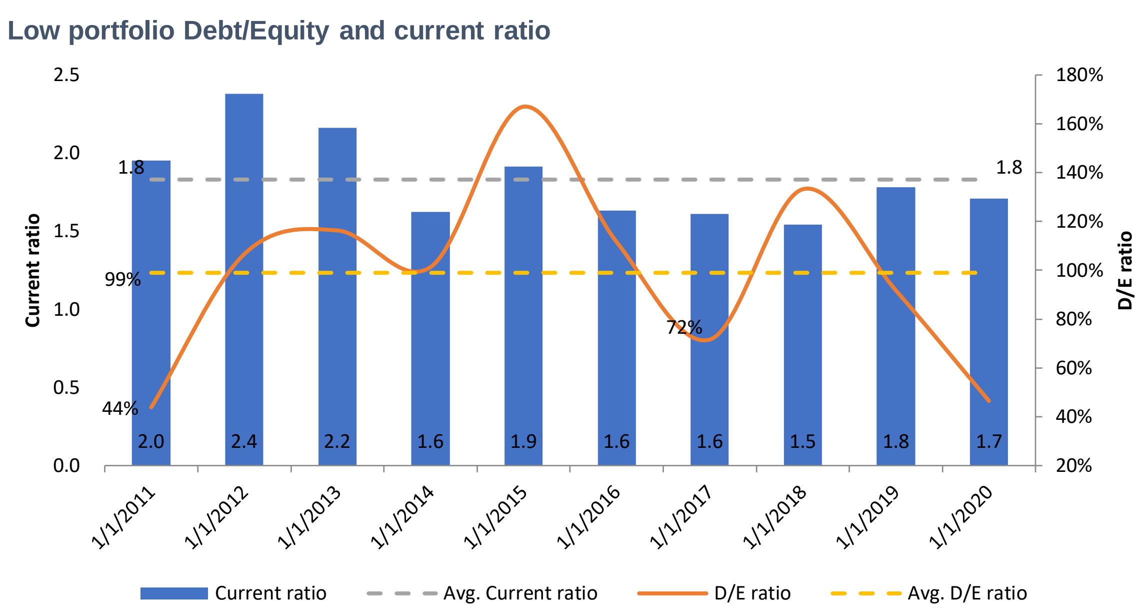
11.6.1.4.2.b Price/earnings, ROE and Governance score – Low



11.6.1.4.3.a Debt-to-equity- and current ratio – High

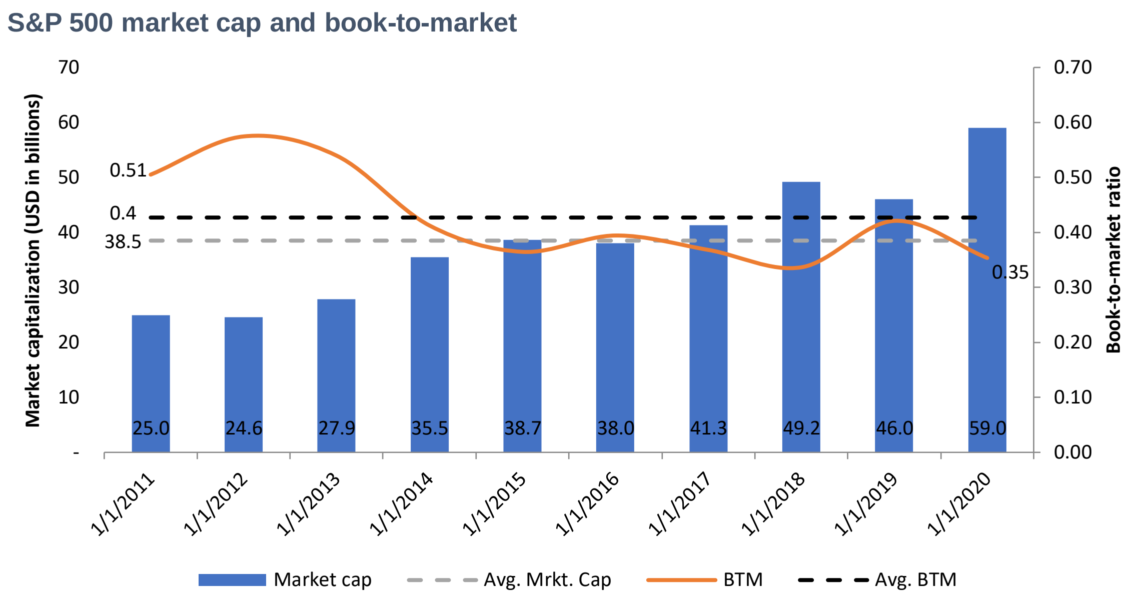


11.6.1.4.3.b Debt-to-equity- and current ratio – Low

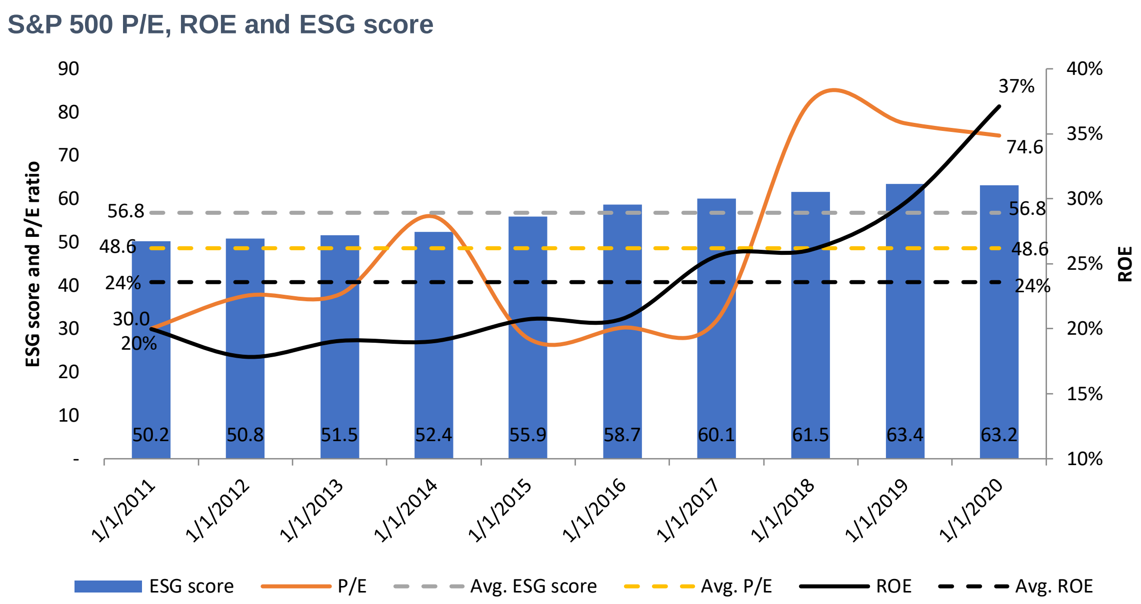


11.6.1.5 S&P 500

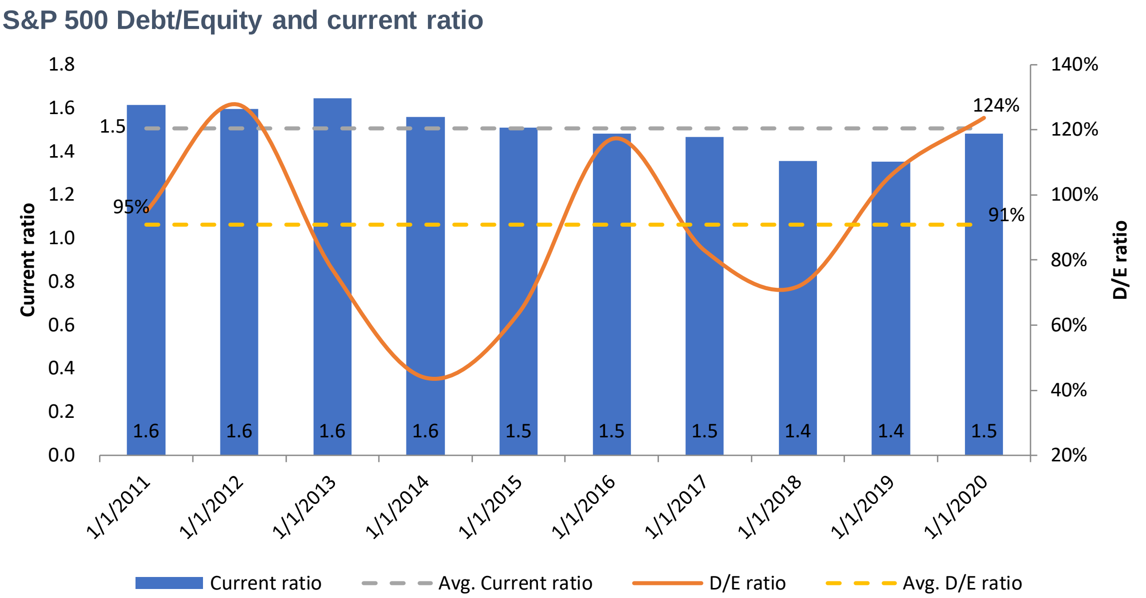
11.6.1.5.1 Market capitalization and book-to-market – S&P 500



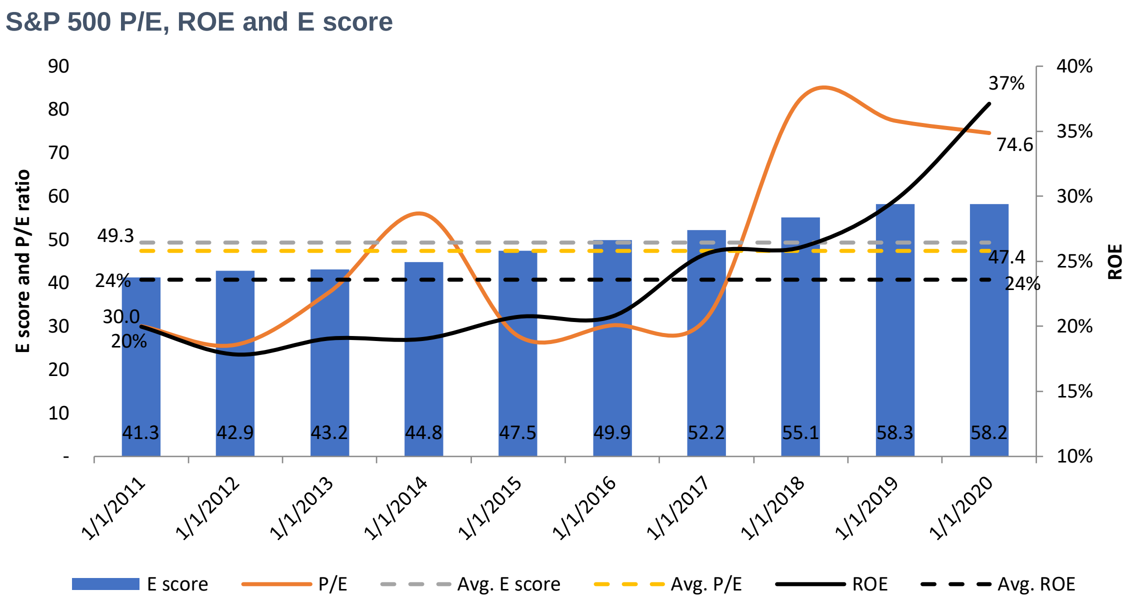
11.6.1.5.2 Price/earnings, ROE and ESG score – S&P 500



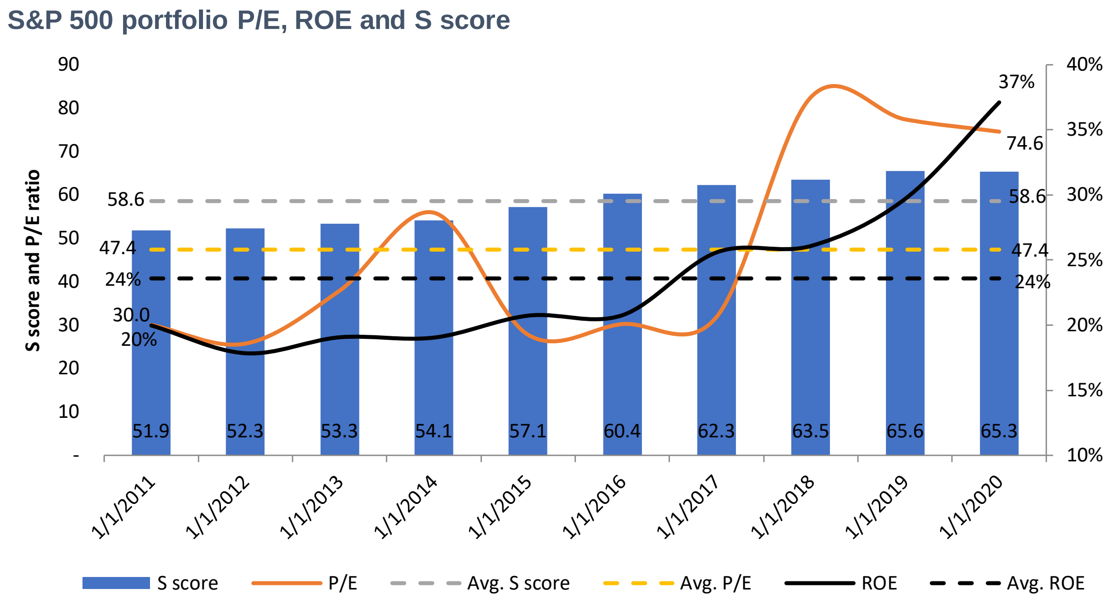
11.6.1.5.3 Debt-to-equity and current ratio – S&P 500



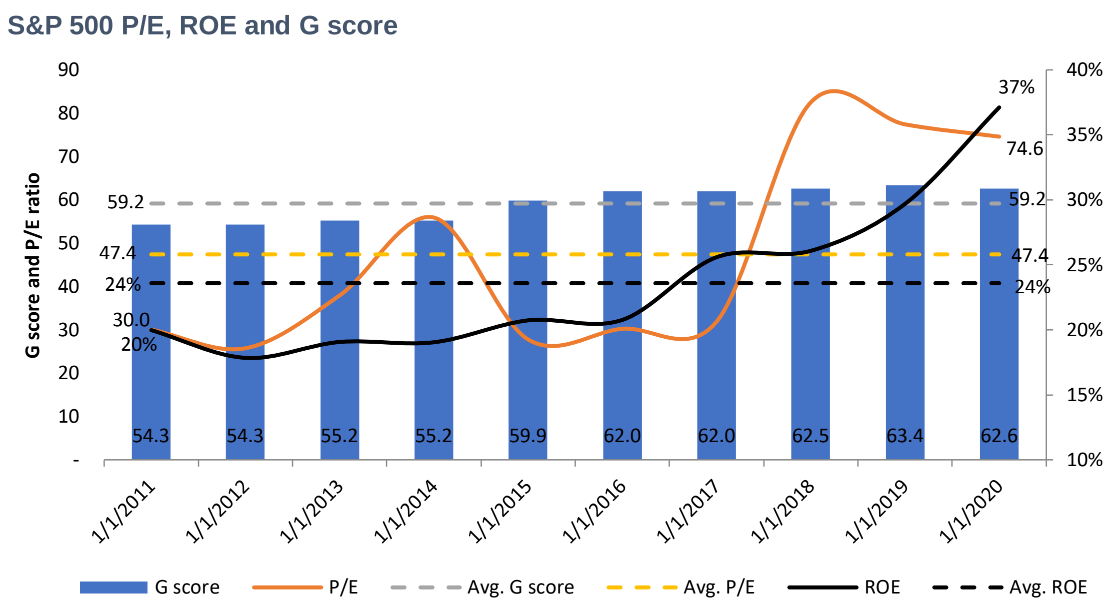
11.6.1.5.4 Price/earnings, ROE and Environmental pillar score – S&P 500



11.6.1.5.5 Price/earnings, ROE and Social pillar score – S&P 500



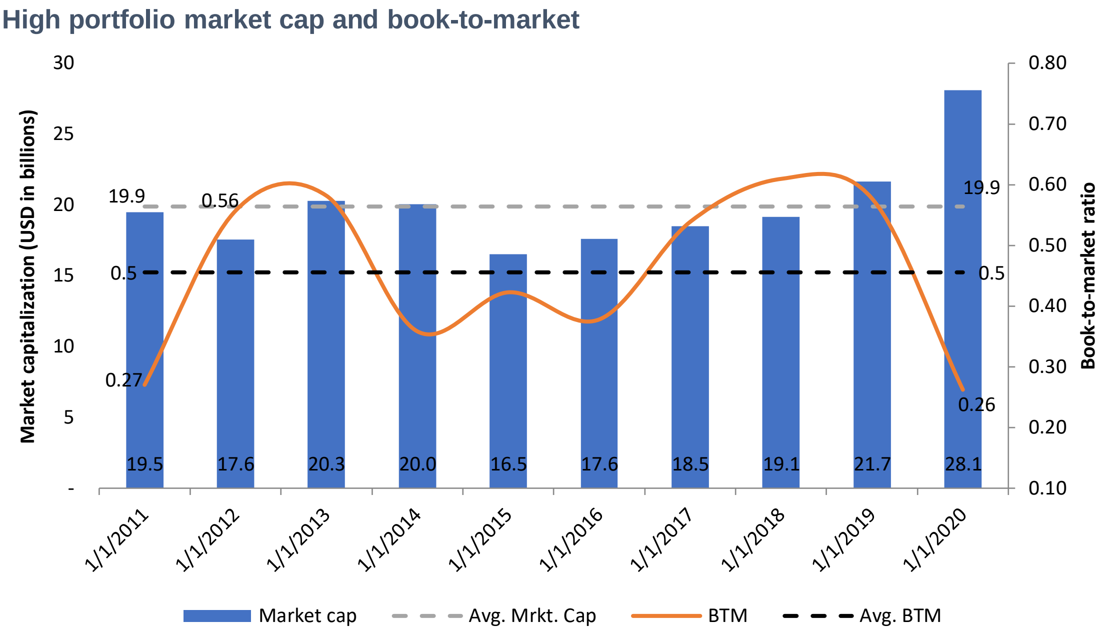
11.6.1.5.6 Price/earnings, ROE and Governance pillar score – S&P 500



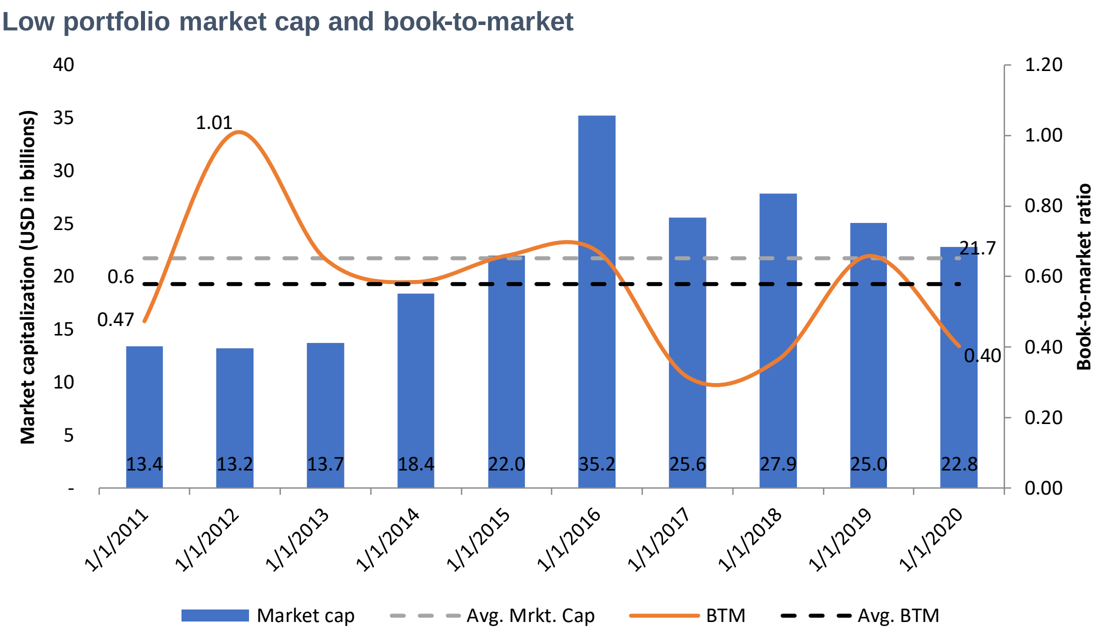
11.6.2 European market

11.6.2.1 ESG portfolios

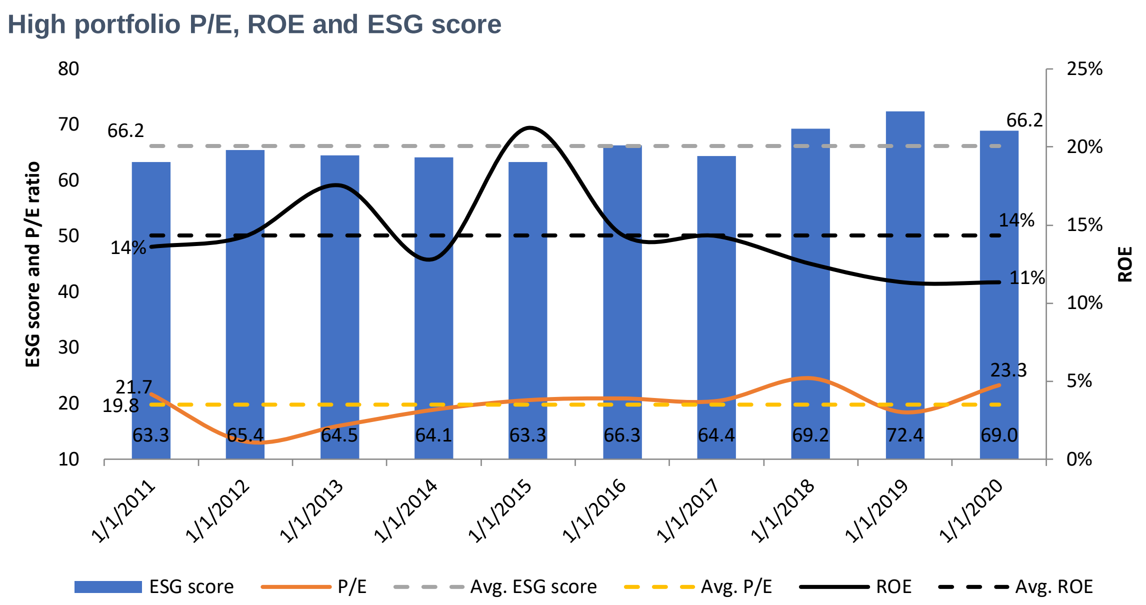
11.6.2.1.1.a Market capitalization and book-to-market - High



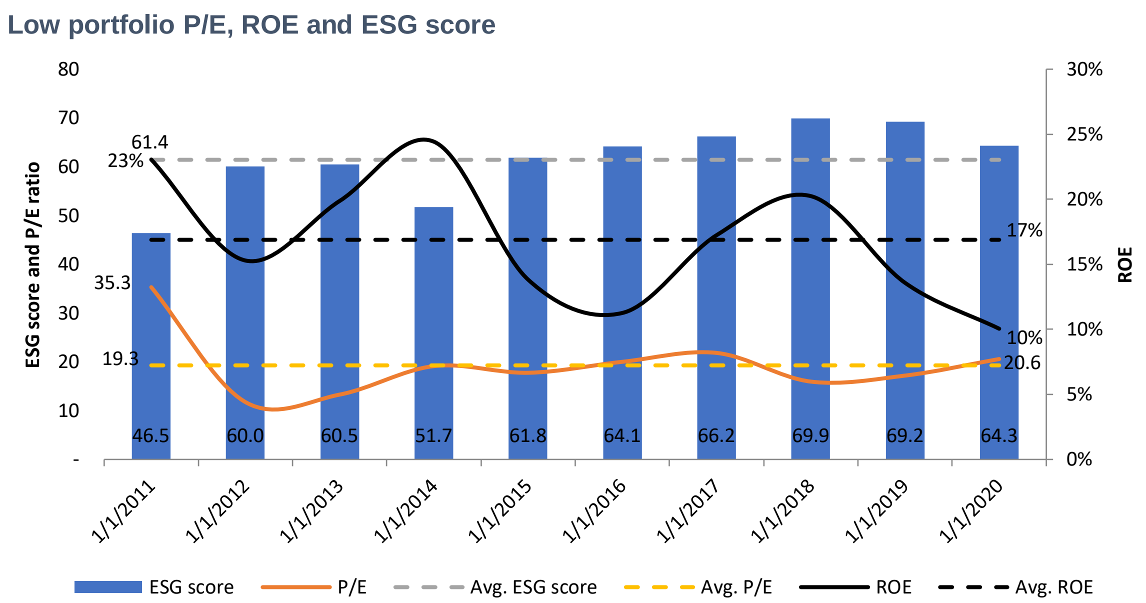
11.6.2.1.1.b Market capitalization and book-to-market - Low



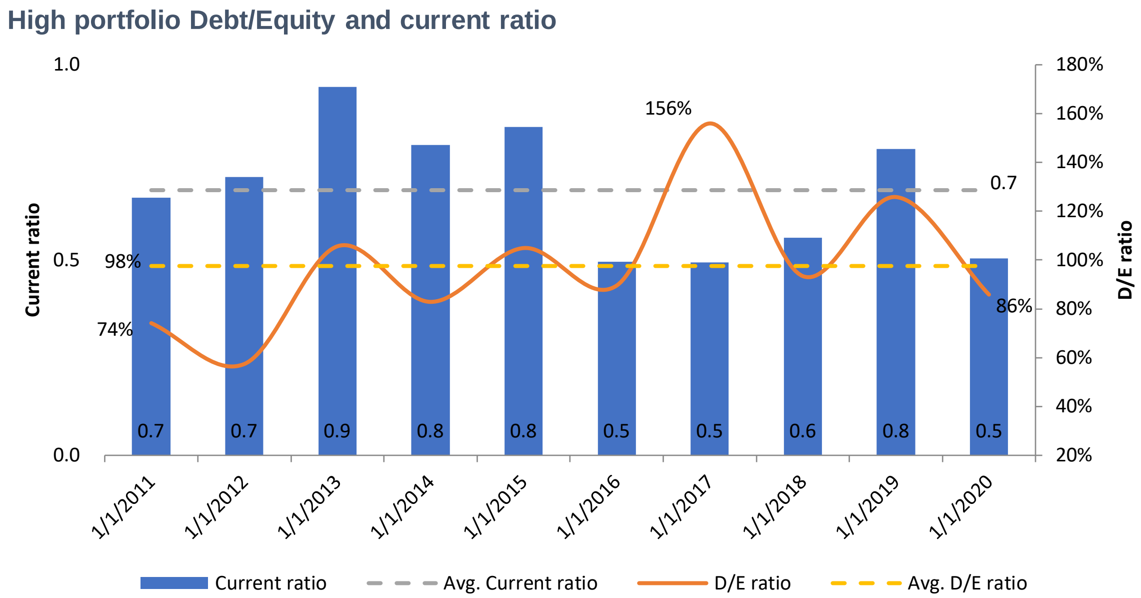
11.6.2.1.2.a Price/earnings, ROE and ESG score - High



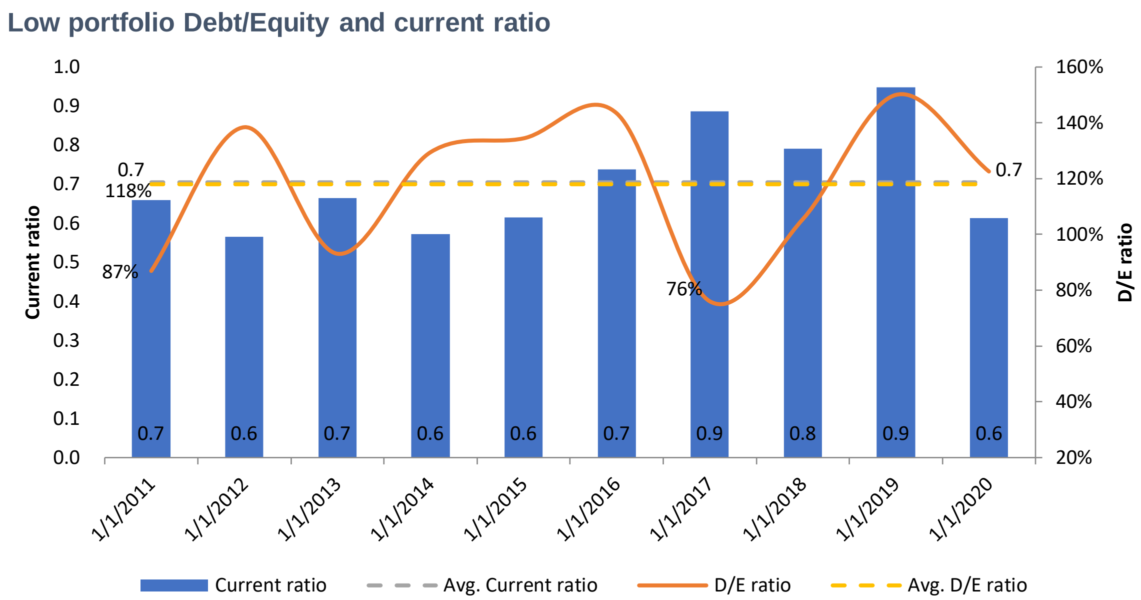
11.6.2.1.2.b Price/earnings, ROE and ESG score - Low



11.6.2.1.3.a Debt-to-equity- and current ratio - High

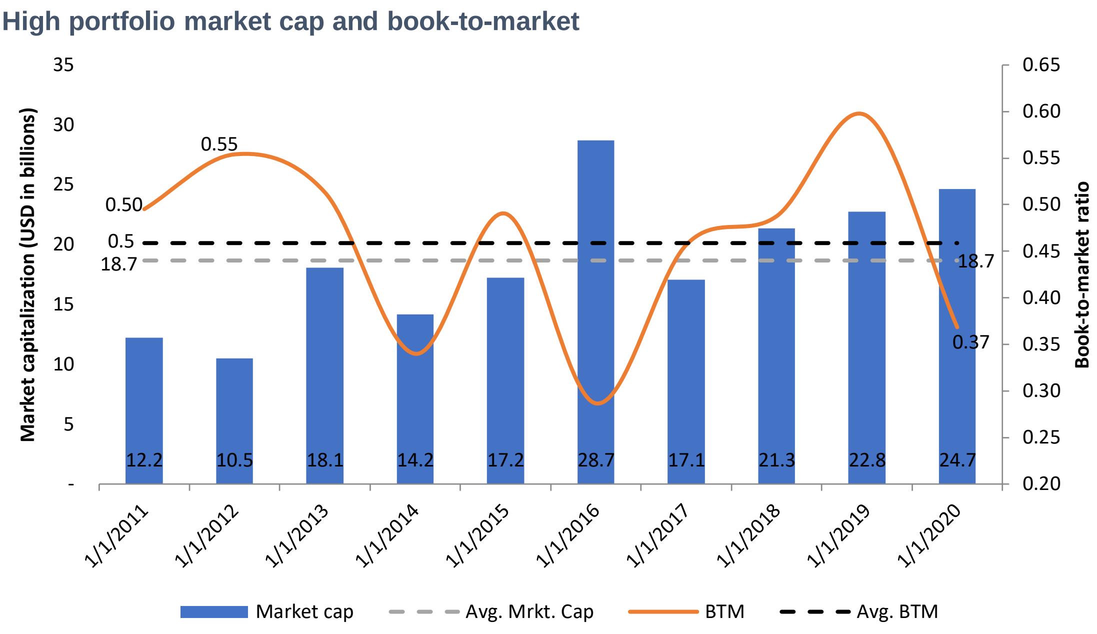


11.6.2.1.3.b Debt-to-equity- and current ratio - Low

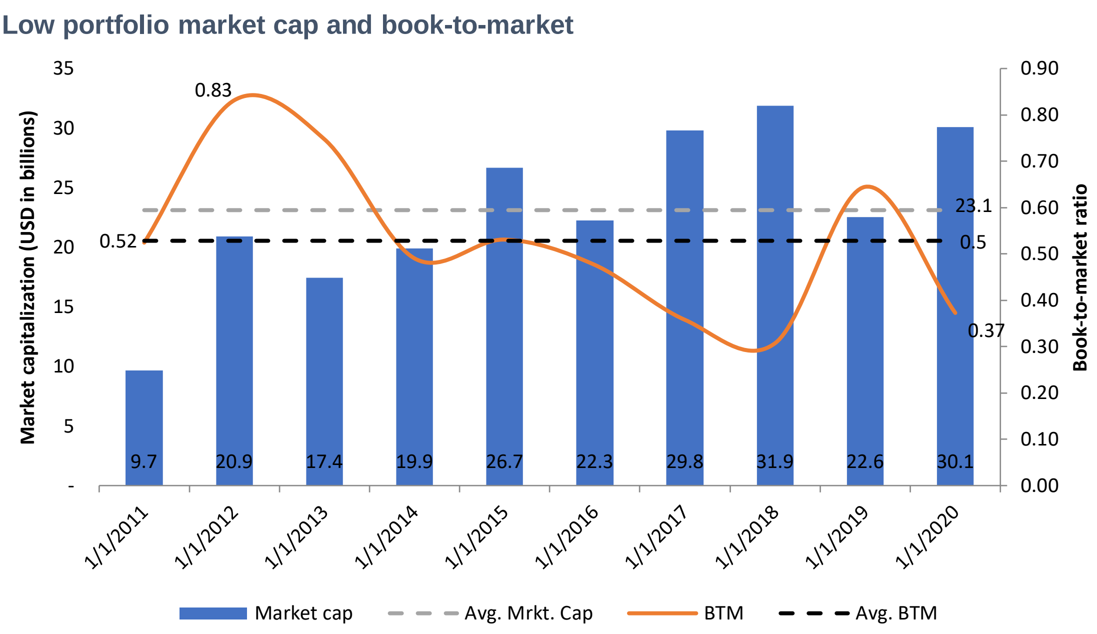


11.6.2.2 Environmental pillar portfolios

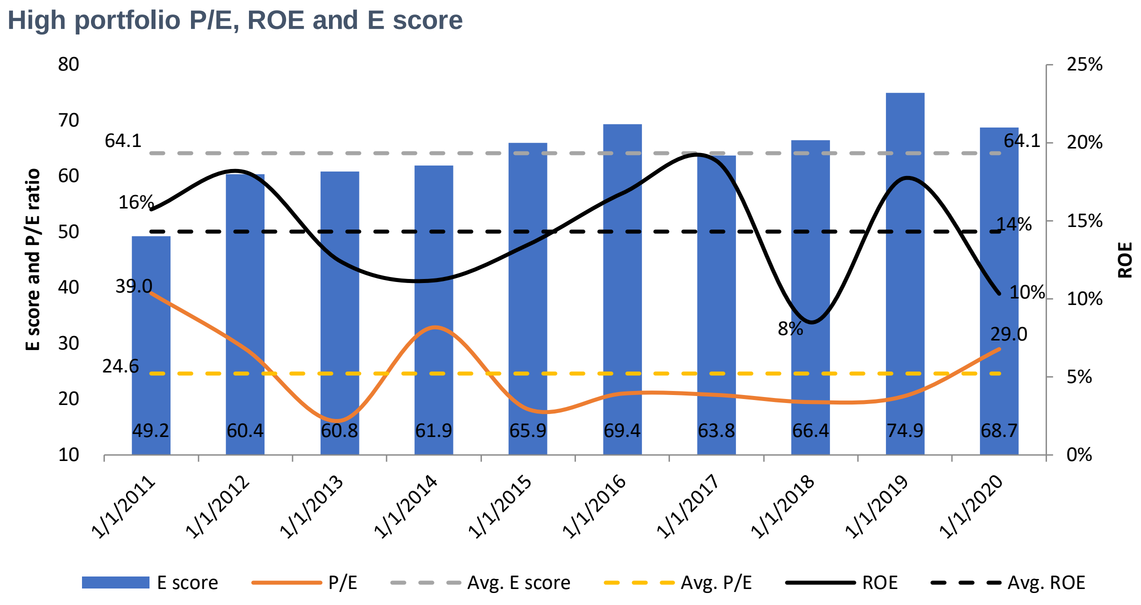
11.6.2.2.1.a Market capitalization and book-to-market - High



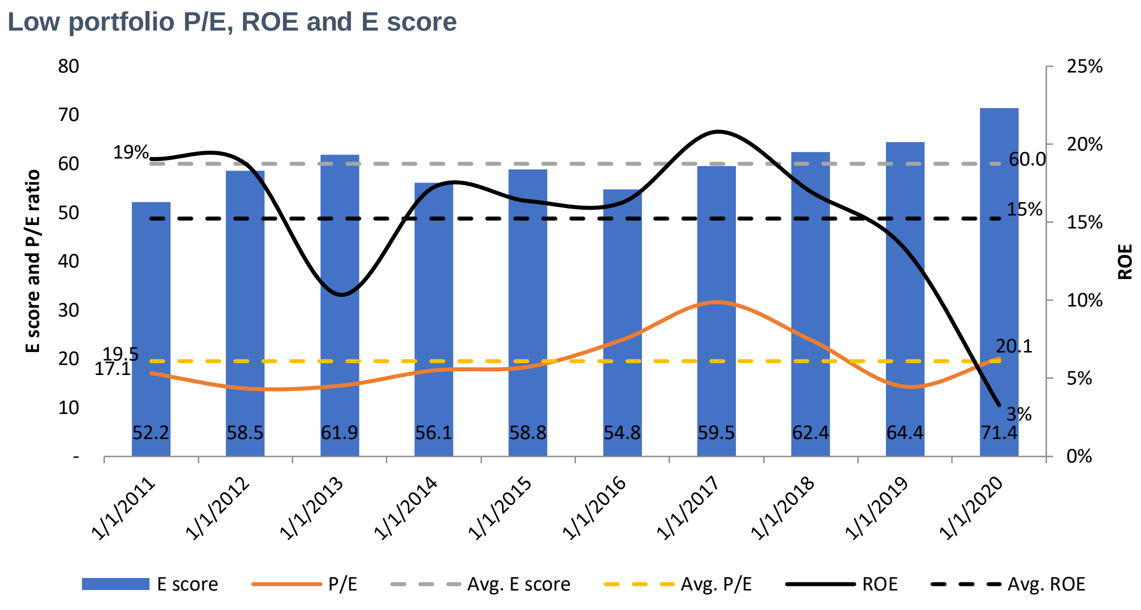
11.6.2.2.1.b Market capitalization and book-to-market - Low



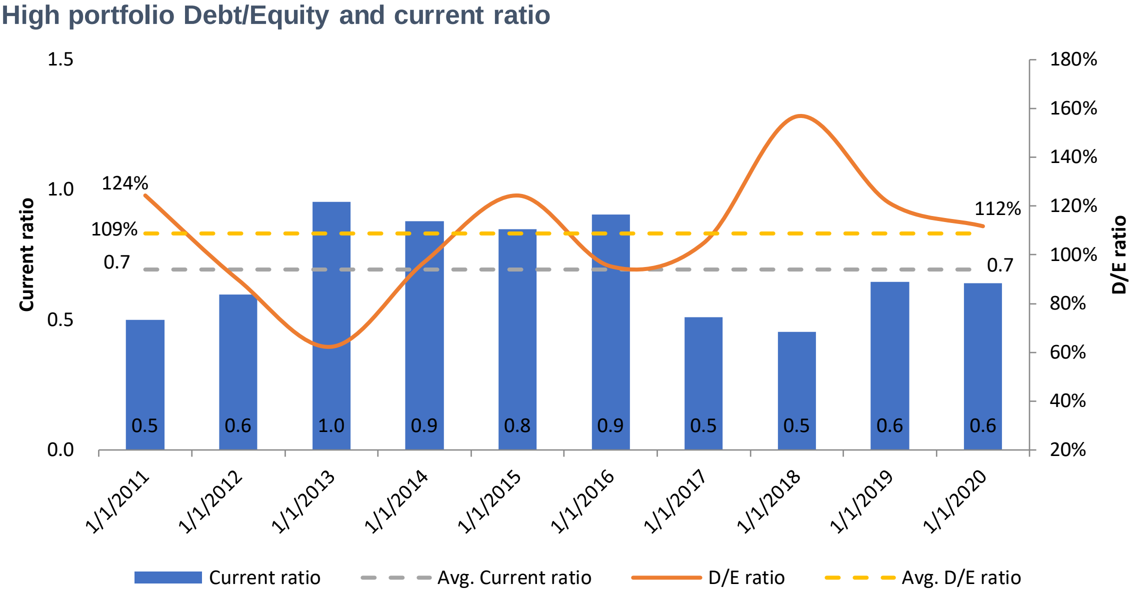
11.6.2.2.2.a Price/earnings, ROE and Environmental score - High



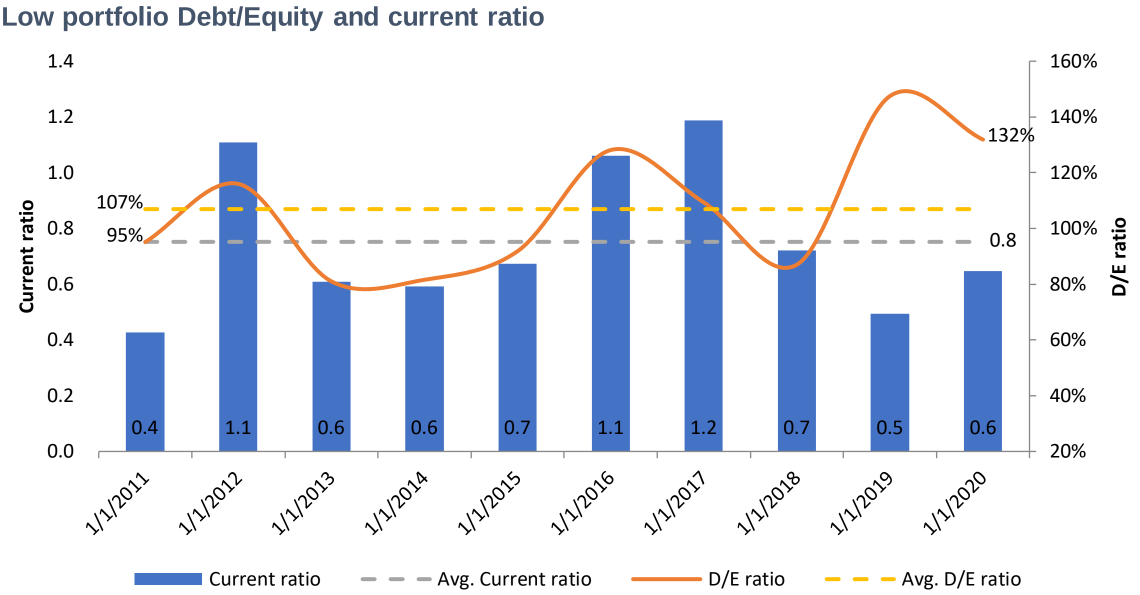
11.6.2.2.2.b Price/earnings, ROE and Environmental score - Low



11.6.2.2.3.a Debt-to-equity- and current ratio - High



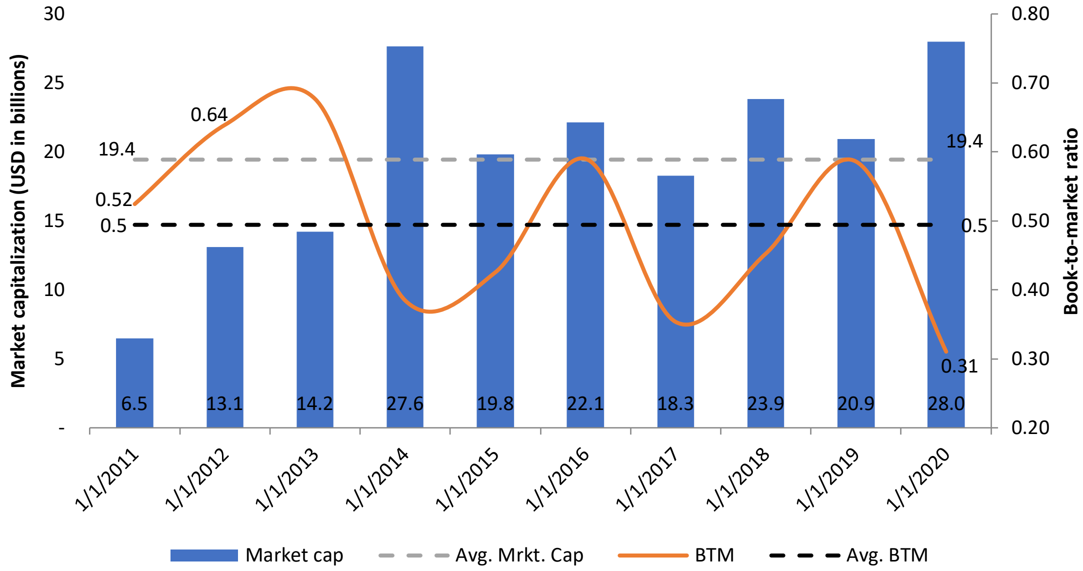
11.6.2.2.3.b Debt-to-equity- and current ratio - Low



11.6.2.3 Social pillar portfolios

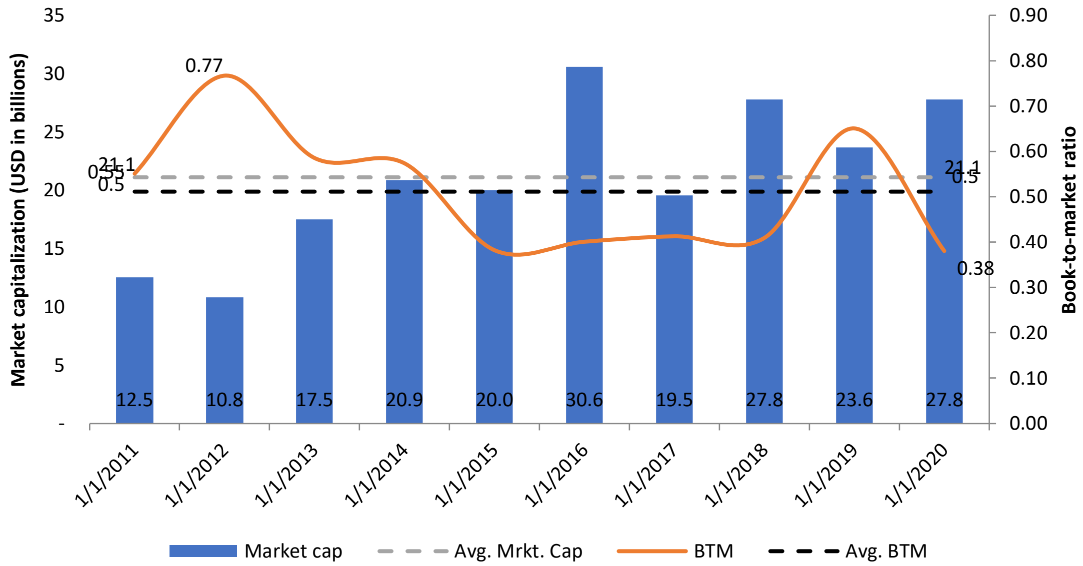
11.6.2.3.1.a Market capitalization and book-to-market - High

High portfolio market cap and book-to-market

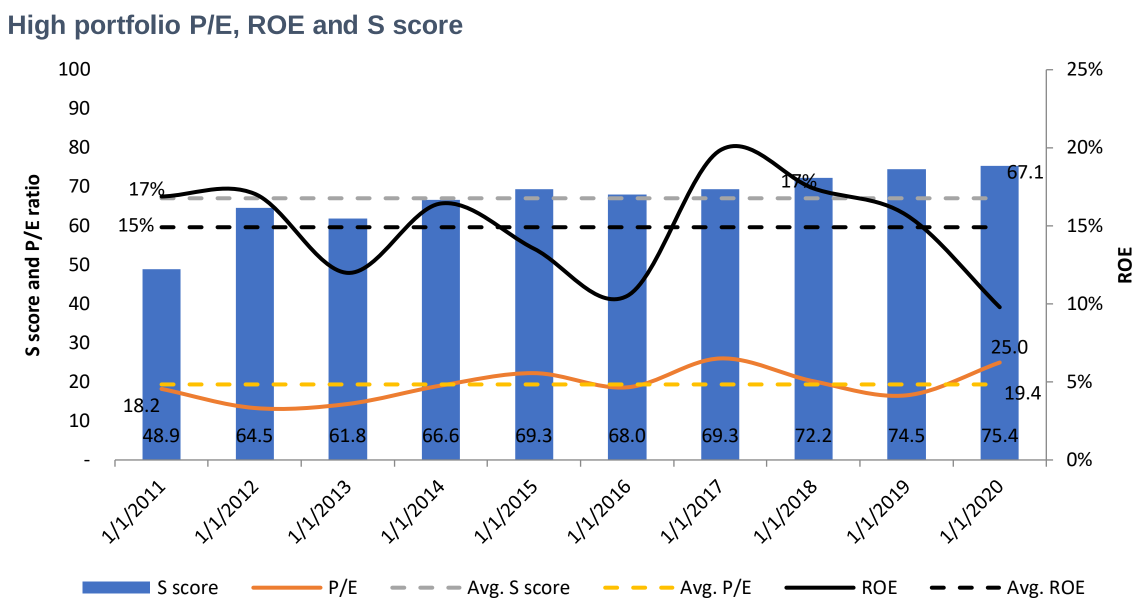


11.6.2.3.1.b Market capitalization and book-to-market - Low

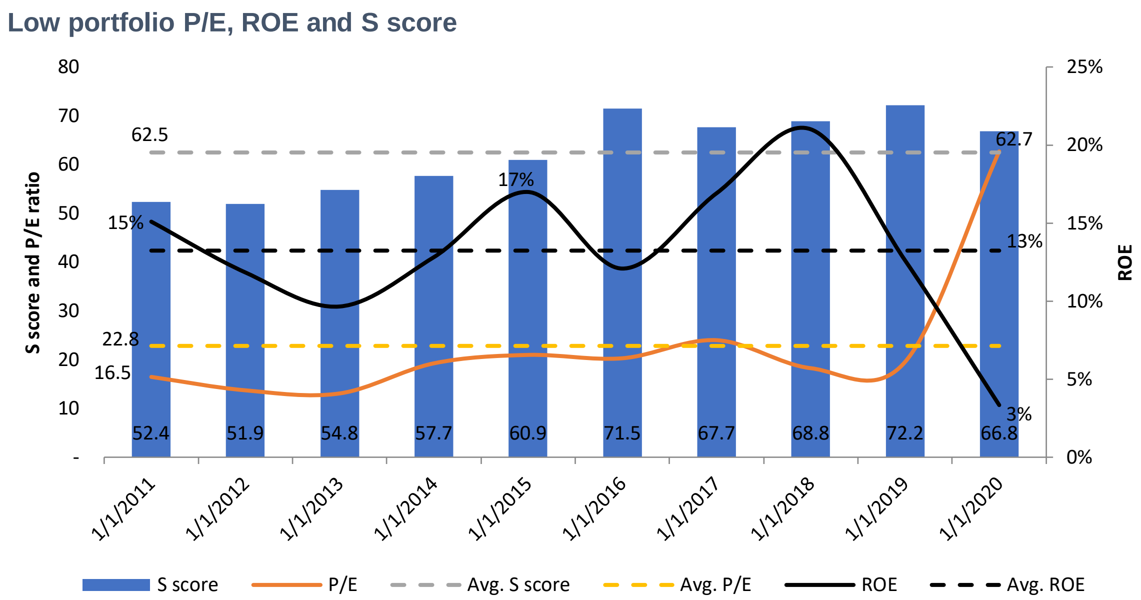
Low portfolio market cap and book-to-market



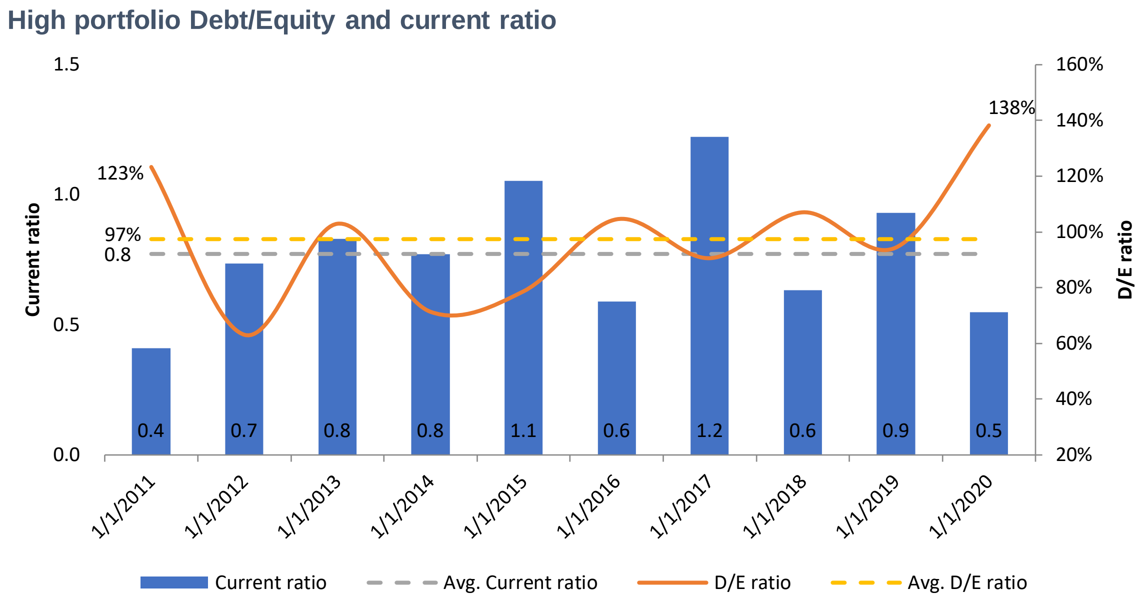
11.6.2.3.2.a Price/earnings, ROE and Social score - High



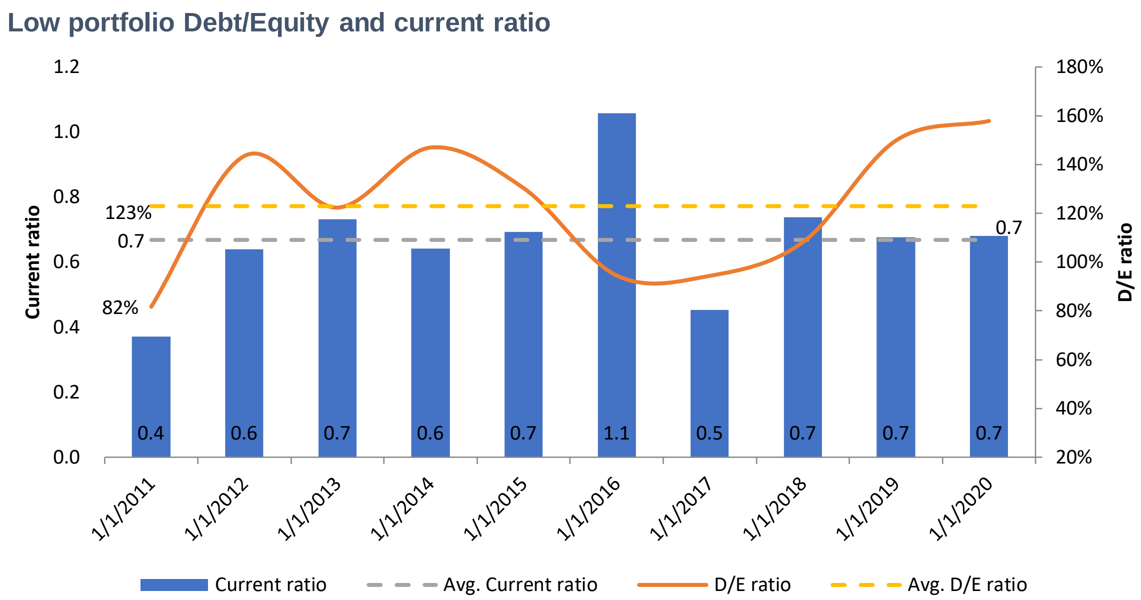
11.6.2.3.2.b Price/earnings, ROE and Social score - Low



11.6.2.3.3.a Debt-to-equity- and current ratio - High

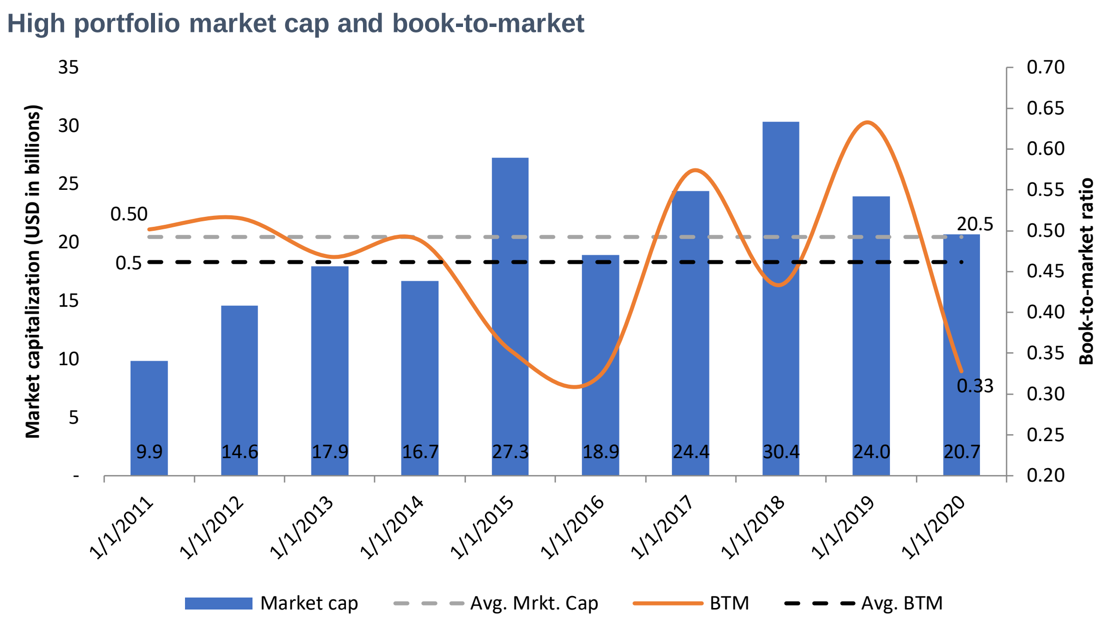


11.6.2.3.3.b Debt-to-equity- and current ratio - Low

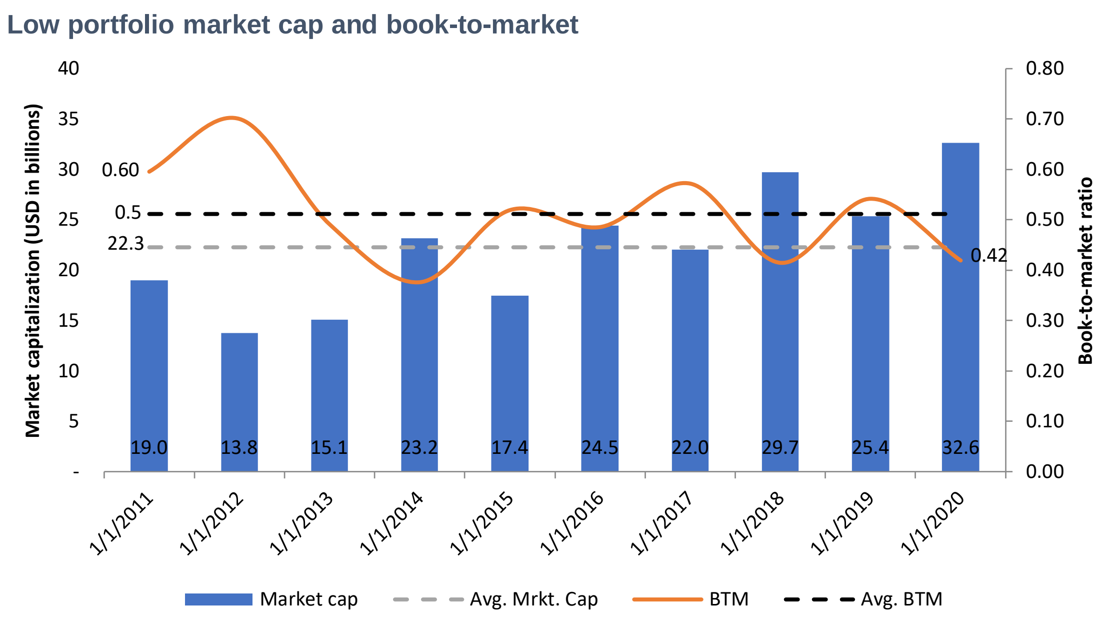


11.6.2.4 Governance pillar portfolios

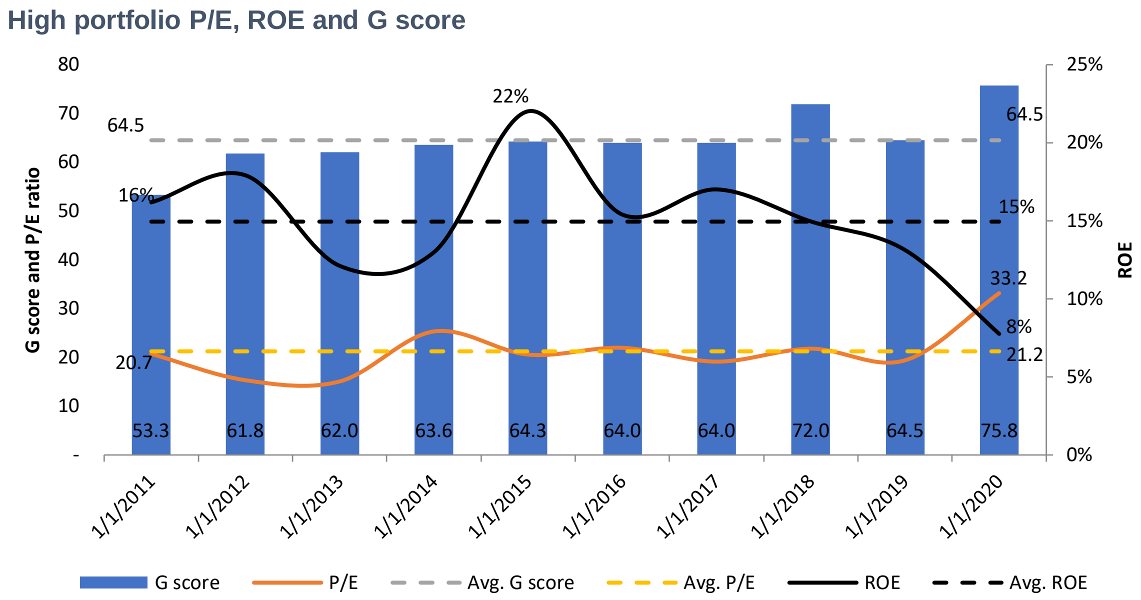
11.6.2.4.1.a Market capitalization and book-to-market - High



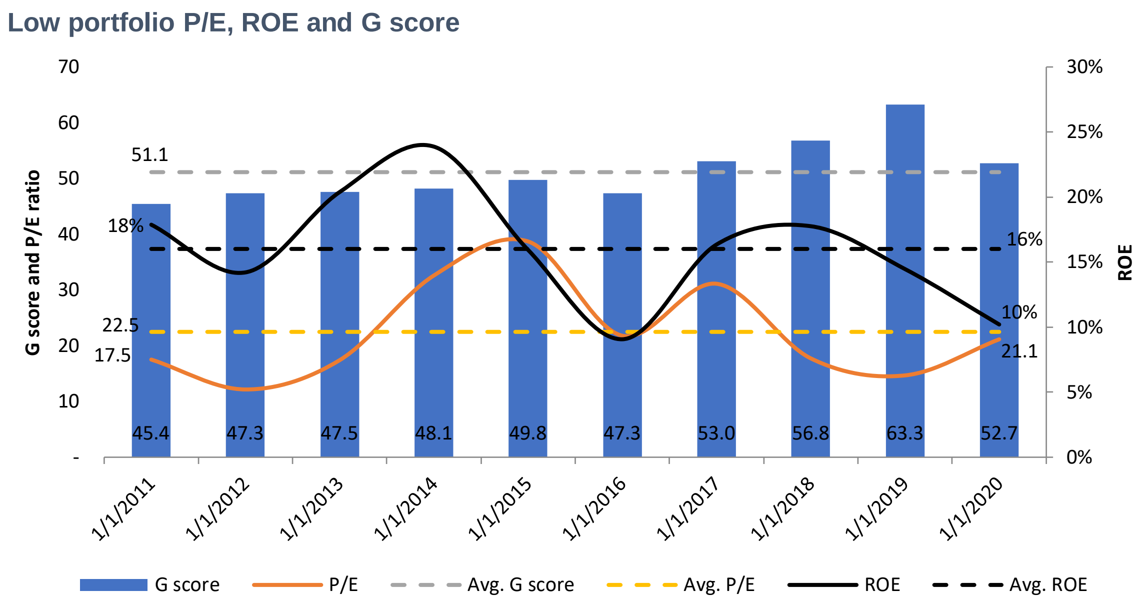
11.6.2.4.1.b Market capitalization and book-to-market - Low



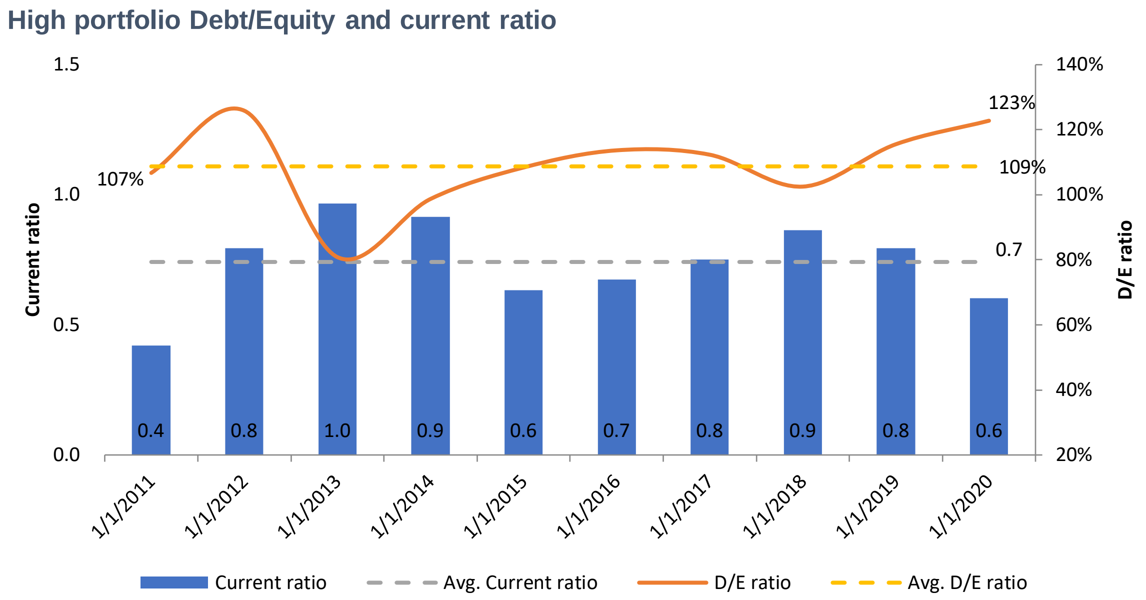
11.6.2.4.2.a Price/earnings, ROE and Governance score - High



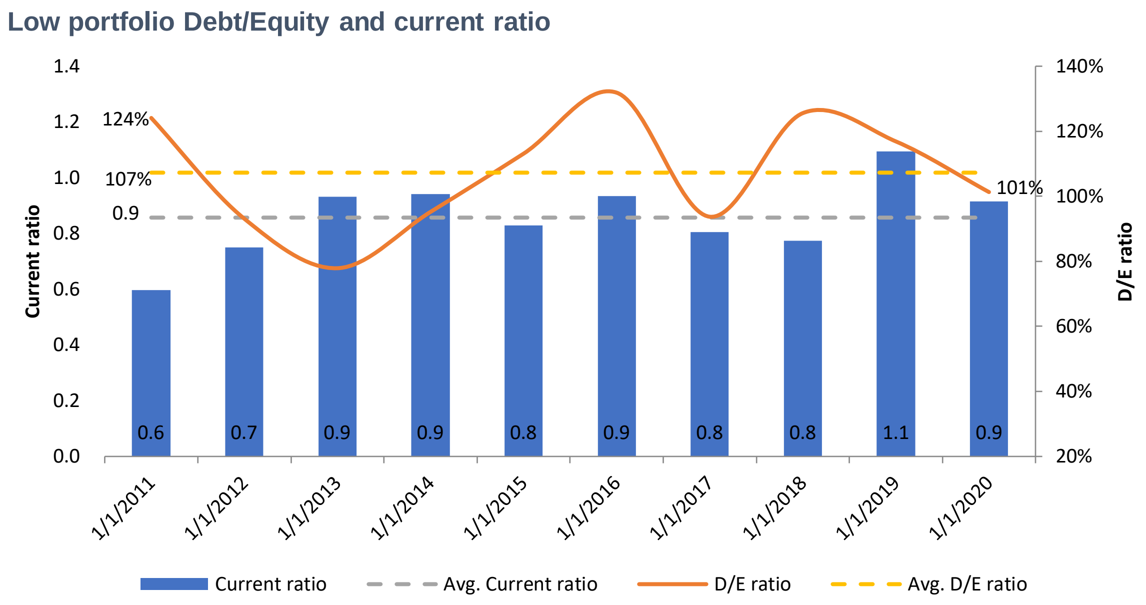
11.6.2.4.2.b Price/earnings, ROE and Governance score - Low



11.6.2.4.2.a Debt-to-equity- and current ratio - High

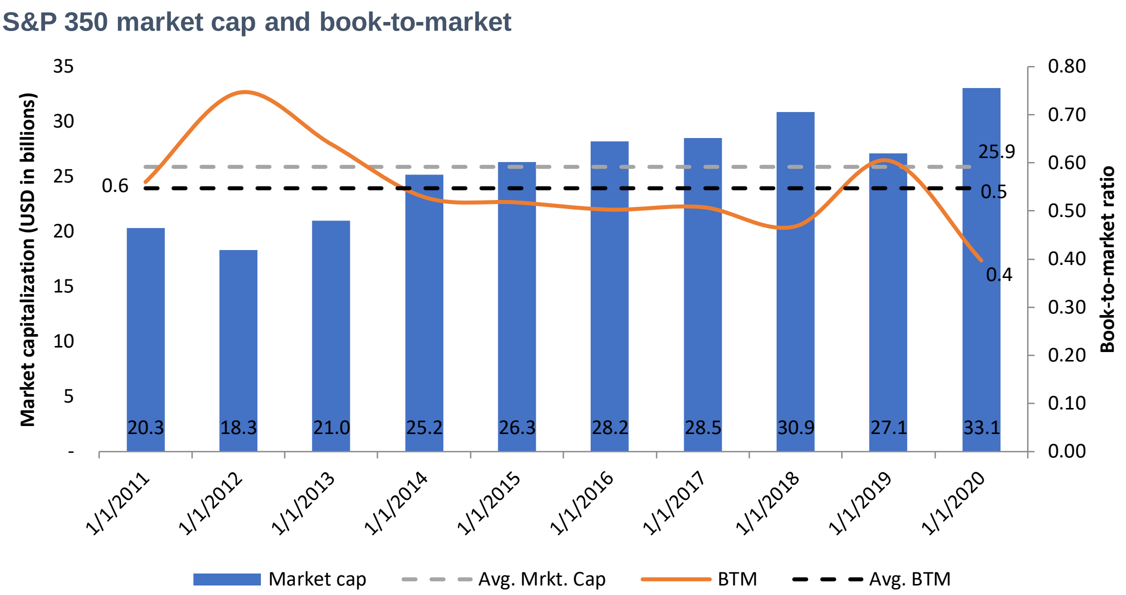


11.6.2.4.2.b Debt-to-equity- and current ratio - Low

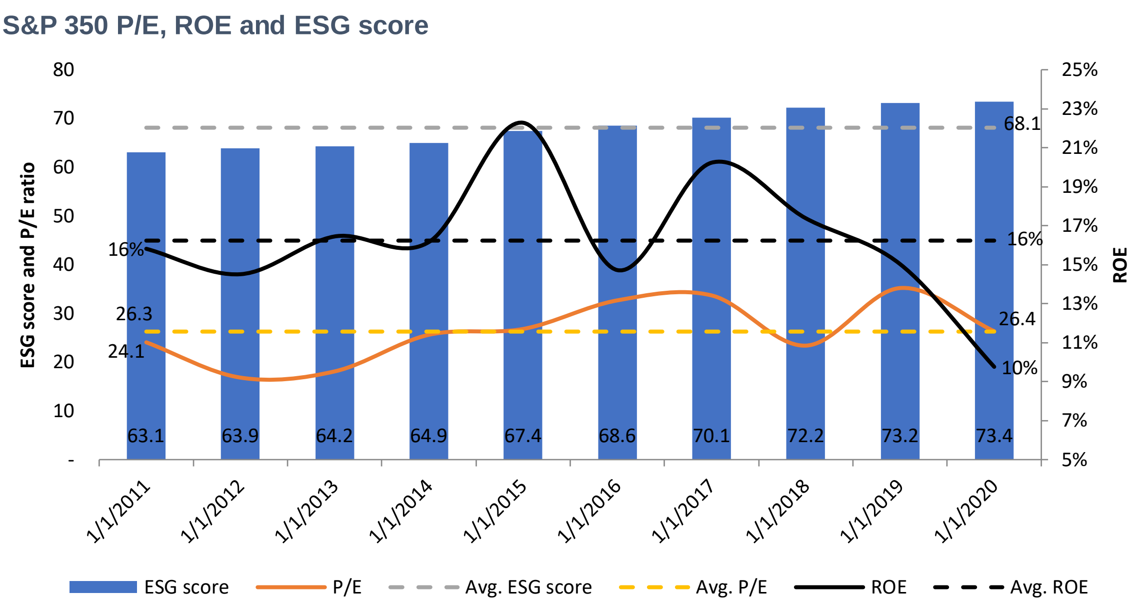


11.6.2.5 S&P 350

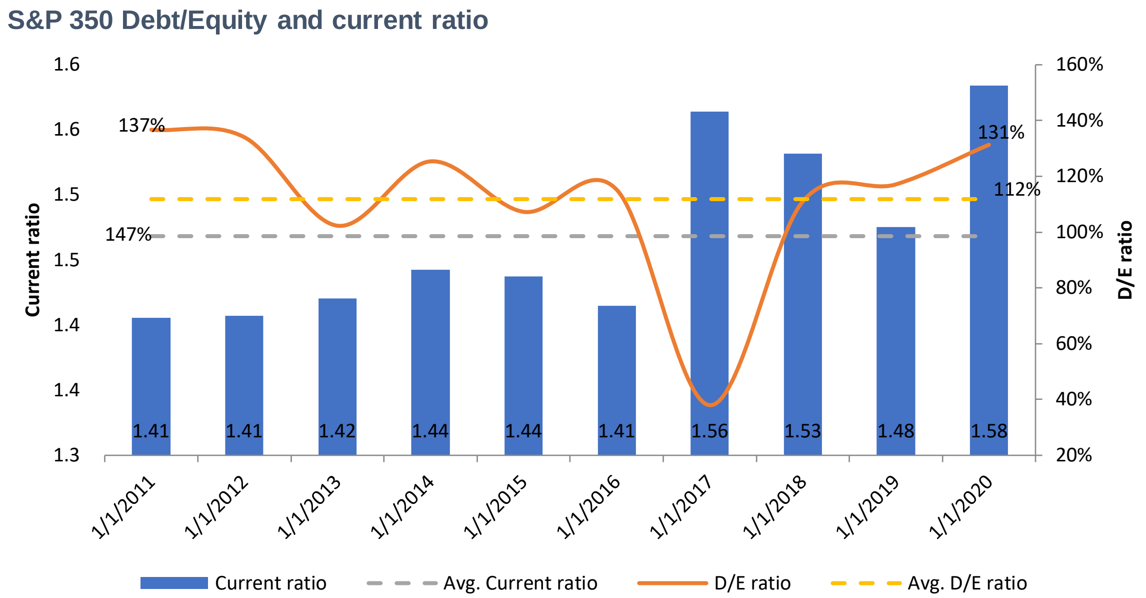
11.6.2.5.1 Market capitalization and book-to-market



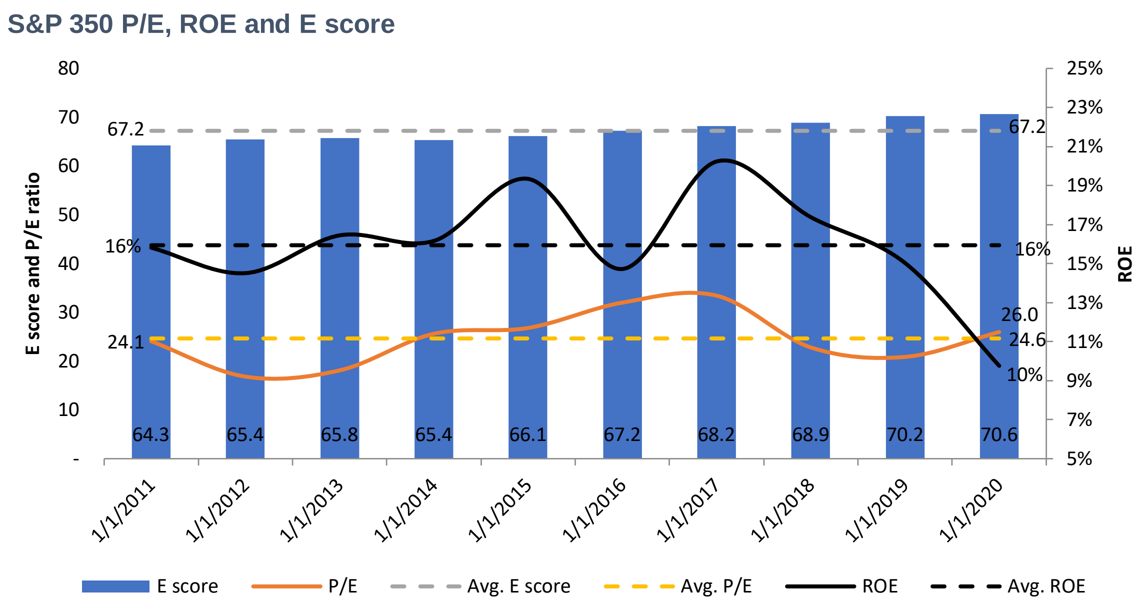
11.6.2.5.2 Price/earnings, ROE and ESG score



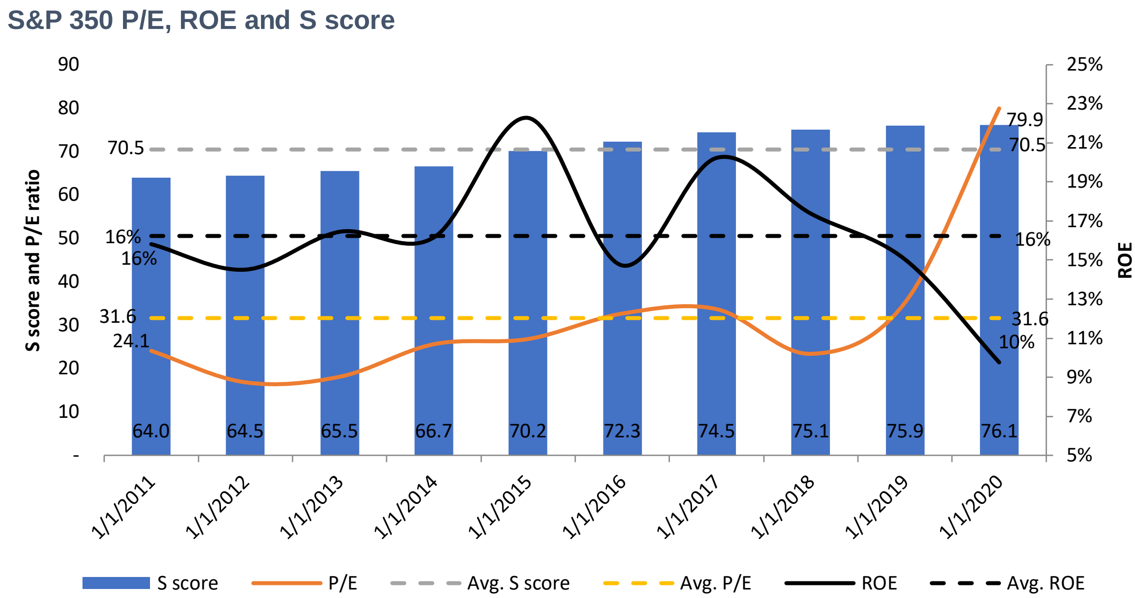
11.6.2.5.3 Debt-to-equity- and current ratio



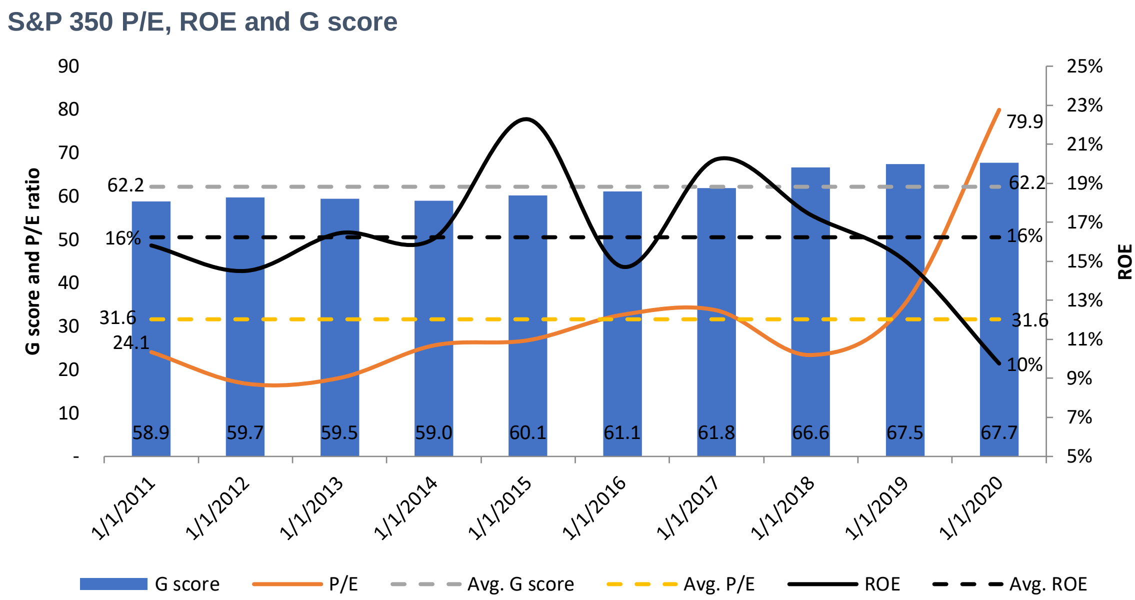
11.6.2.5.4 Price/earnings, ROE and Environmental score



11.6.2.5.5 Price/earnings, ROE and Social score



11.6.2.5.6 Price/earnings, ROE and Governance score



11.7 Robustness check

11.7.1 Portfolios (30%)

11.7.1.1 US

11.7.1.1.1 ESG

	Dependent variable:					
		Highr			Lowr	
	(1)	(2)	(3)	(4)	(5)	(6)
MRP	0.7661***	0.7426***	0.7436***	0.7658***	0.7494***	0.7520***
	(0.7247, 0.8076)	(0.7008, 0.7844)	(0.7008, 0.7865)	(0.7166, 0.8150)	(0.7020, 0.7969)	(0.6996, 0.8044)
SMB		0.4393***	0.5033***		0.3578***	0.3979***
		(0.2941, 0.5845)	(0.3631, 0.6435)		(0.1492, 0.5663)	(0.1741, 0.6218)
HML		-0.0584	-0.0648		-0.1096*	-0.0837
		(-0.1597, 0.0428)	(-0.1700, 0.0403)		(-0.2348, 0.0156)	(-0.2019, 0.0345)
WML			-0.0096			-0.0436**
			(-0.0414, 0.0222)			(-0.0822, -0.0050)
Constant	0.0046***	0.0054***	0.0099	0.0057***	0.0058***	0.0248***
	(0.0034, 0.0059)	(0.0040, 0.0067)	(-0.0040, 0.0237)	(0.0041, 0.0073)	(0.0042, 0.0075)	(0.0077, 0.0418)
Observations	108	108	97	108	108	97
R^2	0.9443	0.9556	0.9553	0.9249	0.9320	0.9345
Adjusted R^2	0.9437	0.9543	0.9534	0.9242	0.9301	0.9317
Residual Std. Error	0.0070 (df = 106)	0.0063 (df = 104)	0.0061 (df = 92)	0.0083 (df = 106)	0.0079 (df = 104)	0.0076 (df = 92)
F Statistic	1,795.6190*** (df = 1; 106)	746.2442*** (df = 3; 104)	491.8811*** (df = 4; 92)	1,304.8930*** (df = 1; 106)	475.3478*** (df = 3; 104)	328.2413*** (df = 4; 92)

Note: The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.

11.7.1.1.2 Environmental

	Dependent variable:					
		Highr			Lowr	
	(1)	(2)	(3)	(4)	(5)	(6)
MRP	0.7561***	0.7370***	0.7298***	0.7977***	0.7680***	0.7791***
	(0.7133, 0.7989)	(0.6941, 0.7800)	(0.6847, 0.7749)	(0.7128, 0.8827)	(0.6906, 0.8455)	(0.6793, 0.8789)
SMB		0.3725***	0.4760***		0.5021***	0.5824***
		(0.1560, 0.5890)	(0.2546, 0.6975)		(0.2482, 0.7560)	(0.3240, 0.8408)
HML		-0.0694	-0.0943		-0.0041	-0.0009
		(-0.1908, 0.0520)	(-0.2254, 0.0367)		(-0.1447, 0.1365)	(-0.1228, 0.1210)
WML			-0.0113			-0.0192
			(-0.0490, 0.0265)			(-0.0636, 0.0252)
Constant	0.0043***	0.0048***	0.0101	0.0039***	0.0051***	0.0136
	(0.0028, 0.0058)	(0.0031, 0.0065)	(-0.0068, 0.0270)	(0.0012, 0.0065)	(0.0025, 0.0078)	(-0.0075, 0.0347)
Observations	108	108	97	108	108	97
R^2	0.9307	0.9388	0.9353	0.8789	0.8930	0.8851
Adjusted R^2	0.9301	0.9370	0.9325	0.8778	0.8899	0.8801
Residual Std. Error	0.0078 (df = 106)	0.0074 (df = 104)	0.0073 (df = 92)	0.0112 (df = 106)	0.0106 (df = 104)	0.0108 (df = 92)
F Statistic	1,423.9450*** (df = 1; 106)	531.5715*** (df = 3; 104)	332.6352*** (df = 4; 92)	769.4493*** (df = 1; 106)	289.3500*** (df = 3; 104)	177.1755*** (df = 4; 92)

Note: The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.

11.7.1.1.3 Social

	Dependent variable:					
		Highr			Lowr	
	(1)	(2)	(3)	(4)	(5)	(6)
MRP	0.7499***	0.7311***	0.7430***	0.7673***	0.7439***	0.7359***
	(0.6970, 0.8027)	(0.6785, 0.7838)	(0.6891, 0.7970)	(0.7186, 0.8160)	(0.6969, 0.7909)	(0.6857, 0.7861)
SMB		0.4085***	0.4275***		0.3682***	0.4613***
		(0.2556, 0.5615)	(0.2565, 0.5985)		(0.1402, 0.5963)	(0.2267, 0.6959)
HML		-0.1250**	-0.0987		0.0341	0.0100
		(-0.2379, -0.0120)	(-0.2227, 0.0253)		(-0.1028, 0.1710)	(-0.1217, 0.1417)
WML			-0.0147			-0.0373*
			(-0.0541, 0.0248)			(-0.0749, 0.0003)
Constant	0.0054***	0.0056***	0.0122	0.0052***	0.0064***	0.0230***
	(0.0040, 0.0068)	(0.0041, 0.0071)	(-0.0054, 0.0298)	(0.0036, 0.0068)	(0.0045, 0.0083)	(0.0064, 0.0396)
Observations	108	108	97	108	108	97
R^2	0.9308	0.9406	0.9402	0.9209	0.9306	0.9294
Adjusted R^2	0.9302	0.9389	0.9376	0.9202	0.9286	0.9264
Residual Std. Error	0.0077 (df = 106)	0.0072 (df = 104)	0.0071 (df = 92)	0.0085 (df = 106)	0.0081 (df = 104)	0.0078 (df = 92)
F Statistic	1,426.7400*** (df = 1; 106)	549.3235*** (df = 3; 104)	361.8463*** (df = 4; 92)	1,234.5950*** (df = 1; 106)	464.7653*** (df = 3; 104)	302.9565*** (df = 4; 92)

Note: The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.

11.7.1.1.4 Governance

	Dependent variable:					
		Highr			Lowr	
	(1)	(2)	(3)	(4)	(5)	(6)
MRP	0.7908***	0.7659***	0.7708***	0.7628***	0.7414***	0.7450***
	(0.7473, 0.8343)	(0.7200, 0.8118)	(0.7233, 0.8183)	(0.7105, 0.8152)	(0.6885, 0.7943)	(0.6837, 0.8064)
SMB		0.4288***	0.5073***		0.4235***	0.4224***
		(0.2736, 0.5840)	(0.3493, 0.6652)		(0.2201, 0.6269)	(0.1721, 0.6727)
HML		-0.0129	-0.0297		-0.0848	-0.0483
		(-0.1287, 0.1028)	(-0.1530, 0.0936)		(-0.2171, 0.0475)	(-0.1887, 0.0921)
WML			0.0025			-0.0375
			(-0.0269, 0.0319)			(-0.0827, 0.0076)
Constant	0.0043***	0.0054***	0.0047	0.0059***	0.0064***	0.0225**
	(0.0030, 0.0057)	(0.0039, 0.0069)	(-0.0083, 0.0176)	(0.0042, 0.0077)	(0.0045, 0.0083)	(0.0026, 0.0424)
Observations	108	108	97	108	108	97
R^2	0.9435	0.9545	0.9530	0.9119	0.9219	0.9205
Adjusted R^2	0.9430	0.9532	0.9509	0.9111	0.9197	0.9171
Residual Std. Error	0.0073 (df = 106)	0.0066 (df = 104)	0.0065 (df = 92)	0.0090 (df = 106)	0.0085 (df = 104)	0.0083 (df = 92)
F Statistic	1,769.9760*** (df = 1; 106)	726.8484*** (df = 3; 104)	466.2781*** (df = 4; 92)	1,097.4000*** (df = 1; 106)	409.2291*** (df = 3; 104)	266.4601*** (df = 4; 92)

Note: The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.

11.7.1.2 Europe

11.7.1.2.1 ESG

	Dependent variable:					
	Highr			Lowr		
	(1)	(2)	(3)	(4)	(5)	(6)
MRP	0.5752***	0.5566***	0.7020***	0.6195***	0.5718***	0.7223***
	(0.3838, 0.7665)	(0.3222, 0.7909)	(0.6313, 0.7727)	(0.4322, 0.8069)	(0.3514, 0.7923)	(0.6610, 0.7836)
SMB		0.5578***	0.5451***		0.5019***	0.4984***
		(0.3513, 0.7642)	(0.3553, 0.7348)		(0.2881, 0.7156)	(0.2838, 0.7129)
HML		0.1288	-0.0038		0.2346**	0.1083**
		(-0.0736, 0.3311)	(-0.1035, 0.0959)		(0.0435, 0.4258)	(0.0059, 0.2108)
WML			0.0314			0.0163
			(-0.0095, 0.0724)			(-0.0228, 0.0555)
Constant	0.0072***	0.0062***	-0.0078	0.0052***	0.0050***	-0.0025
	(0.0047, 0.0097)	(0.0039, 0.0084)	(-0.0266, 0.0110)	(0.0027, 0.0076)	(0.0027, 0.0073)	(-0.0200, 0.0149)
Observations	108	108	96	108	108	96
R^2	0.6771	0.7112	0.8555	0.7228	0.7577	0.8837
Adjusted R^2	0.6740	0.7028	0.8491	0.7202	0.7507	0.8786
Residual Std. Error	0.0156 (df = 106)	0.0149 (df = 104)	0.0104 (df = 91)	0.0151 (df = 106)	0.0142 (df = 104)	0.0098 (df = 91)
F Statistic	222.2311*** (df = 1; 106)	85.3615*** (df = 3; 104)	134.6580*** (df = 4; 91)	276.3760*** (df = 1; 106)	108.4219*** (df = 3; 104)	172.8536*** (df = 4; 91)

Note: The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.

11.7.1.2.2 Environmental

	Dependent variable:					
	Highr			Lowr		
	(1)	(2)	(3)	(4)	(5)	(6)
MRP	0.5933***	0.5737***	0.7201***	0.5987***	0.5622***	0.7040***
	(0.4029, 0.7837)	(0.3405, 0.8068)	(0.6509, 0.7893)	(0.4145, 0.7830)	(0.3434, 0.7810)	(0.6321, 0.7758)
SMB		0.6054***	0.5955***		0.4797***	0.4697***
		(0.3969, 0.8140)	(0.4041, 0.7868)		(0.2784, 0.6809)	(0.2704, 0.6690)
HML		0.1375	-0.0110		0.1894*	0.0444
		(-0.0627, 0.3376)	(-0.1153, 0.0933)		(-0.0042, 0.3830)	(-0.0688, 0.1575)
WML			0.0257			0.0250
			(-0.0170, 0.0684)			(-0.0150, 0.0650)
Constant	0.0068***	0.0057***	-0.0055	0.0056***	0.0053***	-0.0059
	(0.0042, 0.0093)	(0.0034, 0.0080)	(-0.0245, 0.0134)	(0.0033, 0.0080)	(0.0031, 0.0074)	(-0.0240, 0.0122)
Observations	108	108	96	108	108	96
R^2	0.6920	0.7306	0.8657	0.7133	0.7428	0.8745
Adjusted R^2	0.6891	0.7228	0.8598	0.7106	0.7353	0.8690
Residual Std. Error	0.0155 (df = 106)	0.0147 (df = 104)	0.0102 (df = 91)	0.0149 (df = 106)	0.0142 (df = 104)	0.0097 (df = 91)
F Statistic	238.1489*** (df = 1; 106)	93.9922*** (df = 3; 104)	146.6155*** (df = 4; 91)	263.6957*** (df = 1; 106)	100.0943*** (df = 3; 104)	158.5020*** (df = 4; 91)

Note: The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.

11.7.1.2.3 Social

	Dependent variable:					
		Highr			Lowr	
	(1)	(2)	(3)	(4)	(5)	(6)
MRP	0.6004***	0.5719***	0.7197***	0.6033***	0.5498***	0.6948***
	(0.4141, 0.7867)	(0.3473, 0.7966)	(0.6451, 0.7943)	(0.4127, 0.7939)	(0.3282, 0.7714)	(0.6393, 0.7504)
SMB		0.5261***	0.5125***		0.5205***	0.5158***
		(0.3121, 0.7402)	(0.3093, 0.7157)		(0.3243, 0.7167)	(0.3482, 0.6834)
HML		0.1632*	0.0365		0.2588***	0.1108**
		(-0.0294, 0.3558)	(-0.0680, 0.1409)		(0.0696, 0.4481)	(0.0226, 0.1990)
WML			0.0231			0.0342*
			(-0.0133, 0.0595)			(-0.0001, 0.0685)
Constant	0.0068***	0.0061***	-0.0042	0.0046***	0.0045***	-0.0107
	(0.0044, 0.0092)	(0.0041, 0.0082)	(-0.0207, 0.0123)	(0.0022, 0.0071)	(0.0023, 0.0068)	(-0.0260, 0.0046)
Observations	108	108	96	108	108	96
R^2	0.7089	0.7400	0.8654	0.7070	0.7482	0.8788
Adjusted R^2	0.7062	0.7325	0.8595	0.7042	0.7409	0.8734
Residual Std. Error	0.0151 (df = 106)	0.0144 (df = 104)	0.0103 (df = 91)	0.0152 (df = 106)	0.0143 (df = 104)	0.0097 (df = 91)
F Statistic	258.1986*** (df = 1; 106)	98.6755*** (df = 3; 104)	146.2657*** (df = 4; 91)	255.7759*** (df = 1; 106)	102.9996*** (df = 3; 104)	164.8879*** (df = 4; 91)

Note: The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.

11.7.1.2.4 Governance

	Dependent variable:					
		Highr			Lowr	
	(1)	(2)	(3)	(4)	(5)	(6)
MRP	0.5848***	0.5483***	0.6955***	0.6111***	0.5671***	0.7123***
	(0.4025, 0.7670)	(0.3310, 0.7657)	(0.6291, 0.7619)	(0.4085, 0.8137)	(0.3266, 0.8076)	(0.6496, 0.7750)
SMB		0.5428***	0.5122***		0.4603***	0.4466***
		(0.3500, 0.7356)	(0.3124, 0.7121)		(0.2466, 0.6741)	(0.2421, 0.6512)
HML		0.1956**	0.0521		0.2160**	0.0989*
		(0.0099, 0.3813)	(-0.0395, 0.1437)		(0.0157, 0.4163)	(-0.0084, 0.2062)
WML			0.0208			0.0178
			(-0.0206, 0.0622)			(-0.0224, 0.0579)
Constant	0.0064***	0.0059***	-0.0031	0.0059***	0.0057***	-0.0024
	(0.0040, 0.0089)	(0.0036, 0.0082)	(-0.0222, 0.0160)	(0.0035, 0.0082)	(0.0036, 0.0078)	(-0.0203, 0.0155)
Observations	108	108	96	108	108	96
R^2	0.6970	0.7336	0.8611	0.7065	0.7361	0.8773
Adjusted R^2	0.6941	0.7259	0.8550	0.7037	0.7285	0.8719
Residual Std. Error	0.0151 (df = 106)	0.0143 (df = 104)	0.0102 (df = 91)	0.0155 (df = 106)	0.0148 (df = 104)	0.0099 (df = 91)
F Statistic	243.8253*** (df = 1; 106)	95.4610*** (df = 3; 104)	141.0489*** (df = 4; 91)	255.1760*** (df = 1; 106)	96.7207*** (df = 3; 104)	162.6970*** (df = 4; 91)

Note: The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.

11.7.2 Retrieved Fama & French factors

11.7.2.1 US

11.7.2.1.1 ESG

	Dependent variable:			
	Highr		Lowr	
	(1)	(2)	(3)	(4)
MRP	0.7492***	0.7519***	0.7493***	0.7526***
	(0.6870, 0.8114)	(0.6916, 0.8122)	(0.6794, 0.8193)	(0.6818, 0.8234)
FF_SMB		0.0001		-0.000004
		(-0.0009, 0.0011)		(-0.0011, 0.0011)
FF_HML		0.0004		0.0005
		(-0.0004, 0.0012)		(-0.0003, 0.0013)
Constant	0.0045***	0.0047***	0.0065***	0.0066***
	(0.0028, 0.0063)	(0.0028, 0.0066)	(0.0041, 0.0089)	(0.0042, 0.0091)
Observations	108	108	108	108
R^2	0.8800	0.8809	0.8404	0.8420
Adjusted R^2	0.8788	0.8775	0.8389	0.8375
Residual Std. Error	0.0105 (df = 106)	0.0105 (df = 104)	0.0124 (df = 106)	0.0124 (df = 104)
F Statistic	776.9720*** (df = 1; 106)	256.3720*** (df = 3; 104)	558.3102*** (df = 1; 106)	184.7549*** (df = 3; 104)

Note: The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.

11.7.2.1.2 Environmental

	Dependent variable:			
	Highr		Lowr	
	(1)	(2)	(3)	(4)
MRP	0.7606***	0.7599***	0.7468***	0.7484***
	(0.7085, 0.8127)	(0.7097, 0.8101)	(0.6809, 0.8128)	(0.6806, 0.8162)
FF_SMB		0.0001		0.0004
		(-0.0008, 0.0010)		(-0.0006, 0.0015)
FF_HML		-0.0002		0.00002
		(-0.0009, 0.0006)		(-0.0008, 0.0008)
Constant	0.0048***	0.0048***	0.0057***	0.0057***
	(0.0032, 0.0064)	(0.0031, 0.0064)	(0.0032, 0.0081)	(0.0032, 0.0083)
Observations	108	108	108	108
R^2	0.9066	0.9068	0.8425	0.8433
Adjusted R^2	0.9057	0.9041	0.8410	0.8388
Residual Std. Error	0.0092 (df = 106)	0.0093 (df = 104)	0.0122 (df = 106)	0.0123 (df = 104)
F Statistic	1,028.8050*** (df = 1; 106)	337.1665*** (df = 3; 104)	566.9892*** (df = 1; 106)	186.5671*** (df = 3; 104)

Note: The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.

11.7.2.1.3 Social

	Dependent variable:			
	Highr		Lowr	
	(1)	(2)	(3)	(4)
MRP	0.7547^{***}	0.7545^{***}	0.8153^{***}	0.8168^{***}
	(0.7001, 0.8094)	(0.7016, 0.8075)	(0.7451, 0.8855)	(0.7463, 0.8873)
FF_SMB		0.0006		-0.00002
		(-0.0003, 0.0015)		(-0.0011, 0.0010)
FF_HML		-0.0003		0.0002
		(-0.0012, 0.0005)		(-0.0006, 0.0011)
Constant	0.0056^{***}	0.0057^{***}	0.0054^{***}	0.0055^{***}
	(0.0037, 0.0076)	(0.0036, 0.0077)	(0.0032, 0.0076)	(0.0031, 0.0078)
Observations	108	108	108	108
R^2	0.8877	0.8899	0.8769	0.8772
Adjusted R^2	0.8866	0.8867	0.8758	0.8737
Residual Std. Error	0.0102 (df = 106)	0.0102 (df = 104)	0.0116 (df = 106)	0.0117 (df = 104)
F Statistic	837.5370^{***} (df = 1; 106)	280.1026^{***} (df = 3; 104)	755.3730^{***} (df = 1; 106)	247.7177^{***} (df = 3; 104)
Note:	The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.			

11.7.2.1.4 Governance

	Dependent variable:			
	Highr		Lowr	
	(1)	(2)	(3)	(4)
MRP	0.7774^{***}	0.7802^{***}	0.7518^{***}	0.7545^{***}
	(0.7168, 0.8380)	(0.7204, 0.8400)	(0.6747, 0.8289)	(0.6770, 0.8321)
FF_SMB		-0.0001		0.00003
		(-0.0011, 0.0010)		(-0.0011, 0.0012)
FF_HML		0.0005		0.0004
		(-0.0004, 0.0013)		(-0.0005, 0.0014)
Constant	0.0050^{***}	0.0052^{***}	0.0067^{***}	0.0069^{***}
	(0.0030, 0.0070)	(0.0030, 0.0073)	(0.0042, 0.0093)	(0.0043, 0.0095)
Observations	108	108	108	108
R^2	0.8785	0.8798	0.8218	0.8227
Adjusted R^2	0.8773	0.8763	0.8201	0.8176
Residual Std. Error	0.0109 (df = 106)	0.0110 (df = 104)	0.0133 (df = 106)	0.0133 (df = 104)
F Statistic	766.1386^{***} (df = 1; 106)	253.7414^{***} (df = 3; 104)	488.6737^{***} (df = 1; 106)	160.8910^{***} (df = 3; 104)
Note:	The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.			

11.7.2.2 Europe

11.7.2.2.1 ESG

	Dependent variable:			
	Highr		Lowr	
	(1)	(2)	(3)	(4)
MRP	0.5667^{***}	0.5629^{***}	0.6161^{***}	0.5918^{***}
	(0.3774, 0.7559)	(0.3701, 0.7558)	(0.4026, 0.8296)	(0.3762, 0.8073)
FF_SMB		0.0003		0.0022^{**}
		(-0.0015, 0.0022)		(0.00005, 0.0043)
FF_HML		-0.0005		0.0006
		(-0.0021, 0.0010)		(-0.0009, 0.0021)
Constant	0.0073^{***}	0.0071^{***}	0.0083^{***}	0.0084^{***}
	(0.0043, 0.0102)	(0.0047, 0.0095)	(0.0049, 0.0118)	(0.0052, 0.0116)
Observations	108	108	108	108
R^2	0.6211	0.6232	0.5802	0.5928
Adjusted R^2	0.6175	0.6123	0.5763	0.5810
Residual Std. Error	0.0174 (df = 106)	0.0175 (df = 104)	0.0206 (df = 106)	0.0205 (df = 104)
F Statistic	173.7515^{***} (df = 1; 106)	57.3316^{***} (df = 3; 104)	146.5282^{***} (df = 1; 106)	50.4667^{***} (df = 3; 104)
Note:	The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.			

11.7.2.2.2 Environmental

	Dependent variable:			
	Highr		Lowr	
	(1)	(2)	(3)	(4)
MRP	0.5884^{***}	0.5723^{***}	0.6120^{***}	0.5897^{***}
	(0.3973, 0.7795)	(0.3777, 0.7670)	(0.4193, 0.8047)	(0.3920, 0.7873)
FF_SMB		0.0014^{*}		0.0020^{*}
		(-0.0002, 0.0031)		(-0.0001, 0.0041)
FF_HML		-0.0003		0.0001
		(-0.0017, 0.0011)		(-0.0015, 0.0016)
Constant	0.0078^{***}	0.0076^{***}	0.0078^{***}	0.0078^{***}
	(0.0048, 0.0108)	(0.0049, 0.0104)	(0.0047, 0.0110)	(0.0052, 0.0104)
Observations	108	108	108	108
R^2	0.6382	0.6448	0.6234	0.6337
Adjusted R^2	0.6348	0.6346	0.6198	0.6231
Residual Std. Error	0.0174 (df = 106)	0.0174 (df = 104)	0.0187 (df = 106)	0.0186 (df = 104)
F Statistic	187.0073^{***} (df = 1; 106)	62.9334^{***} (df = 3; 104)	175.4300^{***} (df = 1; 106)	59.9706^{***} (df = 3; 104)
Note:	The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.			

11.7.2.2.3 Social

	Dependent variable:			
	Highr		Lowr	
	(1)	(2)	(3)	(4)
MRP	0.6004^{***}	0.5865^{***}	0.6157^{***}	0.5919^{***}
	(0.4141, 0.7867)	(0.3948, 0.7781)	(0.4137, 0.8176)	(0.3867, 0.7972)
FF_SMB		0.0012^{*}		0.0021^{**}
		(-0.0001, 0.0026)		(0.0002, 0.0041)
FF_HML		-0.0004		-0.0001
		(-0.0017, 0.0010)		(-0.0015, 0.0014)
Constant	0.0068^{***}	0.0067^{***}	0.0068^{***}	0.0067^{***}
	(0.0044, 0.0092)	(0.0047, 0.0086)	(0.0036, 0.0101)	(0.0037, 0.0098)
Observations	108	108	108	108
R^2	0.7089	0.7148	0.6081	0.6195
Adjusted R^2	0.7062	0.7065	0.6045	0.6085
Residual Std. Error	0.0151 (df = 106)	0.0151 (df = 104)	0.0194 (df = 106)	0.0193 (df = 104)
F Statistic	258.1986^{***} (df = 1; 106)	86.8647^{***} (df = 3; 104)	164.5105^{***} (df = 1; 106)	56.4358^{***} (df = 3; 104)
Note:	The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.			

11.7.2.2.4 Governance

	Dependent variable:			
	Highr		Lowr	
	(1)	(2)	(3)	(4)
MRP	0.5567^{***}	0.5401^{***}	0.6199^{***}	0.5979^{***}
	(0.3854, 0.7280)	(0.3659, 0.7143)	(0.4237, 0.8161)	(0.3972, 0.7987)
FF_SMB		0.0015		0.0020^{*}
		(-0.0003, 0.0033)		(-0.0001, 0.0040)
FF_HML		0.0003		0.0006
		(-0.0011, 0.0016)		(-0.0008, 0.0021)
Constant	0.0062^{***}	0.0062^{***}	0.0086^{***}	0.0087^{***}
	(0.0035, 0.0089)	(0.0038, 0.0087)	(0.0055, 0.0116)	(0.0059, 0.0115)
Observations	108	108	108	108
R^2	0.6429	0.6504	0.6464	0.6583
Adjusted R^2	0.6395	0.6403	0.6431	0.6484
Residual Std. Error	0.0163 (df = 106)	0.0163 (df = 104)	0.0180 (df = 106)	0.0179 (df = 104)
F Statistic	190.8074^{***} (df = 1; 106)	64.4903^{***} (df = 3; 104)	193.7699^{***} (df = 1; 106)	66.7732^{***} (df = 3; 104)
Note:	The table above presents the OLS regression results of the single-index and multifactor model for the High and Low portfolio expected excess returns indicated as "Highr" and "Lowr", respectively. Columns (1) and (3) outlines the coefficients of the single-index model, while columns (2) and (4) report the OLS estimates of the multifactor models. The dependent variable is the portfolio monthly excess return and the alpha, denoted "Constant", expresses the monthly abnormal return which cannot be attributed to the other risk factors of the model. Below the estimated coefficients are each respective confidence interval presented in parentheses based on the HAC standard errors. Significance levels: * = 10%, ** = 5%, *** = 1%.			

11.8 Excel data

Available upon request.