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ESG investments: Can ESG momentum add alpha?

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Authors: Melanie Christina Damm (116279) & Julie Arvad Tranemose (101141)

Supervisor: Mads Stenbo Nielsen

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Abstract

This thesis contributes both to analysing the relationship between companies' environmental, social and corporate governance (ESG) and financial performance as well as to re-evaluating the existing empirical evidence pertaining to this link. The authors investigate changes in companies' ESG scores, referred to as "ESG momentum", and examine their signal value for predicting stock returns. The data includes ESG data from the MSCI database as well as accounting and stock price data from the S&P 500 IQ platform from 2014 to 2019. The econometrical framework applies an portfolio approach using the Capital Asset Pricing Model and as well as a multi-factor model based on Fama & French (1992) and Carhart (1997). Using these models, the authors compare portfolios consisting of the top improving companies ("positive ESG momentum") to portfolios containing the bottom decreasing companies ("negative ESG momentum") of the ESG momentum spectrum. ESG momentum is constructed separately for developed as well as emerging markets and is further investigated conditional on the initial ESG score.

Although previous empirical research indicates a positive relationship between ESG scores and returns, the results do not exhibit a significant and systematic pattern in the price effects of positive ESG momentum over holding periods of 6, 12, or 18 months. The authors find trading on positive as well as negative ESG momentum to yield positive alphas. In developed markets, they observe that trading on positive ESG momentum yields significant positive alpha in some of the models. However, the evidence is not convincingly a result of positive ESG momentum, as a negative ESG momentum also yields significant alphas. Nevertheless, compelling evidence of positive ESG momentum yielding a positive alpha contingent on a relatively high initial ESG score in developed markets is present. The authors do not find convincing evidence that trading on positive ESG momentum in emerging markets yields abnormal returns in any of the models. In contrast, they find negative ESG momentum yields high abnormal returns dependent on the performance group in emerging markets. Across all regression models, they find the price effects of ESG momentum in emerging markets to be generally higher than in developed markets and that the significant findings are tilted towards a 6-month holding periods in both markets.

Nonetheless, past key performance indicators reveal that positive ESG momentum portfolios show financial outperformance in terms of risk-adjusted returns, especially in developed markets. For emerging markets, positive ESG momentum can act as a protection against downside risk. This thesis concludes by discussing the value of ESG scores in reflecting superior ESG activities and signalling changes in stock prices.

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1 Introduction

In today's world, businesses face a unique set of challenges regarding their long-term sustainability, including climate change, resource constraints on human capital development, and anti-competitive practices. It is increasingly clear that a company's market value is determined by more than financial performance. In many industries, as much as 80% of market capitalisation is made up of intellectual capital, customer relationships, brand value, and other forms of intangible capital (Sustainability Accounting Standards Board (SASB), 2020). Some of these intangibles can be broadly related to ''sustainability,'' ''environmental, social, and governance'' (ESG), as well as ''corporate social responsibility'' (CSR). These terms have been used interchangeably in the past to describe a company's voluntary actions to manage its environmental and social impact and to increase its positive contribution to society.

Recent research has put forward that these issues do not only further social goals but may also increase shareholder value ("doing good by doing well") (Benabou & Tirole, 2010). This business case for ESG creates opportunities and may help companies to navigate ESG-related risks. An analysis found that more than 500bn USD in market value had been lost since 2014 due to ESG controversies, which marks the materiality of reputational risk tied to ESG (BofA Merrill Lynch, 2019). Needless to say, ESG-related opportunities and risks have become a noteworthy part of a company's intangible capital, and it is evident that traditional financial key performance indicators (KPIs) tell only a part of the story.

Consequently, investors want to benefit from a more nuanced understanding of the interrelation between ESG information and corporate value creation (IMF, 2019). Integrating ESG into investment decisions has increased in importance for many investors as more research shows its implications on risk and return (Henriksson, Livnat, Pfeifer, & Stumpp, 2019; Khan, 2019; Renneboog, Ter Horst, & Zhang, 2008). Indeed, mainstream investors' motivation to use ESG information is mostly driven by its relevance to investment performance and increased client demand towards sustainable investment practices (Amel-Zadeh & Serafeim (2018)).

The foundation for integrating ESG into the investment process starts with data. The data challenges originate from the fact that companies have historically not been formally required to report their internal initiatives on ESG aspects. Accompanying the mounting interest in ESG and a company's market and accounting performance in relation to it, specialized sustainability rating institutions[1], which assess a company's ESG standards, emerged over the last decades.

[1] Among the most important raters we find MSCI's KLD, Thomson Reuters ASSET4, Morningstar's Sustainalytics and RobecoSAM.

These sustainability rating agencies aim to rank companies with "ESG scores" and to give investors guidance on investment decisions. Like credit ratings, these ESG scores act like signals and may provide new and valuable information about a company's intangible capital to investors. Since ESG-related issues can be opportunities as well as risks for a company, it is crucial to assess how well a company is prepared to capture those opportunities and overcome the related risks. The increase of quantifiable data has made it possible to effortlessly incorporate ESG information into data-driven strategies.

Some authors argue that changes in ESG scores can be predictors of future stock performance (Kaiser, 2020; Khan, Serafeim, & Yoon, 2016; Nagy, Kassam, & Lee, 2016). Integrating these changes into an investment strategy is often referred to as "ESG momentum". Hence, next to looking at annual, half-year and quarterly filings, that are backward looking indicators of corporate financial performance, looking at companies' ESG score changes reveals additional valuable information. This information can enable investors to assess companies' preparedness to manage events that positively or negatively affect firm value, and hence fair stock prices.

The objective of this thesis is to examine a portfolio strategy based on ESG momentum using a dataset of one of the biggest and most widely used ESG rating agencies. The authors establish a more nuanced understanding of "doing well by doing good" in the sense that preceding efforts to manage ESG opportunities and risks could be an indicator of financial outperformance in the future. This thesis adds complexity to current research by examining the financial performance of an ESG momentum strategy in both developed and emerging markets, which in addition is conditional on the level of the ESG score.

1.1 Research question

This thesis builds on current research by examining the financial performance of trading on ESG momentum conditional on the ESG score. Previous literature has found evidence of a positive effect from increasing ESG disclosure when firms have ESG concerns rather than ESG strengths (Fatemi, Glaum, & Kaiser, 2018). The findings by Fatemi et al. (2018) could suggest that improving from a lower ESG score relative to a high ESG score has a higher price effect. The aim is to examine this effect by splitting the data into performance groups of companies with "low", "average" and "high" ESG scores, and trade on ESG momentum in each performance group. Further, the thesis will examine whether ESG momentum comprises new information, which is not explained by other well-known factors, as a predictors of stock price growth, using the Fama French 3-factor model (Fama & French, 1992) and the momentum factor by Carhart (1997). In addition, due to the differences between investing in developed markets and emerging markets (cf. Investing in emerging markets), the analysis is conducted on these markets separately. This thesis examines if abnormal returns are related to changes in ESG scores and provides international investors with additional insights on how they can integrate ESG as a signal into their investment decisions in a realistic investment environment (cf. Data description). As a result, the research question is formulated as follows:

Does trading on positive ESG momentum generate a positive alpha beyond well-established and empirically researched factors, and is alpha conditional on the initial ESG score?

The analysis is structured in the following 4 sub-questions to answer the general research question:

- *Q1: Does trading on positive ESG momentum yield a positive alpha?*
- *Q2: Does trading on positive ESG momentum yield an alpha beyond the well-established three Fama French factors as well as the momentum factor proposed by Carhart?*
- *Q3: Does trading on positive ESG momentum in emerging markets have a higher positive price effect than in developed markets?*
- *Q4: Does trading on positive ESG momentum on companies with a low ESG score compared to companies with a high ESG score have a higher positive price effect in both developed and emerging markets?*

Initially, an analysis of whether ESG momentum yields a positive alpha over a market proxy in a single index model is conducted. Hereafter, the Fama French factors and Carhart the momentum factor is added to control for the possibility that any alpha found in relation to the market proxy is related to any of the factors. Such a control will allow conclusions with higher conviction of whether the alpha is attributable to ESG momentum. Thereafter, the same analysis on the performance group of companies which are classified with a “low”, “average” and “high” ESG score individually is conducted, in order to determine if the price effect is conditional on the initial ESG score. To address the differences in the developed and emerging markets, the analysis examines if there is a difference in magnitude of a potential price effect by trading on ESG momentum.

1.2 Research perspective

This thesis is founded on a positivistic theory of science with a deductive approach.

Positivism builds on ontological realism, meaning that the objects of science exists independent of the observer. In addition, positivism builds on an objectivist epistemology, meaning that objective knowledge is attainable if it is based on the investigation of observable facts. The methodology of positivism is quantitative, with a goal of arriving at causal laws which control the world and society. The role of the researcher is restricted to data collection and objective interpretation. Thus, the researcher should be neutral and objective in her observation and science should be based on things which are directly observable. (Presskorn-Thygesen, 2012). Scientific recognition is attained by systematic collection of empirical data. Consequently, positivism is led by the principle of verifiability. This means that the researcher can form a theory based on a large amount of collected empirical data, after which the theory is supported by additional observations. An important aspect of positivism is that the observations of the researcher cannot be controlled by theories, expectations or prejudices. (Holm, 2011).

Although positivism advocates for an inductive research approach, the thesis has adopted the deductive approach which is commended by Popper (1974) in his critical rationalism theory of science. The deductive research approach, in contrast to the inductive approach, aims at developing hypotheses by testing existing theories and thereafter designing the research strategy. Popper (1974) criticises positivism by claiming that the neutral observation is not possible, as people always start with an idea of what it is, they want to investigate. In agreement with the view of Popper (1974), the thesis has the intended purpose to investigate the price effect of ESG momentum on stocks, a purpose which arose from previous research and theories about the price effects of ESG scores and stock momentum.

2 Brief history of ESG investments

There has long been a trend towards a higher consideration of environmental, social, and governance issues of companies and investment decisions. Climate change started to reach public opinion outside scientific circles and became a mainstream issue by 1989 (Nulmann, 2015). In 1990, KLD launched one of the first Socially Responsible Investing (SRI) indexes, the 400 Social Index (MSCI, 2020d). By the 2000's CSR had become an important strategic issue for companies (Moura-Leite & Padgett, 2011), and in 2006 the UN launched the Principles of Responsible Investment (PRI) which work to achieve a global sustainable financial system (PRI, 2019b). Moreover, investment analysts issued pessimistic recommendations to high CSR scoring companies during the 1990's, while over time leading up to 2007, more optimistic recommendations were released by analysts about high CSR scoring companies. This supports a gradual changing consensus among investors towards stakeholder theory which was previously more focused on shareholders (Eccles, Ioannou, & Serafeim, 2014). In addition, as a result of the mortgage backed security crisis in 2008, financial markets were put under higher scrutiny with regard to ethics, moral and transparency with more regulation to follow (Nagy et al., 2016).

After the financial crisis, the evolution of ESG finance associations, standards and codes accelerated (IMF, 2019). In 2011, the Sustainable Accounting Standards Board was founded. Further initiatives aimed at protecting the planet and increasing sustainability followed, such as the UN Sustainability Development Goals in 2015 and the Paris Climate Accord in 2016 adding greater momentum to the cause. Regulation of ESG disclosure also increased in recent years. In 2018, the European Commission's Action Plan on Sustainable Finance led to a raft of proposed EU legislation to help embed ESG considerations into the governance standards across the finance sector (Monaghan, 2020).

As of 2019, PRI has more than 2,300 signatories (PRI, 2019a). Morningstar (2020) estimated that funds and ETFs with focus on sustainability raised 20,6 bn USD in assets in 2019 which is four times higher than in 2018, and sustainable investing assets are growing globally with compounded annual growth rates in the range of 6% and 308% between 2014 and 2018[2] (GSI Alliance, 2018). However, the wide-spread shift among mainstream investors to incorporate sustainable investment practices is persistently slow (Friede, Busch, & Bassen, 2015; Monaghan, 2020). There is still a prevalent belief among practitioners, that engaging in ESG related activities means sacrificing returns (Nagy et al., 2016; NN Investment Partners, 2019). This is despite recent studies finding evidence rejecting that hypothesis, including the meta-study by Friede et al. (2015) which collects the results of over

[2] Numbers refer to the 5 largest capital markets: Europe, United States, Canada, Australia/New Zealand and Japan. All CAGRs are calculated based on local currency.

2,200 studies and find that a majority (63%) report a positive relationship between ESG and firm performance.

3 Literature review

3.1 ESG literature review

3.1.1 ESG, firm value and accounting performance

3.1.1.1 Theories on why ESG may increase firm value

3.1.1.1.1 ESG and cost of capital

There are a number of reasons why ESG is believed to create value. Companies with higher ESG scores have been linked to lower systematic risk in several studies, which in turn leads to a lower equity cost of capital and hence results in higher valuation (Bender, Sun, & Wang, 2017; Dunn, Fitzgibbons, & Pomorski, 2017; Giese, Lee, Melas, Nagy, & Nishikawa, 2019). The economic rationale behind these findings is that companies with superior ESG profiles are less exposed to systematic market shocks because of their superior resource management. This results in decreased vulnerability to changes in, for example, global commodity or energy prices (Giese et al., 2019; Gregory, Tharyan, & Whittaker, 2014). Low systematic risk translates into a low market beta in a capital asset pricing model (CAPM), which is often used for calculating the equity cost of capital of an asset. A lower beta results in lower equity cost of capital. If investors require a lower rate of return, the overall cost of capital of a company will decrease, and consequently a company with a lower cost of capital will have a higher valuation in a discounted cash flow model (DCF).

Similarly, a positive correlation has been found between a high ESG score and a lower cost of debt; as high ESG scoring companies are perceived as "good companies" and find it easier to get financing at a lower price (BofA Merrill Lynch, 2019; Clark, Feiner, & Viehs, 2014; Verheyden, Eccles, & Feiner, 2016). Since the cost of debt also determines a company's overall cost of capital, the mechanisms following lower cost of debt also decrease the discount rate in a DCF valuation model and will lead to higher valuations.

3.1.1.1.2 ESG and future cash flows

These results are in line with theories arguing that higher ESG scoring companies are less likely to face reputational risks, while also reflecting better risk management of ESG concerns[3]. Porter & Kramer (2011) argue, that a stakeholder orientation of a company can create economic value and unlock economic value in previously neglected and overlooked societal needs. In addition, many

[3] ESG concerns refers to risks that a company is facing which pose a threat to the value of the company and are related to ESG issues.

externalities created by companies affect their internal value chain. Two prominent examples from developed markets include when Johnson & Johnson discovered that the cost of lost workdays and diminished productivity was more expensive than providing health benefits for employees, as well as when Wal-Mart reduced packaging and rerouted deliveries, thereby saving $200 million even as more products were shipped. In emerging markets, Vodafone launched the M-PESA mobile banking service in Kenya which by 2011 grew to handle 11% of the national GDP. Porter & Kramer (2011) further argue, that creating shared value for business and society is a way to re-legitimise companies in society, and thereby mitigate reputational risk. This company-specific impact of ESG increases future cash flows through an enhanced ability to translate future opportunities into profitability (competitiveness) and through downside risk protection (Giese et al., 2019; Gregory et al., 2014). This has been empirically supported by evidence of higher dividends and lower idiosyncratic risk, which again leads to higher valuation (Giese et al., 2019). Lastly, high social performance can reflect good labour conditions and increases the competitive advantage by attracting high quality employees, leading to higher firm value through a more highly skilled workforce (Guenster, Bauer, Derwall, & Koedijk, 2011).

3.1.1.1.3 ESG and accounting performance

ESG activities have also been found to have a positive association with subsequent accounting performance, measured by the return on equity (ROE) of a company (De & Clayman, 2015). Likewise, Khan et al. (2016) find that higher scoring companies on an industry- and materiality-adjusted rating exhibit higher growth in accounting profitability measures. In addition, Dimson et al., (2015) show that after successful engagements with respect to ESG, particularly on environmental and social issues, companies experience improved sales, employee efficiency, and return on assets (ROA). Moreover, high ESG scoring companies have exhibited lower leverage (Bender et al., 2017) making their stocks potentially less risky. Hence, this stream of research supports the perception of high ESG scores as a quality signal of a stock.

3.1.1.2 Theories on why ESG may decrease firm value

Some researchers have found a neutral or negative relationship between ESG scores and financial performance (Friede et al., 2015; Jayachandran, Kalaignanam, & Eilert, 2013). A classical argument posed by Milton Friedman (1970) is, that a company spending money in on a social purpose takes away money which can be paid out as returns to stockholders, and thus reduces the value of the company. This theory would also support that ESG related costs may outweigh the benefits, and that this can in some cases be difficult to judge accurately before commitments to ESG activities.

3.1.2 ESG and stock performance

Many scholars now argue that the increasing interest in companies which have high level of SRI or ESG activities increases prices of these stocks, while leaving “sin” stocks undervalued as they are carried by fewer investors (Guenster et al., 2011; Riedl & Smeets, 2017). Some studies find that socially responsible investors expect lower financial performance of SRI funds compared to conventional funds, and conclude that the investors are thus sacrificing returns to invest in alignment with social preferences (Renneboog et al., 2008; Riedl & Smeets, 2017). Another core argument against ESG investments’ positive correlation to stock performance, is the limitation in the stock selection due to exclusions. This reduces diversification, and thus must lead to a worse risk-return profile of an ESG portfolio (Barnett & Salomon, 2006; Hong & Kacperczyk, 2009). However, this argument seems to loose relevance when an investor selects stocks based on good ESG characteristics or momentum in any industry (De & Clayman, 2015; Hoepner, 2013).

Since the predominant part of academic literature found a positive link between changes in ESG profiles and company valuations, changes in ESG scores should be predictors for changes in stock returns (Gregory et al., 2014; Henriksson et al., 2019). Hence, if investors do not successfully incorporate ESG in their valuation process, ESG might not be adequately reflected in the current stock prices leaving some companies over- or undervalued. This mispricing could be a source of abnormal returns. Indeed, abnormal returns from CSR historically arose because investors have overlooked the relevance of ESG related information, thus being surprised after earnings announcements and re-evaluated their assessment of companies’ prospects (Huppé, 2011).

Guenster et al. (2011) find evidence for a scenario where eco-efficient firms are not priced correctly in the market, plausibly as investors find it complicated to value the related financial benefits and costs of ESG activities. This theory suggests that markets undervalue eco-efficient firms, as a positive correlation between eco-efficient companies and market value is found, but that environmental information is priced-in with a drift. However, Guenster et al. (2011) also find it plausible, that the market does not associate social and environmental leading firms with lower risk, and thus they are not priced differently than social and environmental laggards. In this case, the value of firms with high social and environmental performances would not differ from the social and environmental laggards.

3.1.3 ESG ratings

When examining the aforementioned relationship between stock performance and a company’s sustainability and deriving investment strategies, practitioners as well as scholars often rely on readily available ESG scores. Despite the common objective of different rating agencies of giving a truthful picture of a company’s ESG history and rank, Chatterji, Durano, Levine, & Touboule (2016) and Dorfleitner, Halbritter, & Nguyen, (2015) find that their ratings show a very low correlation to each other. Even after adjusting for definitional differences in ESG, the authors' findings do not change. A similar study has recently pointed out that ESG ratings between different providers differ due to differences in measurement, scoping and weighting of the distinct ESG pillars and their subcomponents (Berg, Koelbel, & Rigobon, 2019). Moreover, the authors' findings suggest that there is a high degree of subjectivity in the ratings, since sustainability analysts tend to be biased by their general impression of the company when awarding ESG scores. In addition to the aforementioned findings, Doyle (2018) claims that ESG rating agencies reward companies with higher disclosures. It is possible for companies with historically weak ESG practices but robust disclosure, to score in line with or above peers despite overall being exposed to more ESG related risks. He further points out that there is a geographical bias towards firms in regions with high ESG requirements, that industry weighting and company alignment is oversimplified, and that ratings systematically fail in identifying ESG risks. Based on these findings, several authors recommend investors to refine ESG scores and design their own ESG ratings to better address materiality[4] issues (Bender, Bridges, He, Lester, & Sun, 2018; Henriksson et al., 2019; Khan et al., 2016) or to create new ESG scores combining data from different providers (Baltas, 2018; Berg et al., 2019). These approaches find more convincing results indicating an overwhelmingly positive relationship between ESG scores and stock returns.

3.1.4 ESG and other risk factors

Another interesting branch of literature deals with ESG and its relation to firm characteristics. Scholars as well as practitioners confirm a positive relationship between company size and ESG (Baltas, 2018; Bender et al., 2017; Kaiser, 2020). Other scholars found that ESG has stronger predictive power for stock returns in the small- and medium-cap range (250m-9bn USD) than for companies with higher market capitalisations (De & Clayman, 2010). The positive relationship between company size and ESG scores has been found to be stable or to evolve only slowly over time (Bender et al., 2017). Moreover, highly rated ESG companies have been found to have a high sensitivity to value characteristics (Baltas, 2018; Henriksson et al., 2019), although this relationship has not been found stable (Bender et al., 2017; Kaiser, 2020). The relationship between ESG and the momentum factor has been found negative and unstable over time (Baltas, 2018; Bender et al., 2017; Kaiser, 2020).

[4] Materiality refers to the relative importance of a particular ESG sub-component (in terms of opportunities and risk) to a particular industry. Those sub-components will impact financial performance in the future (Khan, 2019).

3.1.5 ESG momentum

The authors hypothesise, that some of the earlier theories regarding stock momentum strategies (cf. Stock momentum), could plausibly be applicable to ESG information. A stock momentum portfolio which generates a positive return, implies that there is a positive autocorrelation between stock returns. Past winners continue to have positive returns and past losers continue to have negative returns. In the same manner, an “ESG momentum” strategy assumes that companies that increased their ESG efforts in the past will have positive stock returns in the future and that companies that do not handle ESG risks and opportunities adequately will be punished with lower or negative stock returns. ESG momentum strategies build on the general theory that a high ESG score equates to higher ability for the firm to avoid ESG-related risks, which will be incorporated into the stock price by the market.

Some authors argue that changes in ESG ratings can be a predictor of future stock performance (Kaiser, 2020; Khan et al., 2016; Nagy et al., 2016). Khan et al., (2016) find that portfolios formed on the basis of high changes in a sustainability index have higher future stock performance compared to a portfolio of low-scoring companies and a portfolio tracking the general market. Other scholars provide evidence that investments into companies that adopt corporate policies related to environmental and social issues before the adoption of such policies became widespread delivered higher stock returns (Eccles et al., 2014). Similarly, successful shareholder engagement in ESG issues that led to changes in business practices has been found to deliver higher abnormal returns over a one year period (Dimson et al., 2015). Moreover, ESG momentum has been incorporated in ESG screening strategies and found to contribute to higher risk-adjusted returns (Kaiser, 2020; Verheyden et al., 2016). However, Kaiser (2020) also finds mixed evidence with respect to an environmental-based momentum strategy and its contribution to positive alpha. A paper by Nagy et al. (2016), finds a significant positive alpha while trading on a positive ESG momentum between 2007 and 2015 with an annual excess return of 2.2%. Nagy et al. (2016) find that the majority of the excess returns can be attributed to idiosyncratic risk, which could be related to ESG signals. Similarly to stock momentum, positive returns from an ESG momentum strategy could be attributed to over- and underreaction theories. This appears to be in line with the previously mentioned fact that ESG scores represent more intangible issues thus making it harder for the market to assess the materiality of ESG related improvements. Guenster et al. (2011) find evidence for firm value creation related to eco-efficiency and argue in support of a theory similar to the conservatism theory, where the stocks are undervalued and later have a price correction.

Some claim that the stock market reflects the value of CSR information, as investor attention to this information has increased. Kurtz & DiBartolomeo (2011) theorise that investors may not get a performance advantage through the use of social or environmental factors because market valuations already correctly incorporate this information. A different finding has been documented by Dimson et al. (2015). The authors of this event study found that already during intra-firm debates, policy and procedural changes, the market gradually adapts to this new information and that there are less abnormal returns possible after ESG policies are introduced and publicly announced. Gloßner (2017) postulates that markets still do not pay much attention to ESG information although they claim otherwise. He ascertains that stock markets are still unable to fully incorporate ESG information, especially ESG risks. The facts that the speed of ESG integration is low (European Commission, 2018) and that existing ESG ratings have several shortcomings, give rise to plausible inefficiency in the market in incorporating ESG related signals into stock prices. This argumentation also leads to a scenario where market participants may not value ESG signals at all, where possible reasons could be found in the difficulty of assessing materiality, or that ESG signals may predominately be a rearrangement of well-traded financial and non-financial signals which are currently already priced in the market.

3.1.6 ESG and relative stock performance

Fatemi, Glaum, & Kaiser (2018) find a general negative impact on firm value from firm disclosure on ESG topics, but a positive effect on firm value from increased disclosure on ESG topics if the firm is classified as having ESG concerns as opposed to ESG strengths. This finding might support a greater price effect from an improvement in ESG scores for low ESG scoring companies relative to high ESG scoring companies, as improvement from an already relatively high ESG score may be marginal as e.g. the added value from good governance decreases, risk management skills are already high, and reputational risks are considered low. Conversely, one might find that it requires a certain level of ESG scores for the market to perceive the added value. If a company increases from a low score, to a level which is still considered low, this effect might not be present.

3.2 Other related literature

3.2.1 Stock momentum and market efficiency

A stock momentum strategy buys past winners and sells past losers and has shown to generate significant positive returns. One of the earlier studies of the stock momentum effect was conducted by Jegadeesh & Titman (1993). The study finds that the positive excess return cannot be attributed to higher systematic risk, but instead finds evidence for a delay in stock price reaction to firm-specific information as a significant contribution to the positive returns of the momentum trading strategy, thus implying market inefficiency. Jegadeesh & Titman (2001) proceeded to find evidence for different theories behind the positive returns on momentum strategies, exploring both under- and overreaction theories. They find evidence supporting the behavioural theory of delayed overreaction in the market, as high prices are followed by a period of negative returns which could account for adjustment to the fundamental value, although this evidence is not very strong for larger firms. Daniel, Hirshleifer, & Subrahmanyam (1998) argue that informed traders have a bias towards attributing picked winners to their selection skills and attribute picked losers to bad luck. As a result, overconfidence pushes prices up above their fundamental value. Another argument posed by Hong, Lim, & Stein (2000), explains a scenario where there are informed investors and "news watcher" investors. The information which the informed investors trade on, is traded on with a delay from the "news watchers", causing positive price autocorrelation. Conversely to overreaction theories, conservatism has often been attributed to the momentum effect (Barberis, Shleifer, & Vishny, 1998). This theory explains the momentum effect by hypothesising that investors are conservative and underreact to market information, thus prices adjust with a lag.

3.2.2 Investing in emerging markets

Differences in investing in emerging as opposed to developed markets have been studied for a long time. Emerging markets exhibit high expected returns as well as high volatility, have historically been weakly integrated into the world capital markets, and are more sensitive to local information[5] (Cakici, Fabozzi, & Tan, 2013; Harvey, 1995). Importantly, the low correlations with developed markets' equity markets significantly reduces the unconditional portfolio risk of an international investor according to the authors. Emerging markets investments today are still subject to higher volatility, low liquidity, and lack of information (Odell & Ali, 2016). Despite the differences between investing in developed and emerging markets, the factors that drive cross-sectional differences in expected stock returns in emerging equity markets are qualitatively similar to those that have been documented for developed markets. Emerging market stocks exhibit momentum, small stocks outperform large stocks, and value stocks outperform growth stocks (Fama & French, 1998; Rouwenhorst, 1999).

Although ESG research is gaining ground in developed markets, less is known about ESG disclosure and its effect in emerging markets. A comparison of studies linking ESG to equity and portfolio performance shows, that studies focusing on an emerging markets sample have a considerably higher share of positive outcomes compared to developed markets (Friede et al., 2015). Sherwood & Pollard (2018) and Auer & Schuhmacher (2016) show that integrating high ESG scoring emerging market equities into institutional portfolios can provide institutional investors the opportunity for higher returns and lower downside risk than non-ESG equity investments. Fatemi et al. (2018) find that the positive effect on firm value from ESG disclosure, given that the firm has ESG concerns, are stronger in countries with weak market-supporting institutions. Similarly, Chauhan & Kumar (2018) find a significant correlation between non-financial disclosure and firm value in emerging markets,

[5] Local Information is information that is specific to the national context that a company is operating in.

and that this effect is attributed to lower cost of capital and higher operating cash flows. Odell & Ali (2016) assert that emerging markets will be the next big jump in portfolio construction and management, and argue that the unique challenges that emerging markets face, such as poverty, urbanization and corruption, make emerging markets particularly well situated to benefit from the sustainable growth and profitability offered by ESG investments. The authors analysed the argument that ESG scores provide additional information, helpful when investing in emerging and frontier markets. This study concludes that the operational challenges that these markets inevitably face, such as uneven governance, weak institutions, and lack of government oversight, provide a clear opportunity for higher risk-adjusted returns in ESG investing than in purely fundamental investing.

4 Theory

4.1 Markowitz's portfolio theory

Markowitz introduced the mean-variance analysis as a the foundation for modern portfolio theory to determine the optimal portfolio over a time period (Markowitz, 1952). The findings of Markowitz (1952) are still highly relevant today. The Capital Asset Pricing Model was built on this theory (among others), which is a core theoretical foundation in many aspects of finance today.

The key assumptions of Markowitz (1952) are, that investors consider different portfolios over a fixed future period and want to maximise the expected return while minimising the variance, thus investors are mean-variance optimising. In addition, investors maximise individual utility functions of terminal wealth (Munk, 2018). Mean-variance efficient portfolios consist of all portfolios where the variance is minimised given the expected return. It follows that all mean-variance efficient portfolios form a hyperbola called the efficient frontier of risky assets. The efficient frontier represents any combination of the minimum variance portfolio and the maximum slope portfolio, where the maximum slope portfolio is the portfolio with the highest return given the level of risk. Investors vary in risk aversion and utility curves and thus, they will prefer different weights of the minimum variance and maximum slope portfolio (Munk, 2018).

James Tobin (1958) extended the modern portfolio theory by Markowitz (1952) with the risk-free rate. Adding the risk-free rate allows investors to have a fraction of their wealth invested in the risk-free rate (e.g. treasury bills) to reduce volatility or to leverage their investment by borrowing at the risk-free rate and invest in stocks. By combining the risk-free rate with the tangency portfolio, investors can obtain the highest expected return per unit of risk, while satisfying their individual utility function and optimal risk level by shifting the weights of the risk-free rate and tangency portfolio. The tangency portfolio is the portfolio which is tangent to the efficient frontier of risky assets when drawing a straight line from the point of the risk-free rate. Thus, the optimal portfolio is the tangency portfolio for all investors, and all efficient portfolios are combinations of the tangency portfolio and the risk-free rate. As the risk-free rate carries no risk, the variance of the risk-free rate and the covariance with any stock are zero. Therefore, the volatility of the optimal portfolio is the standard deviation of the portfolio of risky assets multiplied with the weight of this portfolio (Berk & DeMarzo, 2016).

Diversification is a central part of the modern portfolio theory. By investing in several assets with correlations less than one, the variance of the portfolio can be reduced. At the same time, the expected return of the portfolio remains the weighted average return. Risk can be divided into a systematic and an idiosyncratic part. The systematic risk represents the variance in stock returns which are related to information and factors which affect all stocks in the market (market risk). Idiosyncratic risk represents the variance in stock returns which can be attributed to firm specific information. As a result, idiosyncratic risk can be diversified away since good news will affect some stocks, while bad news will affect others and on average even out. Conversely, all stocks are to some degree correlated with the market, thus systematic risk affects all stocks and cannot be eliminated through diversification (Berk & DeMarzo, 2016). As a result, idiosyncratic risk can be diversified away by investing in a portfolio of risky assets, and an investor can obtain a portfolio with a better risk-return profile.

Equation I. Variance of a portfolio with arbitrary weights (Berk & DeMarzo, 2016):

$$\sigma(r_p) = \sum_i w_i \times \sigma(r_i) \times \rho(r_i, r_p) \qquad \text{I}$$

Where

w_i = *weight of the i'th stock,*

$\sigma(r_i)$ = *standard deviation of the return of the i'th stock,*

$\sigma(r_p)$ = *standard deviation of the return of the portfolio*

$\rho(r_i, r_p)$ = *correlation between the return of the i'th stock and the return of the portfolio*

Equation II. Standard deviation of an equally weighted portfolio (Berk & DeMarzo, 2016):

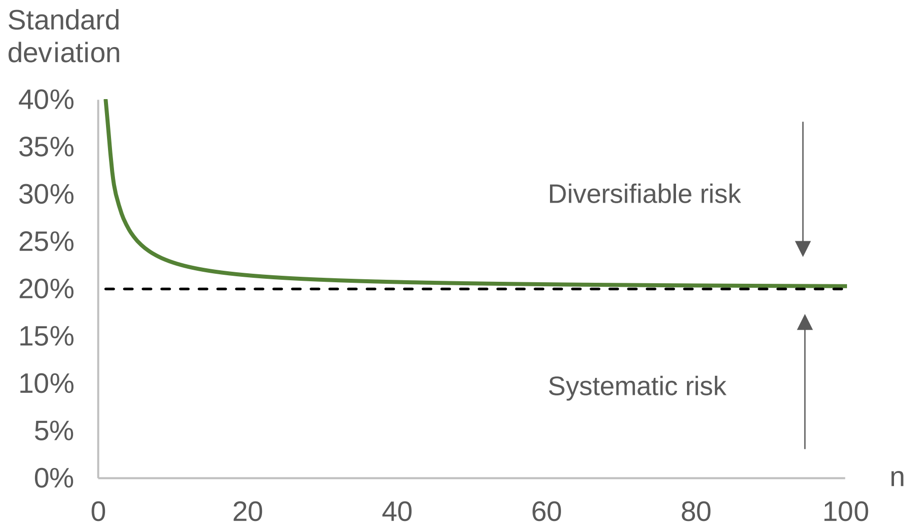
$$\sigma(r_p) = \sqrt{\frac{1}{n}(Avg.\,variance\ of\ individual\ stock) + \left(1 - \frac{1}{n}\right)(Avg.\,covariance\ between\ stocks)} \qquad \text{II}$$

Where n = number of stocks

Equation II makes it evident that the variance decreases with the number of stocks in the portfolio. As the number of assets approaches infinity, the first term approaches zero, while second term approaches the average covariance. The effect of diversification is exponential, with highest incremental effects occurring with e.g. an increase in stocks from one to two stock relative to an increase from 100 stocks to 101 stocks. Consequently, close to all diversifiable risk is diversified away when the number of stocks reaches 30 (Berk & DeMarzo, 2016).

Using equation II, Figure 1 illustrates the diversification of an equally weighted portfolio with an average standard deviation of 40% and an average covariance between stocks of 25%.[6] As the number of stocks increases, the standard deviation of the portfolio will converge to the average covariance of the stocks.

Figure 1: Standard deviation of an equally weighted portfolio with n stocks



Source: Own contribution

Shortcomings of Markowitz's portfolio theory

The mean-variance analysis assumes that investors optimise their wealth at one point in time, the end of the given investment period. In reality, investors typically get utility from consumption at several points in time. In addition, the risk aversion is constant, but the utility of wealth is likely to change over time when new information appears and should also be considered in relation to other welfare measures such as housing decisions or uncertainty of labour income. The mean-variance analysis only considers the mean and variance in the investment decision. Behavioural finance research has shown that people tend to be loss averse and are thus willing to pay for limiting downside risk. Conversely to this argument, the mean-variance analysis treats gains and losses symmetrically. Lastly, the mean-variance analysis is very sensitive to its input factors. In practice,

[6] Calculation: $\sigma(r_p) = \sqrt{\frac{1}{n}(0.40)^2 + \left(1 - \frac{1}{n}\right)(0.25 * 0.40 * 0.40)}$

the mean-variance analysis is conducted using historical returns and variance, which have been shown to be an unreliable predictor of future returns and variance. (Munk, 2018).

4.2 The Capital Asset Pricing Model

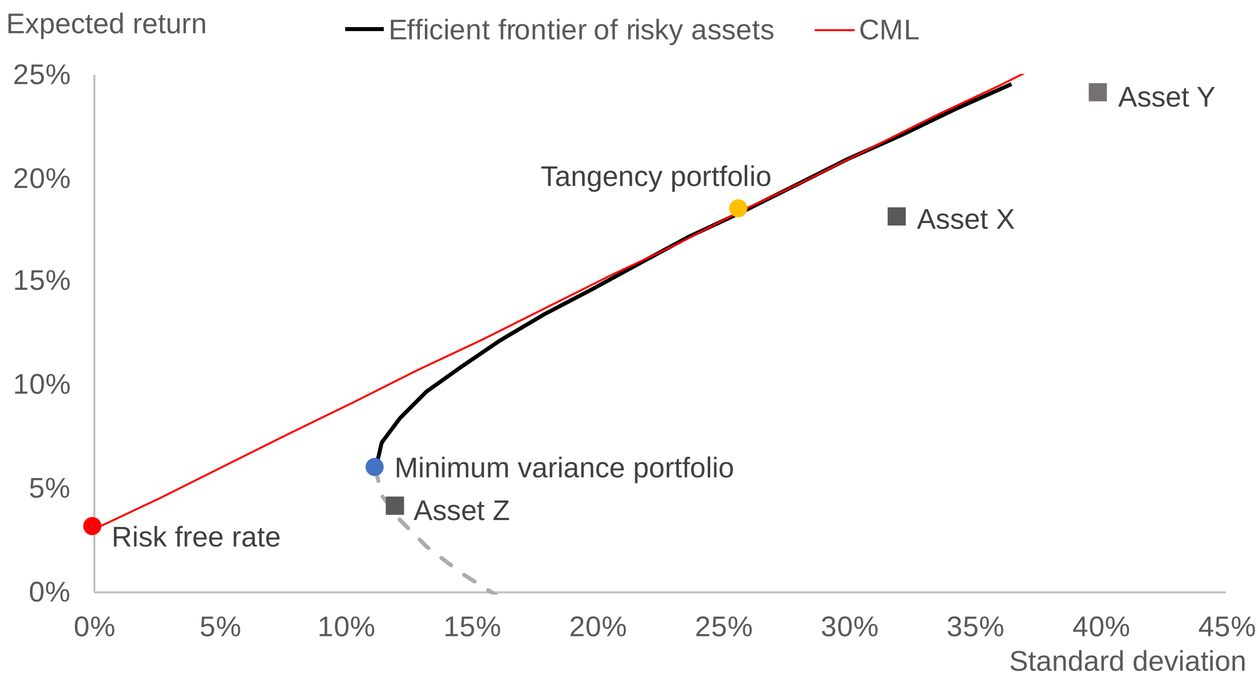
The Capital Asset Pricing Model (CAPM) as it is commonly referred, was developed by Treynor (1961), William Sharpe (1964), John Lintner (1965) and Jan Mossin (1966) and is still a fundamental framework in finance in e.g. estimating cost of capital for companies and evaluating performance of portfolios (Munk, 2018). The CAPM builds on the framework of portfolio theory of mean-variance optimisation by Markowitz (1952). The model adds two more assumptions to the Markowitz (1952) framework: all investors agree on the probability distribution of future stock returns (from time t-1 to time t) and that investors can borrow and lend at the risk-free rate (Munk, 2018). The CAPM model is also frequently referred to as the single index model.

The main assumption of the model are as follows (Berk & DeMarzo, 2016):

1. Investors buy and sell all assets at competitive market prices with no market frictions such as transaction costs or taxes.
2. Investors can borrow and lend at the risk-free interest rate.
3. Investors are mean-variance optimising and risk-averse.
4. All investors have the same investment time horizon.
5. All investors agree on the probability distribution of future returns and thus have homogenous expectation with regard to volatility, correlations and expected returns of the assets in the market.
6. Investors only differ in terms of level of risk aversion.

In consensus with the arguments of James Tobin (1958), all investors invest in the tangency portfolio. As all investors have homogenous expectations in regard to variance and expected returns, all investors will choose the same portfolio to invest in, which is the portfolio with the highest return per unit of risk, i.e. the tangency portfolio. Thus, the tangency portfolio must be the market portfolio. As all investors invest in the same portfolio, the sum of all investors' portfolios must be equal to the value of all risky assets in the market. The market portfolio must then also be value-weighted. Consequently, the fact that the market portfolio is efficient, is a statement of supply equals demand. Investors will vary their weights in the risk-free rate and the market portfolio to align with their risk preferences. Investors can leverage their investment and increase risk by borrowing at the risk-free rate and investing in the market portfolio. The straight line which can be drawn from the risk-free rare to the tangency portfolio is called the Capital Market Line (CML). The slope of the CML is equal to the Sharpe ratio of the market portfolio $\left(\frac{E[r_m]-r_f}{Std[r_m]}\right)$ (cf. Figure 2) (Munk, 2018). The risk-free rate is set such that lending and borrowing brings demand and supply in equilibrium (Fama & French, 2004).

Figure 2: The efficient frontier of risky assets and the CML, example with 3 assets



Source: Own contribution (calculation in Appendix T1)

In equilibrium, the expected return of an investment is in direct relationship to the sensitivity of the investment's return to the expected excess return of the market portfolio:

$$E[r_i] - r_f = \beta_i(E[r_m] - r_f) \qquad \text{III}$$

Where

$$\beta_i = \frac{Cov(r_i, r_m)}{Var(r_m)} = \frac{Corr[r_i, r_m]Std[r_i]}{Std[r_m]}$$

Beta is defined as the covariance of the investment return with the market portfolio return divided by the variance of the market portfolio return. The CAPM is a one period model, which means beta can vary with time. Where beta represents a portfolio, beta is calculated as the weighted average of the betas in the portfolio. The beta measures the sensitivity of the stock's return in relation to the return of the market portfolio, also called the factor sensitivity (systematic risk). Following the fundamental arguments of the Arbitrage Theory of Capital Asset Pricing (Ross, 1976), the risk premium for taking on idiosyncratic risk is zero since idiosyncratic risk can be diversified away. If idiosyncratic risk had a risk premium, investors could buy these stocks while diversifying the risk away, and thus get an additional premium without significant additional risk. This close-to-arbitrage opportunity would be exploited until eliminated by borrowing at the risk-free rate and invest in a large portfolio of assets with risk which exceeds the risk-free rate, until the idiosyncratic risk has been diversified away. This argument follows from the law of one price stating that, if a large portfolio has no risk it must have the price of the risk-free interest rate (Berk & DeMarzo, 2016). Thus, the risk premium of an asset reflects only the systematic risk. As a result, only if the expected return of a stock equals that of the CAPM equation III, the market is in equilibrium where demand equals supply for that asset (Munk, 2018).

While only efficient portfolios are on the CML, e.g. the market portfolio, all assets can be plotted on the Security Market Line (SML). The SML graphs the expected return given the beta of an asset, where the CML graphs the expected return given the standard deviation of returns on an asset (Munk, 2018).

$$SML: \quad E[r_i] = r_f + \beta_i \times E[r_m] \tag{IV}$$

In accordance with the CAPM, a stock located below the SML line is overvalued, while a stock above the SML line is undervalued (Munk, 2018).

Shortcomings of the CAPM

It is unrealistic to assume that all investors have the same belief about the probability distribution of asset returns and have the same investment horizon. Investors are subject to different investment constraints in capital markets (such as market access or taxes), which could explain why investors may hold different portfolios. One could argue, that the market portfolio is held by the average investor, and deviations in portfolios held by investors describe their deviation from the average investor (Munk, 2018).

It is impossible to test the CAPM as the market portfolio is unobservable. The market portfolio theoretically includes all risky assets, including assets such as human capital which can be difficult to observe and estimate. The key equation of CAPM (cf. eq. III) states the relationship between expected returns of an asset and the market beta, which are both unobservable. Thus, the majority of CAPM tests and applications are conducted using proxies such as market indices for estimation of the true CAPM, while statistical tests are conducted to test whether deviations are small enough to assume that the CAPM holds. Since the market beta must be estimated, it will be subject to estimation errors. As a result, measurement errors in the explanatory variable result in the beta (slope) to be biased downwards and the intercept to be biased upwards. Thus, the regression line between expected returns and the beta will appear flatter. Calculating precise estimates of beta of a single stock is difficult, while it can be easier for portfolios. In addition, historical betas have been shown to perform relatively poorly in estimating future betas. (Munk, 2018).

Not surprisingly, due to the listed difficulties in estimating CAPM, empirical tests have found that other variables than the market beta are significant in regressions with the average asset or portfolio returns as an explanatory variable. Examples include the Fama French size factor and the book-to-market factor as well as the Carhart momentum factor (Munk, 2018).

4.3 The Fama French three factor model

Fama & French (1992) developed their well-known multi-factor model using three factors which they found to provide significant explanatory power of the variations in the returns of a market proxy in empirical tests. The model was motivated by empirically observed anomalies in relation to the CAPM (Fama & French, 1992). The findings of the model are still widely applied in finance today, and the model continues to be used in research to test stock returns (Dimson, Marsh, & Staunton, 2017).

As in the CAPM, the market portfolio is a factor in the model. In addition, the researchers found a significant return sensitivity to firm size and the book-to-market ratio. Previous empirical studies documented the size effect, where the average return of firms with low market value of equity were too high given their beta estimate according to the CAPM. Another anomaly is the documented positive relationship between average returns and the ratio of the firm's book value of equity and the market value of equity. (Fama & French, 1992).

Fama & French (1992) make a categorisation of firms into small market capitalisation (lowest 30%), neutral market capitalisation (middle 40%) and big market capitalisation (highest 30%), along one dimension, and into high book-to-market ratios and low book-to-market ratios (parted on the median) on the other dimension. The size factor is constructed as the average of the three small market equity portfolios minus the average of the three big market equity portfolios, referred to as SMB (Small Minus Big). The book-to-market factor, referred to as HML (High Minus Low), is constructed as the average return on the two portfolios with high book-to-market ratios, value portfolios, minus the average return on the two portfolios with low book-to-market ratios, growth portfolios (Fama & French, 1992).

The factor portfolios are based on monthly excess returns on zero-investment portfolios mentioned above without transaction costs. The applied market proxy consists of the value-weighted returns of all NYSE, AMEX and NASDAQ stocks. They find that the SMB and HML factors provide significant explanatory power of market returns in the period between 1963 and 1990. (Fama & French, 1992).

The Fama French three factor model:

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

Where $r_i - r_f$ is the excess return of stock i, $r_m - r_f$ is the excess return of the market portfolio, $\beta_{i,m}$, $\beta_{i,SMB}$, $\beta_{i,HML}$ are the respective factor sensitivities, ε_i is the residual with zero covariance with the three factors, and α_i is the abnormal return which should have the value of zero (Munk, 2018)

The analysis by Fama & French (1992) does not try to uncover why the model performs well, but they suggest that both the SMB and HML factors are proxies of risk factors, if asset pricing is rational. They hypothesise that the positive relationship between book-to-market ratios and average returns is caused by firms with bad prospects, which is signalled by lower stock prices and a low market value relative to book value (they have a higher cost of capital), have higher expected stock returns compared to firms with good prospects. They further hypothesise that small firms are more likely to experience financial distress, which represents a risk factor which is priced into the expected returns since investors require higher returns as compensation.

The empirical returns SMB and HML have varied considerably since Fama & French (1992) published their results in 1992. In some years, large stocks substantially outperformed small stocks, and in some years, firms with low book-to-market ratios substantially outperformed firms with high book-to-market ratios (Munk, 2018).

4.4 The Carhart four factor model

Carhart (1997) proposed an extension of the Fama French three factor model which was motivated by another market anomaly relative to the CAPM, namely the short-term momentum of stock returns. The anomaly was first described by (Jegadeesh & Titman, 1993) while Carhart (1997) found the motivation for this study. Jegadeesh & Titman (1993) found that stocks which had positive (negative) returns in the past 6-month returns continued to have positive (negative) returns in the following 3 to 12 months in the period from 1965 to 1989.

Carhart (1997) finds that his four-factor model significantly improves the regressions' explanatory power of the variation on mutual fund returns during the time period from January 1992 to December 1993 compared to the three Fama French factors.

The Carhart four factor model:

$$r_i - r_f = \alpha_i + \beta_{i,m}(r_m - r_f) + \beta_{i,S}SMB + \beta_{i,H}HML + \beta_{i,W}WML + \varepsilon_i \qquad \text{VI}$$

Where $r_i - r_f$ is the excess return of stock i, $r_m - r_f$ is the excess return of the market portfolio, $\beta_{i,m}, \beta_{i,S}, \beta_{i,H}, \beta_{i,W}$ are the respective factor sensitivities, ε_i is the residual with zero covariance with the three factors, and α_i is the abnormal return which should have the value of zero. WML is the momentum factor, constructed as winners minus losers, which are stocks with positive stock returns minus stocks with negative stock returns.

Implementing a momentum strategy is fairly simple, as it only requires knowledge of past prices. Following this strategy positive returns would suggest that markets are inefficient (cf. Market efficiency) (Munk, 2018). Several theories have been proposed to explain the momentum effect. Examples from the Jegadeesh & Titman (1993) study propose that delayed stock price reactions to firm-specific information and transactions by investors who buy past winners and sell past losers shift stock prices away from their long term value temporarily and cause overreactions. Another frequently supported theory, as made by Daniel, Hirshleifer, & Subrahmanyam (1998), argues that informed traders tend to attribute picked winners to their selection skills and picked losers to bad luck. Consequently, the overconfidence results in an overreaction and pushes stock prices up (Adebambo & Yan, 2016).

Since Carhart published his results, the momentum factor has not always proven to be a profitable strategy. Contrarian strategies[7] have had periods where they outperformed the momentum strategy, an example includes the period from March to May 2009 where the best performing decile of stocks had a return of 8%, while the worst performing decile had a return of 163% (Munk, 2018). However, the momentum strategy continues to be a much debated and researched investment strategy, while conviction of delayed stock price reaction and overreaction theories persist (Adebambo & Yan, 2016).

4.5 Market efficiency

An efficient market is defined as a market where all available information is reflected in the stock prices and prices are an unbiased estimate of the true value of an investment. This means that the theory does not require the market price to be the true value at any given point in time but requires that the errors in the market price is unbiased, i.e. the errors are random. This implies that there is an equal chance of a stock being under- or overvalued, which in turn implies that no investor would be able to consistently find under- and overvalued stocks. Any excess return obtained by an investor would be explained by luck rather than skill (Bodie, Kane, & Marcus, 2010).

Three general levels of market efficiency are defined as weak-form, semi-efficient-form, and strong-form of efficiency. The weak form of market efficiency describes a market where all historical prices are reflected in the current stock prices. Thus, with this level of market efficiency, trading on patterns in stock returns (technical analysis) would provide no opportunity to consistently outperform the market. In the semi-efficient form of market efficiency, the current stock price reflects past prices as well as all publicly available information. Thus, investors trading on e.g. analyses of financial

[7] Contrarian strategies refer to buying past losers and selling past winners (Jegadeesh & Titman, 1993).

statements as well as industry and macro-economic public information (fundamental analysis), would not be able to generate consistent returns which outperform the market. In the strong from on market efficiency, the stock prices reflect all information, both public and private. Thus, inside trading would not generate consistent returns which outperform the market (Bodie et al., 2010).

An investment strategy trading on ESG momentum which generates a consistent excess return compared to the market, would imply that markets are inefficient and would violate the semi-efficient form of market efficiency (given the above definition). ESG scores or ESG related information (from sustainability reports of firms) are publicly available information. If the market were semi-efficient, it would incorporate this information into the stock price immediately as the information became public. A strategy generating consistent excess returns trading ESG momentum, would mean that the value of the ESG information is not incorporated into the stock price promptly and thus would be a violation of this form of market efficiency.

Several studies have found evidence for market anomalies and patterns in past stock returns, which would suggest market inefficiency. Some well-known examples include the P/E-effect and small-firm effect.[8] Many studies have argued that anomalies, such as low P/E ratio stocks having higher returns than high P/E ratio stocks, are not appropriately adjusted for risk. Given two companies with the same earnings expectation, the riskier company would sell at a lower stock price. Consequently, the question about *how* efficient markets are still persist. However, Fama and French argue that their SMB and HML factors may not be evidence of market inefficiency, but consistent with the efficient market hypothesis (EMH). They state that SMB and HML are risk premia as they find evidence of the factors having high market betas. Thus, the factors' systematic risk is higher than the market's, which would justify the higher expected returns following the CAPM model. Although the factors are not risk factors in themselves, they proxy for determinants of risk. In addition, the Fama French three-factor-model proved to be significantly better in explaining stock returns than the single-index model based on the CAPM. (Bodie et al., 2010).

Bodie et al. (2010) argue that enough anomalies have been found in the market to justify the research in underpriced stocks. They conclude that markets must be considered quite efficient in general, where simplistic methods of earning excess returns will quickly be exploited and eliminated in the market. However, they expect that diligent, intelligent or creative investors could gain excess returns although they expect these to be very small. In addition, it is possible that some markets are efficient,

8 The P/E-effect refers to firms with a low price-earnings (P/E) ratio outperforming firms with a high P/E ratio, while the small-form effect refers to firms with a small market capitalization outperforming firms with a large market capitalization (Bodie et al., 2013).

and some are not, while it is also possible that markets are efficient for some investors and not for others. This is a result of market frictions such are differences in tax rates and transaction costs.

4.6 Ordinary Least Squares Regression (OLS)

The OLS is an unbiased and consistent estimator of the relationship between the dependent and independent variable(s), under the assumptions listed below. The OLS regression minimises the sum of squared residuals to obtain the best fitted lined between observations of a dependent variable and one or multiple independent variable(s) (Stock & Watson, 2015).

The OLS multiple linear regression function:

$$\widehat{Y_t} = \widehat{\beta_0} + \widehat{\beta_1}X_{1i} + \cdots + \widehat{\beta_k}X_{ki} + \hat{u}_i$$
$$\widehat{u_\iota} = Y_i - \widehat{Y_\iota} \tag{VII}$$

Where OLS estimators $\widehat{\beta_0}, \widehat{\beta_1}, \dots, \widehat{\beta_k}$ and the error term $\widehat{u_t}$ are estimated from n observations of the dependent variable (Y_i) and the independent variable(s) $(X_{1i}, \dots, X_{ki})$, $i = 1, \dots, n$. They are estimations of their true unknown population coefficients $\beta_0, \beta_1, \dots, \beta_k$ and u_i . $\widehat{\beta_0}$ is the intercept, $\widehat{\beta_1}, \dots, \widehat{\beta_k}$ are the slopes of the corresponding independent variables. $\widehat{Y_\iota}$ is the predicted OLS value of the true value Y_i (Stock & Watson, 2015).

OLS Assumptions

1. The relationship between the dependent variable and the independent variables is linear
2. The independent variables are non-stochastic and uncorrelated with the error term, i.e. independent variables are exogenous
3. The error term $\mathrm{u_i}$ has a conditional mean of zero given $\mathrm{X_i}$
4. The error term has constant variance (homoscedasticity) and is normally distributed
5. The error term is statistically independent, i.e. no autocorrelation in the error term
6. The number of observations is bigger than the number of variables which are estimated
7. There is no multicollinearity between independent variables.
8. Outliers are unlikely.

Given these assumptions, the OLS estimators are jointly normally distributed in large samples with a variance which decreases as the number observations increases (Stock & Watson, 2015).

β_0 is equal to the expected value of Y when all X's are equal to zero. $\widehat{\beta_k}$ is the expected change in Y_i from a unit change in X_{ki}, holding all other independent variables constant.

$$\widehat{\beta_k} = \frac{\sum_{t=1}^{n}(X_t - \bar{X})(Y_t - \bar{Y})}{\sum_{t=1}^{n}(X_t - \bar{X})^2} = \frac{Cov(X,Y)}{Var(X)} \qquad \text{VIII}$$

With a large sample size, $\widehat{\beta_0}, \text{and} \widehat{\beta_1}, \dots, \widehat{\beta_k}$ approach the true value of $\beta_0, and\ \beta_1, \dots, \beta_k$ with high probability, as the variance of $\widehat{\beta_0}, \text{and} \widehat{\beta_1}, \dots, \widehat{\beta_k}$ decreases when the number of observations increases. The joint sample distribution of $\widehat{\beta_0}, \text{and} \widehat{\beta_1}, \dots, \widehat{\beta_k}$ approaches a multivariate normal distribution as the number of observations increases (Stock & Watson, 2015).

The goodness of fit of the linear regression is estimated by the R^2. The R^2 describes the fraction of the dependent variable Y_t which is explained by the independent variable(s) X_t. ESS is the explained sum of squares of the deviations from the average Y_t by $\widehat{Y_t}$, and TSS is the total sum of squares of the deviations from the average Y_t (Stock & Watson, 2015).

$$R^2 = \frac{ESS}{TSS} = \frac{\sum\left(\widehat{Y_i} - \bar{Y}\right)^2}{\sum(Y_i - \bar{Y})^2} = 1 - \frac{SSR}{TSS} \qquad \text{IX}$$

Where R^2 is non-negative and between 0 and 1, and SSR is the sum of squared residuals, $SSR = \sum_{i=1}^{n} \widehat{u_i^2}$. The higher the R^2, the better the independent variable(s) are at describing the variation of the dependent variable (Stock & Watson, 2015).

When several independent variables are used in the OLS regression, the R^2 increases, although including another variable does not necessarily improve the fit of the model. Thus, the adjusted $\overline{R^2}$is applied, which decreases the R^2 when the number of independent variables increase (Stock & Watson, 2015).

$$\overline{R^2} = 1 - \frac{n-1}{n-k-1} * \frac{SSR}{TSS} \qquad \text{X}$$

Adding an independent variable decreases both the SSR as well as $\frac{n-1}{n-k-1}$ as the number of independent variables, k, increases. The change in R^2 is thus dependent on which effect is dominant (Stock & Watson, 2015).

The standard error describes the typical size of a deviation from the regression line (Stock & Watson, 2015).

$$SER = \sqrt{s_{\hat{u}}^2}, \qquad s_{\hat{u}}^2 = \frac{1}{n-k-1}\sum_{t=1}^{n} \widehat{u_t^2} = \frac{SSR}{n-k-1} \qquad \text{XI}$$

Dividing by $n-k-1$ is an adjustment for the downward bias of the intercept and slope of the regression, caused by estimating $k+1$ coefficients and called degrees of freedom (Stock & Watson, 2015).

4.6.1 T-test, p-value and confidence intervals

The t-test is conducted to test whether β_k is statistically different from zero (two-sided test), i.e. if the independent variable can explain any of the variation in the dependent variable with statistical significance. The hypothesis of $\beta_k = 0$ is called the null hypothesis H_0. The alternative hypothesis is then, that β_k is $\neq 0$ (Stock & Watson, 2015).

$$t_k = \frac{\widehat{\beta_k} - 0}{SE(\widehat{\beta_k})} \qquad \text{XII}$$

At a 5% significance level, the critical value is 1.96 and the null hypothesis is rejected if $t > 1.96$. Computing the p-value is an alternative way of testing if $\beta_k = 0$. Assuming that the null hypothesis is correct, the p-value computes the probability of getting results as extreme as the observed results in the hypothesis test. Thus, the null hypothesis can be rejected with a 5% significance level, if the p-value is equal to or below 5% (Stock & Watson, 2015).

A confidence interval can be computed of the true value of the OLS estimators, $\beta_0,$ and $\beta_1, \dots, \beta_k$, using the standard errors of $\widehat{\beta_0},$ and $\widehat{\beta_1}, \dots, \widehat{\beta_k}$. A 95% two-sided confidence interval is calculated with the critical value of 1.96. As the variance of $\widehat{\beta_0},$ and $\widehat{\beta_1}, \dots, \widehat{\beta_k}$ is assumed to be normally distributed, 95% of the observations lie within 1.96 standard deviations. If the confidence interval contains zero, we would fail to reject the null hypothesis (Stock & Watson, 2015).

$$\beta_k^{95\%} = [\widehat{\beta_k} - 1.96 \times SE(\widehat{\beta_k}), \widehat{\beta_k} + 1.96 \times SE(\widehat{\beta_k})] \qquad \text{XIII}$$

4.6.2 Estimation issues

4.6.2.1 Multicollinearity

Perfect multicollinearity occurs when two independent variables are perfectly correlated. The OLS regression cannot be estimated if there is perfect multicollinearity. Imperfect multicollinearity occurs when two independent variables are highly correlated. The OLS regression can be estimated in this case, although at least one of the coefficients of the independent variables will be estimated with inaccuracy, i.e. with a higher variance than if the two independent variables were uncorrelated (Stock & Watson, 2015).

4.6.2.2 Omitted variable bias

If a variable which is correlated to any of the independent variables and which is a determinant of the dependent variable is omitted from the OLS regression, the OLS estimator will suffer from omitted variable bias. This means that the OLS estimator might not be reflect the true value and that of the error term u_i does not have a conditional mean of zero given X_i. The larger the correlation of the independent variable with the error term, the larger the bias. The direction of the bias is conditional on whether the covariance between the independent variable and the error term is negative or positive, as well as the sign of the OLS estimator (Stock & Watson, 2015).

$$\widehat{\beta_k} \xrightarrow{p} \beta_k + \rho_{X,u} \times \frac{\sigma_u}{\sigma_X} \qquad \text{XIV}$$

	$\boldsymbol{Cov(X, u) > 0}$	$\boldsymbol{Cov(X, u) < 0}$
$\boldsymbol{\beta_k > 0}$	Positive bias	Negative bias
$\boldsymbol{\beta_k < 0}$	Negative bias	Positive bias

4.6.2.3 Heteroskedasticity

The multiple OLS regression is homoscedastic if the error term has equal variance conditional on the given values of the independent variables. Even if the error term does not have equal variance, i.e. is heteroskedastic, the OLS estimators are still unbiased and consistent. However, the t-statistic will have a standard normal distribution using standard errors which are not homoscedastic. Consequently, the critical values will be inappropriate (Stock & Watson, 2015).

4.6.2.4 Autocorrelation of the error term

Autocorrelation of the error term often occurs in panel data and time series data, and results in the OLS estimator being biased an inconsistent. Consequently, the standard error (both homoscedastic and heteroskedasticity-robust) are inaccurate and the confidence intervals will also be inaccurate (Stock & Watson, 2015).

4.6.2.5 Sample selection bias

When data is missing, but at random, the sample size is reduced but it does not introduce bias. Similarly, when data is missing based on the value of the independent variable(s), the sample size will be reduced but no bias will be introduced. However, no conclusions would be possible on the excluded values of the independent variable(s). When data is missing as a result of a selection process which is associated to the dependent variable, the independent variable(s) will be correlated with the error term which will bias the OLS estimator (Stock & Watson, 2015).

4.6.2.6 Simultaneity causality bias

Simultaneous causality bias occurs when there is a causal relationship from the independent variable to the dependent variable and also a causal relationship from the dependent variable to the independent variable. This is also referred to as reversed causality and causes the independent variable to be correlated with the error term, introducing a bias in the OLS estimator (Stock & Watson, 2015).

5 Data description

The dataset consists of 35 accounting and stock market variables from the S&P Capital IQ platform (cf. Appendix D1), and 12 variables of ESG data from MSCI (cf. Appendix D2) and includes 5,450 companies. The data covers the timeframe from the end of January 2006 to the end of May 2019 with monthly observations. The following section will outline the variables used for the analysis and compare it to the two benchmarks used in this study, the MSCI World Index and the MSCI Emerging Markets Index.

The companies included in the dataset have been selected such that a certain level of liquidity is to be expected. The monthly average of the daily turnover of shares traded for a given stock must be larger than 10 million USD to be included in the dataset. In addition, there is a constraint on market capitalisation. For the last month in the dataset, the market capitalisation is set to a minimum of 2.5bn USD for the developed markets. Going back in time, the minimum market capitalization at every point in time is set such that it is represents the historic time-equivalent of 2.5bn USD at the most recent date in the dataset. The minimum market capitalization in emerging markets is set to 50% of the minimum of the developed markets for all time periods. This is done to match the overall time variation in the market capitalisation over time. As a result, the data extracted represents a realistic investment for an international investor, as potential worries regarding liquidity are mitigated.

5.1 Definition of ESG

Environmental, social, and governance (ESG) investing is a term that is often used interchangeably with sustainable investing, socially responsible investing, mission-related investing, or screening (MSCI, 2020f). It emerged from the desire to invest sustainably and addresses several investment objectives. There is neither a comprehensive glossary of all ESG terms in the prevailing academic literature or among practitioners (Giese et al., 2019) nor is “ESG investing” a protected term. This implies that financial institutions label different investment strategies with the term ESG. Due to the absence of clear definitions and terminology of ESG, this thesis follows the definition of the MSCI, that defines ESG investing as the consideration of environmental, social and governance factors alongside financial factors in the investment decision-making process (MSCI, 2020f). The MSCI focuses on so-called “Key Issues” when it comes to assessing companies with respect to the different E, S, and G pillars (MSCI, 2020f).

Environmental key issues include climate change, natural resources, pollution and waste, and environmental opportunities. Climate change criteria measure carbon emission, product carbon footprint, financing environmental impact, and climate change vulnerability. The natural resources assessment monitors water stress, biodiversity, land use and raw material sourcing of a company. Pollution and waste deals with toxic emissions, packaging material and electronic- and non-electronic waste. Environmental opportunities are assessed in clean technology, green buildings and renewable energy.

Social key issues look at a company’s human capital, product liability, stakeholder opposition, and social opportunities. In detail, human capital measures labour management, health and safety, human capital development and supply chain labour standards. Product safety comprises product safety and quality, chemical safety, financial product safety, privacy and data security, responsible investments, and health and demographic risk. Stakeholder opposition can be summarized as controversial sourcing practices. Social opportunities include access to communications, finance, and healthcare and opportunities in health and nutrition.

Governance refers to the corporate governance structure and the corporate behaviour of a company. Corporate governance aspects covers the board diversity, executive pay, ownership and control, and accounting standards. Corporate behaviour measures business ethics, anti-competitive practices, tax transparency, corruption and instability, and financial system stability.

While ESG integration, impact investing, and values-based investing are common ESG investing objectives (MSCI, 2018), this thesis focuses on establishing an investment strategy that systematically and explicitly includes ESG risks and opportunities in its capital allocation decision. While different ESG investing approaches exist, this thesis’ research question is based on a best-in-class selection, i.e. preferring companies with better or improving ESG profiles relative to sector peers.

5.2 MSCI ESG scores

The MSCI IVA (intangible value assessment) ESG scores covers more than 13,000 equity and fixed income issuers with available ratings on more than 6,800 companies. The ESG scores build on 37 ESG Key Issues which focus on both the core business of the company and industry issues which can represent considerable risks and opportunities for the company. The issues are then weighted based on a mapping framework created by MSCI to obtain scores which are based on the level of exposure and how the company is managing the issue. The scores are calculated both for the E, S and G issues separately, and an overall ESG score as well as an industry adjusted score are also calculated as final outputs. In addition, the ESG score is ranked in a letter rating from AAA to CCC, where the latter represents the worst score. Each letter score is based on a range of the Industry Adjusted Score (cf.Appendix D5) (MSCI, 2018).

The ratings are built around a framework where the most significant ESG risks and opportunities of the company or industry are identified. This considers the company's exposure to risks or opportunities, how well the company is managing the risks or opportunities as well as the overall outlook for the company compared to its industry peers (MSCI, 2018). Macro data from academic, government and NGO datasets are used to assess the industries and companies, as well as company sustainability reports, annual general meeting reports and proxy reports among other company specific disclosures. The ratings are intended to be relative to standards and performance of the peers of a given company within an industry and is calculated and the end of each calendar year as a forward-looking rating (MSCI, 2018). Appendix D3 shows an illustrative figure of MSCI's rating process and output.

5.2.1 Materiality

MSCI focusses solely on material risks and opportunities when rating a company. They define a risk as material when "it is likely that companies in a given industry will incur substantial costs in connection with it" (MSCI, p. 3, 2018), and an opportunity as material in an industry when "it is likely that companies in a given industry could capitalize on it for profit" (MSCI, p.3, 2018).

5.2.2 Scoring system

The final letter rating is based on aggregated weighted averages of the Key Issues Scores for the individual company and then normalised on industry level.

An issue which has a high environmental or social impact while having a short time to materialize will get the highest weight, while an issue with a low environmental or social impact with a long time to materialize will get the lowest weight. Similarly, in the relation to potential risks, a company with a high exposure to a risk must also have a more comprehensive management thereof to score well. If the company shows that it has developed strategies to manage their risks while also having a track record of managing its risks and opportunities, it will improve the management score (MSCI, 2018). The scoring of opportunities has a slightly different methodology compared to risks. The level of exposure represents the relevance of an opportunity to the current business of the company. The management score is based on the company's ability to capitalize on the opportunity. The lower the exposure to an opportunity, the more constrained the management score is (MSCI, 2018). A graphical representation of the assessment method of risks and opportunities can be found in Appendix D4.

Controversies are assessed on how critical the impact on the environment or society was, and are rated based on the scale of the impact (low to extremely widespread), but also the nature of the impact (minimal to egregious). Controversies trigger a large deduction in the Key Issue Score if they are considered to be a future material risk to the company and an indication of structural issues. However, if there is uncertainty about whether it is an indicator of future material risk, the deduction of the Key Issue Score will be smaller (MSCI, 2018).

The corporate governance Key Issue Score ranges on a scale from 0 to 10. However, the company starts with the highest score of 10, and points are deducted based on the evaluation of the 96 governance Key Metrics. The Key Metrics are parted on metrics related to the board, pay, ownership and control as well as accounting (MSCI, 2018).

The companies are tracked systematically and continuously. In November of every year, the Key Issues are reviewed, companies are analysed in-depth and new scores are calculated. The companies can participate in data verification before the ESG Ratings report is published, where they can provide more information as well as review and comment on the report. New information is incorporated into the reports weekly, and notable changes to the score will result in an analyst review and possibly a new rating outside the annual in-depth score review (MSCI, 2018).

The weighted ESG score, the industry adjusted score and the letter scores are provided in the dataset used for this study. Moreover, the individual E, S and G scores and their weights are also provided in the dataset. However, no insights are provided regarding the underlying annual 37 Key Issues and their weights.

5.3 MSCI benchmark indices

The MSCI World Index is the benchmark for the portfolios in the developed markets. The index constitutes of 1,637 companies as of May 2020, which are selected to reflect the variations in large and mid-cap equity in countries classified as developed markets (Appendix D7) (MSCI, 2020e). The MSCI Emerging Markets Index is the benchmark for the portfolios in the emerging markets. The index constitutes of 1,403 companies as of May 2020. Similar to the MSCI World Index, it is designed to reflect large and mid-cap equity variations in countries classified as emerging markets (Appendix

D7) (MSCI, 2020c). Both indices contain roughly 85 percent of the free float-adjusted[9] market capitalization of each country, and are downloaded from MSCI's database (MSCI, 2020a).

Given the minimum market capitalization of the dataset, these indices are deemed appropriate for the analysis, as they are all skewed towards higher market-cap companies. Close to perfect alignment of developed markets and emerging markets countries between portfolios and the benchmark is also made possible, as the data uses a similar classification of countries and regions[10].

5.4 Benchmark comparison

5.4.1 Regions

The data is split by the 11 MSCI regions to match the MSCI World Index as a benchmark for developed markets and the MSCI Emerging Markets Index for emerging markets. All countries within the regions included in the developed market data and the emerging market data are cross checked to align with the UNs list of developed and developing countries (developing countries referring to emerging markets) (United Nations, 2019). The full country list in each region is provided in Appendix D4 for.

Table 1: Developed and emerging markets split

Developed markets	Emerging markets
North America	Latin America
Europe	Eastern Europe
Pacific	Asia
Japan	Middle East / Africa

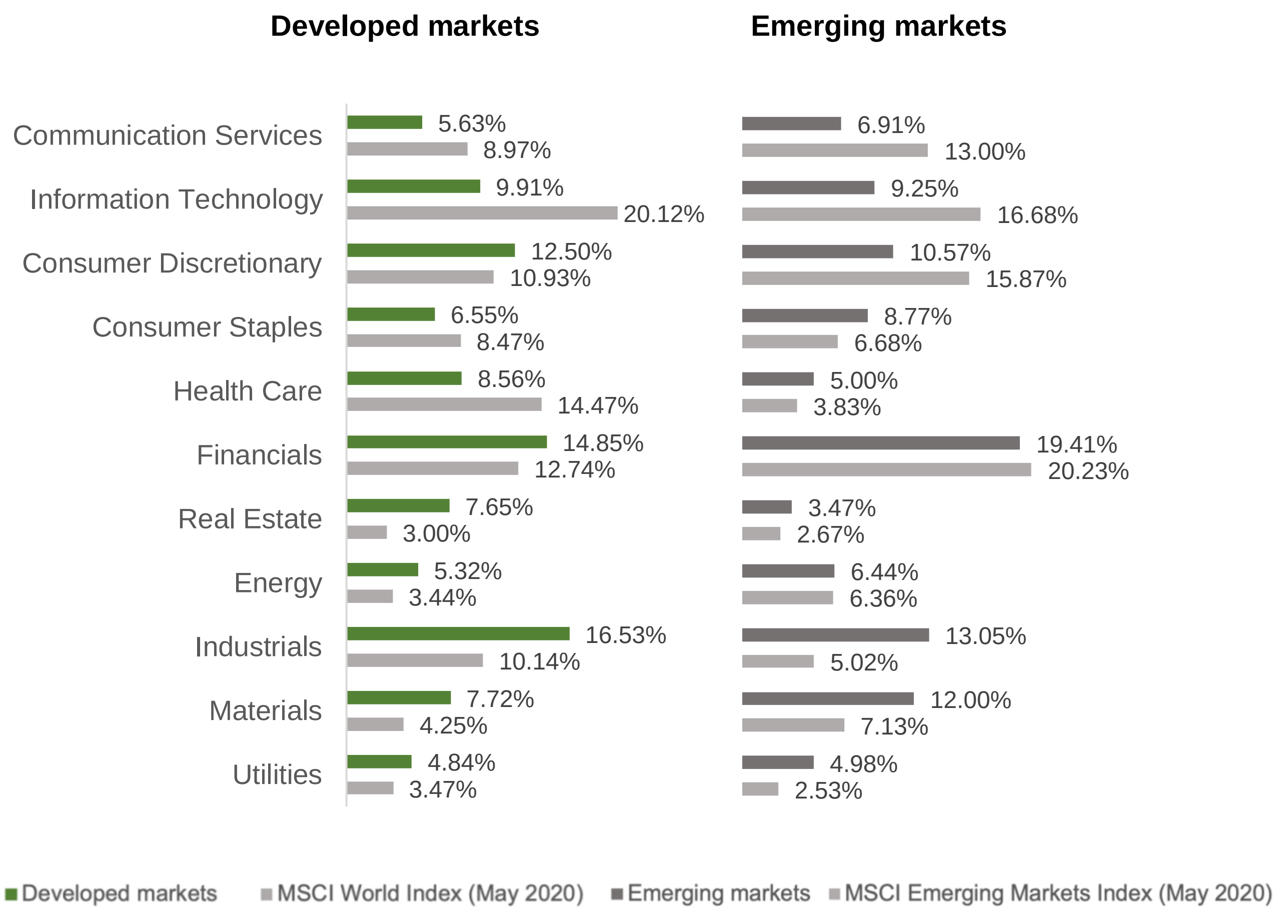
5.4.2 Sector composition

The sector composition of the data in the developed and emerging markets varies very little over the time period between January 2013 and May 2019 (in the range of 0.5 to 3 percentage points within a sector). The average annual composition as well as the benchmark indices as of May 2020 are illustrated in Figure 3. In the emerging markets, the financial sector has the highest share with an average of roughly 19 percent. Generally, financials, industrials and materials dominate the emerging markets with shares of roughly 19 percent, 13 percent, and 12 percent, respectively. In

[9] Free-float adjusted market capitalisation refers to the market capitalization calculated as the stock price multiplied by number of shares outstanding.
[10] Luxembourg, Greece, Cayman Islands and Bermuda is included in the developed markets but not in the MSCI World Index as of May 2020. Panama, Morocco and Israel are included in the emerging markets but not in the MSCI Emerging Markets Index as of May 2020. Greece is included in the developed markets, but was added in the MSCI Emerging Index in 2013 (MSCI, 2020a, 2020b, 2020c).

the developed markets, the materials, financials and consumer discretionary dominate with roughly 16 percent, 15 percent and 12 percent respectively. The real estate sector is notably smaller in the emerging markets at roughly 3 percent, compared to roughly 8 percent in the developed markets. The materials and financials sector are notably bigger in the emerging markets with percentage point differences of around 4 and 5 respectively. Generally, the sector compositions of the data on the two markets do not vary greatly. Hence, the company pools in both markets do not have large differences, which decreases the possibility for bias in the portfolio selection process towards specific sectors and increases the comparability of the markets.

Figure 3: Average annual sector composition 2013-2019



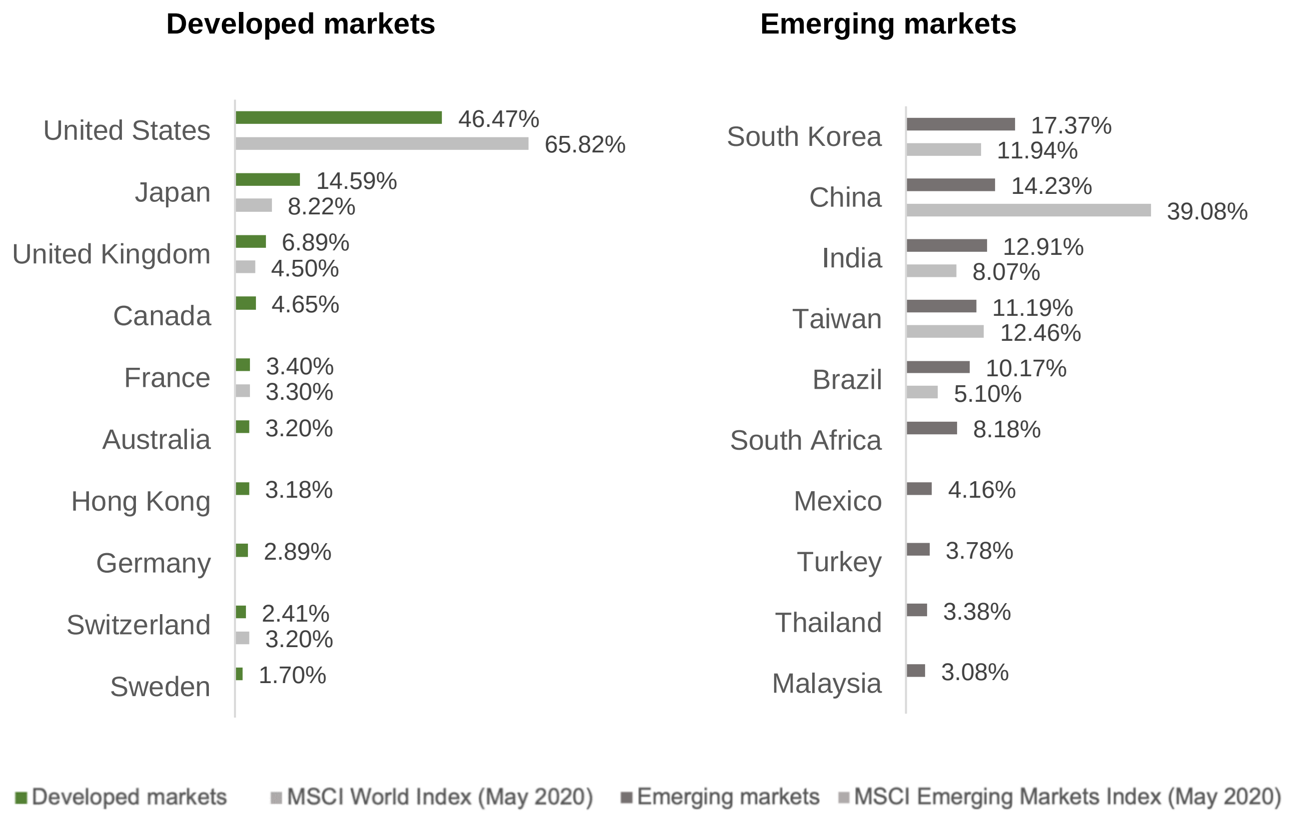
Source: Own contribution, benchmark data from the MSCI database (MSCI, 2020a).

Compared to the sector distribution of the benchmark markets, there are some noteworthy discrepancies compared to the dataset used in this study. In the developed markets, the information technology sector is roughly 10 percentage points smaller than in the MSCI World Index benchmark, while the industrial sector is roughly 7 percentage points larger. In the emerging markets, the information technology sector is also smaller compared to the MSCI Emerging Markets Index benchmark with roughly 8 percentage points. The industrial sector is roughly 8 percentage points bigger in the used dataset compared to the benchmark, while the communication services is roughly 6 percentage points smaller. As these differences change the selection pool, performance discrepancies between the portfolios and the benchmark may be influenced by sector specific factors. However, this depends on the specific sector distribution of the portfolio.

5.4.3 Country composition

The US constitutes a significant share of the stocks in the developed markets with roughly 46 percent. Another significant share of the stocks are Japanese, constituting roughly 15 percent. The distrubtion is similar to the MSCI World Index, where the US constitutes roughly 66 percent and Japan roughly 8 percent, with the remaining countries making up less than 5 percent each (MSCI, 2020e). The country composition is more evenly distributed for the emerging markets. South Korea has the highest share with roughly 17 percent, followed by China and India with roughly 14 and 13 percent respectively. In the MSCI Emerging Markets Index, China has a significantly higher share of roughly 39 percent, while India has a lower share of roughly 12 percent (MSCI, 2020c). In sum, the dataset is highly comparable to the benchmarks, and a representative selection of stocks is available compared to the market benchmarks used in the analysis.

Figure 4: Average annual country composition 2013-2019, top 10 countries



Source: Own contribution, benchmark data from MSCI factsheets (MSCI, 2020e, 2020c).

5.5 General metrics

The metrics in Table 2 serve mainly as a means of benchmarking the same metrics for the portfolios in the analysis.

Table 2: General metrics for developed and emerging markets

	Developed markets	**Emerging markets**
	Avg./median (min./max.)	*Avg./median (min./max.)*
Number of companies	4,329	1,121
Market capitalisation (USD bn)	17.56 / 7.25 (0.74 / 1,099.44)	16.47/ 7.57 (0.45 / 713.45)
Capital expenditure (USD bn)	-1.14 / -0.26 (-40.15/ 0.16)	-1.61 / -0.41 (-53.49/ 0.06)
ROE (%)	18.27 / 12.35 (-1,057.17 / 3,110.89)	16.71 / 13.19 (-97.57 / 373.41)
ROA (%)	6.05 / 5.00 (-21.52 / 175.15)	6.46 / 4.98 (-11.09 / 94.62)
Price-earnings ratio (P/E)	72.90 / 22.11 (-51,611.19 / 267,936.50)	36.57/ 18.99 (-60,487.80 / 43,785.39)
Enterprise value / EBITDA ratio (EV/EBITDA)	14.48/ 10.33 (-64,947.52/ 103,171.10)	4.52/ 9.84 (-51,219.33/ 34,440.12)
Debt-equity ratio (D/E)	2.32 / 1.31 (-388.43/ 334.74)	1.86 / 1.15 (0.04 / 42.50)
Book-to-market ratio (M/B)	0.44 / 0.32 (-73.50 / 63.01)	0.11 / 0.02 (-0.35 / 14.32)
Turnover (USD bn)*	0.10 / 0.042 (0/ 11.47)	0.037 / 0.017 (0/ 4.01)
Current ratio	3.92 / 1.52 (0.05 / 19,868.34)	1.72 / 1.43 (0.27 / 19.16)
ESG score**	5.03 / 5.00	3.92 / 3.80

** Average daily turnover (turnover = volume * price for most traded stock, in USD)*
*** the ESG score refers to the industry adjusted score*

The number of companies is significantly larger in the developed markets, which is mainly due to the data extraction conditions and data availability (cf. Data description). However, both markets contain a large amount of companies. The average market capitalization is similar in the two markets, although the minimum and maximum are smaller for the emerging markets. This suggests that there is a higher amount of companies in the upper range in the emerging markets compared to the developed markets. The average market capitalization in the benchmark for the MSCI World Index is higher, at 24.77 USD bn, while the average for the MSCI Emerging Markets Index is significantly lower at 3.74 USD bn as of May 2020 (MSCI, 2020c, 2020e). Thus, portfolios with a lower average market capitalization are expected in the developed markets, but much higher average market capitalization is expected in the emerging markets.

As expected, the average daily turnover is considerably larger in the developed markets than the emerging markets. However, emerging markets are ensured a reasonable liquidity by the turnover constraint in the data extraction. The median current ratio is also similar in both markets, including the range. The average ROE and ROA are also very close in both markets, although the range is significantly larger in the developed markets.

Given the general stock and accounting metrics of the companies in the dataset in the two markets, the differences in terms of liquidity risk seems to be substantially mitigated. Thus, there seems to be high comparability between the markets as alternative investment markets and the data represents a realistic investment universe for an empirical investor. In particular, the possible investment barriers in emerging markets are substantially mitigating with regard to liquidity.

6 Methodology

6.1 Data cleaning and preparation

6.1.1 Company and ESG data

6.1.1.1 Cleaning

The ESG and accounting and stock market data sets are combined by matching the end-of-month stock price with the ESG data from the beginning of the following month. Afterwards, the two datasets are merged by unique company ID and date to create a joint dataset of company and ESG data. However, there are several companies with the same company ID but with different company names, expressed in different notations and legal forms. These cases[11] display parent companies and their subsidiaries and all duplicates among these cases are eliminated.

In a next step, the authors examine the time series and find that November 2014 data in the ESG dataset is missing and that stock prices and other financial data throughout the dataset is occasionally displayed as “NAs”. The missing data is interpolated for every company. Numerical data is calculated as arithmetic mean of the previous and the subsequent month’s values for every company. Character entries are filled according to the previous months.

The dataset, in particular the stock price data, is checked for outliers and it is observed that some companies have occasionally been assigned a wrong company ticker and hence a wrong stock price.

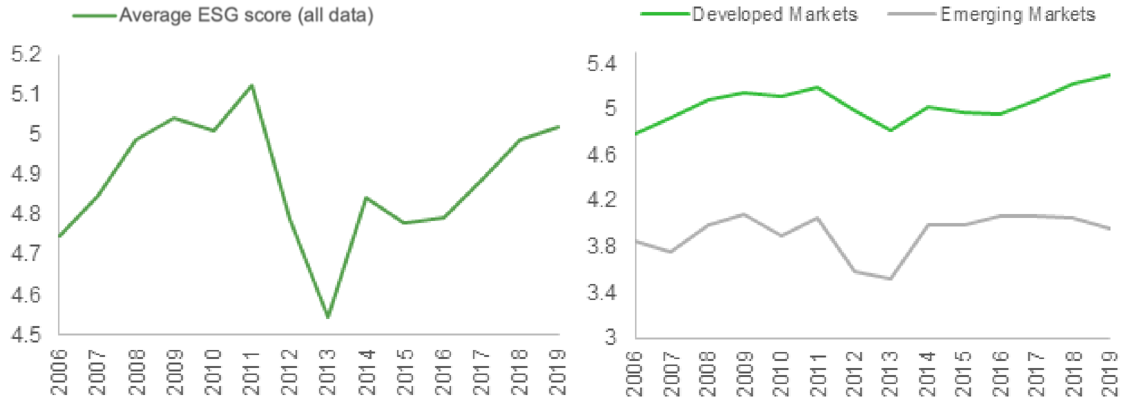
[11] Duplicates made up 2.55% of the total merged dataset.

This results in illogical stock price patterns. The authors check these companies' stock prices against the listings on Yahoo Finance and remove the error-prone rows. For every removed entry, missing data is interpolated using the aforementioned technique again.

6.1.1.2 Preparation

The authors subsequently pay closer attention to the metrics that are relevant for setting up the ESG momentum strategy. This examination reveals a structural change in the average ESG industry adjusted scores (henceforth "ESG scores"). As Figure 5 shows, there was a significant decline in the score around 2011 in both markets. One plausible cause for this decline could be that the number of companies significantly grew from 1,850 companies in 2011 to 3,259 companies in 2013 (Appendix M1). Around this time period, MSCI acquired a number of ESG research companies (MSCI, 2014), which might have increased their coverage and could have initiated the significant increase in companies.[12] Since the ESG score is a measure relative to the companies in one industry (cf. Data description), almost doubling the number of companies can significantly alter the average scores. Consequently, the authors conclude that the comparability of the scores across time and hence the quality of the analysis could be substantially compromised by considering the complete time horizon. Therefore, the data prior to January 2013 is excluded.

Figure 5: Average industry adjusted ESG score 2006-2019



Source: Own contribution

The authors continue to calculate the metrics that are relevant for setting up the ESG momentum strategy for developed and emerging markets separately.

In a first step, the monthly (m) stock price including dividends (P_i^m) for every company (i) is computed in order to capture the significant effect of dividends reinvested on the return.[13] The

[12] In particular we refer to the acquisition of RiskMetrics, KLD, Innovest and IRRC which were leading ESG research and analysis companies (MSCI, 2010, 2014).
[13] Dividends reinvested have the ability boost returns through the compounding effect (Brett, 2020).

authors adjust the given stock price $(adj.P_i^m)$ for the dividends a company pays by using a multiplier provided by the MSCI $(divAdjFactor_i^m)$.

$$P_i^m = adj.P_i^m \times divAdjFactor_i^m \qquad \text{XV}$$

Afterwards, the authors compute total monthly stock returns (r_i^m) representing the sum of the dividend return and the price appreciation.[14] A company's current stock price cum dividend (P_i^m) is divided by its value in the previous month (P_i^{m-1}).

$$r_i^m = \frac{P_i^m}{P_i^{m-1}} - 1 \qquad \text{XVI}$$

To generate value-weighted portfolios for the factor construction using the Fama & French (1992) approach, the authors compute weights (w_i^m) based on market capitalisation $(MarketCap_i^m)$.

$$w_i^m = \frac{MarketCap_i^m}{\sum_{i=1}^{N} MarketCap_i^m} - 1 \qquad \text{XVII}$$

Next, the ratios relevant for constructing a multi-factor model are calculated, such as the book-to-market ratio of equity ($(B/M)_i^m$). To retrieve the B/M ratio per company, its book value per share (BPS_i^m) is divided by its stock price (P_i^m).

$$(B/M)_i^m = \frac{BPS_i^m}{P_i^m} \qquad \text{XVIII}$$

To determine the momentum premium for every month, the authors follow Carhart (1997), and compute the trailing eleven months returns lagged one month $(R1YR_i^m)$ for every company.

$$R1YR_i^m = \frac{P_i^{m-1}}{P_i^{m-12}} - 1 \qquad \text{XIX}$$

6.1.2 Benchmark data

The MSCI World and the MSCI Emerging Markets Gross Index (gross dividends reinvested) are prepared as benchmarks by computing index returns based on the same formula as for the stock returns (eq. XVI). Both time series are normalised to 100 points ensuring better comparability later in the portfolio evaluation process. By choosing the MSCI Gross indices it is ensured that they match

[14] Incorporating dividends in the return calculation makes sense in the light of current ESG research asserting that there is a difference in related dividend payments between high- and low-ESG scoring companies (Giese et al., 2019; Gregory et al., 2014).

the portfolio return computation methodology that includes dividends and assumes their immediate re-investment into the portfolio.

6.1.3 Risk-free rate

Investors are not only interested in the returns that their assets yield but also in the amount that their investment exceeds the risk-free rate which represents their opportunity costs. In order to compute those excess returns, the authors applied the 1-year US treasury constant maturity rate expressed in percentages (r_f^y) from the FRED and adjust it to its monthly equivalent (r_f^m) (FRED Federal Reserve Bank of St. Louis, 2020).

$$r_f^m = \frac{r_f^y/100}{12} \qquad \text{XX}$$

This rate is selected because it is an adequate rate that an international investor would request as a hurdle rate. Since the currency-denoted data has been extracted through a common currency, it makes sense to use the same risk-free rate for both markets, assuming that the interest rate parity holds relatively well. Alternatively, the 1-month or 3-month US treasury constant maturity rate could have been chosen. Both rates behave similar to the 1-year rate but show slightly more extreme "peaks" (cf. Appendix M2). Moreover, since the 1-year rate is higher than the 3-month and 1-month rate in their annualized form, this offers a more conservative approach towards excess returns when using the 1-year rate, which seems preferable in the light of the analysis and investor profile. Note here, that some critics might say that the US treasury rate is too low and that rather a LIBOR rate should be taken into account since rates on loans are often linked to it (Schrimpf & Sushko, 2019). Since the LIBOR is a quoted rate and has been subject to manipulation in the past, the authors prefer a traded treasury rate.

6.2 Portfolio construction

The authors answer the research question through testing the sub-questions using a portfolio comparison approach where they compare a portfolio from the top end of the ESG momentum spectrum to one at the bottom end. This traditional approach is common in ESG research (Giese et al., 2019; Khan, 2019; Nagy et al., 2016). As it is the core of the ESG momentum strategy, the authors are particularly interested in how companies' ESG scores develop over time, i.e. whether their scores increase or decrease. In order to track this trend most adequately this thesis follows a two-step approach, where the provided ESG scores are first corrected for irrational movements and then a 12-month ESG momentum is calculated based on these adjusted ESG scores.

6.2.1 Adjusted ESG scores

First, the authors compute a 12-month simple moving average ($SMA(12)_i^m$) for every company's monthly industry adjusted ESG score (IAS_i^m) to track the average ESG score per company (i) over time and to smoothen out score volatility patterns.

$$SMA(12)_i^m = \frac{1}{12}\sum_{t=1}^{12} IAS_i^{m-12+t} \qquad \text{XXI}$$

This thesis selects a 12-month window because the in-depth ESG assessments take place on an annual basis. Hence, the SMA incorporates new information that potentially changes the ESG score and is further responsive to MSCI's weekly score reviews that might trigger a revaluation of a company due to the release of new and extraordinary ESG-relevant information (cf. MSCI ESG scores).

By smoothening the absolute ESG score over time using a SMA, the authors rule out that the ESG scores fluctuate significantly intra-year from month to month, which has been found to be the case for some companies. These significant up and down movements seem illogical to the ESG methodology and the authors want to ensure that they are not skewing the ESG momentum. The authors see their approach of smoothening the absolute ESG score as a quality check since a SMA affects companies with fluctuating ESG scores more than those with rather stable or trending ESG scores.

Alternatively, an exponential moving average (EMA) could have been chosen, that places more emphasis on the recent data points and thus responds more quickly to changing ESG scores. However, the choice of a 12-month SMA seems a better fit to the perspective of a medium- to long-term ESG-conscious investor who supports the long-term progression in the management of ESG risks and opportunities. The authors want to avoid potential 'noise' in a company's ESG trend, and not follow potential short-term, overheated reactions by the MSCI ranking, which would be captured by an EMA.

6.2.2 ESG Momentum

In a second step, the authors capture the general trend in ESG performance and calculate the 12-month change based on the SMA_i^m for every company and refer to it as "ESG momentum".

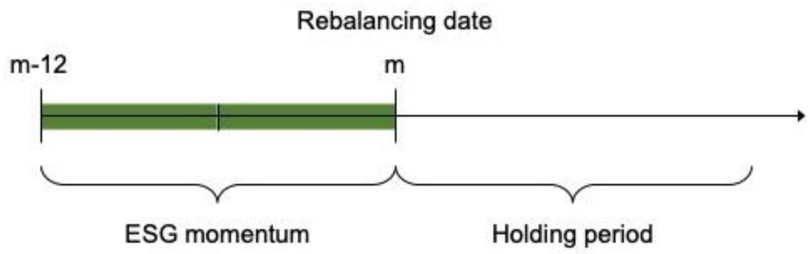
$$ESG\ momentum_i^m = SMA(12)_i^m - SMA(12)_i^{m-12} \qquad \text{XXII}$$

Such as 12-month window for detecting trends has also been the underlying basis for classical stock momentum strategies (Carhart, 1997b; Grinblatt & Titman, 2016; Jegadeesh & Titman, 1993).

Shorter windows have also often been tested in this context by academic scholars (Hong et al., 2000; Jegadeesh & Titman, 1993; Rouwenhorst, 1999), but seem suboptimal in the light of annual ESG score reviews. This approach to determining ESG momentum is closely linked to the research of other scholars that monitor material changes in ESG scores that affect stock prices (Giese et al., 2019; Khan et al., 2016; Nagy et al., 2016).

The authors will use their ESG momentum score to rank and determine top improving ("positive ESG momentum") and decreasing ("negative ESG momentum") companies at every selection / rebalancing date. Figure 6 illustrates a timeline of ESG momentum calculation and subsequent investment.

Figure 6: ESG momentum calculation timeline



Source: Own contribution.

The construction of ESG momentum requires company data 12 months prior to the rebalancing date. Consequently, the sample period will be from January 2014 to June 2019, and hence one year shorter than the cleaned dataset, due to the 12-month lag needed to construct the signal.

6.2.3 Holding periods

It is not obvious which holding periods are the most relevant when it comes to trading on ESG momentum due to the limited research on this particular trading strategy. In early studies of the stock momentum strategy, both short (months) and very long (years) holding periods were examined (Carhart, 1997b; Hong et al., 2000; Jegadeesh & Titman, 1993; Rouwenhorst, 1999). In general, stock momentum strategies have been found rather short-lived, indicating holding periods of several days to three months (Stickel, 1985).

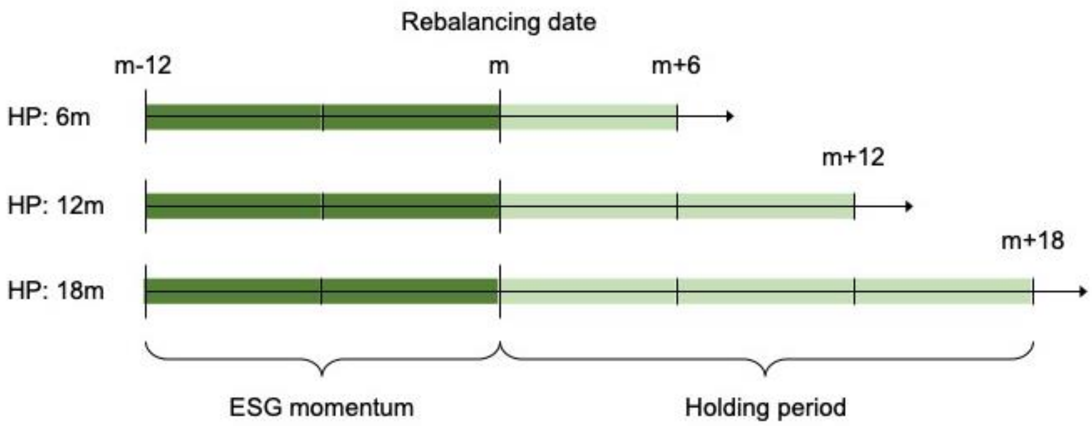
As opposed to stock prices, new ESG scores which can be traded on are usually released in annual ESG score reviews. Exemptions exist for extraordinary events and new information that affect a company's ESG score and these new scores are granted in a weekly review (cf. New information). Generally, however, ESG scores remain rather stable in between annual rating dates. Thus, rebalancing the portfolios more frequently than annually seems only partially value-adding since investors do not necessarily obtain new ESG information to trade on.

The authors hence assume longer holding periods than in a stock momentum strategy to be adequate for an ESG momentum strategy and test several longer time horizons for this strategy. The chosen holding periods are 6, 12, and 18 months. These holding periods start in the spectrum of classical stock momentum holding periods but also incorporate the reasoning that the optimal holding period for ESG momentum stocks could depend on how fast the market reacts to ESG information.

For example, the 6-month holding period represents a rather short holding periods assuming that the market incorporates changes in ESG scores in stock prices within half a year after the change. Longer holding periods represent a longer interval before market reactions, i.e. price effects, arise. However, there is still the possibility that other holding periods might be optimal for ESG momentum, but testing more periods is out of scope of this thesis. Figure 7 illustrates a timeline of ESG momentum calculation and subsequent investment over the three holding periods.

The selection and hence rebalancing of the portfolio take place end of December and June, dependent on the holding period. A detailed timeline visualising the ESG momentum calculation and the rebalancing dates for every holding period over the sample period can be found in Appendix M3.

Figure 7: ESG momentum and holding periods



Notes: "HP" stands for holding period.
Source: Own contribution.

6.2.4 Developed vs emerging markets

6.2.4.1 Company selection

Using the cleaned data universe for developed and emerging markets, the companies are sorted based on their ESG momentum (compare eq. XXII) from "high" to "low" at every rebalancing date. The authors are interested in the tails of this ESG momentum spectrum, in other words in capturing the top improving companies and comparing them to the worst decreasers. Therefore, the authors form deciles based on the ESG momentum spectrum and look at the top (top 10%) and bottom decile (bottom 10%) at every rebalancing date. These companies are experiencing either positive or negative ESG momentum, respectively.

This methodology of parting the dataset into quantiles of different kinds is common in academic practice (Carhart, 1997b; Fama & French, 1992; Hong et al., 2000; Jegadeesh & Titman, 1993; Khan et al., 2016). By choosing deciles, the authors ensure to capture out- and underperforming companies with respect to their ESG score development over the preceding twelve months. It is checked whether the number of companies in each decile is adequately high, ensuring that benefits from diversification (cf. Diversification) still exist. As a target, this thesis aims having minimum 30 companies to be available for investing. It is important to mention that since the number of companies in the dataset is not fixed but rather increasing, the deciles which represent percentages of this data will also increase over time.

6.2.4.2 Portfolio formation

In a next step, the authors investigate whether the companies in the top and bottom decile at each rebalancing date are present over the whole holing period. Companies can exit the data due to several reasons. A company might exit due to bankruptcy, an acquisition or a merger, or because it falls below the market capitalisation or stock liquidity threshold, amongst others. Since it is not obvious, which of the reasons apply, the authors decided to remove companies that leave the dataset over the holding period from the decile, and hence the portfolio. This process will reduce the number of companies selected by 1-5 companies per decile but will still result in an adequate number close to the aim of 30 companies per portfolio.

These narrowed deciles form the ESG momentum portfolios. The authors will assume investment in these portfolios over the subsequent holding period via either a long improving (top decile) or a long decreasing (bottom decile) portfolio. The investment process starts with an initial investment (I_p) of 100 USD equally split over all N companies (i) the day after the first rebalancing date $(I_i^{01/01/2014} = \frac{1}{N} \times 100)$. The value of the portfolio is hence starting at 100 USD and falls and rises with the development of the stocks it consists of. Hence, the monthly return of the portfolio (r_p^m) will be computed based on the monthly changes on its value (V_p^m).

$$V_p^m = \sum_{i=1}^{N} r_i^m \times I_i^{m-1} \qquad \text{XXIII}$$

$$r_p^m = \frac{V_p^m}{V_p^{m-1}} - 1 = \sum_{i=1}^{N} w_i^{m-1} \times r_i^m \qquad \text{XXIV}$$

At every rebalancing date the value of the portfolio will be equally invested into the new set of portfolio companies, i.e. the newly selected companies with the highest (top decile) and lowest (bottom decile) ESG momentum. This methodology mitigates size heterogeneity between the different companies included in the portfolio, as opposed to market-cap weighted portfolios.

This approach implicitly assumes that stock splits are possible and neglects transaction costs that arise when selling and buying stocks at the rebalancing date.[15] However, this thesis will report on the turnover from which differences in transaction costs can be inferred. In both markets, the portfolio formation approach results in the construction of a top and a bottom portfolio for every holding period, which leads to 12 portfolios in total.

6.2.5 Markets conditional on performance groups

6.2.5.1 Construction of performance groups

The fourth research question (Q4) postulates that improving from a low ESG score as opposed to from a high ESG score results in a more substantial price effect. In order to examine this hypothesis, the authors need to categorise the companies accordingly. They part both the developed as well as the emerging markets data into three groups, that they henceforth refer to as “performance groups”. The companies are ranked based on their ESG score from “high” to “low” and use terciles to part the in groups labelled “high”, “average” and “low”. The cut-off points for the performance group “low”, “average” and “high” are presented in Table 3 and remain static over time.

Table 3: Performance group classification

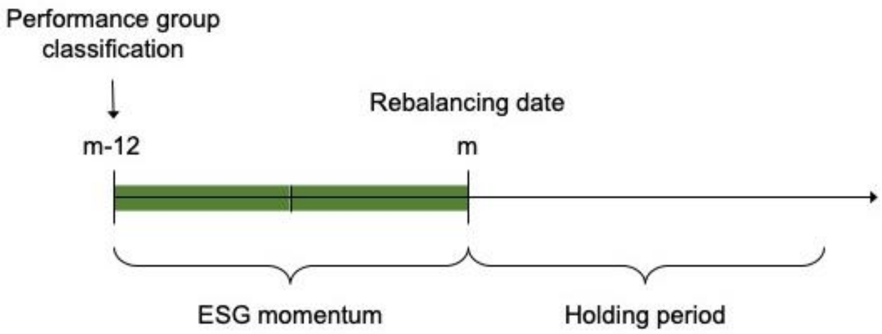
	Developed markets				Emerging markets			
Performance group	⟵ Low ⟶	⟵ Average ⟶		⟵ High ⟶	⟵ Low ⟶	⟵ Average ⟶		⟵ High —
Threshold	0%	33.3%	66.6%	100%	0%	33.3%	66.6%	100%
ESG Score	0.0	3.9	6.1	10.0	0.0	2.7	5.0	10.0

Source: Own contribution.

The categorisation of companies into the three performance groups takes place 12 months prior to the rebalancing date and thus, the selection of companies in the three performance groups can change over the sample period. The date of categorisation represents the same point in time at which the ESG momentum is computed (cf. eq. XXII). Thereby the authors ensure that ESG momentum is calculated based on either a low, average or high ESG score (cf. Figure 8).

[15] Such fees may be taxes, broker commissions, amongst others, that are due at the rebalancing date.

Figure 8: Performance group classification and ESG momentum



Source: Own contribution

MSCI has its own process of classifying companies based on their industry adjusted ESG scores into “leaders”, “average” or “laggards” but does not distinguish between developed and emerging markets (cf. Appendix D4). Due to the scope of the analysis, it is crucial to recall that companies among the emerging markets have lower ESG scores (cf. Table 2). As a result, implementing the overarching categorisation made by the MSCI on both developed and emerging markets would result in very few companies in the performance group “high” in emerging markets and hence in the corresponding ESG momentum portfolio. This would significantly compromise the quality of the analysis, by substantially decreasing diversification and consequently make the results highly dependent on individual stocks. Thus, the authors implement tercile-based cut-off points to the distribution of ESG scores in the two markets. This approach lowers the cut-off points for the emerging markets data and hence increases the pool of companies in the highest performance group. For developed markets, implementing the aforementioned cut-off points, results in performance groups which are very close to the ones defined by the MSCI.

The approach of applying distinct cut-off points to determine performance groups in developed and emerging markets allows for a more nuanced understanding of the relative performance of ESG momentum (Q4). The authors believe that their approach is the optimal method given the drawbacks of using the MSCI classification.

6.2.5.2 Company selection

The authors take the performance group-adjusted datasets to select top improving and worst decreasing companies for the portfolios conditional on a company’s performance group. This process is similar to the selection process of companies for the general market portfolio. However, the authors have to apply an additional pre-screening. They classified companies into three performance groups 12 months prior to a rebalancing date. Again, they do not know whether these companies continue to exist in the dataset, and whether they will be available for an ESG momentum assessment at the rebalancing date. Moreover, in order to compute the SMA (cf. eq. XXI) that the ESG momentum is based on, the authors have to ensure that the company also exists 12 months prior to the performance group classification date, i.e. in total 24 months prior to the selection date. In a last step, the authors test whether a company is available in the investment period, as it is done for the general markets.

When constructing the top and bottom quantiles the companies in each performance group are ranked at every rebalancing date based on their ESG momentum (cf. eq. XXII) from “high” to “low”. The top decile (top 10%) in developed markets and at the top tercile (top 33.3%) in emerging markets are compared to their respective bottom counterpart. The decision of taking terciles instead of deciles in the emerging markets performance groups is due to the circumstance that the number of companies to invest in significantly declines when parting the data into performance groups and the related screenings. Taking the top and bottom decile would compromise the diversification of the portfolios by making the performance highly sensitive to single stocks. A similar differentiation for forming portfolios based on the two markets has been made by Rouwenhorst (1999). The authors acknowledge that terciles might still be prone to ‘noise’ and might hence not capture the tails of the ESG momentum spectrum sufficiently.

6.2.5.3 Portfolio formation

The portfolio formation methodology and computation of the corresponding metrics for the top and bottom portfolio for every performance group follows the same approach as the one for the general markets (cf. eq. XXIII & XXIV). In both markets, the portfolio formation approach results in the construction of a top and a bottom portfolio for every performance group and holding period, which leads to 36 portfolios in total.

The analysis examines 48 portfolios in total in order to tackle the research question and sub-hypotheses Q1 to Q4.

6.3 Portfolio evaluation measures

This section introduces the evaluation metrics that are used to analyse the ESG momentum portfolios from both a performance and a risk perspective. The authors compare the portfolios of top improving and decreasing companies to each other but also to their relevant benchmark. These metrics give additional insights into the characteristics of ESG momentum.

6.3.1 Performance measures

6.3.1.1 Expected return

The expected monthly return $(E[r_p^m])$ for a given portfolio (p), will be calculated using the portfolio's historical monthly returns over the sample period[16].

$$E[r_p^m] = \frac{1}{M}\left(\sum_{m=1}^{M} r_p^m\right), \forall \text{ m} = 1, \dots, 65 \qquad \text{XXV}$$

As it is a standard practice to express returns on an annual basis when assessing a portfolio's ex post performance, the authors annualise the average monthly return using compounding. The expected annual return $(E[r_p^y])$ is consequently the arithmetic mean of the annualised monthly returns.

$$E[r_p^y] = \frac{1}{M}\sum_{m=1}^{M}\left(\left(1 + r_p^m\right)^{12} - 1\right), \forall \text{ m} = 1, \dots, 65 \qquad \text{XXVI}$$

6.3.1.2 Volatility

In order to assess the risk of the portfolios, the authors compute the historical monthly volatility (σ_p^m) of the portfolio and annualise it for obtaining a portfolio's average annual volatility (σ_p^y).

$$\sigma_p^m = \sqrt{\frac{1}{M-1}\left(\sum_{m=1}^{M}\left(r_p^m - E[r_p^m]\right)^2\right)}, \forall \text{ m} = 1, \dots, 65 \qquad \text{XXVII}$$

$$\sigma_p^y = \sigma_p^m \times \sqrt{12} \qquad \text{XXVIII}$$

6.3.1.3 Sharpe ratio

While the expected return and its corresponding volatility are key metrics to assess the attractiveness of a single portfolio, they are less informative for comparing the performance across portfolios. In order to compare portfolios with different expected returns and volatilities to each other, a risk-adjusted reward measure should be taken into account. One risk-reward measures is the Sharpe ratio (SR_p^m) which quantifies the expected excess return ("risk premium") per unit of risk (Bodie, Kane, & Marcus, 2013).

[16] The sample period consists of 65 monthly observations.

$$SR_p^m = \frac{E[r_p^m] - r_f^m}{\sigma_p^m} \qquad \text{XXIX}$$

As for the expected return and volatility, the authors are interested in an adequate estimate of the SR on an annual basis (SR_p^y).

$$SR_p^y = \frac{\frac{1}{M}\sum_{m=1}^{M}\left(\left(1 + \left(r_p^m - r_f^m\right)\right)^{12} - 1\right)}{\sigma_p^y}, \forall \text{ m} = 1, \dots, 65 \qquad \text{XXX}$$

This thesis assumes that investors prefer large expected returns and low risk, hence they wish to see high Sharpe ratios. The Sharpe ratio is often taken into account by investors, although it takes positive, desirable, deviations from the expected return to the same amount into considerations as negative deviations (Bodie et al., 2013).

6.3.1.4 Information ratio

For assessing a portfolio’s ability to generate risk-adjusted excess returns relative to its benchmark, the authors compute the information ratio (IR_p^m), i.e. the ratio of a portfolio’s expected active return to its idiosyncratic risk (Bodie et al., 2013). The information ratio states how far the portfolio will move away from the well-diversified market portfolio.

$$IR_p^m = \frac{E[r_p^m - r_b^m]}{Std(r_p^m - r_b^m)} \qquad \text{XXXI}$$

This ratio can be looked at to determine how much of a portfolio’s return is attributable to its abnormal return as opposed to its market exposure. The higher the information ratio, the better. The active return ($E[r_p^m - r_b^m]$) will be annualised according to eq. XXVI and the tracking error ($Std(r_p^m - r_b^m)$) as in eq. XXVIII to obtain the annualised information ratio.

6.3.1.5 Benchmark correlation

In order to get an overview of a portfolio’s correlation with its benchmark, the authors measure its correlation using Pearson’s correlation coefficient ($\rho(p,b)$) (Bodie et al., 2013).

$$\rho(p,b) = \frac{\sum_{m=1}^{M}(r_p^m - \overline{r_p^m})(r_b^m - \overline{r_b^m})}{\sqrt{\sum_{m=1}^{M}\left(r_p^m - \overline{r_p^m}\right)^2\left(r_b^m - \overline{r_b^m}\right)^2}} \qquad \text{XXXII}$$

6.3.1.6 Total return index

Based on the historical returns of the portfolios, the authors will construct and graphically visualise a total return index (TRI_m) in order to track a portfolio's monthly performance over time and to compare it to its counterpart and benchmark. The TRI will be indexed to 100 at the date 01-01-2014.

$$TRI_m = TRI_{m-1} \times (1 + r_p^m) \qquad \text{XXXIII}$$

The authors are interested in the high water marks (HWM_m) of the index, indicating the highest peak in value that the TRI has experienced up to a specific point in time (s). Comparing the current TRI level to the HWM gives investors an indication of how a portfolio performed most recently.

$$HWM_m = \max_{\mathrm{m \leq s}}\{TRI_m\} \qquad \text{XXXIV}$$

The end-of-sample-horizon RI, corresponding to 05-2019, and the maximum HWM are presented as performance measures for each portfolio in the analysis.

6.3.2 Risk measures

6.3.2.1 Maximum drawdown

The drawdown (DD_m) represents a portfolio's peak-to-trough loss in between HWMs. It is a measure of downside volatility indicating the riskiness of a portfolio.

$$DD_m = \frac{HWM_m - RI_m}{HWM_m} \qquad \text{XXXV}$$

This thesis reports the maximum DD as a risk management measure to illustrate the maximum decline that a portfolio has experienced over its investment horizon.

6.3.2.2 Skewness

In order to give an indication of severe deviations from normality in the return distributions that are not adequately captured by a portfolio's volatility, the authors further look at the skewness of the distribution $(Skew)$.

$$Skew = \frac{\frac{1}{M}\sum_{m=1}^{M}\left(r_p^m - \overline{r_p^m}\right)^3}{\left(\frac{1}{M}\sum_{m=1}^{M}\left(r_p^m - \overline{r_p^m}\right)^2\right)^{\frac{3}{2}}} \qquad \text{XXXVI}$$

The skewness can reveal asymmetries in the tails of a distribution. A positive skewness shows a long tail over positive returns. A negative skewness indicates long tails with regard to negative returns. Such a situation is what investors aim to avoid since it can indicate more adverse losses that are underestimated when looking at a portfolio's volatility (Bodie et al., 2013).

6.3.2.3 Kurtosis

The kurtosis measures the degree of fat tails in the return distribution.

$$Kurtosis = \frac{\frac{1}{M}\sum_{m=1}^{M}\left(r_p^m - \overline{r_p^m}\right)^4}{\left(\frac{1}{M}\sum_{m=1}^{M}\left(r_p^m - \overline{r_p^m}\right)^2\right)^2} \qquad \text{XXXVII}$$

A distribution with a kurtosis larger than 3 has fatter tails than the normal distribution, which means that there is a higher than normal probability of large positive and negative return realizations. Conversely, a kurtosis smaller than 3 indicates flatter tails and hence a lower possibility of large positive and negative return realizations. Higher frequency of extreme negative returns may result from a negative skew and / or a high kurtosis.

6.3.2.4 Value at risk (VaR)

Investors are particularly concerned about this left tail of return distributions and their vulnerability to it. The value at risk (VAR) is the maximum loss over a month with a certain probability (p). The authors calculate the 5% VaR based on the historical, ex post, portfolio return distribution instead of theoretical values based on a normal distribution. They sort the monthly observations from high to low and select the VaR as the 5th percentile of each portfolio's returns over the sample period.

$$VaR_p = q_{0.95} \qquad \text{XXXVIII}$$

A drawback of the VaR is that the VaR constitutes a minimum loss. For the 5% of occasions where the loss exceeds the VaR, it is not evident by how much. As the VaR measures monthly occurrences, the authors do not need to annualize it to compare it to other portfolios.

6.3.2.5 Expected Shortfall

While the VaR assesses tail risk looking at the minimum loss in the 5% worst case scenario, a more realistic view on downside exposure is provided by the expected shortfall (ES_p) given the worst case scenario (Bodie et al., 2013).

$$ES_p = E[Loss \mid Loss > VaR_p] \qquad \text{XXXIX}$$

The expected shortfall measures the value of the average loss exceeding the 5% VaR. The authors choose the historical expected shortfall based on the ex-post return distribution as for the VaR. The magnitude of the expected shortfall is very important and by definition exceeds the VaR.

6.3.3 CAPM alpha and market exposure

In order to test the research question Q1, Q2, and Q4, this thesis builds on the CAPM-based single-index model (cf. CAPM). The returns of the benchmarks MSCI World and MSCI Emerging Markets are calculated following equation XVI. The excess returns are computed using the 1-year US Treasury constant maturity rate for all holding periods, to allow for better comparison of the regression results.

$$r_p^m - r_f^m = \alpha_p^m + \beta_p \times \left(r_m^m - r_f^m\right) + \varepsilon_p^m \qquad \text{XL}$$

The authors are looking at alpha and beta of this equation and their significance level. Alpha postulates the abnormal return that they want to examine in order to accept or reject the research questions and is typically interpreted as a measure of out- or underperformance relative to the market proxy.

6.3.4 Multi-factor alpha and factor exposure

6.3.4.1 Multi-factor model

Acknowledging the increased explanatory power of multi-factor models to decomposing portfolios' excess returns, the authors include three additional explanatory variables in the model (cf. The Fama French three factor model & The Carhart four factor model). The coefficients on these factors can help attribute a proportion of a portfolio's excess return to four widely pursued investment strategies.

$$r_p^m - r_f^m = \alpha_p^m + \beta_m\left(r_m^m - r_f^m\right) + \beta_S SMB^m + \beta_H HML^m + \beta_W WML^m + \varepsilon_p^m \qquad \text{XLI}$$

In this context, this thesis is interested in the sign and magnitude of alpha in order to compare the performance of the top and bottom portfolios to each other (Q2). In order to test the other hypotheses, the authors are interested in the significance and magnitude of alpha when comparing developed and emerging markets (Q3) and the different performance groups to each other (Q4).

6.3.4.2 Factor construction

Consistent with the methodology of Fama & French (1992) and Carhart (1997) (cf. Theory), the authors form double-sorted portfolios to construct the SMB^m, HML^m and WML^m risk premia.

They first rank all companies based on market capitalisation and sort them from small ("Small") to large ("Big") for every month and by splitting the sorted data in two equally sized portfolios. Next, they rank the companies for every month based on their book-to-market ratio (cf. eq. XVIII) from low ("Growth") to high ("Value") and divide them into a "Growth", "Neutral", and "Value" portfolio using a 30%-40%-30% split, respectively. This double sort creates six categories of stocks: "Small-Value" (SV), "Small-Neutral" (SN), "Small-Growth" (SG), "Big-Value" (BV), "Big-Neutral" (BN), and "Big-Growth" (BG). Based on this classification, the so called 2x3 stock portfolios are constructed.

For each month the authors also sort the stocks based on their 11-month lagged one month return ($R1YR$, cf. eq. XIX) from high ("Winners") to low ("Losers") and split the companies into a "High", "Medium", and "Low" portfolio, using a 30%-40%-30% split. By combining this sort with the size classification, six portfolios are obtained: “Small-High (SH)”, “Small-Medium (SM)”, “Small-Low (SL)”, “Big-High (BH)”, “Big-Medium (BM)”, and “Big-Low (BL)”.

For each of the aforementioned portfolios, monthly value-weighted (cf. eq. XVII) returns are computed.

$$r^{m}_{p,value-weighted} = \sum_{i=1}^{N} w^{m}_{i} \times r^{m}_{i} \qquad \text{XLII}$$

To obtain the SMB^m factor, the authors calculate the monthly return difference between the “Small” and the “Big” portfolios.

$$r^{m}_{SMB} = SMB^m = \frac{r^{m}_{SV} + r^{m}_{SN} + r^{m}_{SG}}{3} - \frac{r^{m}_{BV} + r^{m}_{BV} + r^{m}_{BV}}{3} \qquad \text{XLIII}$$

The HML^m factor is constructed computing the excess return of the “Value” portfolios over the “Growth” portfolios.

$$r^{m}_{HML} = HML^m = \frac{r^{m}_{SV} + r^{m}_{BV}}{2} - \frac{r^{m}_{SG} + r^{m}_{BG}}{2} \qquad \text{XLIV}$$

Lastly, WML^m is the return difference between the “High” portfolios over the “Low” portfolios.

$$r^{m}_{WML} = WML^m = \frac{r^{m}_{SH} + r^{m}_{BH}}{2} - \frac{r^{m}_{SL} + r^{m}_{BL}}{2} \qquad \text{XLV}$$

These three factors are computed based on the developed markets and emerging markets raw data separately. All factor portfolios are value-weighted. Fama and French construct the factors (including momentum) separately for developed and emerging markets based on their data library, however, their split into the two markets is not fully congruent with the authors’ classification of the two markets. Therefore, the factors were computed manually to better match the dataset.[17]

6.3.4.3 OLS model estimation and inference

The authors explore differences in returns between the top and bottom portfolio for each holding period using Student’s t-test (cf. Appendix M4). They investigate whether the difference in returns is statistically different from zero at a 5% confidence level using Welch’s approach which assumes unequal variance between the two return series (Stock & Watson, 2015). The authors then estimate

17 As to check for potential deviations in the data universes to the Fama French universe, we compute the correlation between the factors. For developed markets, the factors show a very high correlation to the Fama French factors, but less so for emerging markets (cf. Appendix M5).

the multi-factor model for every portfolio using OLS regressions with the individual portfolio's excess returns as the dependent variable and the four factors premia being the independent variables.

6.4 Econometric considerations

This sections returns to the underlying assumptions of OLS models and the steps that can be taken in order to determine whether those assumptions have been violated (cf. OLS Assumptions). This section is devoted to test and discuss whether the chosen models are in conflict with the most critical econometric assumptions. The methodology and test results can be found in the corresponding appendix. The section concludes with an approach to address model problems, should they be encountered.

6.4.1 Multicollinearity

Since the models are based on widely used and well-researched factors, the authors expect multicollinearity not to be an issue. However, when facing multicollinearity, the concerned explanatory variables have to be removed. As the correlation matrices in Appendix M6 show, some of the explanatory variables show higher degrees of correlation than others. The authors assess the significance of multicollinearity by computing the variance importance factor (VIF_i) following the steps as presented in Appendix M7. The test results imply that multicollinearity is not present in the model.

6.4.2 Heteroscedasticity

The authors further run a Breusch-Pagan test against heteroscedasticity on the models. The Breusch-Pagan test fits a linear regression model to the residuals of our models and rejects the null hypothesis of homoscedasticity if too much of the variance is explained by the additional explanatory variables. It is observable that heteroscedasticity is present in some of the models (cf. Appendix M8) denoted by the test statistic exceeding the critical values for the single index or multi-factor model.

6.4.3 Autocorrelation

Autocorrelation in the residuals might be an issue when omitted factors are autocorrelated. The Breusch-Godfrey test allows the authors to separately test for positive and negative autocorrelation. The results can be found in Appendix M9 and indicate that autocorrelation is indeed an issue in some of the models.

6.4.4 Standard errors

In order to account for heteroscedasticity and autocorrelation in the models, the authors use heteroskedasticity and autocorrelation-consistent (HAC) standard errors following the methodology of Newey and West (Newey & Kenneth, 1987). These standard errors are valid whether or not there is heteroskedasticity, autocorrelation, or both (Stock & Watson, 2015). This adjustment will increase the standard errors for all regression coefficients and will only make the models that do not inhibit autocorrelation or heteroscedasticity more conservative (Stock & Watson, 2015).

6.4.5 Outliers

In order to check whether some of the stock returns computed are atypical from the rest, the authors check all single stocks' returns that are included into a portfolio for outliers using graphical plots (results untabulated). The authors already checked for outliers, incorrect company tickers, and erroneous entries in the data cleaning process and consequently do not find extreme values in the portfolios.

6.5 Selection biases

6.5.1 Sample size and liquidity bias

The dataset and company selection process entail important considerations for interpreting the overall regression results. The data was extracted with a threshold for market capitalisation and liquidity. The dataset only contains large and highly liquid companies that allow their stocks to be traded at rebalancing dates. This threshold in combination with the data cleaning process, will result in a homogenous universe of large, well-established companies and hence our findings will be valid for this type of companies.

6.5.2 Time horizon bias

The selected investment horizon contains 65 monthly observations from January 2014 to June 2019. The time horizon hence started well after the financial crisis and has been characterised by a very large bull market in developed markets. It is possible that the analysis would result in diverse findings under different market conditions, such as e.g. a bear market. These additional robustness tests are out of scope of this thesis and subject to empirical testing.

6.5.3 Survivorship bias

A survivorship bias exists when the average return of a sample of funds is biased by excluding past returns on funds that left the sample because they happened to be unsuccessful (Bodie et al., 2013). This can lead to overly optimistic beliefs about an investment strategy because failures are ignored, such as when companies that no longer exist are excluded from analyses of financial performance (Bodie et al., 2013). It can also lead to the false belief that the outperformances in a group have some special property, rather than just coincidence (Elton, Gruber, & Blake, 1996). In small as well as large samples, this sensitivity to the future survival of stocks does not allow to evaluate portfolios adequately (Grinblatt & Titman, 2016). In the selected sample period, this thesis explicitly assumes that a company is existent over the complete holding period. If not, the authors exclude this company from the ESG momentum portfolio. In reality, such a pre-screening is not possible and therefore, the performance of our strategy executed under real market conditions may not yield the same results.

7 Analysis

The following chapter presents the empirical results. The first section reports on the portfolios based on the general developed and emerging markets data while the second section focuses on both markets divided into performance groups. The sections will present turnover rates and discuss every portfolio from an ESG perspective. Graphs illustrating the sector distributions of the distinct portfolios can be found from Appendix A2 onwards. In order to detect patterns and examine what type of companies constitute the different portfolios, accounting- and market based KPIs are also presented. The main part of the analyses, however, will focus on the historical performance and risk profile of the portfolios and their ability to generate significant alphas as postulated in the research question.

Since the portfolios show recurring patterns throughout the analysis, the authors will comment on them in a more elaborate way when they are presented for the first time, and only refer to them briefly later on. Note that the portfolio description is very detailed and that it aims at giving a broad overview. Connections between the results and the research sub-questions will be established in the sub-conclusions at the end of each section. If the reader wishes to move directly to the summary of our results or to relate our results to our research question, it is recommend reading these two sub-conclusions before reading the detailed portfolio descriptions.

7.1 General markets

7.1.1 Developed markets

The annualised turnover is lowest for the 6-month holding period, while the highest annualised turnover is observed for the 18-month holding period (cf. Table 4). The turnover and the average number of companies are very similar for both the top and bottom portfolios. By construction, the number of companies in the top and bottom portfolios should be similar (cf. Methodology). Consequently, no big differences are expected in terms of transaction costs between the top and bottom portfolios in the respective holding periods. However, since the average number of companies vary with the holding period and since shorter holding periods results is increased number of rebalancing times, the transaction costs can vary significantly with different holding periods.

Table 4: Portfolio turnover

	Top portfolio			**Bottom portfolio**		
Holding period	Avg. turnover	Annualized turnover*	Avg. no. companies	Avg. turnover	Annualized turnover*	Avg. no. companies
6 months	58%	58%	174	59%	58%	176
12 months	86%	86%	167	87%	87%	167
18 months	94%	63%	150	93%	62%	154

**Notes: For the turnover calculation cf. Appendix A1.*

Table 5: Average industry adjusted ESG score

	Top portfolio				Bottom portfolio			
Holding period	Δ SP	BOHP	HP	Δ HP	Δ SP	BOHP	HP	Δ HP
6 months	1.9	5.72	6.13	0.17	-1.7	4.29	4.15	-0.06
12 months	1.9	5.72	6.06	0.47	-1.6	4.30	4.25	0.17
18 months	1.6	5.67	5.85	0.21	-1.4	4.35	4.48	0.17

**Notes: Δ SP = change over selection period, BOHP = score at the beginning of holding period, HP = holding period, Δ HP = change over holding period, the ESG score change refers to changes in the SMA (cf. Adjusted ESG scores).*

Both the top and bottom portfolio have a higher average market capitalisation compared to the average in the dataset of the developed market (17.56 USD bn, cf. Table 2). The bottom portfolios have a higher average ROE, which suggests that the companies in the bottom portfolios on average have a more efficient deployment of equity. The top portfolios show higher P/E as well as a slightly lower B/M ratios compared to the bottom portfolios, but both are significantly lower than the average of the dataset of the developed markets (cf. Table 2). Thus, the top portfolios are considered more expensive portfolios, although cheaper compared to the average of the dataset. In addition, the top portfolios exhibit a higher D/E ratio compared to the bottom portfolios and to the average in the dataset of the developed markets of 2.32 (cf. Table 2). This could be a source of higher default risk but could also represent better exploitation of growth opportunities.

Table 6, Panel A: KPIs for companies in the top portfolio

	6 months		12 months		18 months	
	Mean	Median	Mean	Median	Mean	Median
Market cap. (USD bn)	21.89	9.44	22.34	9.58	25.15	9.93
ROA (%)	5.56	4.61	5.60	4.69	5.52	4.61
ROE (%)	11.00	12.44	8.04	12.64	0.84	12.65
CAPEX (USD bn)	-0.96	-0.30	-0.96	-0.29	-0.83	-0.26
D/E ratio	2.12	0.66	1.92	0.67	4.36	0.73
B/M ratio	0.22	0.45	0.21	0.43	0.22	0.41
Current ratio	2.04	1.32	2.01	1.33	1.88	1.31
EV/EBITDA	12.34	10.53	14.31	10.74	14.64	11.79
P/E ratio	23.44	20.07	23.61	20.58	8.48	22.80

Table 6, Panel B: KPIs for companies in the bottom portfolio

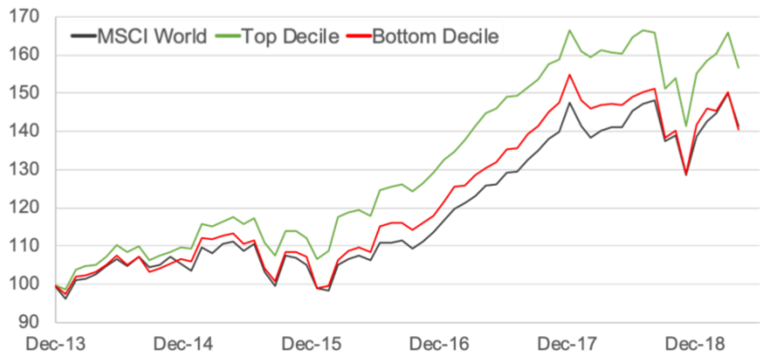
	6 months		12 months		18 months	
	Mean	Median	Mean	Median	Mean	Median
Market cap. (USD bn)	23.81	10.07	24.52	10.10	28.25	12.51
ROA (%)	5.21	4.13	5.05	4.09	5.43	4.17
ROE (%)	15.09	11.35	18.86	11.32	16.70	12.00
CAPEX (USD bn)	-1.28	-0.33	-1.31	-0.35	-1.37	-0.31
D/E ratio	1.18	0.67	1.04	0.69	0.92	0.63
B/M ratio	0.33	0.50	0.35	0.50	0.33	0.45
Current ratio	3.13	1.32	3.95	1.31	4.03	1.36
EV/EBITDA	10.24	10.06	10.30	10.23	12.08	11.31
P/E ratio	0.88	19.48	1.91	19.94	26.59	21.95

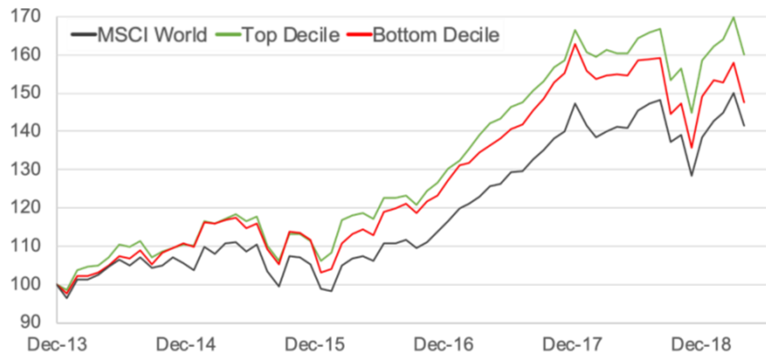
The top portfolio for the 6-month and 12-month holding period has a higher expected return compared to the bottom portfolio and the benchmark. The highest difference in expected returns between the top and bottom portfolio is with the 6-month holding period, with a higher annual expected return of 2.02%-points. The expected return is the same for the top and bottom portfolio with the 18-month holding period, while both still outperform the benchmark. A t-test reveals that all differences in average expected return is significant at a 1% level (cf. Appendix M4). The expected returns' volatility is similar for the top and bottom portfolio as well as the benchmark. Consequently, the top portfolios have higher risk-adjusted returns with higher Sharpe ratio and Information ratio for the 6-month and 12-month holding periods. Generally, the top portfolio has lower level of VaR (5%) as well as excepted shortfall across all holding periods, although the difference is minimal. In addition, both the top and bottom portfolios have significantly fatter tails (kurtosis) compared to the benchmarks, which means both larger positive and negative returns are expected.

Table 7: Individual portfolio overview

		Top decile	Bottom decile	MSCI EM
	6 months			
Performance	Expected return (%)	0.74 (9.30)	0.58 (7.28)	0.59 (7.28)
Performance	Volatility (%)	3.23 (11.21)	3.44 (11.91)	3.26 (11.29)
Performance	Sharpe ratio	0.20 (0.70)	0.14 (0.50)	0.15 (0.53)
Performance	Information ratio	0.17 (0.62)	-0.01 (-0.03)	-
Performance	Benchmark correlation	0.96	0.97	1
Performance	Max. High water mark	166.57	154.88	149.96
Performance	05-2019 TRI	156.61	140.34	141.44
Risk	Max. drawdown (%)	15.04	16.70	13.31
Risk	Skewness	-0.37	-0.41	-0.36
Risk	Kurtosis	1.60	1.29	0.55
Risk	5% VaR (%)	-5.42	-6.55	-5.91
Risk	Expected shortfall (%)	-7.04	-7.70	-6.85
	12 months			
Performance	Expected return (%)	0.78 (9.75)	0.66 (8.20)	
Performance	Volatility (%)	3.22 (11.14)	3.45 (11.96)	
Performance	Sharpe ratio	0.21 (0.74)	0.17 (0.57)	
Performance	Information ratio	0.21 (0.79)	0.08 (0.30)	
Performance	Benchmark correlation	0.96	0.96	
Performance	Max. High water mark	169.74	162.90	
Performance	05-2019 TRI	160.16	147.54	
Risk	Max. drawdown (%)	22.76	30.62	
Risk	Skewness	-0.35	-0.47	
Risk	Kurtosis	1.38	1.37	
Risk	5% VaR (%)	-5.48	-6.37	
Risk	Expected shortfall (%)	-6.96	-7.81	
	18 months			
Performance	Expected return (%)	0.69 (8.61)	0.69 (8.60)	
Performance	Volatility (%)	0.32 (11.06)	0.34 (11.72)	
Performance	Sharpe ratio	0.19 (0.65)	0.18 (0.62)	
Performance	Information ratio	0.11 (0.42)	0.12 (0.46)	
Performance	Benchmark correlation	0.96	0.97	
Performance	Max. High water mark	159.55	164.04	
Performance	05-2019 TRI	151.41	150.70	
Risk	Max. drawdown (%)	16.16	15.70	
Risk	Skewness	-0.49	-0.48	
Risk	Kurtosis	1.32	1.36	
Risk	5% VaR (%)	-5.00	-6.51	
Risk	Expected shortfall (%)	-6.87	-7.51	

Total return indices (TRIs), in USD





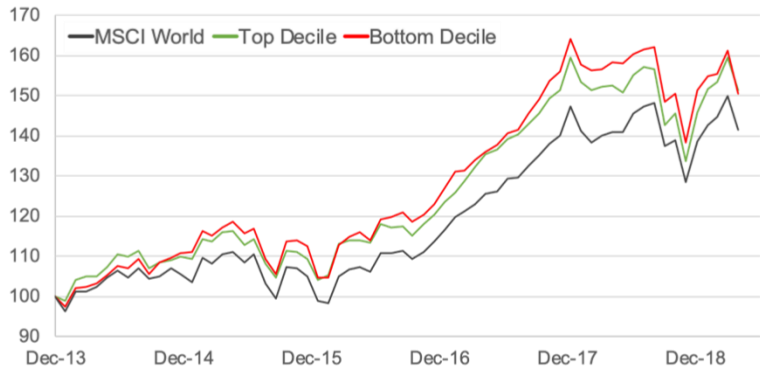


Table 8: Developed markets regression results

	Top Decile 6m		Bottom Decile 6m		Top Decile 12m		Bottom Decile 12m		Top Decile 18m		Bottom Decile 18m	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Market Excess Return	0.9231***	0.9517***	0.9961***	1.0218***	0.9204***	0.9497***	0.9940***	1.0243***	0.9338***	0.9414***	0.9882***	1.0074***
	(0.0438)	(0.0397)	(0.0275)	(0.0397)	(0.0390)	(0.0429)	(0.0318)	(0.0429)	(0.0446)	(0.0373)	(0.0266)	(0.0373)
	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000
Small-Minus-Big	0.5159***		0.5610***		0.4595***		0.5293***		0.3651***		0.4928***	
	(0.1140)		(0.0906)		(0.1093)		(0.1003)		(0.1262)		(0.0898)	
	p = 0.00001		p = 0.0000		p = 0.00003		p = 0.000001		p = 0.0039		p = 0.000000	
High-Minus-Low	-0.0091		0.0839		-0.0074		0.0478		-0.0272		0.0337	
	(0.0952)		(0.0615)		(0.0895)		(0.0699)		(0.0806)		(0.0551)	
	p = 0.9236		p = 0.1724		p = 0.9341		p = 0.4945		p = 0.7360		p = 0.5405	
Winners-Minus-Losers	0.0031		0.0412		-0.0083		0.0136		0.0352		0.0369	
	(0.0714)		(0.0571)		(0.0674)		(0.0596)		(0.0686)		(0.0509)	
	p = 0.9651		p = 0.4710		p = 0.9016		p = 0.8200		p = 0.6081		p = 0.4690	
Alpha	0.0029*	0.0018	0.0025*	-0.0002	0.0032**	0.0022*	0.0027*	0.0006	0.0017	0.0013	0.0027**	0.001
	(0.0015)	(0.0011)	(0.0014)	(0.0011)	(0.0014)	(0.0012)	(0.0014)	(0.0012)	(0.0015)	(0.0011)	(0.0012)	(0.0011)
	p = 0.0558	p = 0.1058	p = 0.0773	p = 0.8784	p = 0.0292	p = 0.0723	p = 0.0560	p = 0.6201	p = 0.2654	p = 0.2192	p = 0.0306	p = 0.3637
Observations	65	65	65	65	65	65	65	65	65	65	65	65
R^2	0.9402	0.9165	0.9601	0.9371	0.9423	0.9231	0.9539	0.9331	0.9358	0.9217	0.9588	0.9402
Adjusted R^2	0.9362	0.9152	0.9575	0.9361	0.9384	0.9219	0.9509	0.932	0.9315	0.9205	0.9561	0.9393
Residual Std. Error	0.0082	0.0094	0.0071	0.0087	0.0080	0.0090	0.0077	0.0090	0.0084	0.0090	0.0071	0.0083
	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)
F Statistic	235.7513***	691.3463***	361.1371***	938.0051***	244.7448***	756.2716***	310.6627***	878.8486***	218.7197***	741.8610***	349.4554***	991.2026***
	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)

Notes:

The table reports the results of the estimation of the multi-factor and single index model for the period 2014-01 to 2019-05. Columns 1, 3, 5, 7, 9, 10, 11 report the OLS estimates for each portfolio's monthly excess return on the multi-factor model. Columns 2, 4, 6, 8, 10, 12 report the coefficients of the single index model. The dependent variable is the respective portfolio's excess return. Alpha is the monthly abnormal return that cannot be attributable to the systematic risk factors. HAC standard errors are reported in parentheses. Portfolios are equally weighted and rebalanced either 6, 12 or 18 months after their formation. The top (bottom) portfolio contains the top (bottom) 10% of companies with respect to ESG momentum at each rebalancing date.

Significance: * 10%, ** 5%, *** 1%

Both the single index model regressions and the multi-factor model regressions support the results of the performance metrics (cf. Table 8). In the single index model, the market excess return is highly significant at a 1% significance level with a very high adjusted R^2 (>0.91) for both the top and bottom portfolio, across all holding periods. The alpha of the single index model is positive and significant at a 10% significance level for the top portfolio with the 12-month holding period, with a monthly alpha of 0.22%. The beta is consistent around 0.95 for the top portfolios while the beta is slightly higher for the bottom portfolios around 1.

In the multi-factor model regressions, the market excess return is again highly significant for all portfolios and the adjusted R^2 increased marginally. The market excess return beta remains slightly higher for the bottom portfolios around 0.99, while the market excess return betas of the top portfolios are around 0.92. The alpha is positive and significant for the top portfolios with a 6-month and 12-month holding period, and amounts to 0.29% and 0.32%, respectively, on a monthly basis. However, the bottom portfolios yield positive and significant alphas in all holding periods, although they are lower compared to the top portfolios for the 6-month and 12-month holding period. Consequently, the alphas do not seem to be attributed to positive ESG momentum. On the contrary, the bottom portfolio outperforms the top portfolio in the 18-month holding period with a significant monthly alpha of 0.27% at a 5% significance level, compared to an insignificant alpha for the top portfolio. In addition, the alpha of the top portfolio with the 12-month holding period increased in significance from the single index regression to the multi-factor model, while more alphas become significant for other portfolios. Thus, we conclude that these alphas are not attributable to the added factors.

Only the SMB factor coefficient is significant and has a high positive coefficient in the range 0.36 to 0.56 in the multi-factor regression. Thus, all portfolios are more exposed to the return variance of small companies, although the market capitalisations of all portfolios are larger than the average in the dataset. Since the adjusted R^2 is very high for the single index regression including only the market excess return, little variance is left to be explained by other factors in the multi-factor regression. Thus, significance of the Fama French factors and the momentum factor was not necessarily expected. However, the HML exhibits a consistent negative beta for the top portfolios across all holding periods, while the bottom portfolios show a consistent positive exposure to the HML factor. This suggests that companies with increasing ESG scores are exposed to the return variance of growth stocks, which is also supported by the lower book-to-market ratio of the top portfolios compared to the bottom portfolios. Still, the evidence is considered very weak.

Table 9: Annualized alphas in the general developed markets

	Annualised multi-factor alpha					Annualised CAPM alpha			
	General market			Significance		General market		Significance	
Holding period	Top	Bottom	Delta	Top	Bottom	Top	Bottom	Top	Bottom
6m	3.54%	3.04%	0.49%	10%	10%	2.18%	-0.24%	No	No
12m	3.91%	3.29%	0.62%	5%	10%	2.67%	0.72%	10%	No
18m	2.06%	3.29%	-1.23%	No	5%	1.57%	1.21%	No	No

The evidence for ESG improving companies outperforming companies with decreasing ESG scores is present in the 6-month to 12-month holding period in the multi-factor regression model. However, the results are weak since firms with decreasing ESG scores also have significant alphas and the difference between the top and bottom portfolio is small. Consequently, it is questionable whether the alphas are attributable to positive ESG momentum. The outperformance between the top and bottom portfolio shifts at the 18-month holding period. The alpha of the bottom portfolio with the 18-month holding period becomes significant at a 5% level in the multi-factor regression, although insignificant in the single index regression. For this holding period, evidence of negative ESG momentum yielding an alpha is thus present. The insignificant alpha in the top portfolio with the 18-month holding period may be attributable to a correction effect in the assessment of the ESG improvement, or a reaction to the ESG score decreasing during the holding period (cf. Table 5), and thus a reaction to new ESG information given the long holding period. Alternatively, the shift may not be attributable to ESG score changes but other market or firm specific factors. Looking at Table 6, Panel A, the average ESG score is increasing over the holding period for the top portfolio which does not support the theory of a reaction to decreasing ESG scores. However, the change in the average ESG score over the holding period of the bottom portfolios with 12-month and 18-month holding periods is positive and larger than for the 6-month holding period. This supports the theory that the shift to a higher stock performance of the bottom portfolio in the 12-month and 18-month holding period in the regressions and expected returns could be due to a change to a positive ESG momentum. However, the contradicting evidence from the top and bottom portfolios makes the results inconclusive regarding this theory.

Looking at the single index model with the 6-month holding period, the relationship between positive ESG momentum and positive alpha appears stronger as the alpha for the top portfolio is positive, while the alpha for the bottom portfolio is negative. However, both for the top and bottom portfolio, the alphas are non-significant. Although the top portfolios exhibit very weak evidence of outperforming the bottom portfolio in the 6-month and 12-month holding period, the top portfolios seem to offer better risk-adjusted returns, with a higher Sharpe ratio and Information ratio across all holding periods (cf. Table 7).

7.1.2 Emerging markets

Next, this thesis analyses portfolios formed based on the emerging markets data. A noteworthy difference to the developed market portfolios is the lower average number of companies in the different portfolios due the lower overall number of companies in the data set (cf. Table 10). Moreover, the top portfolios show a slightly higher average turnover than the bottom portfolios. As in the general developed markets, the turnover expressed in percentages over a 6-month holding period is the lowest. However, it is twice as high in absolute terms since twice the number of companies are held within a year. Hence, an international investor would incur different transaction costs over the investment horizon of the portfolios, which may influence her portfolio choice.

Table 10: Portfolio turnover

	Top portfolio			Bottom portfolio		
Holding period	Avg. turnover	Annualized turnover	Avg. no. companies	Avg. turnover	Annualized turnover	Avg. no. companies
6 months	62%	63%	31	56%	57%	32
12 months	95%	95%	28	86%	86%	29
18 months	96%	64%	24	95%	63%	25

**Notes: For the turnover calculation cf. Appendix A1.*

Table 11 shows the average ESG scores of the companies in the portfolio. While companies selected for the top portfolio tend to experience positive ESG momentum of 1.47 to 1.65 points, this strong increase is not stable over the holding period. These companies tend to only increase their ranking over a 6-month holding period (Δ HP = 0.13) which contrasts the findings from the developed markets portfolios, where the top portfolio companies continue to increase their scores over all holding periods. The moderate positive trend for the top portfolios reverses in the 18-month holding period (-0.02). The bottom portfolio exhibits an opposite effect. While it continues to fall in its ESG score over a 6-month holding period (Δ HP = -0.10), it increases over an 18-month holding period (0.17). Consequently, there is a “reversal effect” in the longevity of ESG score changes for both portfolios the longer a portfolio is held. The magnitude of this reversal effect, however, is small which indicates that these companies do not necessarily continue experiencing ESG momentum the way they did over the selection period.

Table 11: Average industry adjusted ESG score

	Top portfolio				Bottom portfolio			
Holding period	Δ SP	BOHP	HP	Δ HP	Δ SP	BOHP	HP	Δ HP
6 months	1.65	5.11	5.20	0.13	-1.33	3.64	3.57	-0.10
12 months	1.65	5.18	5.11	0.00	-1.33	3.55	3.64	0.02
18 months	1.47	5.35	5.25	-0.02	-1.33	3.37	3.63	0.17

**Notes: Δ SP = change over selection period, BOHP = score at the beginning of holding period, HP = holding period, Δ HP = change over holding period, the ESG score change refers to changes in the SMA (cf. Adjusted ESG scores).*

Table 12 provides company KPIs for every emerging market portfolio. When comparing the market capitalisations across portfolios, it is evident that on average both portfolios have higher market capitalisations than among the emerging markets (16.47bn USD, cf. Table 2) with the top portfolios showing higher values than the bottom portfolios. The top portfolio further exhibits a higher ROE than the bottom portfolio over all holding periods, while the opposite holds for the ROA. The comparably high P/E ratios for the bottom portfolio indicate that the market expects these companies to have high future earnings and is hence willing to pay a higher price for these stocks. When looking at the sector distribution, an overweight of companies in the financial sector is observed in the top portfolio, while the bottom portfolio contains an above-average number of companies in the materials and industrials sector compared to the benchmark (cf. Appendix A3). This indicates that those sectors seem predominantly better (worse) equipped to exploit ESG opportunities and mitigate ESG risks. This fact could explain the difference in CAPEX between the two portfolios, assuming industrials and materials companies having higher expenditures with respect to property, plants and equipment, amongst others.

Table 12, Panel A: KPIs for the top portfolio

	6 months		**12 months**		**18 months**	
	Mean	Median	Mean	Median	Mean	Median
Market cap. (USD bn)	24.34	9.44	27.17	9.81	20.90	9.32
ROA (%)	5.09	3.27	4.67	2.89	4.37	2.82
ROE (%)	14.64	13.35	13.81	13.21	13.27	12.30
CAPEX (USD bn)	-1.27	-0.27	-1.32	-0.29	-0.73	-0.30
D/E ratio	0.98	0.58	1.03	0.60	1.22	0.68
B/M ratio	0.30	0.84	0.36	0.58	0.34	0.60
Current ratio	12.82	1.18	3.84	1.14	4.58	1.12
EV/EBITDA	113.93	10.93	50.00	10.64	21.96	11.15
P/E ratio	24.92	18.30	20.22	16.98	15.86	17.53

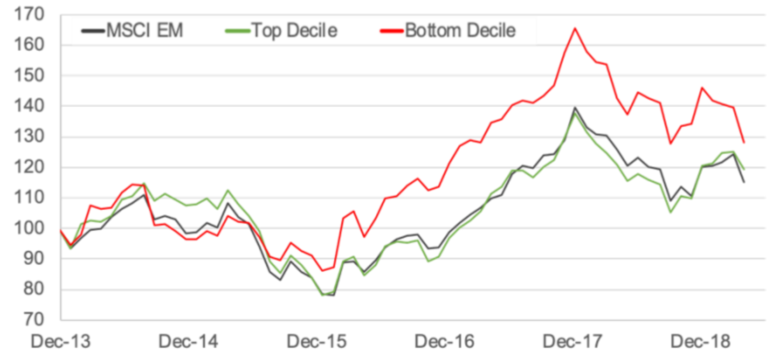
Table 12, Panel B: KPIs for the bottom portfolio

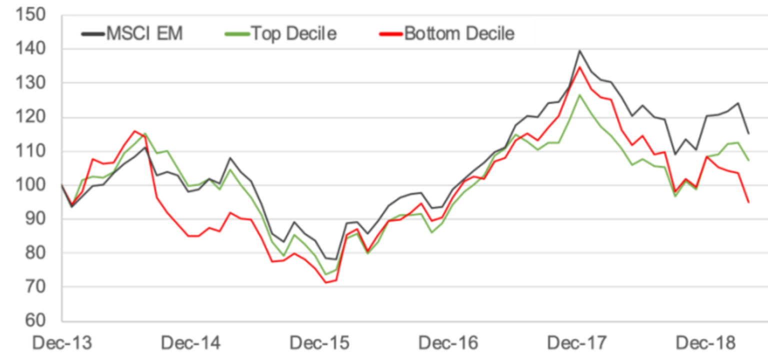
	6 months		**12 months**		**18 months**	
	Mean	Median	Mean	Median	Mean	Median
Market cap. (USD bn)	22.69	9.96	24.22	10.52	17.18	8.87
ROA (%)	5.28	3.96	5.23	3.81	4.83	3.52
ROE (%)	11.96	11.30	11.97	11.34	11.10	10.50
CAPEX (USD bn)	-2.22	-0.52	-2.26	-0.58	-1.55	-0.49
D/E ratio	0.94	0.56	1.03	0.60	1.06	0.58
B/M ratio	0.38	0.62	0.35	0.64	0.35	0.64
Current ratio	1.84	1.36	1.81	1.32	1.91	1.33
EV/EBITDA	-24.90	8.75	48.58	8.41	54.04	9.70
P/E ratio	27.86	17.36	27.98	17.36	25.57	17.88

Table 13: Individual portfolio overview

		Top decile	Bottom decile	MSCI EM
	6 months			
Performance	Expected return (%)	0.38 (4.60)	0.50 (6.22)	0.31 (3.84)
Performance	Volatility (%)	4.62 (16.01)	4.99 (17.28)	4.45 (15.41)
Performance	Sharpe ratio	0.06 (0.22)	0.08 (0.29)	0.05 (0.18)
Performance	Information ratio	0.04 (0.13)	0.09 (0.32)	-
Performance	Benchmark correlation	0.94	0.90	1
Performance	Max. High water mark	137.60	165.58	139.66
Performance	05-2019 TRI	119.21	128.24	115.18
Risk	Max. drawdown (%)	32.04	24.69	29.43
Risk	Skewness	0.10	0.41	0.10
Risk	Kurtosis	-0.30	1.56	0.14
Risk	5% VaR (%)	-6.90	-7.59	-7.15
Risk	Expected shortfall (%)	-8.02	-9.21	-8.08
	12 months			
Performance	Expected return (%)	0.21 (2.59)	0.06 (0.74)	
Performance	Volatility (%)	4.66 (16.15)	5.31 (18.41)	
Performance	Sharpe ratio	0.03 (0.09)	-0.00 (-0.02)	
Performance	Information ratio	-0.06 (-0.22)	-0.10 (-0.36)	
Performance	Benchmark correlation	0.93	0.89	
Performance	Max. High water mark	126.36	134.64	
Performance	05-2019 TRI	107.24	95.10	
Risk	Max. drawdown (%)	38.53	35.96	
Risk	Skewness	0.25	0.17	
Risk	Kurtosis	-0.45	1.62	
Risk	5% VaR (%)	-6.68	-7.29	
Risk	Expected shortfall (%)	-7.62	-10.51	
	18 months			
Performance	Expected return (%)	0.11 (1.28)	0.28 (3.46)	
Performance	Volatility (%)	4.30 (14.91)	5.27 (18.24)	
Performance	Sharpe ratio	0.00 (0.01)	0.04 (0.13)	
Performance	Information ratio	-0.10 (-0.37)	-0.01 (-0.04)	
Performance	Benchmark correlation	0.90	0.86	
Performance	Max. High water mark	133.88	127.19	
Performance	05-2019 TRI	100.96	110.08	
Risk	Max. drawdown (%)	27.99	39.36	
Risk	Skewness	-0.17	0.09	
Risk	Kurtosis	-0.56	0.52	
Risk	5% VaR (%)	-6.50	-7.50	
Risk	Expected shortfall (%)	-7.97	-10.19	

Total return indices (TRIs), in USD





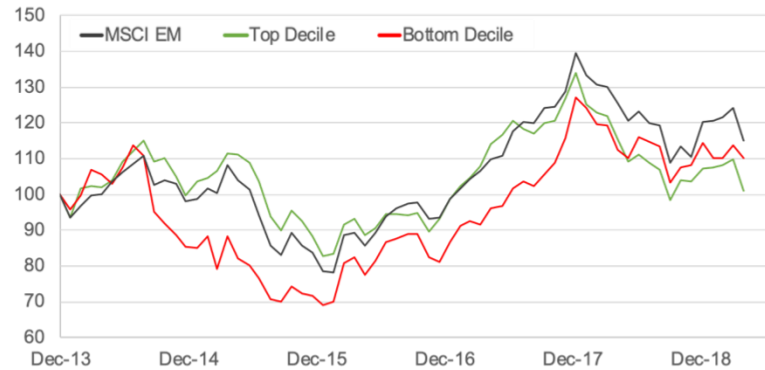


Table 14: Emerging markets regression results

	Top Decile 6m		Bottom Decile 6m		Top Decile 12m		Bottom Decile 12m		Top Decile 18m		Bottom Decile 18m	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Market Excess Return	1.0501***	0.9714***	1.0255***	1.0108***	1.0338***	0.9778***	1.0828***	1.0601***	0.9548***	0.8669***	1.0199***	1.0219***
	(0.0579)	(0.0822)	(0.0911)	(0.0822)	(0.0557)	(0.0914)	(0.0994)	(0.0914)	(0.0627)	(0.0809)	(0.0935)	(0.0809)
	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000
Small-Minus-Big	0.2531**		0.4583***		0.1923		0.4795**		0.2041*		0.3635	
	(0.1131)		(0.1757)		(0.1258)		(0.2223)		(0.1163)		(0.2214)	
	p = 0.0253		p = 0.0091		p = 0.1264		p = 0.0310		p = 0.0795		p = 0.1007	
High-Minus-Low	-0.1197		0.0077		-0.1162		0.0058		-0.1862**		0.0457	
	(0.0734)		(0.0965)		(0.0734)		(0.1038)		(0.0774)		(0.1462)	
	p = 0.1029		p = 0.9361		p = 0.1136		p = 0.9553		p = 0.0162		p = 0.7547	
Winners-Minus-Losers	0.0946		-0.0528		0.029		-0.0305		0.0661		-0.0479	
	(0.0703)		(0.1014)		(0.0681)		(0.1082)		(0.0760)		(0.1182)	
	p = 0.1787		p = 0.6026		p = 0.6698		p = 0.7784		p = 0.3840		p = 0.6852	
Alpha	0.0011	0.0007	0.0053	0.0019	-0.0014	-0.001	0.001	-0.0027	-0.0031	-0.0018	0.003	-0.0004
	(0.0028)	(0.0027)	(0.0035)	(0.0027)	(0.0032)	(0.0031)	(0.0037)	(0.0031)	(0.0033)	(0.0034)	(0.0051)	(0.0034)
	p = 0.6930	p = 0.8054	p = 0.1251	p = 0.4970	p = 0.6715	p = 0.7594	p = 0.7801	p = 0.3941	p = 0.3497	p = 0.6002	p = 0.5534	p = 0.9172
Observations	65	65	65	65	65	65	65	65	65	65	65	65
R^2	0.897	0.8755	0.8485	0.8117	0.8843	0.8717	0.8196	0.787	0.8305	0.8015	0.7686	0.7467
Adjusted R^2	0.8901	0.8736	0.8383	0.8087	0.8765	0.8697	0.8076	0.7836	0.8192	0.7984	0.7532	0.7427
Residual Std. Error	0.0153	0.0164	0.0201	0.0218	0.0164	0.0168	0.0233	0.0247	0.0183	0.0194	0.0262	0.0267
	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)
F Statistic	130.6242***	443.1802***	83.9791***	271.5546***	114.5915***	428.0328***	68.1487***	232.7455***	73.4990***	254.3845***	49.8318***	185.7310***
	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)

Notes:

The table reports the results of the estimation of the multi-factor and single index model for the period 2014-01 to 2019-05. Columns 1, 3, 5, 7, 9, 10, 11 report the OLS estimates for each portfolio's monthly excess return on the multi-factor model. Columns 2, 4, 6, 8, 10, 12 report the coefficients of the single index model. The dependent variable is the respective portfolio's excess return. Alpha is the monthly abnormal return that cannot be attributable to the systematic risk factors. HAC standard errors are reported in parentheses. Portfolios are equally weighted and rebalanced either 6, 12 or 18 months after their formation. The top (bottom) portfolio contains the top (bottom) 10% of companies with respect to ESG momentum at each rebalancing date.

Significance: * 10%, ** 5%, *** 1%

The top portfolio's expected annual return (4.60%) is above that of the benchmark (3.84%) for a 6-month holding period while it falls below it for longer holding periods, which mirrors the graphical trend of the TRI (cf. Table 13). The bottom portfolio's expected annual return is highest for a 6-month holding period (6.22%), plunges over a 12-month holding period (0.74%) and recovers over an 18-month holding period (3.46%). Over a 6-month holding period, the bottom portfolio outperforms the top portfolio, with this difference being statistically significant (cf. Appendix M4). Taking the volatility of the two portfolios into account, both portfolios' Sharpe ratios decrease with longer holding periods. Both portfolios have the highest Sharpe ratio over a 6-month holding period, with 0.29 for the bottom, and 0.22 for the top portfolio, while at the same time outperforming the benchmark (0.18). The longer the holding periods for the bottom portfolio, the higher the downside risk becomes, which is measured in an increased maximum drawdown and expected shortfall compared to the benchmark and the top portfolio. Hence, the optimal holding period for both portfolios appears to be 6 months.

Table 14 shows the results of the single index regression models. The models exhibit high adjusted R^2 (0.75-0.88) and a high sensitivity to the market ($\beta_M \approx$ 1.00). Generally, the goodness of fit of the models is higher for the top portfolio than for the bottom portfolio and is the highest over a 6-month holding period for both portfolios (R^2= 0.81-0.88). The already high goodness of fit leaves relatively little room for adding additional potentially significant regressors without blurring the true explanatory power of the multi-factor model. The insignificant alphas across all models indicate that there is no convincing evidence that trading on ESG momentum yields promising results.

When looking at the multi-factor models, a small increase in the adjusted R^2 for all portfolios is observable when adding additional significant explanatory variables (cf. Table 14). The very noteworthy outperformance of the bottom portfolio for a 6-month holding period is expressed in an alpha close to 10% significance (reg. (3), p-value = 0.1251), which is in line with graphical observations of the TRI. All other alphas are found highly insignificant. This observation might indicate that observed financial out- and underperformance based on ESG momentum is mainly attributable to other systematic risk factors. When looking at precisely these factors, both portfolios exhibit highly statistically significant coefficients ($\beta_M \approx$ 1.00) on the market factor, indicating that the portfolio returns move approximately in parallel to and are mainly attributable to market movements. Moreover, both portfolios show a positive exposure to SMB with p-values either significant or close to significance. This observation is in line with the lower average market capitalisations of emerging markets companies in the dataset. Although the top portfolio is only found to have significant negative loading on HML for an 18-month holding period (reg. (9)), the p-values for the negative factor coefficients over the other holding periods are very close to significance. Hence, the top portfolio is tilted towards the characteristics of growth stocks. This observation does not hold for the bottom portfolio.

Table 15: Annualised alphas across emerging markets portfolios

	Annualised multi-factor alpha					Annualised CAPM alpha			
	General market			Significance		General market		Significance	
Holding period	Top	Bottom	Delta	Top	Bottom	Top	Bottom	Top	Bottom
6m	1.33%	6.55%	-4.93%	No	No	0.84%	2.30%	No	No
12m	-1.67%	1.21%	-2.84%	No	No	-1.19%	-3.19%	No	No
18m	-3.66%	3.66%	-7.08%	No	No	-2.14%	-0.48%	No	No

The aggregated results (cf. Table 15) do not provide any evidence that the positive ESG momentum portfolios outperform negative ESG momentum portfolios. The strategy does not yield a significant alpha in the single index (Q1) nor in the multi-factor model (Q2). No evidence is observed indicating that a specific holding period is more adequate for trading on improving ESG scores. Although all alphas are found insignificant, their signs may indicate that positive ESG momentum leads to positive abnormal returns over a short holding while negative ESG momentum generates positive abnormal returns over all holding periods. This would be in line with the performance metrics that suggest that the best holding period is 6 months for both portfolios. Here, historical KPIs also do not build a strong case for positive ESG momentum.

Moreover, the portfolios are all highly exposed to fluctuations in the market and the majority of them moderately to the size factor. This confirms previous findings that ESG is positively related to market capitalisation (Bender et al., 2018; Velte, 2017). The negative loadings on the value factor for the top portfolios appear in line with the fact that these portfolios are not heavily invested in sectors with traditionally large asset bases. It seems puzzling that old-economy and partially state-owned companies that have value stock characteristics do not significantly contribute to explaining returns of the bottom portfolios although these companies represent a substantial thereof. On the contrary, while Friede, Busch, & Bassen (2015), Odell & Ali (2016), and Sherwood & Pollard (2018) found positive links between high ESG scores and outperformance being more pronounced in emerging markets than in developed markets, the results of this study cannot support these findings.

The “reversal effect” in the continuity of ESG momentum during longer holding periods is another striking insight (cf. Table 11). It could indicate that positive as well as negative ESG momentum reverses after approximately 6 months for almost half of the companies.

7.1.3 Sub-conclusion

In order to answer our research question (Q1) of whether trading on positive ESG momentum yields a statistically significant alpha, the authors look at alpha from the single index models in developed and emerging markets. In the developed markets, the top portfolio is the only portfolio which shows a positive annual alpha of 2.76% over a 12-month holding period at a 10% significance level. This supports the theory that trading on positive ESG momentum yields a positive alpha. For emerging markets, however, this conclusion does not hold due to the absence of statistically significant results. Here, trading on positive ESG momentum does not yield significant alpha.

The authors further examine the significance of alpha resulting from the multi-factor model (Q2) and afterwards compare the magnitude of the alphas between developed and emerging markets to each other (Q3).

In the developed markets portfolios, there are significant alphas in the top portfolios for 6-month and 12-month holding periods. However, the bottom portfolios also show significant alphas for a 6-month and 12-month holding period. The differences in the alphas between top and bottom portfolios are small and no compelling evidence of the alphas being attributable to ESG momentum is present. The alpha of the bottom portfolio with the 18-month holding period becomes significant at a 5% level in the multi-factor model, although it was insignificant in the single index model. For this holding period, evidence of negative ESG momentum yielding an alpha is thus present. In addition, the top portfolios with the 6-month and 12-month holding periods have higher risk-adjusted returns with higher Sharpe and information ratios. Given the results of both the single index model and the multi-factor model, no compelling evidence of a positive ESG momentum yielding a positive alpha is observed.

In the emerging markets portfolios, the results are statistically insignificant across all models, indicating that trading on ESG momentum does not yield significant alpha. Hence, excess returns must be explained by other risk factors. Shedding light on the magnitude and sign of the insignificant alphas, indicates that portfolios trading on negative ESG momentum outperform those trading on positive ESG momentum over all holding periods.

Consequently, the price effect of positive ESG momentum is higher in developed markets as no significant results were present in the emerging markets portfolios. However, the results are still weak for the developed markets, given lack of compelling evidence of the alphas being attributable to ESG momentum.

7.2 Performance Groups

7.2.1 Developed markets

7.2.1.1 Performance group "low"

The turnover rates of the top and bottom portfolios in the performance group "low" are very similar (cf. Table 16), and also comparable to the turnover in the portfolio of the general developed markets. Thus, no substantial differences in terms of transaction costs are present between the top and bottom portfolio for a given holding period.

Table 16: Portfolio turnover

	Top portfolio			Bottom portfolio		
Holding period	Avg. turnover	Annualized turnover*	Avg. no. companies	Avg. turnover	Annualized turnover*	Avg. no. companies
6 months	65%	67%	65	60%	59%	67
12 months	88%	88%	65	88%	88%	67
18 months	96%	64%	59	91%	61%	61

**Notes: For the turnover calculation cf. Appendix A1.*

Table 17: Average industry adjusted ESG score

	Top portfolio				Bottom portfolio			
Holding period	Δ SP	BOHP	HP	Δ HP	Δ SP	BOHP	HP	Δ HP
6 months	1.7	4.01	4.09	0.20	-1.8	2.55	2.58	-0.04
12 months	1.7	4.15	4.33	0.41	-1.6	2.58	2.65	0.25
18 months	1.6	4.09	4.38	0.29	-1.5	2.53	2.70	0.19

**Notes: Δ SP = change over selection period, BOHP = score at the beginning of holding period, HP = holding period, Δ HP = change over holding period, the ESG score change refers to changes in the SMA (cf. Adjusted ESG scores).*

All portfolios have a higher average market capitalisation compared to the dataset average of 17.56 USD bn. The top portfolios have a negative average ROE, which decreases substantially with the increase of the holding period. The bottom portfolios have a positive average ROE of a similar magnitude to the dataset of the developed markets for the 6-month holding period, which decreases with the increase of the holding period. Thus, the bottom portfolios generally have a more efficient deployment of equity. In terms of operating efficiency, the bottom and top portfolios have similar ROAs which are proportional to the dataset average of 6.05 (cf. Table 2). The top portfolios with the 6-month and 12-month holding periods have significantly lower B/M ratios compared to the bottom portfolios over the same holding periods and are thus relatively more expensive. The D/E ratio is consistently higher for the top portfolios compared to the bottom portfolios as well as the market average of 2.3 (cf. Table 2). This could be due to the slightly higher percentage of companies from the more capital-intensive utility sector in the top portfolios, with 8%-9% for the top portfolios and 4%-6% for the bottom portfolios.

Table 18, Panel A: KPIs for companies in the top portfolio

	6 months		12 months		18 months	
	Mean	Median	Mean	Median	Mean	Median
Market cap. (USD bn)	26.06	10.65	26.53	10.41	26.59	11.49
ROA (%)	5.75	4.74	5.73	4.89	5.59	4.75
ROE (%)	-5.57	12.13	-9.76	12.57	-21.58	12.51
CAPEX (USD bn)	-0.85	-0.24	-0.86	-0.24	-0.93	-0.26
D/E ratio	2.78	0.75	1.08	0.79	5.68	0.84
B/M ratio	0.19	0.42	0.12	0.40	0.34	0.41
Current ratio	2.23	1.37	2.20	1.39	1.83	1.32
EV/EBITDA	13.45	11.57	13.76	11.67	13.29	11.87
P/E ratio	23.27	21.58	24.33	22.22	20.94	22.44

Table 18, Panel B: KPIs for companies in the bottom portfolio

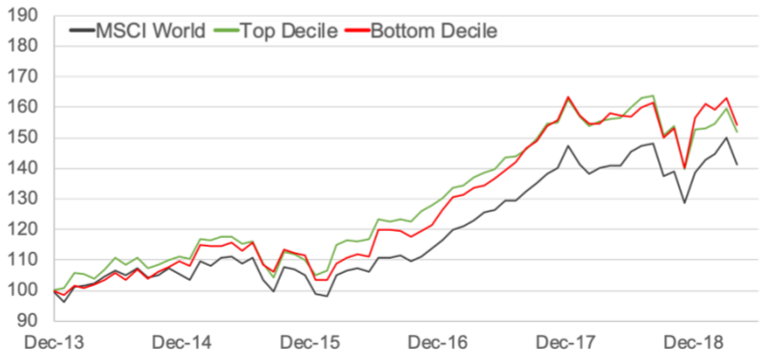
	6 months		12 months		18 months	
	Mean	Median	Mean	Median	Mean	Median
Market cap. (USD bn)	25.30	9.67	24.47	9.10	27.07	11.14
ROA (%)	5.33	4.36	5.21	4.32	5.43	4.34
ROE (%)	26.24	11.48	16.09	11.52	13.83	11.62
CAPEX (USD bn)	-1.26	-0.30	-1.24	-0.24	-1.24	-0.25
D/E ratio	1.20	0.67	1.17	0.66	1.03	0.68
B/M ratio	0.34	0.46	0.36	0.44	0.28	0.46
Current ratio	2.51	1.40	2.60	1.44	2.61	1.41
EV/EBITDA	13.12	10.97	10.51	11.12	9.18	11.36
P/E ratio	-29.41	20.67	-56.49	21.18	24.85	21.34

Table 19 makes it clear, that there is no notable performance difference between the performance of the top and bottom portfolios in the 6-month and 12-month holding periods, both in terms of expected return and volatility. Both portfolios outperform the benchmark in the 6-month and 12-month holding period in terms of expected return and Sharpe ratio, which as a result is unlikely due to changes in ESG scores. The bottom portfolio has the highest expected return with the 18-month holding period, which is higher than both the benchmark and the top portfolio. The difference in average return compared to the top portfolio is significant at a 1% significance level. In addition, the kurtosis is significantly higher for both the top and bottom portfolios compared to the benchmark, which means more extreme values for returns have higher probabilities of occurring.

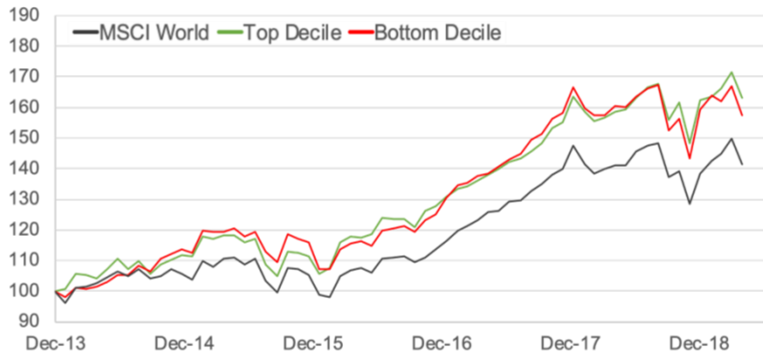
Table 19: Individual portfolio overview

		Top decile	Bottom decile	MSCI EM
	6 months			
Performance	Expected return (%)	0.70 (8.74)	0.73 (9.06)	0.59 (7.28)
	Volatility (%)	3.31 (11.46)	3.42 (11.84)	3.26 (11.29)
	Sharpe ratio	0.19 (0.64)	0.19 (0.65)	0.15 (0.53)
	Information ratio	0.10 (0.36)	0.11 (0.41)	-
	Benchmark correlation	0.94	0.93	1
	Max. High water mark	163.93	163.52	149.96
	05-2019 TRI	152.05	154.19	141.44
Risk	Max. drawdown (%)	14.82	14.21	13.31
	Skewness	-0.28	-0.08	-0.36
	Kurtosis	1.50	1.56	0.55
	5% VaR (%)	-4.76	-6.07	-5.91
	Expected shortfall (%)	-6.97	-7.24	-6.85

Total return indices (TRIs), in USD



		Top decile	Bottom decile
	12 months		
Performance	Expected return (%)	0.81 (10.16)	0.76 (9.49)
	Volatility (%)	3.29 (11.41)	3.45 (11.95)
	Sharpe ratio	0.22 (0.76)	0.19 (0.67)
	Information ratio	0.18 (0.69)	0.15 (0.55)
	Benchmark correlation	0.93	0.94
	Max. High water mark	163.18	157.34
	05-2019 TRI	171.45	167.25
Risk	Max. drawdown (%)	11.62	14.27
	Skewness	-0.30	0.29
	Kurtosis	1.12	1.67
	5% VaR (%)	-4.92	-5.67
	Expected shortfall (%)	-6.87	-7.53



		Top decile	Bottom decile
	18 months		
Performance	Expected return (%)	0.72 (8.98)	0.88 (11.07)
	Volatility (%)	3.30 (11.45)	3.26 (11.31)
	Sharpe ratio	0.19 (0.66)	0.24 (0.84)
	Information ratio	0.11 (0.40)	0.25 (0.92)
	Benchmark correlation	0.93	0.93
	Max. High water mark	161.05	179.94
	05-2019 TRI	153.85	170.74
Risk	Max. drawdown (%)	14.72	11.82
	Skewness	-0.47	-0.27
	Kurtosis	1.44	1.69
	5% VaR (%)	-4.38	-5.72
	Expected shortfall (%)	-7.00	-7.04

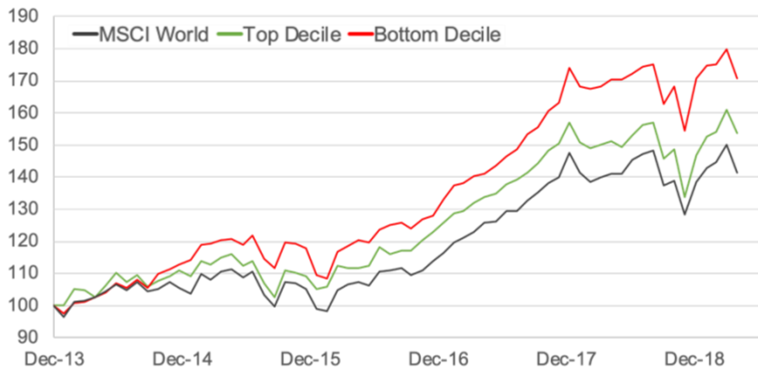


Table 20: Developed markets – performance group "low" – regressions results

	Top Decile 6m		Bottom Decile 6m		Top Decile 12m		Bottom Decile 12m		Top Decile 18m		Bottom Decile 18m	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Market Excess Return	0.9410***	0.9533***	0.9614***	0.9757***	0.9248***	0.9423***	0.9801***	0.9975***	0.9609***	0.9437***	0.9360***	0.9358***
	(0.0555)	(0.0614)	(0.0523)	(0.0614)	(0.0537)	(0.0552)	(0.0445)	(0.0552)	(0.0644)	(0.0538)	(0.0539)	(0.0538)
	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000
Small-Minus-Big	0.5570***		0.5678***		0.5259***		0.4930***		0.4227**		0.4512***	
	(0.1686)		(0.1728)		(0.1761)		(0.1414)		(0.1835)		(0.1550)	
	p = 0.0010		p = 0.0011		p = 0.0029		p = 0.0005		p = 0.0213		p = 0.0037	
High-Minus-Low	0.068		-0.0165		-0.0501		-0.0138		-0.0017		-0.003	
	(0.1049)		(0.0836)		(0.0927)		(0.0878)		(0.1134)		(0.0971)	
	p = 0.5168		p = 0.8434		p = 0.5893		p = 0.8755		p = 0.9880		p = 0.9751	
Winners-Minus-Losers	0.0766		0.0532		0.0285		0.0315		0.1246		0.0787	
	(0.0801)		(0.0808)		(0.0784)		(0.0763)		(0.0879)		(0.0865)	
	p = 0.3392		p = 0.5105		p = 0.7163		p = 0.6797		p = 0.1562		p = 0.3625	
Alpha	0.0037	0.0014	0.0025	0.0015	0.0029	0.0025*	0.0026	0.0017	0.0024	0.0016	0.0041**	0.0032**
	(0.0024)	(0.0015)	(0.0020)	(0.0015)	(0.0023)	(0.0015)	(0.0018)	(0.0015)	(0.0027)	(0.0015)	(0.0017)	(0.0015)
	p = 0.1182	p = 0.3657	p = 0.1997	p = 0.3173	p = 0.2097	p = 0.0862	p = 0.1515	p = 0.2382	p = 0.3785	p = 0.2705	p = 0.0122	p = 0.0258
Observations	65	65	65	65	65	65	65	65	65	65	65	65
R^2	0.9035	0.8788	0.8919	0.8645	0.8962	0.8691	0.9063	0.8866	0.8891	0.8657	0.8929	0.8722
Adjusted R^2	0.897	0.8769	0.8846	0.8623	0.8892	0.867	0.9	0.8848	0.8817	0.8635	0.8858	0.8701
Residual Std. Error	0.0106	0.0116	0.0116	0.0127	0.0110	0.0120	0.0109	0.0117	0.0114	0.0122	0.0110	0.0118
	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)
F Statistic	140.3879***	456.9870***	123.6967***	401.8196***	129.4691***	418.2076***	145.0782***	492.7920***	120.2754***	406.0296***	125.0636***	429.8544***
	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)

Notes:

The table reports the results of the estimation of the multi-factor and single index model for the period 2014-01 to 2019-05. Columns 1, 3, 5, 7, 9, 10, 11 report the OLS estimates for each portfolio's monthly excess return on the multi-factor model. Columns 2, 4, 6, 8, 10, 12 report the coefficients of the single index model. The dependent variable is the respective portfolio's excess return. Alpha is the monthly abnormal return that cannot be attributable to the systematic risk factors. HAC standard errors are reported in parentheses. Portfolios are equally weighted and rebalanced either 6, 12 or 18 months after their formation. The top (bottom) portfolio contains the top (bottom) 10% of companies with respect to ESG momentum at each rebalancing date.

Significance: * 10%, ** 5%, *** 1%

Looking at the regression results of the single index model, both the top and bottom portfolio have an exposure to the benchmark between to 0.94 and 1 with an adjusted R^2 around 0.87. The top portfolio alpha is significant at a 10% significance level in the 12-month holding period yielding 0.25% on a monthly basis, which is similar to the results of the general developed market portfolios. The bottom portfolio has a significant alpha (at the 5% significance level) in the 18-month holding period with a monthly alpha of 0.32%, which confirms the results of the reported performance metrics.

In the multi-factor model, the alpha of the bottom portfolio with an 18-month holding period remains significant (at the 5% significance level) with an increased monthly alpha of 0.41%. No significance is observed for the alpha for the top portfolio with the 12-month holding period. The market excess return coefficient remains highly significant across all portfolios with a similar beta to the single index model, while the adjusted R^2 only increases marginally. Due to a very high R^2 in the single index model, little variance is left for additional variables to explain, which could partly explain why the HML and WML factors are insignificant.

Similar to the developed market portfolios, only the SMB factor is significant (at a 1% significance level) for all portfolios across all holding periods with a high and positive coefficient in the range of 0.42 to 0.57. Consequently, all portfolios are positively exposed to the return volatility of small cap companies. The positive exposure could be related to the fact that companies with a high ESG score are known to have a high market capitalisation bias (cf. ESG and other risk factors) and the performance group “low” might by construction have a small capitalisation bias. However, the average market capitalisation of all portfolios is higher than the average of the dataset as seen in Table 2. Consequently, the alpha of the bottom portfolio with an 18-month holding period, as seen in the single index model, does not seem to be attributable to the Fama French risk factors or the momentum factor, as the alpha persists in the multi-factor model. This supports that decreasing ESG scores in the performance group “low” may be related to alpha with a holding period of 18 months.

Table 21: Annualised alphas across performance group "low" portfolios

	Annualised multi-factor alpha					Annualised CAPM alpha			
	Performance group "low"			Significance		Performance group		Significance	
Holding period	Top	Bottom	Delta	Top	Bottom	Top	Bottom	Top	Bottom
6m	4.53%	3.04%	1.49%	No	No	1.69%	1.81%	No	No
12m	3.54%	3.17%	0.37%	No	No	3.04%	2.06%	10%	No
18m	2.92%	5.03%	-2.11%	No	5%	1.94%	3.91%	No	5%

The bottom portfolio outperforms the top portfolio in the multi-factor regression with a significant alpha of 5.03% annually in the 18-month holding period, where the top portfolio has an insignificant annualised alpha of 2.92%. However, in the single index regression, the top portfolio shows a significant annualised alpha of 3.04% at a 10% significance level, which disappears in the multi-factor regression. In Table 17 it becomes evident, that the bottom portfolios with 12-month and 18-

month holding periods have on average increasing ESG scores, which could explain why the performance in terms of expected return and significance of alpha increases with the length of the holding period. In addition, the top portfolio with the 12-month holding period displays a significant average increase in the ESG score over the investment period compared to the other holding periods, which is also the holding period which exhibits the highest expected return and the only significant alpha in the single index regression for the top portfolios. Thus, some correlation between increasing ESG scores and stock returns seems to be present. In sum, no convincing evidence is present of companies with increasing ESG scores outperforming companies with decreasing ESG scores, since the significance of the alpha in the 12-month holding period for the top portfolio disappears in the multi-factor regression. More convincing evidence of the contrary is present for the 18-month holding period with a significant alpha, higher expected return, and higher risk-adjusted returns of the bottom portfolio.

7.2.1.2 Performance group "average"

The performance group "average" exhibits a similar turnover compared to the general developed market portfolios and the performance group "low" across all holding periods. Thus, differences in transaction costs are negligible across the top and bottom portfolio for a given holding period and in comparison to the other performance group.

Table 22: Portfolio turnover

	Top portfolio			**Bottom portfolio**		
Holding period	Avg. turnover	Annualized turnover*	Avg. no. companies	Avg. turnover	Annualized turnover*	Avg. no. companies
6 months	61%	62%	87	62%	62%	86
12 months	88%	88%	85	88%	88%	84
18 months	94%	63%	76	94%	63%	77

**Notes: For the turnover calculation cf. Appendix A1.*

Table 23: Average industry adjusted ESG score

	Top portfolio				**Bottom portfolio**			
Holding period	Δ SP	BOHP	HP	Δ HP	Δ SP	BOHP	HP	Δ HP
6 months	1.9	5.49	5.63	0.19	-1.6	4.31	4.39	-0.05
12 months	1.8	5.46	5.63	0.31	-1.5	4.26	4.36	0.06
18 months	1.7	5.60	5.92	0.34	-1.5	4.22	4.34	0.17

**Notes: Δ SP = change over selection period, BOHP = score at the beginning of holding period, HP = holding period, Δ HP = change over holding period, the ESG score change refers to changes in the SMA (cf. Adjusted ESG scores).*

Similar to the portfolios in the performance group "low", both the top and bottom portfolios have a higher average market capitalisation compared to the dataset's average across all holding periods. The average ROE is substantially higher for the bottom portfolios across all holding periods, which again implies that the bottom portfolios, on average, have a more efficient deployment of equity. The

P/E ratio is significantly higher for the top portfolio with a 6-month holding period compared to the corresponding bottom portfolio, which indicates that the market expects high future earnings of the companies in the portfolio. In the same holding period, the top portfolio had a much lower average B/M ratio than the bottom portfolio. In addition, the EV/EBITDA ratio is higher for top portfolio over 6-month and 12-month holding periods compared to the corresponding bottom portfolios. This collectively indicates that the top portfolio is considered more expensive compared to the bottom portfolio.

Table 24, Panel A: KPIs for the top portfolio

	6 months		**12 months**		**18 months**	
	Mean	Median	Mean	Median	Mean	Median
Market cap. (USD bn)	24.74	10.23	24.65	9.52	23.45	10.27
ROA (%)	5.68	4.63	5.74	4.76	5.34	4.45
ROE (%)	1.93	12.93	0.16	13.05	-2.28	12.70
CAPEX (USD bn)	-0.78	-0.27	-0.85	-0.27	-0.84	-0.29
D/E ratio	2.48	0.69	2.58	0.70	1.30	0.76
B/M ratio	0.13	0.41	0.11	0.39	0.16	0.40
Current ratio	2.31	1.34	2.11	1.35	1.81	1.28
EV/EBITDA	13.05	11.48	13.49	11.78	13.58	11.74
P/E ratio	23.08	22.19	21.53	22.93	-8.10	22.91

Table 24, Panel B: KPIs for the bottom portfolio

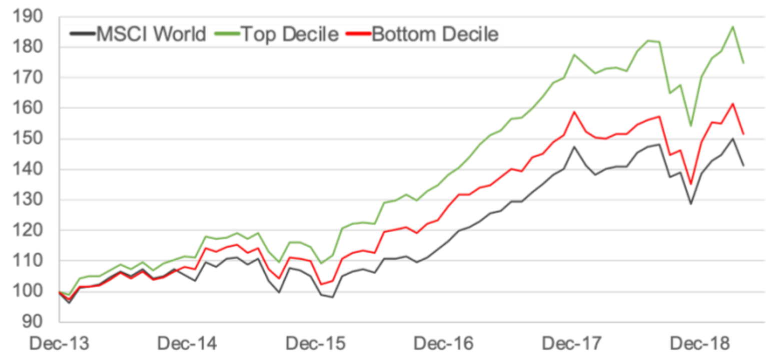
	6 months		**12 months**		**18 months**	
	Mean	Median	Mean	Median	Mean	Median
Market cap. (USD bn)	25.79	11.33	25.47	10.71	29.21	13.35
ROA (%)	5.46	4.48	5.38	4.44	5.84	4.46
ROE (%)	3.49	12.13	16.40	12.23	19.08	12.49
CAPEX (USD bn)	-1.18	-0.31	-1.26	-0.30	-1.38	-0.32
D/E ratio	1.13	0.63	1.20	0.67	0.96	0.62
B/M ratio	0.26	0.44	0.26	0.44	0.27	0.46
Current ratio	4.85	1.38	5.13	1.37	5.62	1.37
EV/EBITDA	-2.03	10.67	-3.01	10.99	13.63	10.87
P/E ratio	-17.19	20.95	-42.75	21.59	29.70	21.46

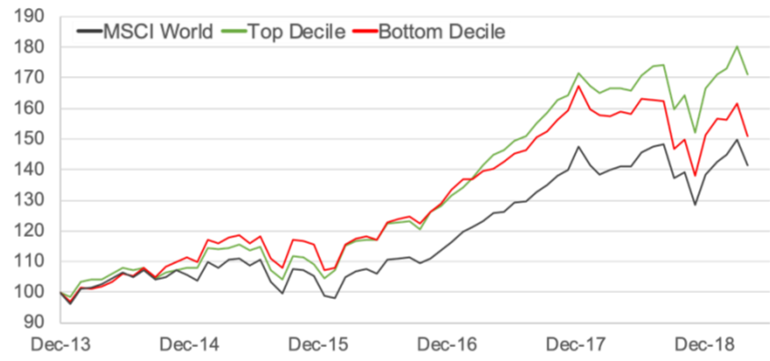
The top portfolio outperforms the bottom portfolio most in the 6-month holding period in terms of expected return, with a significant difference in average returns at a 1% significance level. Both the top portfolio and the bottom portfolio substantially outperform the benchmark over this holding period as well, with an annualised expected return of 11.56% of the top portfolio compared to 8.72% for the bottom portfolio and 7.28% for the benchmark (cf. Table 25). The volatility is very similar for both portfolios in the 6-month holding period, which results in a better risk-adjusted return for the top portfolio when looking at both the Sharpe and information ratio. The outperformance of the top portfolio decreases as the holding period increases, while the difference in average returns stays significant at a 1% level (cf. Appendix M4). Similar to the market portfolio and the performance group "low", the kurtosis is significantly higher compared to the benchmark for both the top and bottom portfolio which means that larger positive and negative returns are expected.

Table 25: Individual portfolio overview

		Top decile	Bottom decile	MSCI EM
	6 months			
Performance	Expected return (%)	0.92 (11.56)	0.70 (8.72)	0.59 (7.28)
	Volatility (%)	3.25 (11.26)	3.35 (11.60)	3.26 (11.29)
	Sharpe ratio	0.25 (0.88)	0.18(0.63)	0.15 (0.53)
	Information ratio	0.31 (1.17)	0.11 (0.44)	-
	Benchmark correlation	0.95	0.96	1
	Max. High water mark	186.65	161.48	149.96
	05-2019 TRI	174.84	151.76	141.44
Risk	Max. drawdown (%)	15.16	15.02	13.31
	Skewness	-0.46	-0.25	-0.36
	Kurtosis	1.91	1.13	0.55
	5% VaR (%)	-5.19	-6.04	-5.91
	Expected shortfall (%)	-7.22	-7.21	-6.85
	12 months			
Performance	Expected return (%)	0.88 (11.09)	0.70 (8.71)	
	Volatility (%)	3.22 (11.16)	3.5 (12.14)	
	Sharpe ratio	0.25 (0.85)	0.17 (0.60)	
	Information ratio	0.28 (1.07)	0.11 (0.43)	
	Benchmark correlation	0.95	0.96	
	Max. High water mark	180.37	167.19	
	05-2019 TRI	171.07	151.15	
Risk	Max. drawdown (%)	12.59	17.56	
	Skewness	-0.32	-0.47	
	Kurtosis	1.33	1.38	
	5% VaR (%)	-5.00	-6.49	
	Expected shortfall (%)	-6.88	-7.85	
	18 months			
Performance	Expected return (%)	0.73 (9.11)	0.72 (8.98)	
	Volatility (%)	3.15 (10.92)	3.28 (11.35)	
	Sharpe ratio	0.20 (0.71)	0.19 (0.67)	
	Information ratio	0.12 (0.46)	0.14 (0.52)	
	Benchmark correlation	0.94	0.96	
	Max. High water mark	165.62	166.40	
	05-2019 TRI	155.36	153.99	
Risk	Max. drawdown (%)	17.65	15.03	
	Skewness	-0.56	-0.50	
	Kurtosis	1.52	1.23	
	5% VaR (%)	-4.48	-6.22	
	Expected shortfall (%)	-6.80	-7.35	

Total return indices (TRIs), in USD





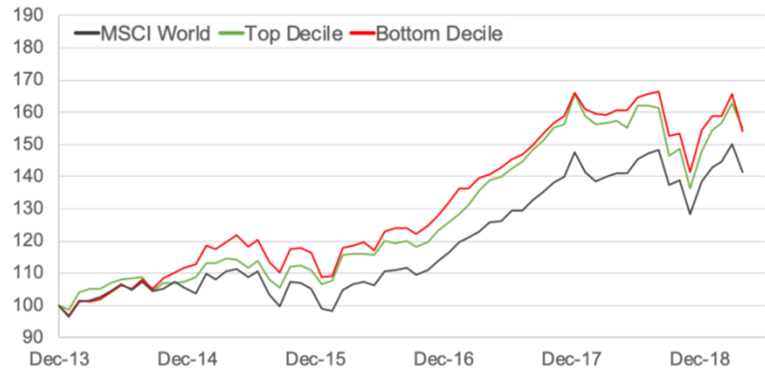


Table 26: Developed markets - performance group "average"- regression results

	Top Decile 6m		Bottom Decile 6m		Top Decile 12m		Bottom Decile 12m		Top Decile 18m		Bottom Decile 18m	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Market Excess Return	0.9262***	0.9468***	0.9590***	0.9863***	0.9075***	0.9393***	1.0111***	1.0374***	0.9127***	0.9067***	0.9400***	0.9653***
	(0.0542)	(0.0427)	(0.0323)	(0.0427)	(0.0423)	(0.0415)	(0.0364)	(0.0415)	(0.0588)	(0.0425)	(0.0295)	(0.0425)
	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000
Small-Minus-Big	0.4512***		0.5180***		0.3628***		0.4540***		0.2518		0.4946***	
	(0.1457)		(0.0940)		(0.1274)		(0.1107)		(0.1747)		(0.1010)	
	p = 0.0020		p = 0.000000		p = 0.0044		p = 0.00005		p = 0.1497		p = 0.000001	
High-Minus-Low	-0.0803		0.0419		-0.0992		0.0419		-0.0875		-0.0064	
	(0.1012)		(0.0733)		(0.0953)		(0.0743)		(0.0967)		(0.0727)	
	p = 0.4274		p = 0.5674		p = 0.2979		p = 0.5731		p = 0.3655		p = 0.9302	
Winners-Minus-Losers	-0.0011		0.0192		-0.0537		0.0106		0.0419		0.01	
	(0.0837)		(0.0668)		(0.0754)		(0.0653)		(0.0784)		(0.0625)	
	p = 0.9894		p = 0.7736		p = 0.4764		p = 0.8705		p = 0.5927		p = 0.8729	
Alpha	0.0033*	0.0036***	0.0031*	0.0012	0.0025	0.0032**	0.0027*	0.0009	0.0009	0.0019	0.0026	0.0015
	(0.0017)	(0.0012)	(0.0017)	(0.0012)	(0.0017)	(0.0013)	(0.0016)	(0.0013)	(0.0018)	(0.0013)	(0.0016)	(0.0013)
	p = 0.0538	p = 0.0023	p = 0.0617	p = 0.3083	p = 0.1466	p = 0.0105	p = 0.0828	p = 0.4642	p = 0.5992	p = 0.1318	p = 0.1162	p = 0.2314
Observations	65	65	65	65	65	65	65	65	65	65	65	65
R^2	0.9213	0.8988	0.9422	0.9211	0.9186	0.902	0.9426	0.9277	0.8919	0.8774	0.9394	0.9183
Adjusted R^2	0.9161	0.8972	0.9383	0.9198	0.9132	0.9005	0.9388	0.9266	0.8847	0.8754	0.9354	0.917
Residual Std. Error	0.0094	0.0104	0.0083	0.0095	0.0095	0.0102	0.0087	0.0095	0.0107	0.0111	0.0084	0.0095
	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)
F Statistic	175.6024*** (df = 4; 60)	559.5174*** (df = 1; 63)	244.3206*** (df = 4; 60)	735.3263*** (df = 1; 63)	169.3450*** (df = 4; 60)	580.0167*** (df = 1; 63)	246.4030*** (df = 4; 60)	808.7727*** (df = 1; 63)	123.7971*** (df = 4; 60)	450.7516*** (df = 1; 63)	232.6775*** (df = 4; 60)	708.3624*** (df = 1; 63)

Notes:

The table reports the results of the estimation of the multi-factor and single index model for the period 2014-01 to 2019-05. Columns 1, 3, 5, 7, 9, 10, 11 report the OLS estimates for each portfolio's monthly excess return on the multi-factor model. Columns 2, 4, 6, 8, 10, 12 report the coefficients of the single index model. The dependent variable is the respective portfolio's excess return. Alpha is the monthly abnormal return that cannot be attributable to the systematic risk factors. HAC standard errors are reported in parentheses. Portfolios are equally weighted and rebalanced either 6, 12 or 18 months after their formation. The top (bottom) portfolio contains the top (bottom) 10% of companies with respect to ESG momentum at each rebalancing date.

Significance: * 10%, ** 5%, *** 1%

The results of the single index regression as well as the multi-factor regression confirm the takeaways from the performance metrics (cf. Table 26). In the single index regression, the alpha of the top portfolio with the 6-month holding period is highly significant at a 1% significance level, with a monthly alpha of 0.36%. The top portfolio with the 12-month holding period also exhibits a significant monthly alpha of 0.32% at a 5% significance level, while all other alphas are insignificant. Similar to the results of the developed market portfolios and the performance group “low”, the beta of the market excess return is highly significant for all portfolios with a value in the range of 0.90 to 1, and consistently slightly higher for the bottom portfolio. The R^2 is again, very high at around 0.90.

In the multi-factor model, the alpha of the top portfolio with the 6-month holding period remains significant with a monthly alpha of 0.33%, although only at a 10% significance level. In conclusion, the alpha is not attributable to the Fama French factors or the momentum factor in this portfolio. However, the bottom portfolio yields significant alphas with the 6-month and 12-month holding periods of 0.31% and 0.27%, respectively. The market excess return remains highly significant for all portfolios, and the betas continue to be higher for the bottom portfolio. The SMB factor is highly significant and all portfolios, except the bottom portfolio with 18-month holding period, are positively exposed to this factor in a similar magnitude to the portfolios in the performance group “low”.

Table 27: Annualised alphas across performance group "average" portfolios

	Annualised multi-factor alpha					Annualised CAPM alpha			
	Performance group "average"			Significance		Performance group		Significance	
Holding period	Top	Bottom	Delta	Top	Bottom	Top	Bottom	Top	Bottom
6m	4.03%	3.78%	0.25%	10%	10%	4.41%	1.45%	1%	No
12m	3.04%	3.29%	-0.25%	No	10%	3.91%	1.09%	5%	No
18m	1.09%	3.17%	-2.08%	No	No	2.30%	1.81%	No	No

There is evidence that the top portfolio is in fact outperforming the bottom portfolio, especially in the shorter term (6 months) as the significant alpha in the single index regression stays significant in the multi-factor regression, although at a higher significance level. However, the results are considered weak as the bottom portfolio also yields a significant positive alpha in the multi-factor regression, and the difference between the alphas in the top and bottom portfolio becomes very small. Still, there is evidence of the top portfolio offering better risk-adjusted returns when considering the Sharpe and information ratios, particularly with the 6-month and 12-month holding period.

Similar to the results of the developed market portfolios and the performance group “low”, the bottom portfolio tends to outperform the top portfolio with the 18-month holding period when looking at the multi-factor regression. In the performance group “average” the outperformance of the bottom portfolio is not significant, although the annualised alpha of 3.17% would be significant at a 12% significance level. Thus, the same arguments for this trend apply to the “average” performance group. The outperformance could be a result of increasing ESG scores during the holding period, given that the ESG scores have their annual review during the 18 months. As seen in Table 23, the average ESG score of the portfolio does in fact increase over the holding period, especially for the 18-month holding period. The average increase in ESG score also grows progressively for the top portfolios with longer holding period, although the performance does not increase with the length of the holding period. Thus, no clear relationship between increasing ESG scores during the holding period and the portfolio performance is identified.

7.2.1.3 Performance group "high"

Similar to the other performance groups, the annualised turnover is lowest for the 6-month holding period as the companies continue to have highly increasing ESG scores in the following 6-months. In addition, differences in transaction costs are negligible across the top and bottom portfolio for a given holding period, as the turnover is very similar.

Table 28: Portfolio turnover

	Top portfolio			Bottom portfolio		
Holding period	Avg. turnover	Annualized turnover*	Avg. no. companies	Avg. turnover	Annualized turnover*	Avg. no. companies
6 months	57%	56%	74	57%	57%	77
12 months	89%	89%	72	85%	85%	71
18 months	94%	63%	67	93%	62%	66

**Notes: For the turnover calculation cf. Appendix A1.*

Table 29: Average industry adjusted ESG score

	Top portfolio				Bottom portfolio			
Holding period	Δ SP	BOHP	HP	Δ HP	Δ SP	BOHP	HP	Δ HP
6 months	1.8	7.28	7.53	0.17	-1.4	6.35	6.41	-0.11
12 months	1.7	7.31	7.48	0.58	-1.3	6.29	6.41	-0.05
18 months	1.5	7.42	7.54	0.16	-1.3	6.38	6.34	0.05

**Notes: Δ SP = change over selection period, BOHP = score at the beginning of holding period, HP = holding period, Δ HP = change over holding period, the ESG score change refers to changes in the SMA (cf. Adjusted ESG scores).*

Once more, the average market capitalisation is higher for all portfolios in comparison to the average of the dataset. In addition, the ROE is higher for the top portfolios across all holding periods compared to the bottom portfolios. Thus, similar to the portfolios in the other performance groups, the bottom portfolios, on average, have a more efficient deployment of equity. The P/E ratio is significantly higher for the top portfolio with the 6-month holding period compared to the bottom portfolio, while the opposite applies to the portfolios with the 18-month holding period. Thus, the top portfolio is comparably more expensive with the 6-month holding period, while the opposite applies to the portfolios with the 18-month holding period. The current ratio is significantly higher for the bottom portfolios, which indicate a higher short-term liquidity. However, the current ratio of the top portfolios would not be considered worrying since it is substantially above 1.

Table 30, Panel A: KPIs for the top portfolio

	6 months		12 months		18 months	
	Mean	Median	Mean	Median	Mean	Median
Market cap. (USD bn)	24.34	10.52	25.20	10.44	26.40	10.92
ROA (%)	5.60	4.73	5.91	4.99	5.75	4.92
ROE (%)	19.72	13.15	9.99	13.51	12.08	13.62
CAPEX (USD bn)	-0.89	-0.33	-0.930	-0.32	-0.90	-0.31
D/E ratio	1.14	0.64	1.11	0.62	1.52	0.63
B/M ratio	0.31	0.40	0.19	0.39	0.22	0.39
Current ratio	1.89	1.29	1.69	1.32	1.70	1.28
EV/EBITDA	12.78	11.21	17.93	11.40	15.25	11.82
P/E ratio	24.05	22.00	23.29	22.62	-20.25	23.59

Table 30, Panel B: KPIs for the bottom portfolio

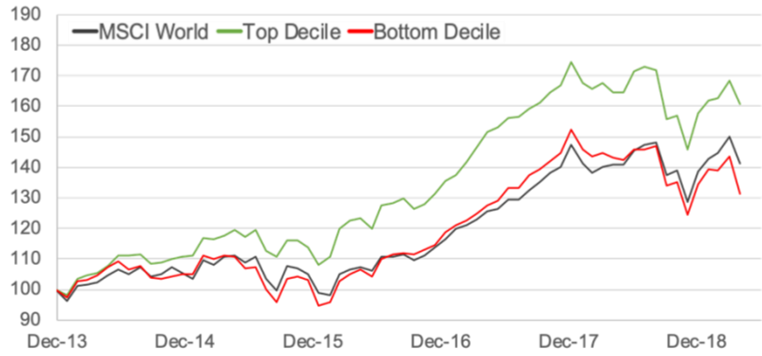
	6 months		12 months		18 months	
	Mean	Median	Mean	Median	Mean	Median
Market cap. (USD bn)	27.24	13.63	26.42	12.90	30.02	16.51
ROA (%)	5.19	3.85	5.00	3.85	5.25	4.06
ROE (%)	24.53	11.68	16.78	12.09	19.89	12.60
CAPEX (USD bn)	-1.31	-0.43	-1.26	-0.40	-1.35	-0.45
D/E ratio	1.35	0.69	1.20	0.71	1.06	0.63
B/M ratio	0.27	0.48	0.32	0.49	0.42	0.48
Current ratio	5.18	1.30	8.01	1.32	6.21	1.33
EV/EBITDA	11.55	10.63	10.79	10.83	10.06	10.97
P/E ratio	9.06	21.37	27.43	22.10	22.94	21.47

The top portfolio with the 6-month holding period substantially outperforms the benchmark and the bottom portfolio in terms of expected return. The expected annualised return is 9.81%, while it is just 5.95% for the bottom portfolio and 7.28% for the benchmark. The difference in the average return between the top and bottom portfolio is significant at a 1% significance level for all holding periods. The top portfolio shows a slightly lower volatility compared to the bottom portfolio and the benchmark in this holding period, which results in better risk-adjusted returns with a significantly better Sharpe ratio as well as information ratio. In addition, the top portfolio has a noteworthy lower VaR (5%) compared to the bottom portfolio in the 6-month holding period by 2.08 percentage points. The performance of the top portfolio decreases and the performance of the bottom portfolio increases in terms of expected return and Sharpe ratio as the holding period increases. Thus, the outperformance of the top portfolio decreases as the holding period increases. Similar to the portfolios in the other performance groups, both the top and bottom portfolio have fatter tails (higher kurtosis) compared to the benchmark, which means higher positive and negative returns are expected.

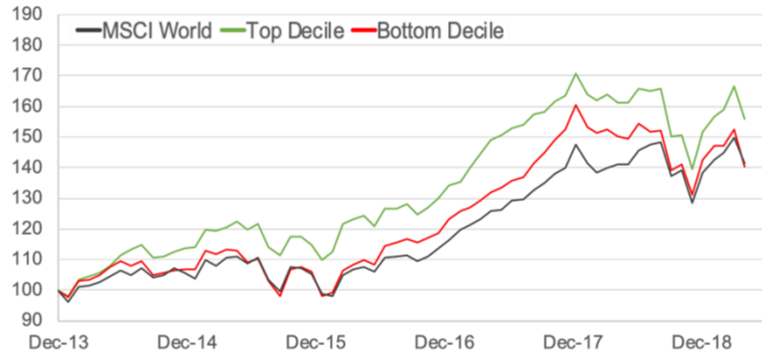
Table 31: Individual portfolio overview

		Top decile	Bottom decile	MSCI EM
	6 months			
Performance	Expected return (%)	0.78 (9.81)	0.48 (5.95)	0.78 (9.81)
	Volatility (%)	3.20 (11.08)	3.26 (12.45)	3.20 (11.08)
	Sharpe ratio	0.23 (0.75)	0.11 (0.38)	0.23 (0.75)
	Information ratio	0.16 (0.59)	-0.10 (-0.38)	0.16 (0.59)
	Benchmark correlation	0.93	0.96	0.93
	Max. High water mark	174.57	152.43	174.57
	05-2019 TRI	160.69	131.20	160.69
Risk	Max. drawdown (%)	16.42	18.44	16.42
	Skewness	-0.48	-0.63	-0.48
	Kurtosis	1.15	1.01	1.15
	5% VaR (%)	-5.02	-7.82	-5.02
	Expected shortfall (%)	-6.75	-8.44	-6.75

Total return indices (TRIs), in USD



		Top decile	Bottom decile	MSCI EM
	12 months			
Performance	Expected return (%)	0.74 (9.24)	0.58 (7.25)	0.74 (9.24)
	Volatility (%)	3.31 (11.46)	3.57 (12.36)	3.31 (11.46)
	Sharpe ratio	0.20 (0.68)	0.15 (0.48)	0.20 (0.68)
	Information ratio	0.12 (0.46)	-0.00 (-0.01)	0.12 (0.46)
	Benchmark correlation	0.93	0.96	0.93
	Max. High water mark	170.87	160.47	170.87
	05-2019 TRI	155.84	140.29	155.84
Risk	Max. drawdown (%)	18.33	18.31	18.33
	Skewness	-0.60	-0.41	-0.60
	Kurtosis	1.26	0.77	1.26
	5% VaR (%)	-5.87	-7.05	-5.87
	Expected shortfall (%)	-7.38	-7.75	-7.38



		Top decile	Bottom decile	MSCI EM
	18 months			
Performance	Expected return (%)	0.73 (9.06)	0.56 (6.93)	0.73 (9.06)
	Volatility (%)	3.33 (11.53)	3.48 (12.06)	3.33 (11.53)
	Sharpe ratio	0.19 (0.66)	0.14 (0.47)	0.19 (0.66)
	Information ratio	0.12 (0.46)	-0.03 (-0.11)	0.12 (0.46)
	Benchmark correlation	0.94	0.96	0.94
	Max. High water mark	161.00	150.22	161.00
	05-2019 TRI	154.38	138.28	154.38
Risk	Max. drawdown (%)	15.70	16.52	15.70
	Skewness	-0.41	-0.31	-0.41
	Kurtosis	0.97	1.23	0.97
	5% VaR (%)	-4.59	-6.56	-4.59
	Expected shortfall (%)	-6.78	-7.59	-6.78

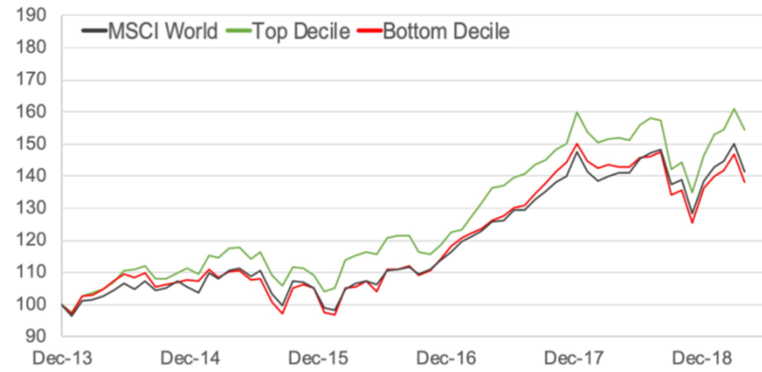


Table 32: Developed markets - performance group "high"- regression results

	Top Decile 6m		Bottom Decile 6m		Top Decile 12m		Bottom Decile 12m		Top Decile 18m		Bottom Decile 18m	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Market Excess Return	0.8892***	0.9126***	1.0350***	1.0613***	0.9124***	0.9463***	1.0164***	1.0524***	0.9610***	0.9637***	1.0127***	1.0286***
	(0.0599)	(0.0405)	(0.0341)	(0.0405)	(0.0624)	(0.0367)	(0.0323)	(0.0367)	(0.0614)	(0.0444)	(0.0342)	(0.0444)
	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000
Small-Minus-Big	0.4533***		0.4370***		0.4283**		0.3931***		0.2174		0.4109***	
	(0.1709)		(0.1164)		(0.1739)		(0.1055)		(0.1634)		(0.1151)	
	p = 0.0081		p = 0.0002		p = 0.0138		p = 0.0002		p = 0.1832		p = 0.0004	
High-Minus-Low	0.0598		0.1719*		0.0055		0.1384		-0.0672		0.0899	
	(0.1252)		(0.0905)		(0.1306)		(0.0944)		(0.0989)		(0.0697)	
	p = 0.6330		p = 0.0576		p = 0.9662		p = 0.1425		p = 0.4969		p = 0.1968	
Winners-Minus-Losers	0.0235		0.0381		-0.0246		-0.0063		0.0147		0.0451	
	(0.0916)		(0.0691)		(0.0990)		(0.0663)		(0.0850)		(0.0683)	
	p = 0.7972		p = 0.5814		p = 0.8034		p = 0.9243		p = 0.8626		p = 0.5089	
Alpha	0.0045***	0.0024*	0.0026	-0.0013	0.003	0.0018	0.0030*	-0.0003	0.0009	0.0016	0.002	-0.0004
	(0.0017)	(0.0014)	(0.0019)	(0.0014)	(0.0018)	(0.0013)	(0.0018)	(0.0013)	(0.0020)	(0.0012)	(0.0016)	(0.0012)
	p = 0.0097	p = 0.0788	p = 0.1752	p = 0.3251	p = 0.1092	p = 0.1789	p = 0.0958	p = 0.8317	p = 0.6501	p = 0.1894	p = 0.2069	p = 0.7238
Observations	65	65	65	65	65	65	65	65	65	65	65	65
R^2	0.8785	0.861	0.9416	0.9243	0.8813	0.8652	0.9393	0.9228	0.8971	0.8898	0.9379	0.9258
Adjusted R^2	0.8705	0.8588	0.9377	0.9231	0.8734	0.863	0.9353	0.9216	0.8903	0.888	0.9338	0.9246
Residual Std. Error	0.0115	0.0121	0.0090	0.0100	0.0118	0.0123	0.0091	0.0100	0.0110	0.0112	0.0090	0.0096
	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)
F Statistic	108.5073***	390.3322***	241.8351***	769.2154***	111.3986***	404.2999***	232.1347***	753.4566***	130.8032***	508.5628***	226.7123***	785.6722***
	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)

Notes:

The table reports the results of the estimation of the multi-factor and single index model for the period 2014-01 to 2019-05. Columns 1, 3, 5, 7, 9, 10, 11 report the OLS estimates for each portfolio's monthly excess return on the multi-factor model. Columns 2, 4, 6, 8, 10, 12 report the coefficients of the single index model. The dependent variable is the respective portfolio's excess return. Alpha is the monthly abnormal return that cannot be attributable to the systematic risk factors. HAC standard errors are reported in parentheses. Portfolios are equally weighted and rebalanced either 6, 12 or 18 months after their formation. The top (bottom) portfolio contains the top (bottom) 10% of companies with respect to ESG momentum at each rebalancing date.

Significance: * 10%, ** 5%, *** 1%

In the single index regression, the top portfolio with a 6-month holding period yields a significant monthly alpha (at a 10% significance level) of 0.24%. Although no other alpha is significant, the signs of the alphas are noteworthy. The top portfolios have positive alphas, while the bottom portfolios have negative alphas. The market excess return is highly significant for all portfolios and across all holding periods, while the bottom portfolio has a slightly higher beta just above 1 and the top portfolio has a beta in the range of 0.91-0.96. Thus, the bottom portfolio is more exposed to fluctuations of the market. The adjusted R^2 is again rather high in the range of 0.86 to 0.92.

In the multi-factor regression, the alpha of the top portfolio with the 6-month holding period increased in magnitude and in significance, which is supportive of the results of the performance metrics. The alpha is significant at a 1% level with a monthly alpha of 0.45%. In conclusion, the alpha is likely not attributable to the Fama French factors or the momentum factor. However, the bottom portfolio with the 12-month holding period has a significant monthly alpha of 0.30% at a 10% significance level. The top portfolio with the 12-month holding period has a close to significant monthly alpha of 0.30%, with a p-value of 0.1092. Thus, the outperformance of the bottom portfolio for the 12-month holding period is negligible and the alphas are unlikely to be attributable to ESG momentum. The adjusted R^2 only increased marginally from the single index regression to the multi-factor regression.

Similar to the results of the other performance groups, the exposure to the SMB factor is positive and highly significant for all portfolios in a similar magnitude to the portfolios in the performance group "average", except for the bottom portfolio with 18-month holding periods. Only the bottom portfolio with the 6-month holding period has a significant positive exposure to the HML factor (at a 10% significance level), while the bottom portfolios with 12-month and 18-month holding periods show positive exposures close to significance with p-values of 0.1425 and 0.1968 respectively. Other studies have reported evidence of a positive exposure of companies with high ESG scores to value factors (cf. ESG and other risk factors), thus the observed significant positive exposure to the HML factor is consistent with these studies. However, the evidence is weak since only one portfolio has a significant coefficient and this coefficient is small in magnitude.

Table 33: Annualised alphas across performance group "high" portfolios

	Annualised multi-factor alpha					Annualised CAPM alpha			
	Performance group "high"			Significance		Performance group		Significance	
Holding period	Top	Bottom	Delta	Top	Bottom	Top	Bottom	Top	Bottom
6m	5.54%	3.17%	2.37%	1%	No	2.92%	-1.55%	10%	No
12m	3.66%	3.66%	0.00%	No	10%	2.18%	-0.36%	No	No
18m	1.09%	2.43%	-1.34%	No	No	1.94%	-0.48%	No	No

The strongest evidence of outperformance of the portfolios with positive ESG momentum over the portfolios with negative ESG momentum is found in the performance group "high". The 6-month holding period exhibits significant alphas in both the single index and the multi-factor regression for the top portfolios, while the bottom portfolios do not yield significant alphas in this holding period. This is supported by the fact that alphas of the bottom portfolios are negative while alphas of the top portfolios are positive, although mostly insignificant. Again, the performance metrics show evidence of better risk-adjusted returns for the top portfolios, specifically for the 6-month holding period. Similar to the other performance groups, the bottom portfolio outperforms the top portfolio in terms of alpha with the 18-month holding period in the multi-factor regression, although the alphas are insignificant. Thus, similar conclusions account for the performance group "high". Table 29 shows that the bottom portfolio exhibits a small average increase in its ESG score for the 18-month holding period, while the other holding periods continue to have decreasing ESG scores. However, the performance generally decreases with the length of the holding period for the bottom portfolios in terms of expected return and the alpha of the regressions. As a result, nNo clear relationship appears to be present between the average increase of the ESG score over the holding period and the expected return and significant alphas of the top portfolios. Thus, there is no convincing evidence of the relationship between the two.

7.2.1.4 Summary

All portfolios in all performance groups have a higher than average market capitalisation and fatter tails compared to the benchmark. In general, the bottom portfolios have a higher ROE compared to the top portfolios in all performance groups across all holding periods. The turnovers are very similar for the given holding periods for all performance groups, and thus differences in terms of transaction costs can be disregarded.

In the performance group "low", evidence of companies with decreasing ESG scores outperforming companies with increasing ESG scores were present for the 18-month holding period. The bottom portfolio has a significant annualised alpha of 3.91% and 5.03% in the single index regression and the multi-factor regression respectively at a 5% significance level, while the top portfolio has no significant alphas in this holding period. In addition, the bottom portfolio has a higher expected return and a better risk-adjusted return with an annualised Sharpe ratio of 0.84 compared to 0.66 for the top portfolio. This supports that a negative ESG momentum yields a positive alpha with an 18-month holding period (Q1).

In the performance group "average", the top portfolio with a 6-month holding period outperforms its counterpart with significant annualised alphas of 4.41% and 4.03% in the single index regression and the multi-factor regression, respectively. Still, the results are considered weak as the bottom portfolio also has a significant positive alpha in the multi-factor regression, which results in a very small difference in alpha. However, evidence of the top portfolio offering better risk-adjusted returns when looking at the Sharpe and information ratio persists with the 6-month and 12-month holding periods. The annualised Sharpe ratio is 0.88 for the top portfolio compared to 0.63 for the bottom portfolio with the 6-month holding period. Still, both portfolios outperform the benchmark.

Table 34: Developed markets - annualised alphas across performance groups

	Annualised multi-factor alpha					Annualised CAPM alpha			
	Performance group "low"			Significance		Performance group		Significance	
Holding period	Top	Bottom	Delta	Top	Bottom	Top	Bottom	Top	Bottom
6m	4.53%	3.04%	1.49%	No	No	1.69%	1.81%	No	No
12m	3.54%	3.17%	0.37%	No	No	3.04%	2.06%	10%	No
18m	2.92%	5.03%	-2.11%	No	5%	1.94%	3.91%	No	5%

	Annualised multi-factor alpha					Annualised CAPM alpha			
	Performance group "average"			Significance		Performance group		Significance	
Holding period	Top	Bottom	Delta	Top	Bottom	Top	Bottom	Top	Bottom
6m	4.03%	3.78%	0.25%	10%	10%	4.41%	1.45%	1%	No
12m	3.04%	3.29%	-0.25%	No	10%	3.91%	1.09%	5%	No
18m	1.09%	3.17%	-2.08%	No	No	2.30%	1.81%	No	No

	Annualised multi-factor alpha					Annualised CAPM alpha			
	Performance group "high"			Significance		Performance group		Significance	
Holding period	Top	Bottom	Delta	Top	Bottom	Top	Bottom	Top	Bottom
6m	5.54%	3.17%	2.37%	1%	No	2.92%	-1.55%	10%	No
12m	3.66%	3.66%	0.00%	No	10%	2.18%	-0.36%	No	No
18m	1.09%	2.43%	-1.34%	No	No	1.94%	-0.48%	No	No

Performance group "high" presents the strongest evidence for positive ESG momentum generating a positive alpha. The top portfolio with the 6-month holding period significantly outperforms the benchmark and the bottom portfolio in terms of expected return, while the slightly lower volatility leads to better risk-adjusted returns with a notably better annualised Sharpe ratio of 0.75 compared to 0.38 in the bottom portfolio. The top portfolio with the 6-month holding period yields significant alphas in both the single index regression and the multi-factor regression with annualised alphas of 2.92% and 5.54% respectively, while the bottom portfolios show no significant alphas. In addition, the alpha increases in significance from the single index model with a level of 10% to a level of 1% in the multi-factor model.

As a result, there is no evidence of companies with positive ESG momentum at a lower absolute ESG score level experiencing a higher price effect compared to positive ESG momentum at a higher absolute level. In fact, evidence of the contrary is present (Q4). There is convincing evidence that positive ESG momentum generating an alpha for companies which improve from a relatively high ESG score is present with a holding period of 6 months in the performance group "high" (Q2). The study of ESG momentum by Nagy et al. (2016) finds an annualised alpha of 2.2%, while there is a significantly higher alpha of 5.54% in this performance group for a 6-month holding period in this analys.

In the performance group “low”, there is convincing evidence of the bottom portfolio outperforming the top portfolio with the 18-month holding period. The bottom portfolio exhibits significant annualised alphas of 3.91% and 5.03% in the single index and the multi-factor regression, respectively, while the top portfolio yields no significant alphas in this holding period. However, the average change in ESG scores over the holding period is in fact increasing, which has potential to drive the increasing performance. Thus, some evidence persists of companies with decreasing ESG scores generating higher returns compared to companies with increasing ESG scores, although the evidence of the relationship is not compelling. These results support a theory where a relatively high initial ESG score is required for the market to value the increase in the ESG score. An additional interesting insight is, that the bottom portfolios do not generally show a trend of being punished by the market, as these portfolios still tend to follow the market returns closely or to outperform it.

7.2.2 Emerging markets

7.2.2.1 Performance group “low”

The authors further examine portfolios conditional on performance groups formed on emerging markets data. The turnover in the performance group “low” is generally lower compared to the general emerging market, which is in line with the fact, that there are fewer companies to select from when segmenting the market into top and bottom portfolios (cf. Table 35). Different turnovers result in different transaction costs which in turn influences investment decisions to some extent.

Table 35: Portfolio turnover

	Top portfolio			Bottom portfolio		
Holding period	Avg. turnover	Annualized turnover*	Avg. no. companies	Avg. turnover	Annualized turnover*	Avg. no. companies
6 months	43%	43%	36	37%	38%	37
12 months	67%	67%	32	67%	67%	35
18 months	75%	50%	27	74%	49%	28

**Notes: For the turnover calculation cf. Appendix A1.*

In terms of absolute ESG scores, the companies in the top portfolio have a lower ESG score than the companies selected for the bottom portfolio, indicating that industry laggards in the performance group “low” tend to accelerate their ESG effort more than companies with scores at the upper end of the ESG score spectrum in this performance group (cf. Table 36, BOHP). Generally, companies selected for the top portfolio continue to increase their ESG scores over the holding period of the portfolio with the increase being higher than in the general emerging markets portfolios. Hence, ESG momentum tends to be more persistent in the performance group “low” (cf. Δ HP). The bottom portfolio continues to decrease its ESG score only over the 6-month holding period (Δ HP = -0.04) while experiencing an increase over the longer holding periods, which is also observable in the general emerging markets portfolio (Δ HP = 0.16). However, the magnitude of this increase is approximately half the size of their top portfolio counterparts.

Table 36: Average industry adjusted ESG score

	Top portfolio				Bottom portfolio			
Holding period	Δ SP	BOHP	HP	Δ HP	Δ SP	BOHP	HP	Δ HP
6 months	0.92	2.35	2.54	0.18	-0.87	3.64	1.65	-0.04
12 months	0.93	2.37	2.59	0.31	-0.86	3.55	1.71	0.12
18 months	0.83	2.25	2.59	0.29	-0.83	3.37	1.70	0.16

**Notes: Δ SP = change over selection period, BOHP = score at the beginning of holding period, HP = holding period, Δ HP = change over holding period, the ESG score change refers to changes in the SMA (cf. Adjusted ESG scores)*

When observing the average market capitalisation of both portfolios in Table 37, the top portfolio contains slightly larger companies and their average market capitalization is higher than that of the emerging markets data set (Table 2, 16.47bn USD). The B/M ratios are lower for the top portfolio, indicating that the market expects them to have higher future earnings than the companies in the bottom portfolio which makes their stocks more expensive. The EV/EBITDA multiples also value the companies contained in the top portfolio higher.

Table 37, Panel A: KPIs for the top portfolio

	6 months		12 months		18 months	
	Mean	Median	Mean	Median	Mean	Median
Market cap. (USD bn)	21.31	8.87	21.72	8.46	22.58	9.20
ROA (%)	5.21	3.79	5.30	4.16	5.03	3.72
ROE (%)	13.76	12.63	14.08	12.53	12.87	11.99
CAPEX (USD bn)	-1.27	-0.35	-1.45	-0.38	-1.48	-0.31
D/E ratio	1.15	0.56	1.13	0.58	1.20	0.61
B/M ratio	0.29	0.54	0.29	0.55	0.28	0.58
Current ratio	21.43	1.28	22.72	1.28	4.12	1.27
EV/EBITDA	95.22	10.71	43.57	10.42	6.86	10.40
P/E ratio	31.37	18.15	-7.59	17.78	23.14	17.83

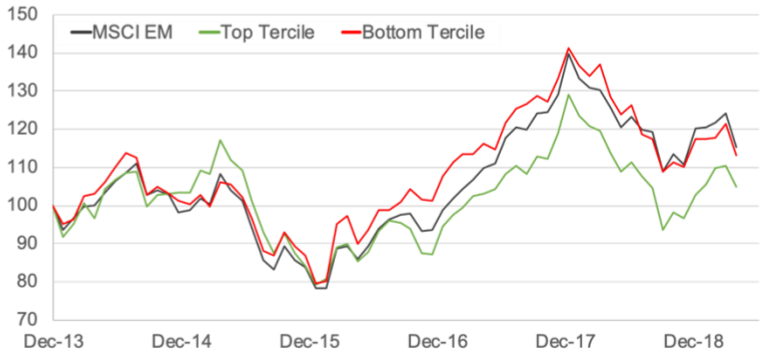
Table 37, Panel B: KPIs for the bottom portfolio

	6 months		12 months		18 months	
	Mean	Median	Mean	Median	Mean	Median
Market cap. (USD bn)	19.29	8.78	20.44	8.63	18.64	9.99
ROA (%)	5.10	4.30	5.21	4.19	5.36	4.30
ROE (%)	12.11	11.93	11.74	11.74	12.48	12.16
CAPEX (USD bn)	-1.52	-0.52	-1.54	-0.50	-1.53	-0.62
D/E ratio	1.08	0.61	1.07	0.59	1.15	0.60
B/M ratio	0.38	0.62	0.35	0.62	0.35	0.61
Current ratio	1.91	1.36	1.93	1.35	2.04	1.39
EV/EBITDA	11.65	9.25	7.28	9.27	11.39	8.78
P/E ratio	-5.81	17.82	27.27	18.41	23.72	17.44

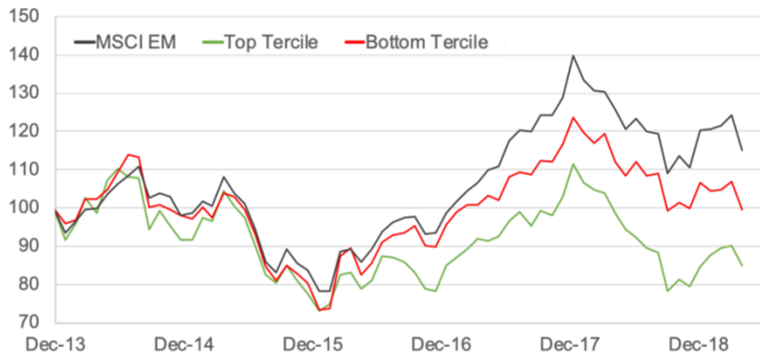
Table 38: Individual portfolio overview

		Top tercile	Bottom tercile	MSCI EM
	6 months			
Performance	Expected return (%)	0.42 (5.12)	0.50 (6.21)	0.31 (3.84)
	Volatility (%)	4.81 (16.65)	4.74 (16.42)	4.45 (15.41)
	Sharpe ratio	0.07 (0.24)	0.09 (0.30)	0.05 (0.18)
	Information ratio	0.06 (0.21)	0.10 (0.37)	-
	Benchmark correlation	0.93	0.92	1
	Max. High water mark	144.45	155.84	139.66
	05-2019 TRI	121.74	128.16	115.18
Risk	Max. drawdown (%)	30.44	28.00	29.43
	Skewness	-0.13	0.54	0.10
	Kurtosis	-0.67	2.22	0.14
	5% VaR (%)	-7.79	-7.13	-7.15
	Expected shortfall (%)	-8.76	-8.34	-8.08

Total return indices (TRIs), in USD



		Top tercile	Bottom tercile
	12 months		
Performance	Expected return (%)	0.11 (1.31)	0.31 (3.73)
	Volatility (%)	5.04 (17.47)	4.87 (16.87)
	Sharpe ratio	0.00 (0.01)	0.04 (0.15)
	Information ratio	-0.10 (-0.34)	-0.01 (-0.02)
	Benchmark correlation	0.91	0.93
	Max. High water mark	124.61	136.22
	05-2019 TRI	98.88	113.12
Risk	Max. drawdown (%)	30.59	33.83
	Skewness	-0.03	0.37
	Kurtosis	-0.45	2.14
	5% VaR (%)	-7.80	-8.47
	Expected shortfall (%)	-9.90	-9.58



		Top tercile	Bottom tercile
	18 months		
Performance	Expected return (%)	0.46 (5.66)	0.30 (3.67)
	Volatility (%)	5.25 (18.20)	4.83 (16.75)
	Sharpe ratio	0.07 (0.25)	0.04 (0.15)
	Information ratio	0.07 (0.24)	-0.01 (-0.03)
	Benchmark correlation	0.91	0.93
	Max. High water mark	156.10	135.83
	05-2019 TRI	123.48	112.93
Risk	Max. drawdown (%)	29.43	31.31
	Skewness	0.09	0.37
	Kurtosis	-0.28	1.14
	5% VaR (%)	-7.98	-6.96
	Expected shortfall (%)	-9.08	-8.74

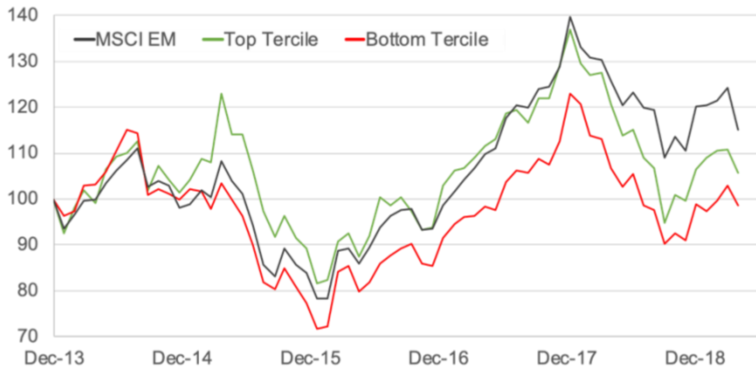


Table 39: Emerging markets - performance group "low"- regression results

	Top Tercile 6m		Bottom Tercile 6m		Top Tercile 12m		Bottom Tercile 12m		Top Tercile 18m		Bottom Tercile 18m	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Market Excess Return	1.0310***	1.0027***	0.9638***	0.9848***	1.0690***	1.0282***	1.0200***	1.0209***	1.1280***	1.0764***	1.0312***	1.0100***
	(0.0617)	(0.0818)	(0.0787)	(0.0818)	(0.0729)	(0.0813)	(0.0799)	(0.0813)	(0.0750)	(0.0677)	(0.0747)	(0.0677)
	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000
Small-Minus-Big	0.2189**		0.1887		0.3820***		0.2409		0.3191*		0.1664	
	(0.1087)		(0.1525)		(0.1348)		(0.1622)		(0.1708)		(0.1607)	
	p = 0.0441		p = 0.2161		p = 0.0046		p = 0.1376		p = 0.0617		p = 0.3005	
High-Minus-Low	0.0613		0.0933		0.057		0.1015		0.0299		0.0074	
	(0.0836)		(0.0953)		(0.0727)		(0.1004)		(0.1392)		(0.1022)	
	p = 0.4640		p = 0.3280		p = 0.4328		p = 0.3123		p = 0.8302		p = 0.9424	
Winners-Minus-Losers	0.1194		-0.021		0.12		0.0501		0.1454*		0.0452	
	(0.0876)		(0.0774)		(0.0903)		(0.0782)		(0.0761)		(0.0975)	
	p = 0.1729		p = 0.7856		p = 0.1838		p = 0.5220		p = 0.0562		p = 0.6433	
Alpha	0.0047	0.001	0.0050*	0.0019	0.0027	-0.0021	0.004	-0.0001	0.0053	0.0013	0.0016	-0.0002
	(0.0036)	(0.0023)	(0.0030)	(0.0023)	(0.0031)	(0.0023)	(0.0031)	(0.0023)	(0.0041)	(0.0023)	(0.0039)	(0.0023)
	p = 0.1924	p = 0.6614	p = 0.0927	p = 0.4063	p = 0.3704	p = 0.3465	p = 0.1986	p = 0.9495	p = 0.1921	p = 0.5781	p = 0.6819	p = 0.9454
Observations	65	65	65	65	65	65	65	65	65	65	65	65
R^2	0.8713	0.8615	0.8627	0.853	0.8425	0.8231	0.8788	0.8693	0.8451	0.8298	0.8683	0.8643
Adjusted R^2	0.8627	0.8593	0.8536	0.8507	0.832	0.8203	0.8707	0.8672	0.8348	0.8271	0.8595	0.8622
Residual Std. Error	0.0178	0.0180	0.0182	0.0183	0.0207	0.0214	0.0175	0.0178	0.0214	0.0219	0.0181	0.0180
	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)
F Statistic	101.5429***	391.9604***	94.2670***	365.5350***	80.2311***	293.1437***	108.7133***	418.9010***	81.8370***	307.1118***	98.9041***	401.3172***
	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)

Notes:

The table reports the results of the estimation of the multi-factor and single index model for the period 2014-01 to 2019-05. Columns 1, 3, 5, 7, 9, 10, 11 report the OLS estimates for each portfolio's monthly excess return on the multi-factor model. Columns 2, 4, 6, 8, 10, 12 report the coefficients of the single index model. The dependent variable is the respective portfolio's excess return. Alpha is the monthly abnormal return that cannot be attributable to the systematic risk factors. HAC standard errors are reported in parentheses. Portfolios are equally weighted and rebalanced either 6, 12 or 18 months after their formation. The top (bottom) portfolio contains the top (bottom) 33.3% of companies with respect to ESG momentum at each rebalancing date.

Significance: * 10%, ** 5%, *** 1%

In terms of performance (cf. Table 38), the best holding period for the top ESG momentum portfolio is an 18-month holding period yielding 5.66% annual return with an annual Sharpe ratio of 0.25. For the bottom portfolio, the 6-month holding period results in the highest expected annual return (6.21%), the highest annualized Sharpe (0.30) and information ratio (0.37). The longer the bottom portfolio is held, the lower the expected return and the Sharpe ratio. Moreover, the bottom portfolio exhibits fatter tails (kurtosis) than the top portfolio. Over a 12-month holding period, both portfolios exhibit an adverse risk-return trade-off displayed in very low Sharpe ratios and even negative information ratios. This riskiness is also mirrored by expected shortfalls close to 10% and the worst maximum drawdowns for both portfolios. The presented performance and risk measures indicate that the optimal holding periods for the top and bottom portfolio are 18 and 6 months, respectively.

The CAPM models (cf. Table 39) show adjusted R^2 between 0.82-0.87 and hence a high goodness of fit for both portfolios across all holding periods. Although no portfolio exhibits a significant alpha, the signs of the alphas are positive, except for both portfolios over a 12-month holding period. All portfolios are highly positively exposed to the market ($\beta_M \approx 1.00$), with the top portfolio exhibiting a slightly increased exposure. The insignificant alphas across all models indicate that an ESG momentum strategy yields returns beyond the fluctuations of the market.

In the multiple regression model (cf. Table 39), alpha for the bottom portfolio is significant at a 10% level and yields 0.50% monthly (6.17% annually). All other regressions do not show significant alphas, indicating no significant contribution of ESG momentum to the excess returns generated by the portfolios. Again, both portfolios are highly positively exposed to market fluctuations, with the top portfolio exhibiting a slightly increased exposure. The top portfolio shows significant exposure to SMB at a moderate level ($\beta_S \approx$ 0.22-0.38). No portfolio is significantly exposed to value or growth and momentum has significant explanatory power at a moderate level (reg (9), $\beta_W \approx 0.15$) for the top portfolio over an 18-month holding period only.

Table 40: Annualised alphas across performance group "low" portfolios

	Annualised multi-factor alpha					Annualised CAPM alpha			
	Performance group "low"			Significance		Performance group		Significance	
Holding period	Top	Bottom	Delta	Top	Bottom	Top	Bottom	Top	Bottom
6m	5.79%	6.17%	-0.38%	No	10%	1.21%	2.30%	No	No
12m	3.29%	4.91%	-1.62%	No	No	-2.49%	-0.12%	No	No
18m	6.55%	1.94%	4.61%	No	No	1.57%	-0.24%	No	No

In the performance group "low", ESG momentum yields statistically significant patterns of alphas (cf. Table 40). However, the results indicate that the bottom portfolio only significantly outperforms the top portfolio in terms of alpha over a 6-month holding period. Some indicative evidence towards the benefits of positive ESG momentum becomes evident when combining the information provided by key performance indicators and the signs and magnitudes of the alphas over longer holding periods.

Positive ESG momentum in emerging markets might require some time to unfold price effects, which is in line with De & Clayman (2010) who found significant and large alphas to arise over longer holding periods.

7.2.2.2 Performance group "average"

In the performance group "average", turnover rates are similar to those seen in the performance group "low" (cf. Table 41). In this performance group all portfolios are less heavily invested in materials and more in the financial sector, indicating that this performance group is sourcing from a slightly different universe of companies (cf. Appendix A8).

Table 41: Portfolio turnover

	Top portfolio			**Bottom portfolio**		
Holding period	Avg. turnover	Annualized turnover*	Avg. no. companies	Avg. turnover	Annualized turnover*	Avg. no. companies
6 months	41%	40%	43	41%	41%	44
12 months	66%	66%	37	67%	67%	39
18 months	75%	50%	32	75%	50%	32

**Notes: For the turnover calculation cf. Appendix A1*

Companies experiencing positive ESG momentum generally have a lower ESG score while ones experiencing negative ESG momentum are commonly rated higher (cf. Table 42). This is in line with the findings from the performance groups "low". The results indicate that companies in the top portfolio continue to increase their ESG score over a 6-month and 12-month holding period, while on average decreasing (Δ HP = -0.02) over an 18-month holding period. The bottom portfolio continues to decrease its average ESG score over the shorter holding periods while increasing again over longer holding periods. Hence, there is a reversal in ESG momentum in both portfolios over the longest holding period.

Table 42: Average industry adjusted ESG score

	Top portfolio				**Bottom portfolio**			
Holding period	Δ SP	BOHP	HP	Δ HP	Δ SP	BOHP	HP	Δ HP
6 months	1.02	4.19	4.30	0.12	-0.90	3.48	3.50	-0.06
12 months	1.00	4.23	4.37	0.31	-0.89	3.44	3.48	-0.03
18 months	0.96	4.34	4.33	-0.02	-0.90	3.37	3.36	0.16

**Notes: Δ SP = change over selection period, BOHP = score at the beginning of holding period, HP = holding period, Δ HP = change over holding period, the ESG score change refers to changes in the SMA (cf. Adjusted ESG scores)*

When observing the portfolio KPIs (cf. Table 43), it is evident that the top portfolios consist of larger companies and yield a higher ROE ratio compared to the bottom portfolio. However, the bottom portfolios show higher operating efficiency (ROA). Nevertheless, in terms of EV/EBITDA and P/E multiples, the companies in the top portfolio are the higher scoring ones, which may indicate higher future expected earnings or lower cost of capital (Reilly & Damodaran, 1995), which are both attributes of high ESG scoring companies (Giese et al., 2019).

Table 43, Panel A: KPIs for the top portfolio

	6 months		**12 months**		**18 months**	
	Mean	Median	Mean	Median	Mean	Median
Market cap. (USD bn)	24.11	9.68	25.84	10.12	22.66	9.67
ROA (%)	5.01	3.61	5.00	3.52	4.93	3.40
ROE (%)	14.63	13.66	15.25	13.85	14.21	12.88
CAPEX (USD bn)	-1.26	-0.35	-1.29	-0.35	-1.44	-0.46
D/E ratio	1.06	0.62	1.12	0.63	1.17	0.66
B/M ratio	0.36	0.60	0.37	0.83	0.36	0.72
Current ratio	1.47	1.20	1.48	1.21	1.44	1.19
EV/EBITDA	93.18	10.01	47.90	10.12	4.01	9.42
P/E ratio	34.38	16.60	27.98	16.21	20.04	15.60

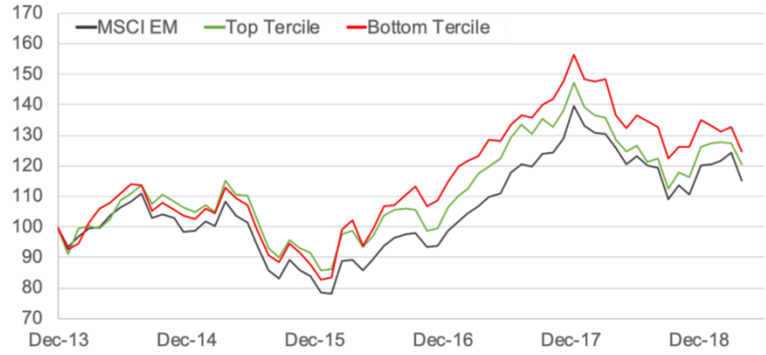
Table 43, Panel B: KPIs for the bottom portfolio

	6 months		**12 months**		**18 months**	
	Mean	Median	Mean	Median	Mean	Median
Market cap. (USD bn)	20.79	9.40	20.34	8.99	22.21	9.97
ROA (%)	5.09	4.20	5.20	4.27	5.17	4.55
ROE (%)	12.43	11.62	13.00	11.84	12.37	12.29
CAPEX (USD bn)	-2.23	-0.51	-1.99	-0.51	-2.24	-0.60
D/E ratio	0.96	0.58	0.97	0.59	0.98	0.59
B/M ratio	0.39	0.70	0.36	0.69	0.37	0.70
Current ratio	1.70	1.33	1.97	1.31	1.78	1.28
EV/EBITDA	40.81	8.43	37.68	8.20	18.14	7.90
P/E ratio	-6.16	16.17	23,83	16,25	-13.85	15.67

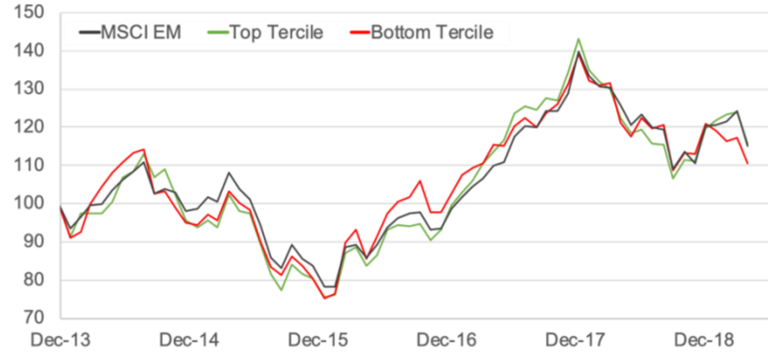
Table 44: Individual portfolio overview

Total return indices (TRIs), in USD

	6 months	Top tercile	Bottom tercile	MSCI EM
Performance	Expected return (%)	0.40 (4.85)	0.45 (5.59)	0.31 (3.84)
	Volatility (%)	4.74 (16.43)	4.90 (16.97)	4.45 (15.41)
	Sharpe ratio	0.07 (0.23)	0.08 (0.26)	0.05 (0.18)
	Information ratio	0.05 (0.19)	0.08 (0.28)	-
	Benchmark correlation	0.95	0.93	1
	Max. High water mark	147.28	156.34	139.66
	05-2019 TRI	120.34	124.51	115.18
Risk	Max. drawdown (%)	25.38	27.54	29.43
	Skewness	0.18	0.42	0.10
	Kurtosis	-0.07	1.48	0.14
	5% VaR (%)	-6.94	-7.83	-7.15
	Expected shortfall (%)	-8.36	-8.12	-8.08



	12 months	Top tercile	Bottom tercile
Performance	Expected return (%)	0.34 (4.21)	0.29 (3.48)
	Volatility (%)	4.93 (17.07)	5.17 (17.91)
	Sharpe ratio	0.05 (0.18)	0.04 (0.13)
	Information ratio	0.02 (0.06)	-0.01 (-0.05)
	Benchmark correlation	0.94	0.93
	Max. High water mark	143.03	139.23
	05-2019 TRI	115.75	110.55
Risk	Max. drawdown (%)	33.03	34.02
	Skewness	0.18	0.17
	Kurtosis	-0.21	0.80
	5% VaR (%)	-7.59	-8.43
	Expected shortfall (%)	-8.36	-9.30



	18 months	Top tercile	Bottom tercile
Performance	Expected return (%)	0.24 (2.91)	0.40 (4.86)
	Volatility (%)	5.04 (17.45)	4.80 (16.62)
	Sharpe ratio	0.03 (0.10)	0.06 (0.22)
	Information ratio	-0.04 (-0.13)	0.04 (0.16)
	Benchmark correlation	0.91	0.92
	Max. High water mark	147.49	139.34
	05-2019 TRI	107.76	120.23
Risk	Max. drawdown (%)	31.37	34.90
	Skewness	0.11	0.12
	Kurtosis	-0.23	0.20
	5% VaR (%)	-8.00	-7.16
	Expected shortfall (%)	-8.58	-8.97

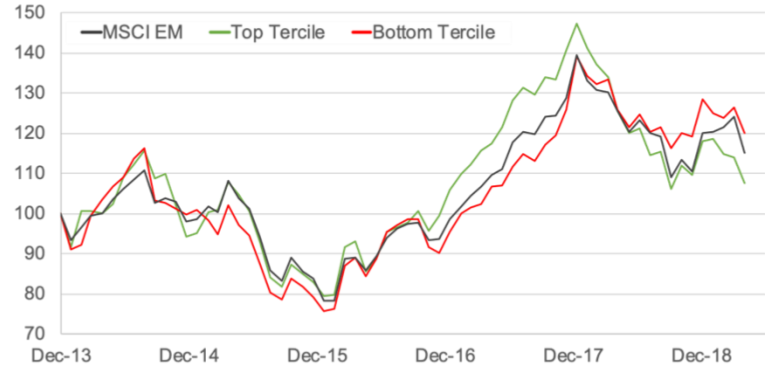


Table 45: Emerging markets - performance group "average"- regression results

	Top Tercile 6m		Bottom Tercile 6m		Top Tercile 12m		Bottom Tercile 12m		Top Tercile 18m		Bottom Tercile 18m	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Market Excess Return	1.0484***	1.0129***	1.0050***	1.0253***	1.0751***	1.0455***	1.0735***	1.0777***	1.0921***	1.0341***	0.9801***	0.9916***
	(0.0564)	(0.0715)	(0.0673)	(0.0715)	(0.0572)	(0.0669)	(0.0693)	(0.0669)	(0.0620)	(0.0614)	(0.0697)	(0.0614)
	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000	p = 0.0000
Small-Minus-Big	0.2006*		0.3640***		0.1561		0.4244**		0.3370**		0.4629***	
	(0.1095)		(0.1371)		(0.1370)		(0.1685)		(0.1587)		(0.1329)	
	p = 0.0672		p = 0.0080		p = 0.2547		p = 0.0118		p = 0.0338		p = 0.0005	
High-Minus-Low	0.0471		0.1430*		-0.0249		0.1152		-0.0502		0.1661**	
	(0.0782)		(0.0771)		(0.0940)		(0.0827)		(0.0978)		(0.0723)	
	p = 0.5474		p = 0.0639		p = 0.7912		p = 0.1635		p = 0.6078		p = 0.0217	
Winners-Minus-Losers	0.1347**		-0.0065		0.043		0.0069		0.0744		0.0273	
	(0.0654)		(0.0670)		(0.0786)		(0.0743)		(0.0924)		(0.0994)	
	p = 0.0394		p = 0.9233		p = 0.5844		p = 0.9264		p = 0.4212		p = 0.7835	
Alpha	0.0041*	0.0008	0.0068***	0.0013	0.0013	0.0002	0.0050*	-0.0005	0.0014	-0.0008	0.0077***	0.0008
	(0.0023)	(0.0023)	(0.0026)	(0.0023)	(0.0034)	(0.0025)	(0.0027)	(0.0025)	(0.0039)	(0.0024)	(0.0027)	(0.0024)
	p = 0.0679	p = 0.7290	p = 0.0081	p = 0.5532	p = 0.7092	p = 0.9391	p = 0.0613	p = 0.8494	p = 0.7132	p = 0.7337	p = 0.0043	p = 0.7310
Observations	65	65	65	65	65	65	65	65	65	65	65	65
R^2	0.9127	0.902	0.8919	0.8661	0.8955	0.8914	0.886	0.8595	0.8498	0.8325	0.8848	0.847
Adjusted R^2	0.9069	0.9004	0.8847	0.864	0.8885	0.8897	0.8784	0.8573	0.8398	0.8299	0.8771	0.8446
Residual Std. Error	0.0145	0.0150	0.0167	0.0181	0.0165	0.0164	0.0180	0.0195	0.0202	0.0208	0.0168	0.0189
	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)
F Statistic	156.8135***	579.6664***	123.8072***	407.6191***	128.5269***	517.0701***	116.5741***	385.5172***	84.8552***	313.1695***	115.1722***	348.7884***
	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)

Notes:

The table reports the results of the estimation of the multi-factor and single index model for the period 2014-01 to 2019-05. Columns 1, 3, 5, 7, 9, 10, 11 report the OLS estimates for each portfolio's monthly excess return on the multi-factor model. Columns 2, 4, 6, 8, 10, 12 report the coefficients of the single index model. The dependent variable is the respective portfolio's excess return. Alpha is the monthly abnormal return that cannot be attributable to the systematic risk factors. HAC standard errors are reported in parentheses. Portfolios are equally weighted and rebalanced either 6, 12 or 18 months after their formation. The top (bottom) portfolio contains the top (bottom) 33.3% of companies with respect to ESG momentum at each rebalancing date.

Significance: * 10%, ** 5%, *** 1%

Similar to the observations in the general emerging markets portfolios, the 6-month holding period is the best holding period for both portfolios in the performance group “average” (cf. Table 44). With this particular holding period, the top portfolio exhibits the highest expected annual return (4.85%) and highest annual Sharpe ratio (0.23). Both ratios decline with longer holding periods and the annual information ratio even becomes negative (-0.13). With longer holding periods, the VaR and the expected shortfall increase for the top portfolio, which marks the increased riskiness of the portfolio. The bottom portfolio also shows the highest expected annual return (5.59%) and annual Sharpe ratio (0.26) with rebalancing every 6 months. Although this portfolio also performs well with 4.86% expected annual return over an 18-month holding period, its risk measures, such as maximum drawdown and expected shortfall increase with an 18-month holding period. Hence, both portfolios offer the best risk-return trade-off over a 6-month holding period.

The goodness of fit of the CAPM models is high ($R^2 =$ 0.83-0.90) and the models show high exposure to market fluctuations ($\beta_M =$ 1.00) (cf. Table 45). Nevertheless, the results do not display any significant alphas. However, the signs and magnitudes of alpha indicate that the top portfolio exhibits decreasing alphas with longer holding periods while the bottom portfolio exhibits the highest alpha over a 6-month and 18-month holding period. Given the insignificant results, ESG momentum does not contribute actively to portfolio excess returns over any holding period.

In the multi-factor models, significant positive alphas are observed for the top and bottom portfolio with a 6-month holding period of 0.41% and 0.68% monthly, respectively (cf. Table 45). These alphas accumulate to 5.03% and 8.47% annually. This outperformance confirms the performance of the TRI that moves above the benchmark index. The multi-factor models also show significant alphas for the bottom portfolio for a 12-month and an 18-month holding period. These alphas amount to 0.50% and 0.77% on a monthly basis and are significant at a 10% and 1% level, respectively. In other words, investing in the bottom portfolios with 12- or 18-month rebalancing yields an alpha of 6.17% or 9.64% on an annual basis, respectively. The adjusted R^2 is highest for a 6-month holding period. All regressions show highly positive exposure to market fluctuations. Moreover, all portfolios show moderately significant positive exposure to SMB ($\beta_S =$ 0.20-0.46), except for the top portfolio for a 12-month holding period The bottom portfolio shows small but significant exposure to HML over a 6- and 18-month holding period ($\beta_H <$ 0.2). WML seems to only contribute to the top portfolio with a 6-month holding period ($\beta_W =$ 0.13).

Table 46: Annualised alphas across performance group "average" portfolios

	Annualised multi-factor alpha					Annualised CAPM alpha			
	Performance group "average"			Significance		Performance group		Significance	
Holding period	Top	Bottom	Delta	Top	Bottom	Top	Bottom	Top	Bottom
6m	5.03%	8.47%	-3.44%	10%	1%	0.96%	1.57%	No	No
12m	1.57%	6.17%	-4.60%	No	10%	0.24%	-0.60%	No	No
18m	1.69%	9.64%	-7.95%	No	1%	-0.96%	0.96%	No	No

The performance group "average" shows some evidence supporting an ESG momentum strategy (cf. Table 46). However, alphas are predominantly statistically significant for the bottom portfolio and the bottom portfolio strongly outperforms the top portfolio over all holding periods. The magnitude of these alphas is very high. For the top portfolio, alpha is only found significant for the shortest holding period. The size bias observed in the previous holding period still persists and is supported by the fact that this performance group has a higher average market capitalisation in both portfolios than the other performance groups. The regression results are in line with the historical performance and risk indicators. The top portfolio performs best with a 6-month holding period, while the bottom portfolio has the highest expected return and the best risk-return trade-off with a 12- and 18-month holding period.

7.2.2.3 Performance group "high"

In the performance group "high", turnover rates are similar to the ones observed in the other performance groups (cf. Table 47). The sector distributions of all portfolios look similar to the benchmark and reveal that the portfolio companies are more evenly distributed across sectors compared to the other performance groups (cf. Appendix A9).

Table 47: Portfolio turnover

	Top portfolio			Bottom portfolio		
Holding period	Avg. turnover	Annualized turnover*	Avg. no. companies	Avg. turnover	Annualized turnover*	Avg. no. companies
6 months	40%	39%	46	37%	37%	47
12 months	71%	71%	43	62%	62%	44
18 months	77%	51%	36	65%	43%	37

**Notes: For the turnover calculation cf. Appendix A1.*

Table 48 shows that the top improving companies are predominantly the ones with lower average ESG scores from which they experience their positive ESG momentum. These companies tend to increase their ESG score during the holding period with this effect diminishing with longer holding periods (compare Δ HP). The bottom portfolios are lower in their average ESG score during the investment period (HP).

Table 48: Average industry adjusted ESG score

	Top portfolio				Bottom portfolio			
Holding period	Δ SP	BOHP	HP	Δ HP	Δ SP	BOHP	HP	Δ HP
6 months	1.19	6.37	6.47	0.12	-0.78	5.79	5.69	-0.09
12 months	1.14	6.53	6.47	0.05	-0.79	5.72	5.61	0.05
18 months	1.00	6.59	6.49	0.01	-0.79	5.77	5.59	-0.16

**Notes: Δ SP = change over selection period, BOHP = score at the beginning of holding period, HP = holding period, Δ HP = change over holding period, the ESG score change refers to changes in the SMA (cf. Adjusted ESG scores).*

The company KPIs reveal that the average market capitalisation of both portfolios is similar for a 6- and 12-month holding period (cf. Table 49). However, this performance group exhibits slightly lower average market capitalisations compared to the other performance groups. Furthermore, the spreads between the portfolio's average B/M ratios and the EV/EBITDA are considerably low compared to the other performance groups. When comparing the top and bottom portfolios to each other, the top portfolio exhibits higher growth prospects as measured in a much higher average P/E ratio but lower CAPEX than the bottom portfolio.

Table 49, Panel A: KPIs for the top portfolio

	6 months		12 months		18 months	
	Mean	Median	Mean	Median	Mean	Median
Market cap. (USD bn)	19.73	10.29	19.92	10.23	20.70	10.35
ROA (%)	5.92	3.76	5.63	3.49	5.76	3.73
ROE (%)	17.47	13.93	16.98	13.72	15.96	13.95
CAPEX (USD bn)	-0.81	-ß.26	-0.86	-0.25	-0.92	-0.24
D/E ratio	0.90	0.59	0.95	0.59	0.88	0.61
B/M ratio	0.28	0.53	0.28	0.54	0.31	0.52
Current ratio	1.31	1.15	1.73	1.16	1.31	1.16
EV/EBITDA	22.29	10.38	23.69	10.26	20.32	10.49
P/E ratio	49.68	18.64	53.73	18.57	73.73	18.62

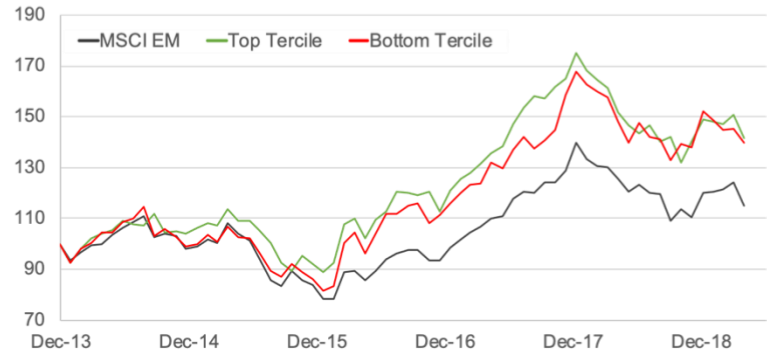
Table 49, Panel B: KPIs for the bottom portfolio

	6 months		12 months		18 months	
	Mean	Median	Mean	Median	Mean	Median
Market cap. (USD bn)	19.80	11.00	19-59	10.96	16.98	10.46
ROA (%)	5.72	4.23	5.78	4.18	5.37	3.80
ROE (%)	15.53	13.62	15.27	13.72	15.39	12.89
CAPEX (USD bn)	-1.33	-0.34	-1.34	-0.36	-0.92	-0.33
D/E ratio	1.02	0.58	1.03	0.62	1.01	0.62
B/M ratio	0.33	0.52	0.34	0.52	0.29	0.55
Current ratio	1.68	1.23	1.70	1.19	1.53	1.22
EV/EBITDA	-123.35	10.11	-121.96	10.14	48.29	10.46
P/E ratio	21.05	18.80	21.50	18.93	22.35	19.29

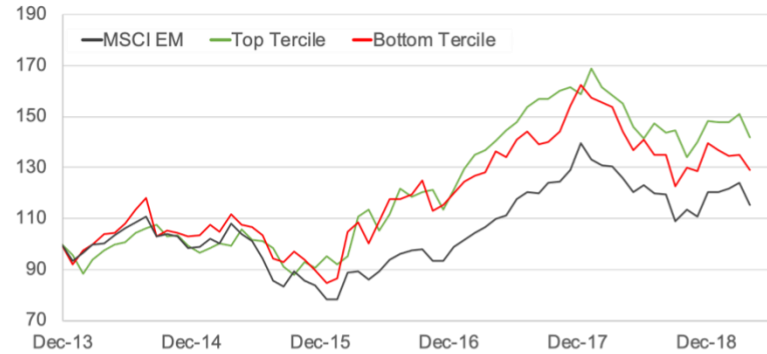
Table 50: Individual portfolio overview

		Top tercile	Bottom tercile	MSCI EM
	6 months			
Performance	Expected return (%)	0.64 (7.97)	0.65 (8.09)	0.31 (3.84)
Performance	Volatility (%)	4.64 (16.09)	5.27 (18.25)	4.45 (15.41)
Performance	Sharpe ratio	0.12 (0.41)	0.11 (0.37)	0.05 (0.18)
Performance	Information ratio	0.08 (0.28)	0.14 (0.53)	-
Performance	Benchmark correlation	0.57	0.89	1
Performance	Max. High water mark	174.99	167.76	139.66
Performance	05-2019 TRI	141.55	139.79	115.18
Risk	Max. drawdown (%)	24.55	28.92	29.43
Risk	Skewness	0.30	0.66	0.10
Risk	Kurtosis	0.51	1.58	0.14
Risk	5% VaR (%)	-6.99	-7.21	-7.15
Risk	Expected shortfall (%)	-7.35	-8.21	-8.08

Total return indices (TRIs), in USD



		Top tercile	Bottom tercile	MSCI EM
	12 months			
Performance	Expected return (%)	0.64 (7.98)	0.54 (6.62)	
Performance	Volatility (%)	4.55 (15.76)	5.41 (18.74)	
Performance	Sharpe ratio	0.12 (0.42)	0.08 (0.29)	
Performance	Information ratio	0.06 (0.20)	0.08 (0.32)	
Performance	Benchmark correlation	0.16	0.89	
Performance	Max. High water mark	168.57	162.34	
Performance	05-2019 TRI	142.00	129.05	
Risk	Max. drawdown (%)	20.50	28.27	
Risk	Skewness	0.35	0.38	
Risk	Kurtosis	0.63	1.96	
Risk	5% VaR (%)	-7.01	-8.70	
Risk	Expected shortfall (%)	-7.43	-10.06	



		Top tercile	Bottom tercile	MSCI EM
	18 months			
Performance	Expected return (%)	0.31 (3.75)	0.30 (3.71)	
Performance	Volatility (%)	4.40 (15.26)	5.05 (17.48)	
Performance	Sharpe ratio	0.05 (0.17)	0.04 (0.15)	
Performance	Information ratio	0.00 (-0.01)	0.00 (-0.01)	
Performance	Benchmark correlation	0.58	0.56	
Performance	Max. High water mark	142.63	128.08	
Performance	05-2019 TRI	114.86	112.38	
Risk	Max. drawdown (%)	25.15	37.82	
Risk	Skewness	0.29	0.19	
Risk	Kurtosis	0.46	0.53	
Risk	5% VaR (%)	-7.33	-7.38	
Risk	Expected shortfall (%)	-7.68	-8.98	

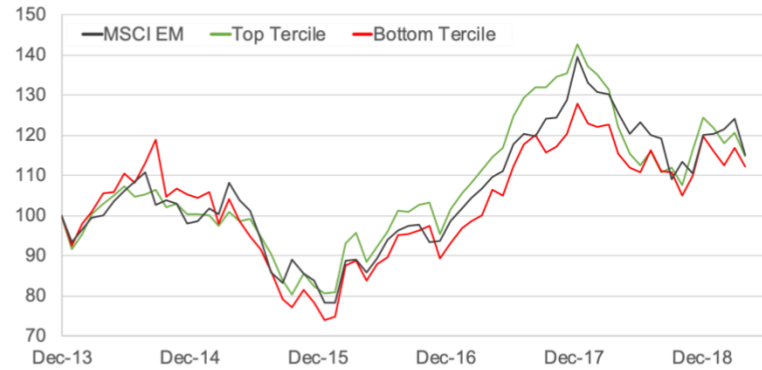


Table 51: Emerging markets - performance group "high"- regression results

	Top Tercile 6m		Bottom Tercile 6m		Top Tercile 12m		Bottom Tercile 12m		Top Tercile 18m		Bottom Tercile 18m	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Market Excess Return	0.5704***	0.5969***	1.1278***	1.0657***	0.2219	0.1591	1.1741***	1.0827***	0.5738***	0.5755***	0.5741***	0.6399***
	(0.1684)	(0.1457)	(0.0863)	(0.0954)	(0.1412)	(0.1103)	(0.0918)	(0.1049)	(0.1543)	(0.1328)	(0.1620)	(0.1485)
	p = 0.0008	p = 0.00005	p = 0.0000	p = 0.0000	p = 0.1161	p = 0.1494	p = 0.0000	p = 0.0000	p = 0.0002	p = 0.00002	p = 0.0004	p = 0.00002
Small-Minus-Big	0.1326		0.6258***		0.0217		0.6569***		0.3094		0.0439	
	(0.2677)		(0.1530)		(0.3568)		(0.1779)		(0.2629)		(0.2613)	
	p = 0.6204		p = 0.00005		p = 0.9516		p = 0.0003		p = 0.2393		p = 0.8667	
High-Minus-Low	0.0708		-0.0527		-0.1372		-0.0553		0.0591		0.1205	
	(0.1849)		(0.0882)		(0.2381)		(0.1031)		(0.1662)		(0.1748)	
	p = 0.7017		p = 0.5498		p = 0.5645		p = 0.5915		p = 0.7220		p = 0.4907	
Winners-Minus-Losers	-0.0523		0.0134		0.074		0.1121		-0.0177		-0.1206	
	(0.1894)		(0.0987)		(0.2065)		(0.0878)		(0.1661)		(0.1728)	
	p = 0.7827		p = 0.8923		p = 0.7203		p = 0.2016		p = 0.9150		p = 0.4853	
Alpha	0.0062	0.0042	0.0073**	0.0032	0.0033	0.0052	0.0070**	0.002	0.0043	0.0009	0.0025	0.0007
	(0.0066)	(0.0049)	(0.0035)	(0.0029)	(0.0085)	(0.0057)	(0.0035)	(0.0032)	(0.0066)	(0.0046)	(0.0069)	(0.0053)
	p = 0.3498	p = 0.3930	p = 0.0392	p = 0.2719	p = 0.6946	p = 0.3618	p = 0.0441	p = 0.5222	p = 0.5161	p = 0.8458	p = 0.7200	p = 0.8931
Observations	65	65	65	65	65	65	65	65	65	65	65	65
R^2	0.3348	0.3263	0.8621	0.8093	0.0377	0.0242	0.8442	0.7921	0.3581	0.3376	0.3349	0.3186
Adjusted R^2	0.2905	0.3156	0.8529	0.8063	-0.0265	0.0087	0.8338	0.7888	0.3153	0.3271	0.2906	0.3077
Residual Std. Error	0.0392	0.0385	0.0202	0.0232	0.0462	0.0454	0.0221	0.0249	0.0365	0.0362	0.0425	0.0420
	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)	(df = 60)	(df = 63)
F Statistic	7.5495***	30.5135***	93.7978***	267.4136***	0.5870	1.5615	81.2794***	239.9917***	8.3683***	32.1119***	7.5534***	29.4499***
	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)	(df = 4; 60)	(df = 1; 63)

Notes:

The table reports the results of the estimation of the multi-factor and single index model for the period 2014-01 to 2019-05. Columns 1, 3, 5, 7, 9, 10, 11 report the OLS estimates for each portfolio's monthly excess return on the multi-factor model. Columns 2, 4, 6, 8, 10, 12 report the coefficients of the single index model. The dependent variable is the respective portfolio's excess return. Alpha is the monthly abnormal return that cannot be attributable to the systematic risk factors. HAC standard errors are reported in parentheses. Portfolios are equally weighted and rebalanced either 6, 12 or 18 months after their formation. The top (bottom) portfolio contains the top (bottom) 33.3% of companies with respect to ESG momentum at each rebalancing date.

Significance: * 10%, ** 5%, *** 1%

With expected annual returns of 7.97% and 8.09%, the best holding period for the top and bottom portfolio is 6 months (cf. Table 50). This expected return decreases with longer holding periods. The magnitude of the difference in price effects across holding periods is large, with the expected annual return being more than twice as high for the 6-month compared to the 18-month holding period for both portfolios. The Sharpe and information ratios of both portfolios are also superior for a 6-month holding period, which confirms the high outperformance of both portfolios with respect to the benchmark. Especially the information ratio of the bottom portfolio for a 6-month holding period can be considered as high (0.53). From a risk management perspective, both portfolios also have the best risk measures when rebalanced every 6 months, expressed in low maximum drawdowns, VaRs, and expected shortfalls. Despite the positive performance outlook of the bottom portfolio with a 12-month holding period, its risk metrics reveal that it is comparably risky, expressed in a high kurtosis, and the highest expected shortfall (10.06%) of all emerging markets portfolios based on performance groups. Surprisingly, the top portfolio shows much lower correlation to the benchmark compared to all portfolios across all performance groups. This is expected to influence the regression results; especially the very low correlation for a 12-month holding period (0.16) may potentially problematic since the CAPM theory as well as Fama and French assume that returns are somewhat correlated to market movements. The historical performance and risk measures reveal that the optimal holding periods are tilted towards shorter time horizons with 6 months being optimal for the bottom portfolio and 6 to 12 months for the top portfolio.

In the single index model, the top portfolio is significantly moderately exposed to the market factor for the 6-month ($\beta_M = 0.60$) and 18-month holding periods ($\beta_M = 0.57$) (cf. Table 51). The corresponding alphas are insignificant. R^2 of these models is low ($R^2 \approx 0.3$) which is expected due to low correlation of the top portfolios to the benchmark. Over a 6-month holding period, the sensitivity of the top portfolio to the market factor becomes small and insignificant (β_M = 0.16), which is not surprising due to corresponding low correlation coefficient reported in Table 50. Consequently, the goodness of fit of the model is small ($R^2 \approx 0.02$). Although alpha is statistically significant at a 10% level, the low R^2 indicates that other variables than the market excess return explaining the observations better. The bottom portfolios continue to be significantly and positively exposed to the market with this relationship being less pronounced for the 18-month holding period ($\beta_M = 0.64$). For the bottom portfolio, the goodness of fit is higher for the 6- and 12-month holding period ($R^2 \approx 0.80$), compared to the 18-month holding period ($R^2 \approx 0.32$), which is again attributable to the portfolio's low correlation to the benchmark. Since all alphas in the bottom portfolio continue to be insignificant, no evidence is found that there is a significant tendency of one portfolio to outperform the benchmark or evidence for benefits from applying a positive ESG momentum strategy.

In the multi-factor model, the bottom portfolio shows significant alphas over a 6-month and 12-month holding period. These monthly alphas contribute 0.73% and 0.70% to the portfolio's excess returns, respectively. The magnitude of the effect is impressive, totalling to 9.12% and 8.73% on an annual level. In the same regressions, the bottom portfolio is also significantly and highly exposed to the market excess return as well as significantly and moderately to SMB. The goodness of fit of the model explaining the excess returns for the bottom portfolio continues to be high for the 6- and 12-month holding period but low for the 18m holding period (adjusted R^2 = 0.29). Alphas on all top portfolios are statistically insignificant. The market excess return only contributes explanatory power to the top portfolios' excess returns for 6 and 18-month holding period. For the top portfolio with a 12-month holding period, the alphas are all found insignificant. This causes the adjusted R^2 to become inflated and negative. Hence, the regression model is not adequate for this particular portfolio. This leads to the conclusion that the high expected returns that were observed in Table 50 are attributable to something other than the chosen factors. This might be in line with Cakici et al. (2013) who highlight the importance of local factors on price effects in emerging markets. All other factors across all holding periods are found insignificant for the top portfolio, which is also expressed in a lower adjusted R^2 compared to the corresponding CAPM regressions. The goodness of fit of the model explaining the excess returns for the bottom portfolio continues to be high for the 6- and 12-month holding period but low for the 18m holding period (adjusted R^2 = 0.29).

Table 52: Annualised alphas across performance group "high" portfolios

	Annualised multi-factor alpha					Annualised CAPM alpha			
	Performance group "high"			Significance		Performance group		Significance	
Holding period	Top	Bottom	Delta	Top	Bottom	Top	Bottom	Top	Bottom
6m	7.70%	9.12%	-1.42%	No	5%	5.16%	4.03%	No	No
12m	4.03%	8.73%	-4.70%	No	5%	6.42%	2.43%	10%	No
18m	5.28%	3.04%	2.24%	No	No	1.09%	0.84%	No	No

The analysis of the performance group "high" supports the previous findings that negative ESG momentum leads to significant alpha in more cases compared to positive ESG momentum (cf. Table 52). The results provide convincing evidence that the bottom portfolio strongly outperforms the top portfolio due to the magnitude of the alphas and their significance over the two shorter holding periods. These findings are in line with the observations of historical performance and risk measures. However, in this performance group, alphas are only statistically significant for the bottom portfolios. Nonetheless, the top portfolio has a very good risk-adjusted performance with a 6- and 12-month holding period, when comparing it to the benchmark. The overall results lead to the conclusion that trading on negative ESG momentum is the more profitable trading strategy.

7.2.2.4 Summary

Table 53 illustrates the regression results with annualised alphas to get a better overview of all performance groups and portfolios in the emerging markets group. Comparing the results to the research question and sub-questions, leads to the following summary.

Table 53: Emerging markets - annualised alphas across performance groups

	Annualised multi-factor alpha					Annualised CAPM alpha			
	Performance group "low"			Significance		Performance group		Significance	
Holding period	Top	Bottom	Delta	Top	Bottom	Top	Bottom	Top	Bottom
6m	5.79%	6.17%	-0.38%	No	10%	1.21%	2.30%	No	No
12m	3.29%	4.91%	-1.62%	No	No	-2.49%	-0.12%	No	No
18m	6.55%	1.94%	4.61%	No	No	1.57%	-0.24%	No	No

	Annualised multi-factor alpha					Annualised CAPM alpha			
	Performance group "average"			Significance		Performance group		Significance	
Holding period	Top	Bottom	Delta	Top	Bottom	Top	Bottom	Top	Bottom
6m	5.03%	8.47%	-3.44%	10%	1%	0.96%	1.57%	No	No
12m	1.57%	6.17%	-4.60%	No	10%	0.24%	-0.60%	No	No
18m	1.69%	9.64%	-7.95%	No	1%	-0.96%	0.96%	No	No

	Annualised multi-factor alpha					Annualised CAPM alpha			
	Performance group "high"			Significance		Performance group		Significance	
Holding period	Top	Bottom	Delta	Top	Bottom	Top	Bottom	Top	Bottom
6m	7.70%	9.12%	-1.42%	No	5%	5.16%	4.03%	No	No
12m	4.03%	8.73%	-4.70%	No	5%	6.42%	2.43%	10%	No
18m	5.28%	3.04%	2.24%	No	No	1.09%	0.84%	No	No

Since it is not observable that the top portfolios outperforming the bottom portfolios, trading on positive ESG momentum does not systematically yield a significant alpha. Referring to the initial hypotheses (Q1 and Q2), top ESG momentum portfolios do not outperform bottom portfolios in terms of alpha, but rather the opposite holds. Moreover, the price effect is strongest in the performance group “high” as opposed to “low” when looking at the delta in alpha (Q4). An interesting side-result is that the performance group “average” has been found to show more statistically significant results than the other performance groups and that the magnitude of these alphas are also high. Previous literature has always focused on the tails of ESG score ranges and hence this finding leaves room for further research.

Generally, it is evident, that shorter holding periods yield better and more significant results for top and bottom portfolios. Due to the fact that there are positive price effects on top as well as bottom portfolios following an ESG momentum strategy, it is not beneficial to short the bottom portfolios’ companies since their returns are positive and large in magnitude. Almost throughout all performance groups, the portfolios’ excess returns are highly sensitive to market fluctuations and moderately exposed to the size factor. Value and momentum rarely show significant coefficients.

It is still worth mentioning that trading on positive ESG momentum can lead to financial outperformance in terms of various risk and return measures when segmenting the market into performance groups and comparing them against a well-recognised benchmark. This is in line with the observation of Sherwood & Pollard (2018) and other scholars who show that ESG integration into the investment process in emerging markets can provide lower downside risk.

7.2.3 Sub-conclusion

As for the general market portfolios, alpha from the single index models (Q1) is examined to determine the price effect attributable to positive ESG momentum across all performance groups. In the developed markets, the model exhibits significant alphas for the top portfolio for the all performance groups for either the 6-month or 12-month holding period or both. Thus, a trend towards positive ESG momentum yielding a positive alpha is present. The strongest results are displayed for the performance group “average” with an annualised alpha of 4.41% in the 6-month holding period at a 1% significance level, and with an annualised alpha of 3.91% in the 12-month holding period at a 5% significance level. In the performance group “low” there is a significant positive alpha for the bottom portfolio with the 18-month holding period, which contradicts the overall trend. However, the results are compelling towards a positive relationship between ESG momentum and alpha. In the emerging markets portfolios, the top portfolio with a 12-month holding period in the performance group “high” yields an annual alpha of 6.42% at a significance level of 10%. In sum, the emerging markets portfolios do not show convincing evidence of a positive ESG momentum strategy, as all other alphas are insignificant.

In order to answer the other research questions, the authors look at the differences in alphas from top and bottom portfolios, resulting from the multi-factor models (Q2), and derive whether trading on positive ESG momentum leads to a higher price effect in emerging markets than in developed markets (Q3).

In the developed markets, only the performance group “high” exhibits convincing evidence that positive ESG momentum yields a positive alpha with a 6-month holding period. In the single index model, there is an annualised alpha of 2.92%, which increases to 5.54% in the multi-factor model. In addition, the top portfolio with the 6-month holding period exhibits better risk-adjusted returns. The performance group “average” shows some weak evidence for the 6-month holding period which is not convincingly attributable to positive ESG momentum, as the bottom portfolio also shows a significant alpha. No significant alphas are present in the performance group “low” for the top portfolios. However, compelling evidence for negative ESG momentum yielding a positive alpha is present for the 18-month holding period in both the single index and multi-factor model. Consequently, the price effect of positive ESG momentum is higher in performance group “high” compared to performance group “low”.

In emerging markets, the performance groups “low” and “high” do not provide evidence that trading on positive ESG momentum yields statistically significant alpha. In the performance group “average”, there is weak evidence towards our research question. However, the bottom portfolios exhibit annual alphas of 8.47% and 9.64% for a 6- and 18-month holding period, respectively, at a 1% significance level. The other performance groups also show some evidence, that portfolios with negative ESG momentum significantly outperform their counterparts.

Generally, we see stronger price effects for positive ESG momentum yielding a positive alpha in the performance group “high” in the developed markets, as this is the only performance group where convincing results are present. On the contrary, a stronger price effects for negative ESG momentum yielding a positive alpha is observed in emerging markets. In the performance group “average”, the bottom portfolio with a 6-month holding period is significantly outperforming it’s developed markets counterpart, both in terms of magnitude of alpha and significance. In general, higher volatility in the emerging markets (cf. Investing in emerging markets) can be expected, which may contribute to the fact that a broader range of the magnitude in alphas in emerging markets is visible.

We examine the research question of whether positive ESG momentum has a higher price effect in the performance group “low” as opposed to “high” (Q4) by comparing the alphas from the two performance groups to each other. There is compelling evidence of positive ESG momentum yielding a positive alpha for the 6-month holding period in the performance group “high”, while the opposite holds for the performance group “low” for the 18-month holding period. In emerging markets, no evidence supporting the research question is present when looking at the two performance groups in direct comparison. However, the results suggest that the opposite is true for negative ESG momentum. For negative ESG momentum, the magnitude of the positive price effect is higher in the performance group “high” for a 6- and 12-month holding period than for their counterparts in the performance group “low”. Thus, there is a higher price effect of positive ESG momentum in developed markets compared to emerging markets. However, the performance group “high” has a higher price effect compared to the performance group “low”, which is the opposite effect of what Q4 suggests.

8 Discussion

8.1 Critical reflection on own approach

8.1.1 Data

The empirical results of this thesis are highly dependent on the provided data set and are subject to several limitations. First of all, the dataset was extracted in a way that it is prone to the survivorship bias towards large and highly liquid firms. This heavily influenced the company selection and portfolio formation process and might hamper the analysis from finding significant results since previous scholars found the benefits of ESG investments to be more pronounced in a small and medium capitalisation range (De & Clayman, 2010). Moreover, the reliability of the provided ESG scores was doubtful before 2013 and led to the exclusion of this early stage of the sample period. Consequently, it was not possible to test the robustness of the results over distinct shorter time horizons, due to a low number of observations when further dividing the sample period. Such short time horizons would have compromised the quality of the models. This relatively short historical coverage is a major and widely recognized problem of ESG scores which makes the search for statistically significant patterns more challenging and prevents an assessment of the long-term performance of high ESG scoring companies (Breedt, Ciliberti, Gualdi, & Seager, 2019).

8.1.2 Methodology

Second, the authors are aware that their results are subject to several issues of arbitrary choice in the methodological approach and portfolio construction. They made several assumptions regarding the optimal risk-free rate, the most adequate benchmark, and portfolio weighting, amongst others. Since the concept of ESG momentum is novel in financial literature, the ESG momentum construction requires a detailed discussion. ESG momentum is based on companies' industry adjusted ESG scores, which implies that scores can also change due to shifts in the industry's ESG performance. In other words, a company's score can change although the company is not actively pursuing ESG opportunities or improving its ESG risk management practices. Consequently, companies could be misleadingly categorised into the top or bottom portfolio. Although the authors used deciles to select the tails of the ESG momentum spectrum, this fact might still bias the results of the top and bottom portfolios. Especially in the performance groups in emerging markets, less data is available and a broader ESG momentum range (terciles) is used to form top and bottom portfolios. This makes it more likely that companies that are neither top nor bottom bias our results in both portfolios.

The ESG momentum calculation horizon of 12 months was chosen based on the consideration that ESG scores are mostly updated on an annual basis (cf. Data description) and because of the aim of assessing the long-term trend of companies' ESG performance. However, shorter ESG momentum horizons, e.g. 6 or 9 months, might still be worth exploring. The same argument holds for the different holding periods. As the most significant results are found over shorter holding periods, future research could examine distinct shorter holding periods to examine whether extraordinary weekly score reviews drive the regression results or if the tilt towards shorter holding periods might be explained by something other than ESG momentum.

Another aspect worth mentioning is that the results of the models could be dependent on the cut-off points for the distinct performance groups. As the authors decided to observe relative performance in emerging and developed markets separately, a logical next step would be to examine overarching ESG cut-off points.

8.2 Relation to other ESG research

8.2.1 ESG momentum & sustainability

The presented results add to the growing body of literature on ESG scores and financial performance. First of all, the ESG ranking of the portfolios over the holding period shows that portfolios based on positive ESG momentum continue to have higher ESG scores over the sample period than portfolios formed on negative ESG momentum. The results in the general developed as well as emerging markets and across all performance groups indicate that applying a positive ESG momentum strategy results in a portfolio with relatively high ESG scores[18]. Hence, by choosing performance groups, investors can discriminate between high and low ESG scoring companies and follow the investment strategy that is most in line with their ESG score preferences. This contrasts the concerns of Kaiser (2020), who argues that an ESG momentum strategy might take a perverse twist on the application of ESG ratings. This thesis concludes that while investors support the transition of companies from low to high ESG scores, they still get rewarded with a high average ESG score on their portfolios. However, it must be said that an ESG momentum strategy in itself does not necessarily lead to a sustainable portfolio[19].

8.2.2 ESG momentum & performance

This thesis produces evidence that portfolios based on positive ESG momentum can outperform conventional benchmark indices. The authors demonstrate that in developed markets, trading on positive ESG momentum can lead to higher expected and superior risk-adjusted returns compared to negative ESG momentum which was suggested by Verheyden, Eccles, & Feiner (2016) who followed a mixed strategy including ESG momentum. Moreover, in both markets, positive ESG

[18] As compared to the cut-off points of 6.1 in developed and 5.0 in emerging markets (cf. Table 3).
[19] As mentioned in the Data description, ESG rating agencies rank all available stocks disregarding their business model. Hence, controversial firms and "sin" stocks might still be included in the portfolios.

momentum in performance group “high” outperforms positive ESG momentum in performance group “low” in terms of expected and risk-adjusted returns[20]. The results of trading on positive ESG momentum in developed markets are further in line with the vote-count and meta study of Friede, Busch, & Bassen (2015) since the performance group “high” shows a highly significant alpha. Despite the findings[21] of the authors that the benefits of high ESG scores have been confirmed in emerging markets literature more often, the results do not reflect these findings, due to the absence of statistically significant alphas. The results regarding positive and statistically significant alphas for the bottom portfolios in emerging markets could be in line with research concluding that low ESG scoring companies, e.g. socially controversial firms, outperform the market in terms of stock returns since ESG-conscious investors shun the stocks of these companies (Hong & Kacperczyk, 2009). If there is a sufficient number of investors that choose high ESG scoring stocks over low ESG scoring stocks, the expected returns of the latter should be higher.

Overall, alphas associated with ESG momentum are tilted towards shorter holding periods, which contrasts the literature that finds the benefits of higher ESG efforts to lead to significant alpha over longer-term horizons (Bender et al., 2018).

Looking at accounting performance, the authors also find indicative results pointing towards higher return on equity and return on assets of positive ESG momentum companies compared to negative ESG momentum companies and when comparing performance group “high” to “low” in both markets. These findings are in line with previous research that found high scoring ESG companies to be related to higher accounting performance (De & Clayman, 2015; Dimson et al., 2015; Gregory et al., 2014).

8.2.3 ESG momentum & risk

Looking at metrics that measure the riskiness of portfolios, positive ESG momentum portfolios have mostly outperformed their counterparts in developed markets in terms of volatility[22]. This result also largely holds in emerging markets, and additionally when comparing performance groups “high” to “low” in both markets which is in line with Giese, Lee, Melas, Nagy, & Nishikawa (2019) and Hong & Kacperczyk (2009). In addition, emerging markets show lower maximum drawdowns when comparing top and bottom portfolios, which is in line with Odell & Ali (2016) and Sherwood & Pollard (2018). Moreover, in emerging markets, trading on positive ESG momentum in the performance

[20] As measured in Sharpe and information ratio.

[21] The authors found overwhelmingly positive relationships between high ESG scores and corporate financial performance which they define as accounting-based, market-based, as well as performance of ESG portfolios, amongst others.

[22] Volatility refers to historical stock volatility and not residual volatility resulting from a factor model, which would be a measure of purely idiosyncratic risk.

group “high” outperforms its counterpart in the performance group “low” in terms of VaR and expected shortfall, which is in line with Giese et al. (2019). The results show that downside risk protection through high ESG scores is more consistent in emerging markets.

The chosen ESG momentum strategy shows some consistent characteristics when it comes to systematic risk factors measured by the betas of the multi-factor models. The authors find positive ESG momentum portfolios to carry predominantly lower systematic market risk in developed markets, which is in line with Bauer, Koedijk, & Otten (2005) and Giese et al. (2019), while they find the opposite to hold for most of the emerging markets portfolios. The magnitude of this relation is overwhelmingly large, which was to be expected based on the documented high benchmark correlation. Furthermore, positive ESG momentum has a positive relationship with the size factor. Although a positive correlation between large capitalisation and high ESG scores has been confirmed by many scholars before (Bender et al., 2017; Kaiser, 2020; Velte, 2017), the empirical results still seem feasible due to the extraction of the data set with a large capitalisation bias. The lower end of the market capitalization range of the selected companies seems to outperform the upper end. This appears plausible since even the lower-end companies are large enough to be expected to have capital available to invest into ESG-related issues and also to benefit from superior ESG compliance due to high media coverage and attention. Hence, in the selected market capitalisation range, the benefits of high ESG scores diminish with increasing size, which has also been found by De & Clayman (2015). In this particular case, these findings indicate that controlling for market capitalisation would help to isolate the effect of ESG momentum in future research.

8.3 Market efficiency

Returning to the market efficiency theory, an efficient market requires that the market price of a stock is unbiased, i.e. errors in the market prices are random. Consequently, under market efficiency there is an equal chance of a stock being under- or overvalued, and any given investor would not be able to consistently identify under- or overvalued stocks (cf. Market efficiency). If markets were efficient, the alphas of our regression models would not be statistically different from zero. Given our regression analysis, we are only able to address the semi-strong form of efficiency and will only be making assumptions about this form of market efficiency. Our analysis does not aim to test market efficiency and is not designed to do so[23], although it is still possible to make some inferences. Theoretically, the market portfolio represents the value-weighted portfolio of all risky assets. Consequently, the benchmark indices used as market proxies are not equal to the theoretical market portfolio. Thus, the inferences made about market efficiency are based on the assumption that the

[23] The semi-efficient form of efficiency is often tested using event studies.

benchmarks are adequate proxies for the true market portfolio. Market efficiency is usually tested using the CAPM. We will however also address the alphas of the multi-factor model with regard to market efficiency.

In the emerging markets, only a significant alpha in the performance group “high” in the single index regression model is present. Thus, in accordance with the CAPM, no evidence of markets being inefficient for the remaining portfolios is present, given the chosen market proxies. The regression outputs of the multi-factor regressions show evidence of market inefficiency with positive and significant alphas, however mainly for the bottom portfolios. In the developed markets, significant alphas from portfolios with a positive ESG momentum are present for the 6-month and 12-month holding periods in the single index model. In the multi-factor regressions, the alphas from the single index model remain significant, although significant alphas are also found in the portfolios with negative ESG momentum. However, strong results of positive ESG momentum yielding a positive alpha are present for the performance group “high” with a 6-month holding period.

As discussed in the Theory chapter, if trading of ESG momentum yields a significant alpha, it would be a violation of the semi-strong form of market efficiency as new publicly available information about a company’s ESG score is not immediately reflected in the stock price[24]. Thus, we do find compelling evidence of a violation of the semi-strong form of market efficiency both in developed markets and in emerging markets. In the developed markets, the inefficiency is directed at companies with positive ESG momentum. In the emerging markets, the inefficiency is directed at companies with negative ESG momentum, although the evidence is weaker as significant alphas are mainly present in the multi-factor regressions. For the holding periods where significant positive alphas are present for both the top and bottom portfolios, we cannot conclude with conviction that the alphas are likely to be attributable to ESG momentum. Thus, for these portfolios we cannot infer that there is a violation of the semi-strong form of efficiency as a result of public information about ESG performance.

In general, insignificant alphas when trading on ESG momentum could be a result of a number of things. First, markets could of course be efficient in the semi-strong form. However, the semi-strong form of market efficiency would be violated if the stock prices do not immediately reflect the new public information about ESG performance. Changes in ESG scores may be reflected in the stock price much quicker than the time horizons which our analysis is testing, which could lead to insignificant alphas. Thus, insignificant alphas in our regressions do not necessarily mean that markets are efficient in the semi-strong form. Second, ESG scores are reviewed in depth annually and only adjusted for significant events and occurrences intra year. Thus, it is plausible that investors

[24] The statement is valid under the assumption, that the alpha is attributable to ESG momentum.

gather information about ESG related topics individually prior to the release of the ESG scores and make investment decisions based on the collected information. As a result, when the ESG scores are published, investors may already have made their investment decisions based on information which is comprised in the score. Third, differences in ESG ratings by different providers (Berg, Koelbel, & Rigobon, 2019) may cause significant differences in reactions by the market participants to changes in ESG scores or result in lack of confidence in the scores, which could make stock price reactions less pronounced.

8.4 ESG scores as a signal of value

In general, there is not strong evidence of positive ESG momentum yielding a positive alpha in either developed or emerging markets. Thus, the ESG score could be questioned as a signal of value.

High ESG scores have often been referred to as a quality sign of a stock (cf. Literature review), while many papers have mention sources of value creation through better relationships with stakeholders, reduced inefficiencies, attracting quality employees and improved access to finance (Bender et al., 2017). However, some studies have investigated the E, S and G scores separately in relation to financial performance and found significant positive outperformance (De & Clayman, 2015; Dimson et al., 2015). The studies on E, S, and G as separate factors could suggest that the ESG score might be too complex as it accounts for many diverse aspects related to E, S, and G. This in turn makes it harder for market participants to assess the materiality and value of an increasing ESG score. Thus, the lack of strong evidence could be a result of the complexity of the ESG score as a collective value signal of these many-fold issues.

On the contrary, the generally weak evidence of positive ESG momentum yielding a positive alpha might not be because the ESG score is too complex as a signal. Peloza (2009) argues that the financial value of corporate social performance (CSP) may not be visible in end state measures such as stock prices. The stock price is affected by many issues related to the business, industry, competition, regulation and macro-economic changes, which can result in the positive or negative effect of CSP being drowned by this “noise”. The same argument could account for the ESG score and explain why it is difficult to obtain consistent and significant results in the regression models, which build on stock price data.

9 Conclusion

9.1 Summary of empirical results

This thesis examines whether trading on positive ESG momentum generates a positive alpha beyond well-established and empirically researched factors, and whether alpha is conditional on the initial ESG score. The authors examined this research question in developed and emerging markets over a 6-, 12- and 18-month holding period.

In the general market portfolios in the developed markets, we do not find compelling evidence of positive ESG momentum yielding a positive alpha. Although the single index model exhibits a significant positive alpha with a 12-month holding period, both the bottom and top portfolio yield significant positive alphas in the multi-factor model. In addition, the difference in alpha is small and we cannot conclude with conviction that the alpha is attributable to ESG momentum. For all general emerging markets portfolios, there is no relationship between positive ESG momentum and a positive alpha since no strongly statistically significant alphas are observable. As a result, we do not find convincing evidence that trading on positive ESG momentum yields abnormal returns in either developed or emerging markets.

In regard to ESG momentum conditional on performance groups, the top portfolio in performance group “high” in developed markets exhibits strong evidence of positive ESG momentum yielding a positive alpha with a 6-month holding period. The top portfolio has a persistent positive alpha in both the single index model and the multi-factor model. The performance group “average” does not exhibit compelling results, while the performance group “low” exhibited compelling evidence of negative ESG momentum yielding a positive alpha, with persistent positive alphas in both the single index model and the multi-factor model. Thus, the positive price effect of positive ESG momentum is higher in the performance group “high” compared to performance group “low”. In addition, the bottom portfolios do not generally show a trend of being punished by the market in the developed markets, as these portfolios still tend to follow the market returns closely or outperform the benchmark. In all emerging markets portfolios, the authors do not find compelling evidence that trading on positive ESG momentum yields a positive alpha. Surprisingly the performance group “average” in emerging markets shows the most compelling evidence that trading on negative ESG momentum delivers high abnormal returns.

In general, we see that developed markets yield higher alphas for a positive ESG momentum strategy. However, disregarding the significance of alpha, we see the positive price effect to be higher in emerging markets for both top and bottom portfolios. In regard to the hypothesised stronger positive price effect of positive ESG momentum from a low ESG score compared to a high ESG score we find evidence of the opposite in the developed markets. In emerging markets, the authors find that portfolios with negative ESG momentum outperform their counterparts and that the magnitude of these alphas is higher in the performance group “high” as opposed to “low”.

This thesis shows that ESG momentum has different effects on return and risk measures in developed and emerging markets. Trading on positive ESG momentum in developed markets yields predominantly higher risk-adjusted returns than a conventional benchmark. Moreover, in emerging markets trading on positive ESG momentum overwhelmingly results in better risk metrics compared to its counterpart and benchmark. The benefits of positive ESG momentum seem to be predominantly present over shorter holding periods. Overall, there is no strong evidence of positive ESG momentum yielding a positive alpha in developed and emerging markets. Some studies have found significant alphas when trading on the E, S and G scores separately (De & Clayman, 2015; Dimson et al., 2015), which could suggest that ESG scores may be too complex a signal of value, leading to insignificant results. However, stock prices are affected by many issues related to competition, regulation and macro-economic conditions among others (Peloza, 2009). Thus, ESG scores may not be too complex as a signal but could rather be drowned by this “noise” in stock markets.

These findings join the ranks of literature that finds mixed evidence regarding the relationship between positive ESG performance and stock outperformance opportunities and provide more nuanced evidence to previous studies suggesting abnormal returns attributable to an ESG portfolio strategy (Eccles et al., 2014; Giese et al., 2019; Kaiser, 2020; Nagy et al., 2016). The thesis adds complexity to the relationship between stock returns and ESG scores by examining the financial performance of an ESG momentum strategy conditional on performance groups. The main and side results on backwards-looking KPIs and forward-looking stock market measures are of relevance for academics and investors, as they provide additional insights into how to integrate ESG into investment decisions as a signal.

9.2 Validity and reliability

Validity and reliability are two quality criteria of scientific research. Validity is a question of whether the data collected is adequate in describing the phenomenon that it is sought to describe (Olsen & Pedersen, 2003). The results of our research approach show a high degree of validity. The data we used is adequate in describing our research question and interpreting the empirical results consisting of stock price data and ESG data. The sample was drawn from a recognised data base, although the results are limited to companies with larger market capitalisation as a result of the data extraction (cf. Data description).

Reliability is a question of whether the methodology of arriving at the result is well-defined and whether consistent results can be expected at repeated trials (Carmines & Zeller, 2011). We followed a very well-defined and reliable approach which builds upon well researched methodologies that have been widely applied by academic scholars. Thus, the approach is very replicable. However, capital markets are dynamic and complex, and it is challenging to conclude that repeated trials would yield consistent results over time. The chosen models are measuring the contribution of ESG momentum to portfolio returns and hence the subject of interest in our research question. We included several factors in our models that have been found to have a high explanatory power of portfolio excess returns.[25] Hence, we minimized the risk that factors other than ESG momentum and the included factors explain our excess returns.

9.3 The future of ESG scores

Emerging artificial intelligence systems might help to increase the signal value of the ESG score, by drawing on larger amounts of ESG related data which can be analysed by ESG rating agencies. Such systems are on the rise in the financial sector, where an example includes the Alpha-dig system of Deutsche Bank (Deutsche Bank, 2018). In addition, artificial intelligence may facilitate more frequent ESG score updates without losing quality, as the technology can help speed up the data collection and evaluation process. This would in turn result in more relevant information in the sense of increased timeliness of information about ESG performance.

[25] Fama & French (1992) found their factors to explain over 90% of the variation in stock returns.

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11 Appendix

11.1 Appendix of theory chapter

Appendix T1: Calculation of the efficient frontier

**formulas are in matrix notation*

Asset	E[r]	Std
X	18%	32%
Y	24%	40%
Z	4%	12%
Tangency portfolio	18%	25.71%
Minimum variance portfolio	6%	11%
Risk-free rate	3%	0%

Covariance matrix

Asset	X	Y	Z
X	10%	5%	0%
Y	5%	16%	0%
Z	0%	0%	1%

Auxiliary constants:

$A = \mu \cdot \Sigma^{-1} \mu > 0,\; B = \mu \cdot \Sigma^{-1} \mathbf{1},\; C = \mathbf{1} \cdot \Sigma^{-1} \mathbf{1},\; D = AC - B^2 > 0$

Where μ equals vector of expected returns of risky assets and Σ^{-1} equals the inverse covariance matrix of the risky assets.

The minimum variance portfolio

The weights of the risky assets in the portfolio are given by $\pi_{min} = \frac{1}{C} \Sigma^{-1} \mathbf{1}$**,** with expected return and variance $\bar{\mu}_{min} = \frac{B}{C},\; \sigma^2_{min} = \frac{1}{C}$

The tangency portfolio

If $B \neq C\, r_f$

The weights of the risky assets in the portfolio are given by $\pi_{tan} = \frac{1}{B - C\, r_f} \Sigma^{-1} (\mu - r_f \mathbf{1})$**,**with expected return and variance $\bar{\mu}_{tan} = \frac{A - B\, r_f}{B - C\, r_f},\; \sigma^2_{tan} = \frac{A - 2B\, r_f + C\, r_f^2}{(B - C\, r_f)^2}$, where r_f is the risk-free rate.

The efficient frontier is constructed as the expected return and standard deviation from altering the weight in the minimum variance portfolio and the tangency portfolio. (Munk, 2018).

11.2 Appendix of data description chapter

Appendix D1: Accounting and stock market data

Variable	Abreviation
Global Industry Classification Standard code	gics
Current Assets	CA
Cash and Short-term Investments	CSTI
Current Liabilities	CL
Current Long-term Debt	CLTD
Current Income Taxes Payable	CITP
Total Liabilities	TL
Total Debt	TD
Book Value Per Share	BPS
Earnings Per Share	EPS
EBITDA	EBITDA
EBIT	EBIT
Cash Flow From Operations	CFFO
Capital Expenditure	CAPEX
Sales Per Share	SPS
Tangible Book Value Per Share	TBPS
Dividend Per Share	DPS
Funds From Operations	FFO
Long-term Debt	LTD
Total Common Equity	TCE
Gross Profit	GP
Total Assets	TA
Total Equity	TEQT
Depreciation and Amortization	DA
Net Debt	ND
Return on Equity	ROE
Return on Assets	ROA
Tangible book value	TBV
Net Income	NI
Goodwill	GW
Market capitalization (in USD)	mcapUSD
Share price (in USD)	priceUSD
Total Enterprise Value (in USD)	tevUSD

Average Daily Turnover (turnover = volume * price for most traded stock, in USD)	adtUSD
Shares Outstanding	ShOut

Calculated variables

Debt-equity ratio	$= \frac{total\ debt}{total\ equity}$
Book-to-market ratio	$= \frac{BPS \times shares\ outstanding}{market\ capitalisation}$
P/E ratio	$= \frac{stock\ price}{EPS}$
EV / EBITDA	$= \frac{total\ enterprise\ value}{EBITDA}$
Current ratio	$= \frac{current\ assets}{current\ liabilities}$

Appendix D2: MSCI ESG variables

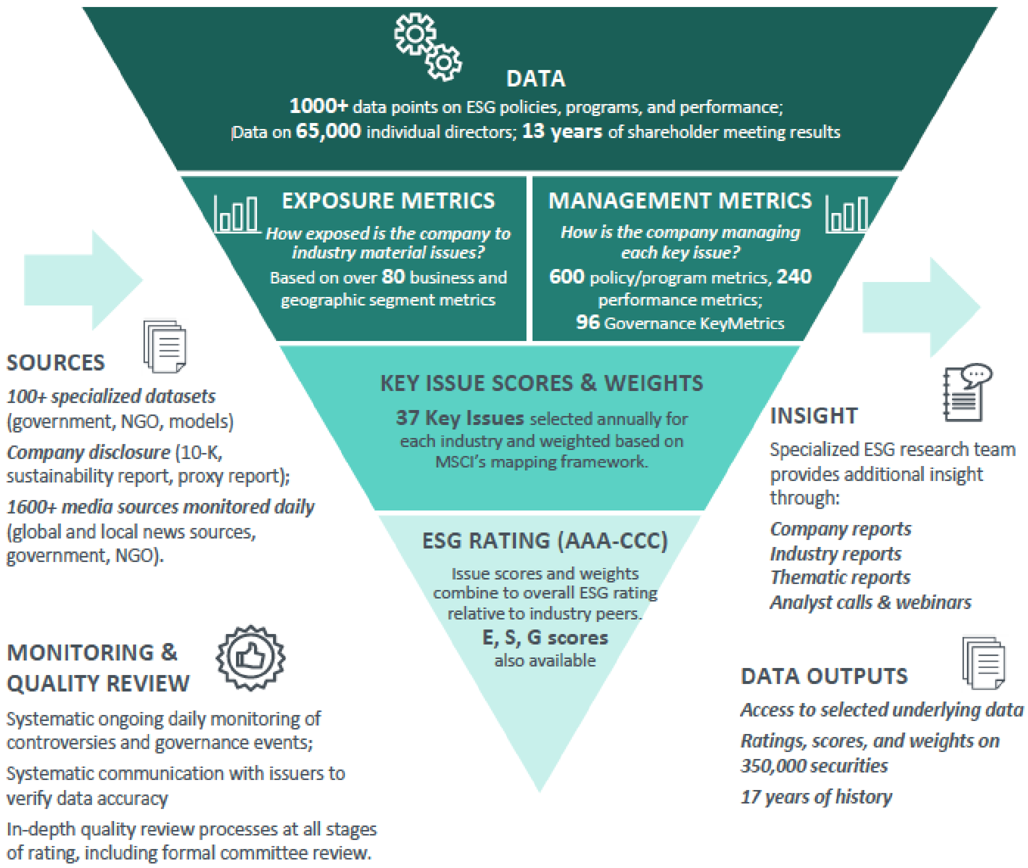
Variable	**Abreviation**
Environmental pillar score	E.score
Environmental pillar weight in overall ESG	E.weight
Social pillar score	S.score
Social pillar weight in overall ESG score	S.weight
Governance pillar score	G.score
Governance pillar weight in overall ESG score	G.weight
Weighted average score	Weighted.avg.score
Industry adjusted score	Industry.adj.score
IVA Company rating (letter score)	IVA.company.rating
IVA Rating date	IVA.rating.date

Countries within regions

North America	Bermuda, Canada, Cayman Islands, United States
Europe	Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom
Pacific	Australia, Hong Kong, New Zealand, Singapore
Japan	Japan

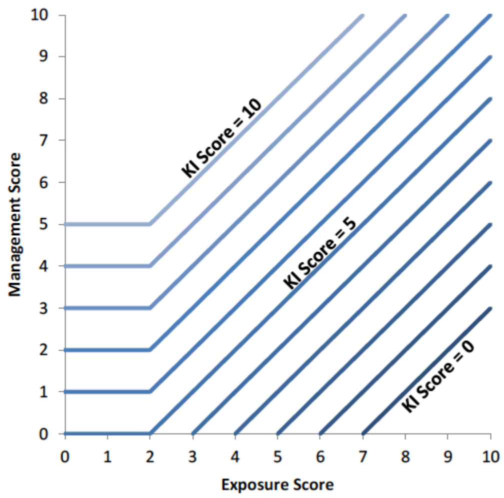
Latin America	Argentina, Brazil, Chile, Colombia, Mexico, Panama, Peru
Eastern Europe	Czech Republic, Hungary, Poland, Russia
Asia	China, India, Indonesia, Malaysia, Philippines, South Korea Taiwan, Thailand
Middle East / Africa	Egypt, Israel, Morocco, South Africa, Turkey, United Arab Emirates

Appendix D3: ESG scoring framework (MSCI, 2018)

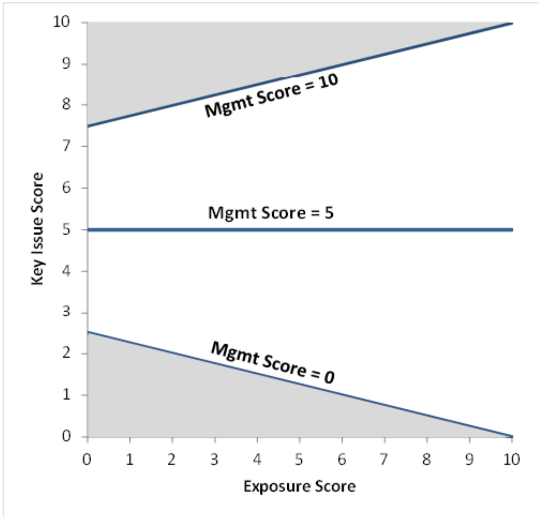


Appendix D4: Assessment methods of risks and opportunities (MSCI, 2018)

Risks



Opportunities



Appendix D5: Letter rating

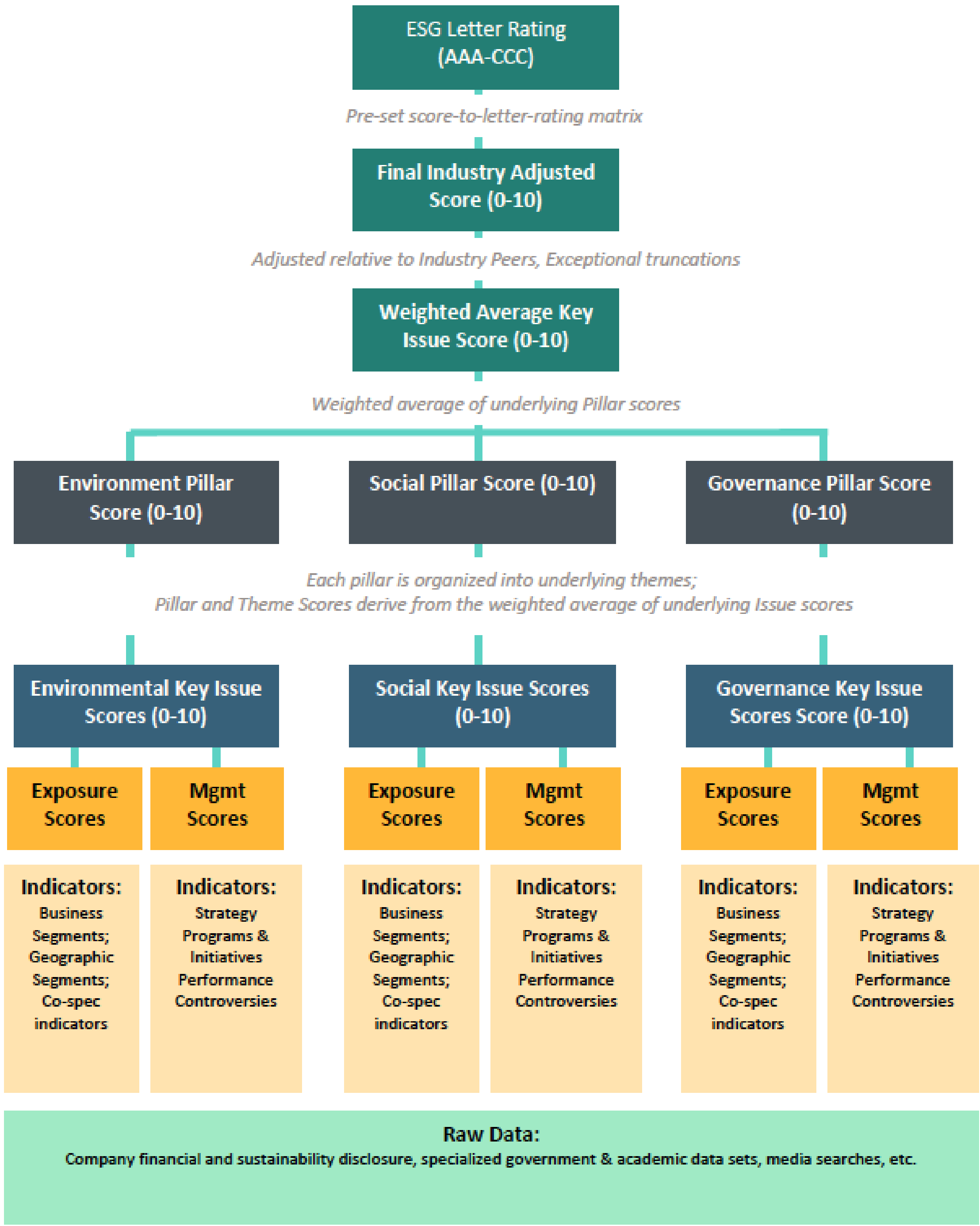
Letter Rating	Final Industry-Adjusted Company Score
AAA	8.6* - 10.0
AA	7.1 – 8.6
A	5.7 – 7.1
BBB	4.3 – 5.7
BB	2.9 – 4.3
B	1.4 – 2.9
CCC	0.0 – 1.4

Appendix D6: Identifying Key Issues

Figure 1 MSCI ESG Key Issue Hierarchy

3 Pillars	10 Themes	37 ESG Key Issues	
Environment	Climate Change	Carbon Emissions Product Carbon Footprint	Financing Environmental Impact Climate Change Vulnerability
	Natural Resources	Water Stress Biodiversity & Land Use	Raw Material Sourcing
	Pollution & Waste	Toxic Emissions & Waste Packaging Material & Waste	Electronic Waste
	Environmental Opportunities	Opportunities in Clean Tech Opportunities in Green Building	Opp's in Renewable Energy
Social	Human Capital	Labor Management Health & Safety	Human Capital Development Supply Chain Labor Standards
	Product Liability	Product Safety & Quality Chemical Safety Financial Product Safety	Privacy & Data Security Responsible Investment Health & Demographic Risk
	Stakeholder Opposition	Controversial Sourcing	
	Social Opportunities	Access to Communications Access to Finance	Access to Health Care Opp's in Nutrition & Health
Governance	Corporate Governance*	Board* Pay*	Ownership* Accounting*
	Corporate Behavior	Business Ethics Anti-Competitive Practices Tax Transparency	Corruption & Instability Financial System Instability

** Corporate Governance Theme carries weight in the ESG Rating model for all companies. In 2018, we introduce sub-scores for each of the four underlying issues: Board, Pay, Ownership, and Accounting.*

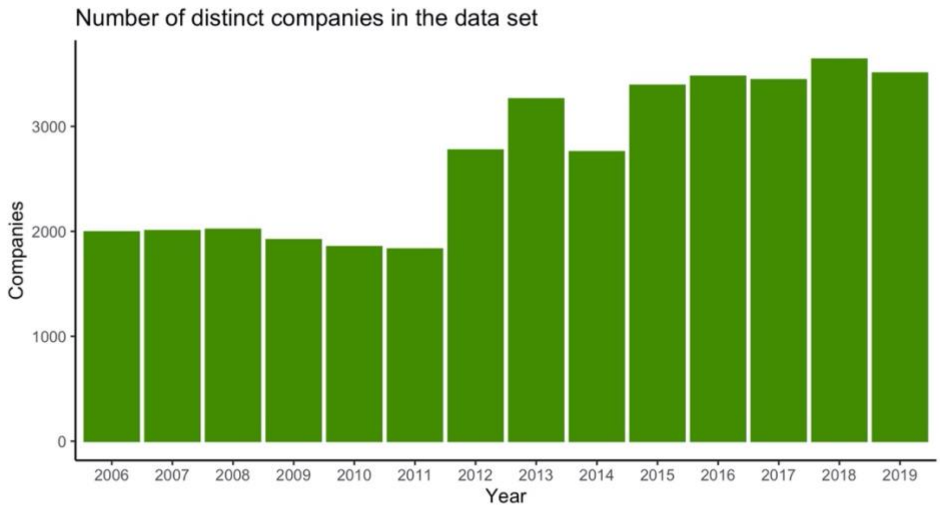

ESG Letter Rating (AAA-CCC)
Pre-set score-to-letter-rating matrix
Final Industry Adjusted Score (0-10)
Adjusted relative to Industry Peers, Exceptional truncations
Weighted Average Key Issue Score (0-10)
Weighted average of underlying Pillar scores
Environment Pillar Score (0-10)
Social Pillar Score (0-10)
Governance Pillar Score (0-10)
Each pillar is organized into underlying themes;
Pillar and Theme Scores derive from the weighted average of underlying Issue scores
Environmental Key Issue Scores (0-10)
Social Key Issue Scores (0-10)
Governance Key Issue Scores Score (0-10)
Exposure Scores
Mgmt Scores
Exposure Scores
Mgmt Scores
Exposure Scores
Mgmt Scores
Indicators: Business Segments; Geographic Segments; Co-spec indicators
Indicators: Strategy Programs & Initiatives Performance Controversies
Indicators: Business Segments; Geographic Segments; Co-spec indicators
Indicators: Strategy Programs & Initiatives Performance Controversies
Indicators: Business Segments; Geographic Segments; Co-spec indicators
Indicators: Strategy Programs & Initiatives Performance Controversies
Raw Data:
Company financial and sustainability disclosure, specialized government & academic data sets, media searches, etc.

Appendix D7: Benchmark countries

MSCI World Index ***as of May 2020***	Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the United Kingdom and the United States (MSCI, 2020e).
MSCI Emerging Markets Index ***as of May 2020***	Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Korea, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Qatar, Russia, Saudi Arabia, South Africa, Taiwan, Thailand, Turkey and United Arab Emirates (MSCI, 2020c).

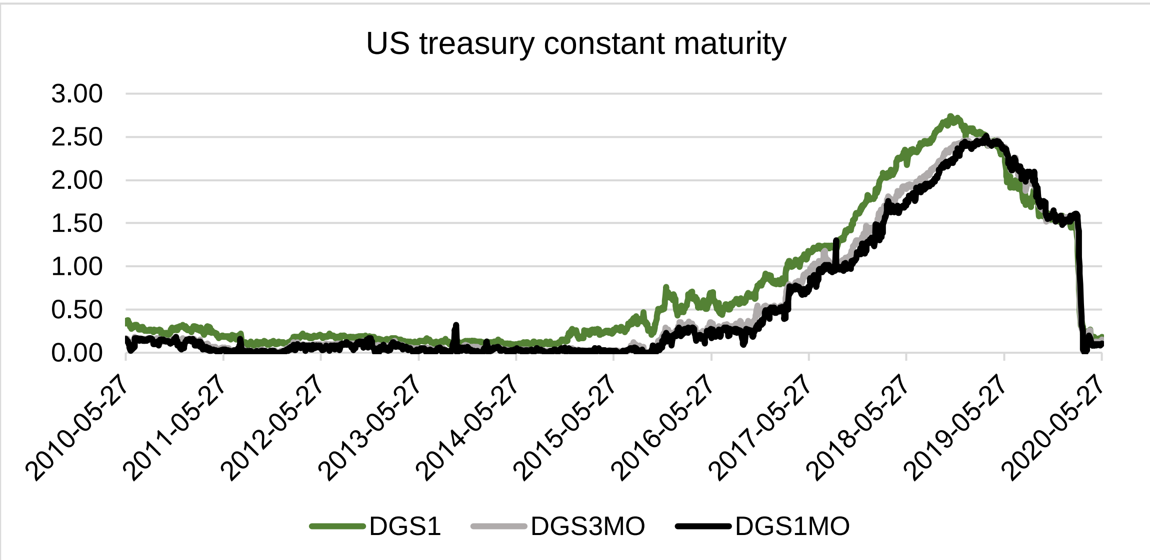
11.3 Appendix of methodology

<u>Appendix M1: Number of distinct companies in the overall data set</u>



Source: Own contribution

<u>Appendix M2: US treasury rates in comparison</u>

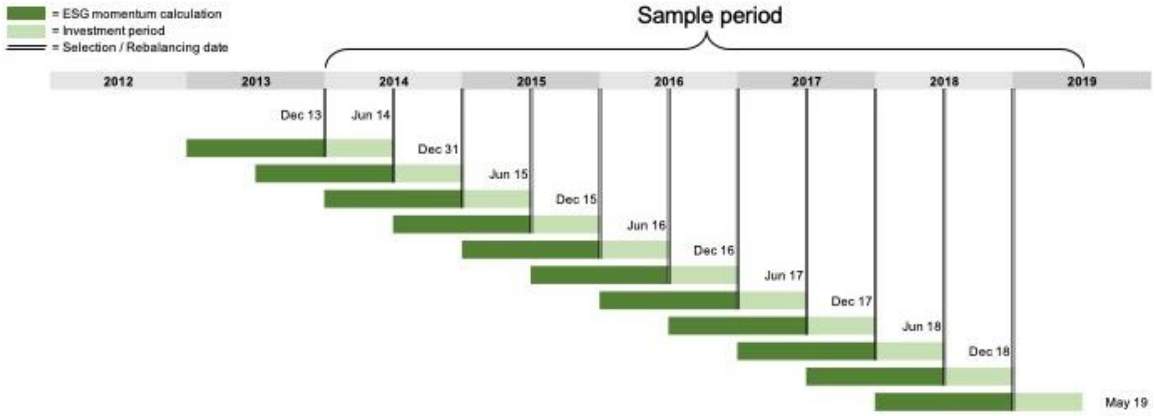


Notes: DGS1 (1 year treasury constant maturity), DGS3MO (3 months treasury constant maturity), and DGS1MO (1 month treasury constant maturity)

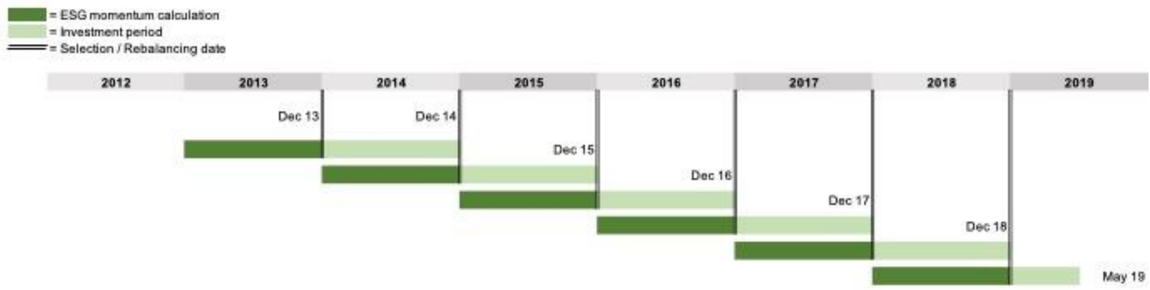
Source: Own contribution (data downloaded from FRED (https://fred.stlouisfed.org/categories/115))

Appendix M3: ESG momentum calculation horizon and investment periods

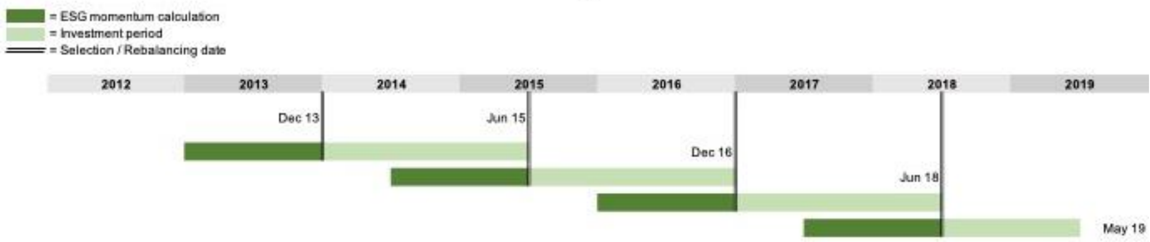
6-month holding period



12-month holding period



18-month holding period



Source: Own contribution

Appendix M4: T-test on difference in returns

t-test on return difference		
	Developed markets	**Emerging markets**
Test statistic	**General Market**	**General Market**
Holding period	Delta Returns	Delta Returns
6m	16.05***	-7.91***
12m	9.91***	1.48
18m	-6.93***	7.16***
	Performance groups	**Performance groups**
Test statistic	**Performance group "low"**	**Performance group "low"**
Holding period	Delta Returns	Delta Returns
6m	7.87***	-6.17***
12m	0.46	-8.75***
18m	-10.01***	14.76***
Test statistic	**Performance group "average"**	**Performance group "average"**
Holding period	Delta Returns	Delta Returns
6m	12.42***	-6.1209***
12m	3.67***	-2.1158***
18m	-8.68***	2.87***
Test statistic	**Performance group "high"**	**Performance group "high"**
Holding period	Delta Returns	Delta Returns
6m	15.53***	7.50***
12m	19.39***	2.80***
18m	15.51***	5.60***

*Notes: Welch-test assuming unequal variance between the return time series of the top and bottom portfolio. * 10% significance, ** 5% significance, *** 1% significance*

Appendix M5: Correlation between own factors and Fama French factors

Developed Markets

	Fama French factors*				
	Risk-free rate	**Market excess return**	**SMB**	**HML**	**WML**
1 Year treasury risk-free rate	0.97				
MSCI World excess return		0.99			
SMB			0.72		
HML				0.87	
WML					0.93

Notes: Factors downloaded from the Fama French data library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)

Emerging markets

	Fama French factors*				
	Risk-free rate	**Market excess return**	**SMB**	**HML**	**WML**
1 Year treasury risk-free rate	0.97				
MSCI EM excess return		0.99			
SMB			-0.03		
HML				0.54	
WML					0.63

Notes: Factors downloaded from the Fama French data library (https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html)

Appendix M6: Factor cross-correlation matrices

Developed markets

	MSCI World excess return	SMB	HML	WML
MSCI World excess return	1	-0.11	-0.14	0.20
SMB	-0.11	1	-0.69	0.12
HML	-0.14	-0.69	1	-0.38
WML	0.20	0.12	-0.38	1

Emerging markets

	MSCI World excess return	SMB	HML	WML
MSCI World excess return	1	-0.15	-0.25	-0.16
SMB	-0.15	1	-0.37	0.43
HML	-0.25	-0.37	1	-0.312
WML	-0.16	0.43	-0.31	1

Appendix M7: Test for multicollinearity

The significance of multicollinearity can be assessed by computing the variance importance factor (VIF_i), which measures how much the variance of a regression coefficient is inflated due to multicollinearity in the model.

$$VIF_i = \frac{1}{1 - R_i^2}$$

The test runs a series of regressions for each of the explanatory variables (i), where the other explanatory variables are used as regressors. R_i^2 is the resulting R^2 from the auxiliary regression of the explanatory variables. As a rule of thumb, a VIF value that exceeds 10 indicates a problematic amount of collinearity (James, Witten, Hastie, & Tibshirani, 2014).

VIF test statistics

Developed markets			
MSCI World excess return	SMB	HML	MOM
1.246522	1.122905	2.158294	2.464133
Emerging markets			
MSCI EM excess return	SMB	HML	MOM
1.307862	1.180472	1.373875	1.369558

Appendix M8: Test for heteroscedasticity

The Breusch-Pagan test fits a linear regression model to the residuals of a linear regression model rejects the null hypothesis of homoscedasticity if too much of the variance is explained by the additional explanatory variables. The authors build an auxiliary regression model that describes the squared residuals (u_t^2) from the regression models as a function of the explanatory variables (Z_m) from that first regression.

$$E(u_m^2) = \delta_1 + \delta_2 Z_{2m} + \cdots + \delta_p Z_{pm}$$

The test statistic ($LM(H)$) is computed using R^2 of the model and the sample size (n) and is χ^2 - distributed with $p - 1$ degrees of freedom.

$$LM(H) = n \times R^2 \sim \chi^2_{p-1}$$

Breusch-Pagan test statistics

Test statistics for Breusch-Pagan test against heteroskedasticity

	Developed markets				Emerging markets			
	Multi factor regression		CAPM		Multi factor regression		CAPM	
Test statistic	General market		General market		General market		General market	
Holding period	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom
6m	9.39*	0.53	0.06	0.00	1.38	2.85	0.02	1.96
12m	10.95**	0.62	0.00	0.97	2.28	4.00	1.02	0.19
18m	6.22	1.42	2.33	0.08	1.78	6.12	1.23	0.81

	Performance groups				Performance groups			
	Performance group "low"				Performance group "low"			
Test statistic	Multi factor regression		CAPM		Multi factor regression		CAPM	
Holding period	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom
6m	3.80	6.84	1.33	5.12**	2.34	5.74	0.40	2.64
12m	3.45	2.88	0.70	1.00	4.93	5.38	2.44	1.41
18m	10.54**	8.26*	3.05*	1.80	12.59**	1.34	8.57**	1.01

	Performance group "average"				Performance group "average"			
Test statistic	Multi factor regression		CAPM		Multi factor regression		CAPM	
Holding period	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom
6m	9.40*	1.41	0.19	1.76	1.46	6.79	0.10	2.78*
12m	7.61	3.00	0.02	0.93	1.76	5.56	0.06	0.14
18m	6.49	4.46	4.24**	0.79	0.29	6.06	0.11	1.56

	Performance group "high"				Performance group "high"			
Test statistic	Multi factor regression		CAPM		Multi factor regression		CAPM	
Holding period	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom
6m	9.40*	1.41	0.19	1.76	2.34	11.11**	0.07	4.92**
12m	7.61	3.00	0.02	0.93	2.05	6.95	0.04	2.07
18m	6.49	4.46	4.24**	0.79	2.10	0.72	0.10	0.02

*Notes: * 10% significance, ** 5% significance, *** 1% significance*

Appendix M9: Test for serial correlation

The Breusch-Godfrey test allows to separately test for positive and negative autocorrelation. The authors run the test with one lag (u_{m-1}), which is the most common form.

$$u_m = \phi_1 u_{m-1} + \varepsilon_m \qquad \varepsilon_m \sim i.i.d.(0, \sigma^2), m = 1, \dots, M$$

If ϕ_1 is statistically different from 0, the null hypothesis of no autocorrelation is rejected.

Breusch-Godfrey test statistics

Test statistics for Breusch-Godfrey test for serial correlation								
	Developed markets				**Emerging markets**			
	Multi factor regression		**CAPM**		**Multi factor regression**		**CAPM**	
Test statistic	**General Market**		**General Market**		**General Market**		**General Market**	
Holding period	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom
6m	0.82	3.58*	0.00	1.54	0.04	1.77	0.31	0.61
12m	0.97	7.59***	0.19	3.96*	0.04	2.25	0.00	1.42
18m	0.13	6.43**	0.08	2.50	0.26	0.52	0.25	0.77
	Performance groups				**Performance groups**			
	Performance group "low"				**Performance group "low"**			
Test statistic	**Multi factor regression**		**CAPM**		**Multi factor regression**		**CAPM**	
Holding period	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom
6m	1.95	1.16	0.91	2.09	1.92	0.44	1.40	1.30
12m	2.09	2.02	2.76	3.19*	4.41**	0.66	4.60**	0.86
18m	0.22	4.16**	0.91	5.33**	2.71	0.14	3.57*	0.11
	Performance group "average"				**Performance group "average"**			
Test statistic	**Multi factor regression**		**CAPM**		**Multi factor regression**		**CAPM**	
Holding period	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom
6m	0.14	2.78	0.00	2.72	3.25*	0.46	5.45**	0.64
12m	1.35	2.89	0.65	1.71	0.01	0.42	0.26	0.00
18m	1.21	3.05*	0.47	1.43	0.81	0.11	0.14	1.66
	Performance group "high"				**Performance group "high"**			
Test statistic	**Multi factor regression**		**CAPM**		**Multi factor regression**		**CAPM**	
Holding period	Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom
6m	0.06	0.03	0.23	0.14	9.76***	0.71	10.79***	1.59
12m	0.05	0.13	0.19	0.08	0.66	0.28	0.50	1.14
18m	1.19	2.60	2.62	1.90	4.92**	6.80**	4.10**	8.64***

*Notes: * 10% significance, ** 5% significance, *** 1% significance*

11.4 Appendix of the analysis

Appendix A1: Calculation of the annualized turnover

$$Annualised\ turnover_{6\ months} = \frac{Number\ of\ companies\ sold_{t=0.5} + Number\ of\ companies\ sold_{t=1}}{Number\ of\ companies_{t=0.5} + Number\ of\ companies_{t=1}}$$

$$Annualised\ turnover_{12\ months} = Turnover(12months)$$

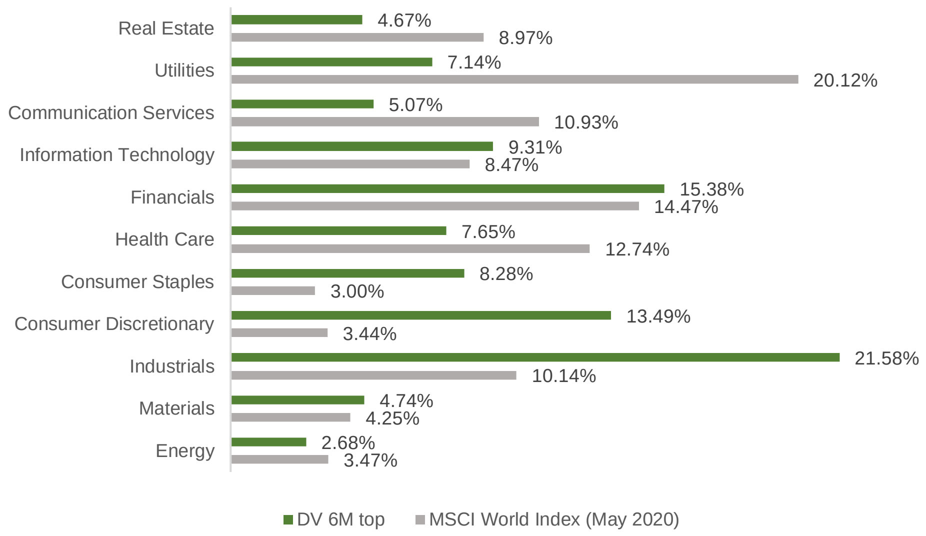
$$Annualised\ turnover_{18\ months} = Turnover(18\ months) * \frac{2}{3}$$

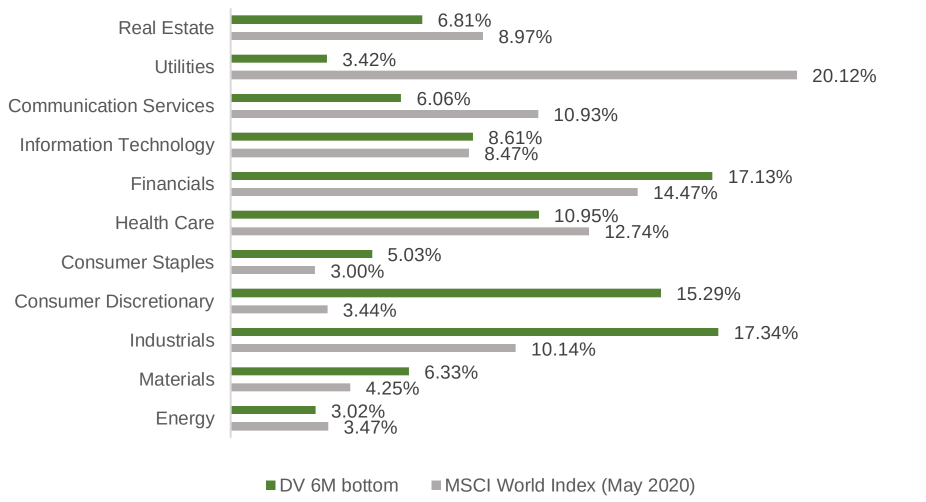
11.4.1 General markets portfolios – Sector distribution

11.4.1.1 Developed markets

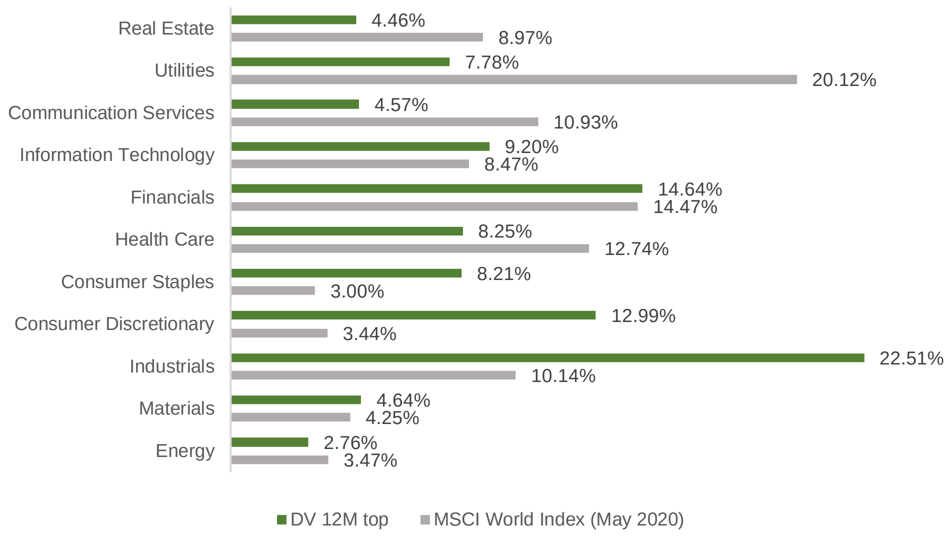
Appendix A2: General developed markets portfolios – sector distribution

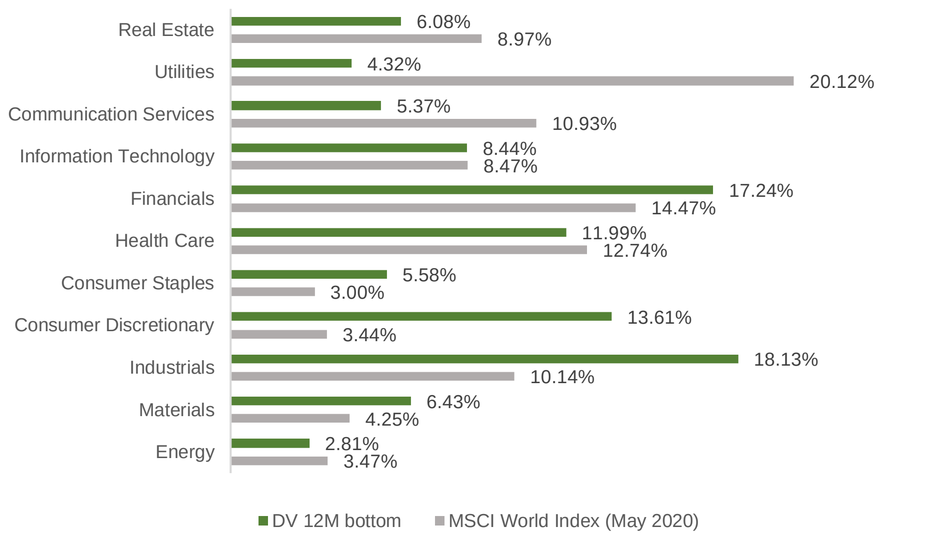
6-month holding period



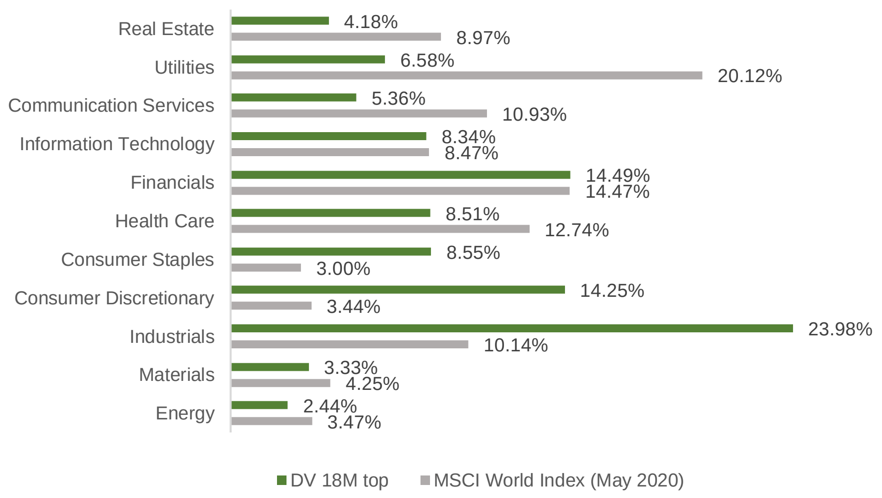


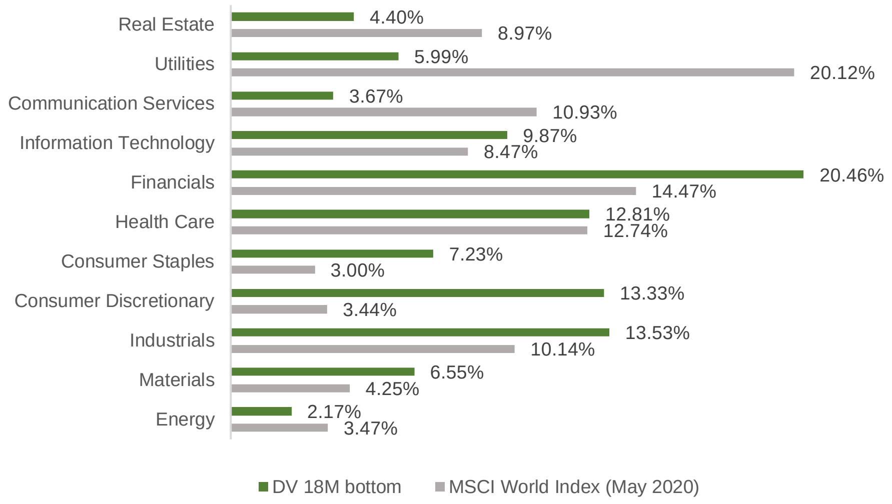
12-month holding period





18-month holding period

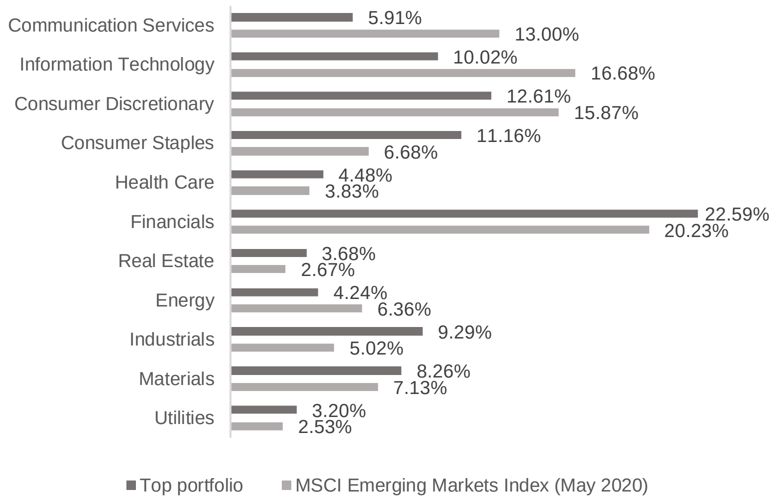


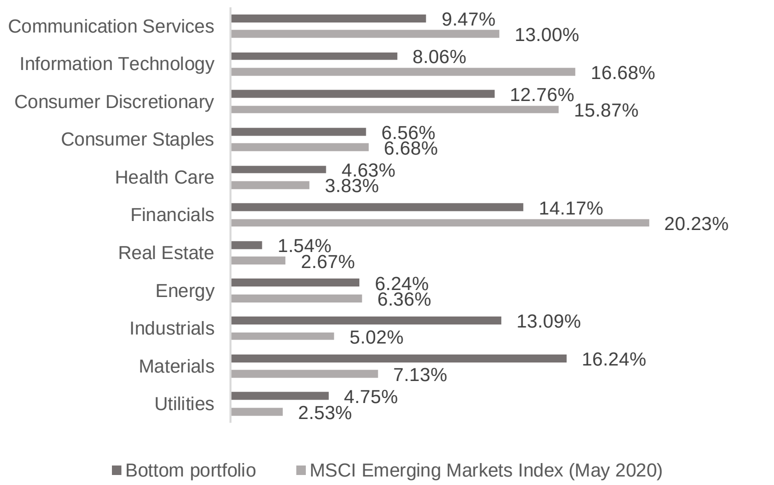


11.4.1.2 Emerging markets

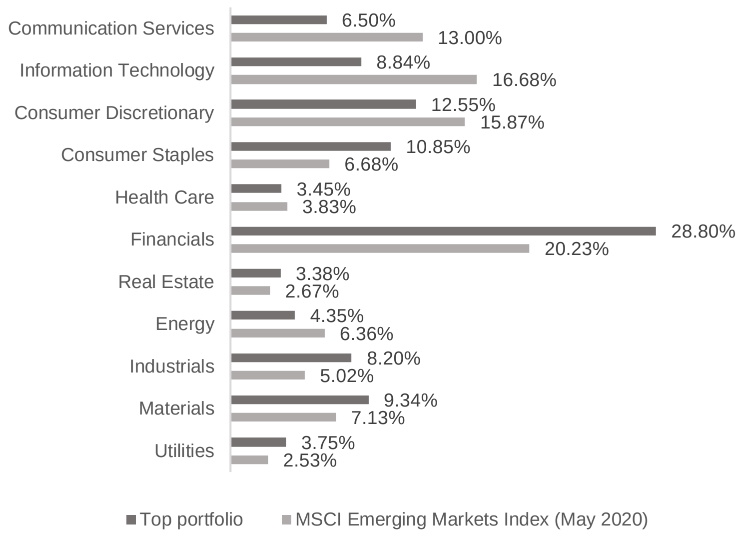
<u>Appendix A3: General emerging markets portfolios – sector distribution</u>

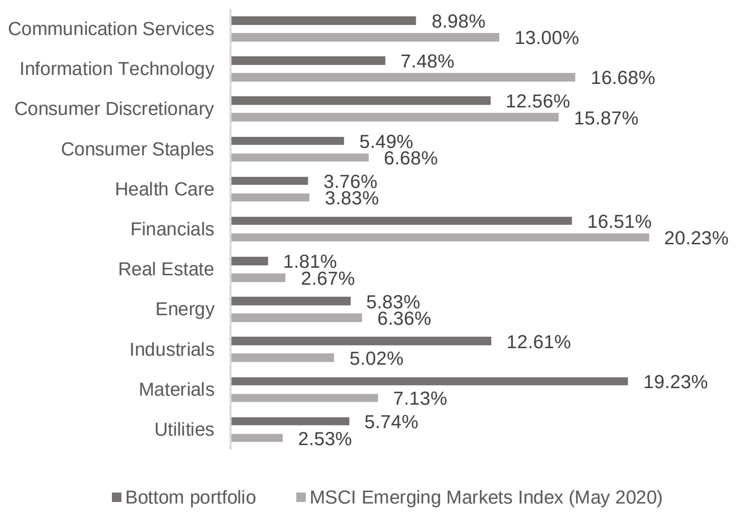
6-month holding period



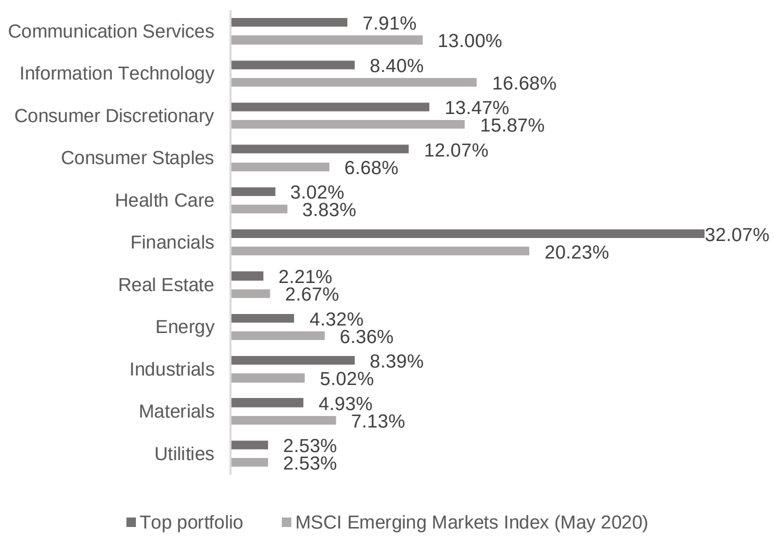


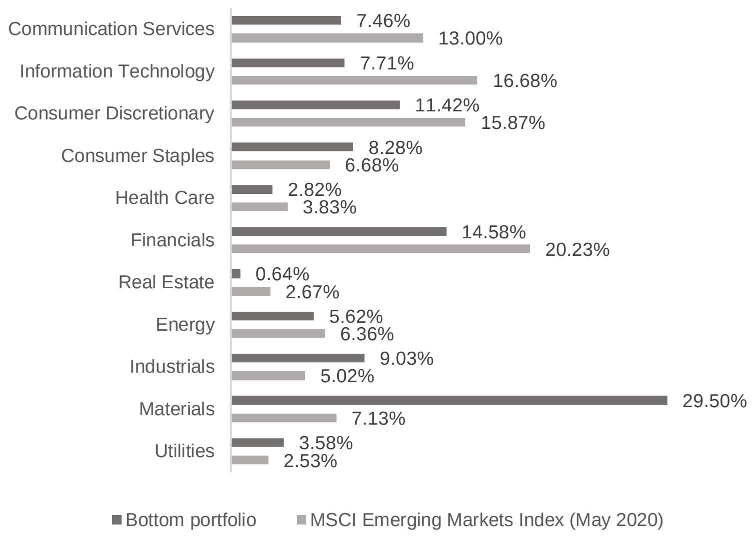
12-month holding period





18-month holding period



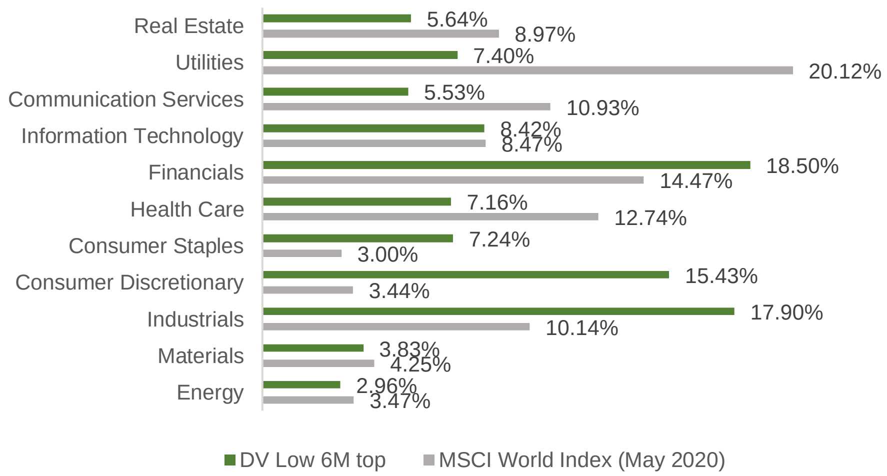


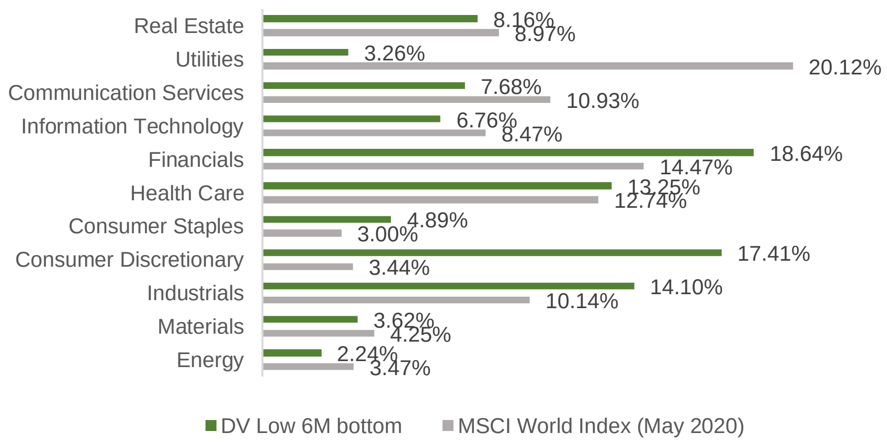
11.4.2 Performance group portfolios – Sector distribution

11.4.2.1 Developed markets

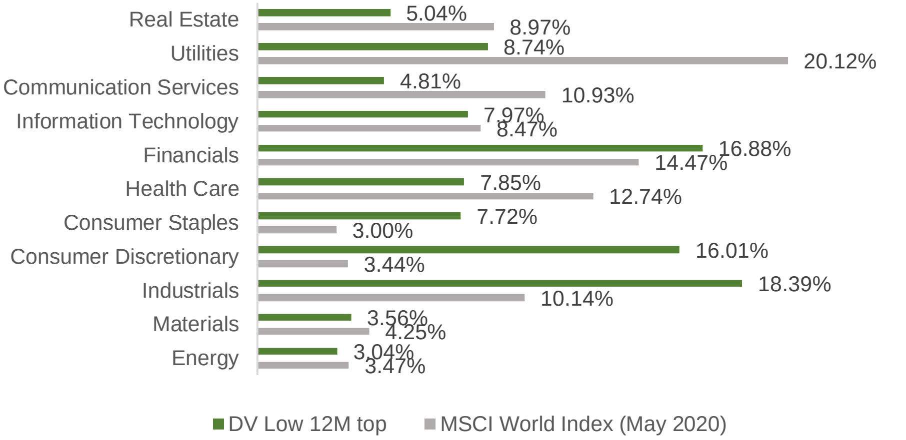
<u>Appendix A4: Developed markets portfolios – Performance group “low” – sector distribution</u>

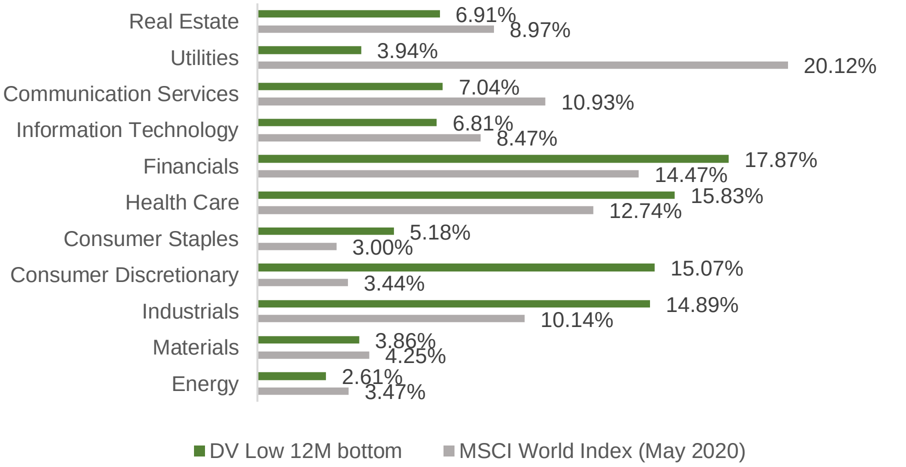
6-month holding period



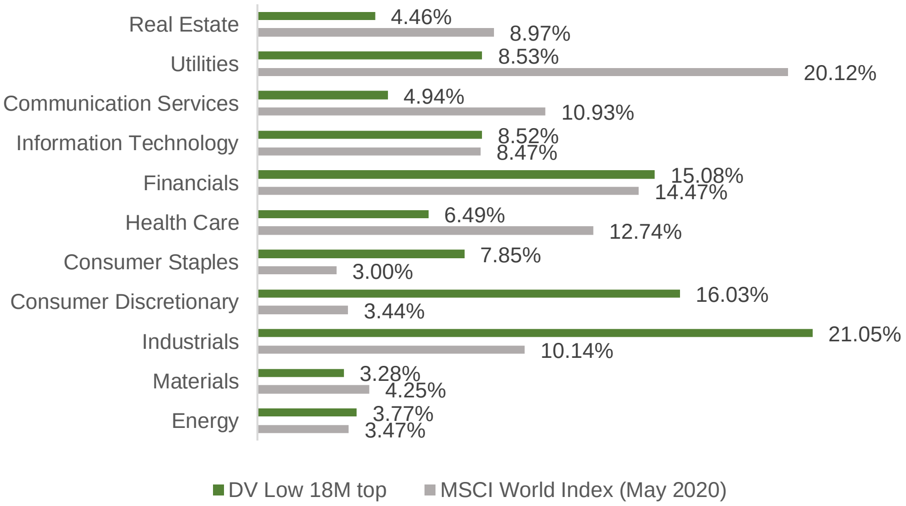


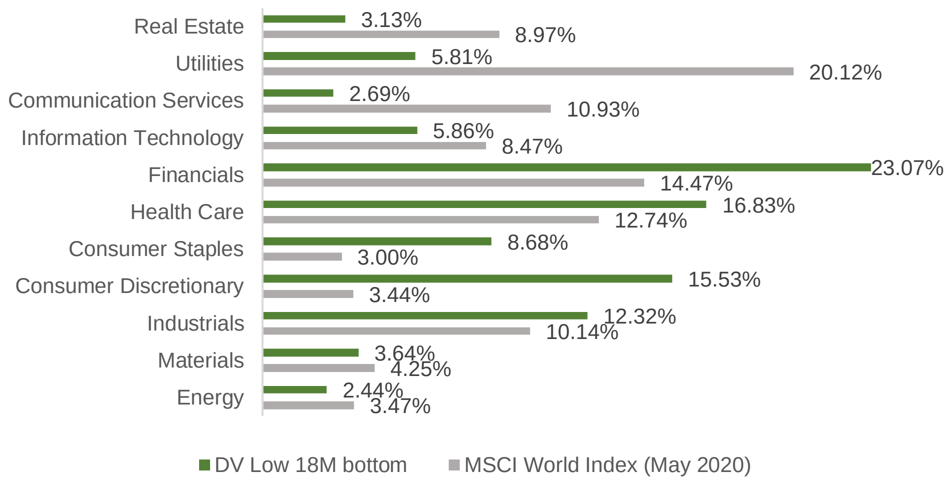
12-month holding period





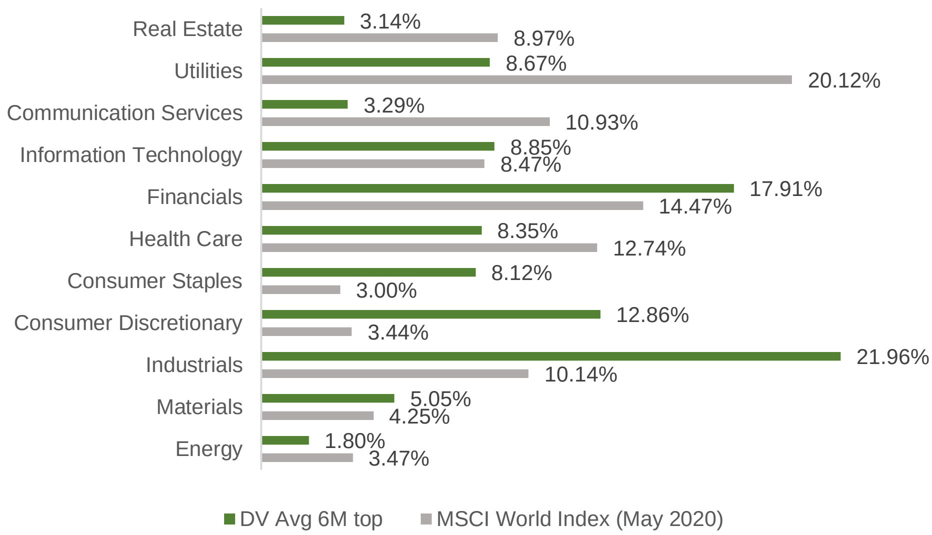
18-month holding period

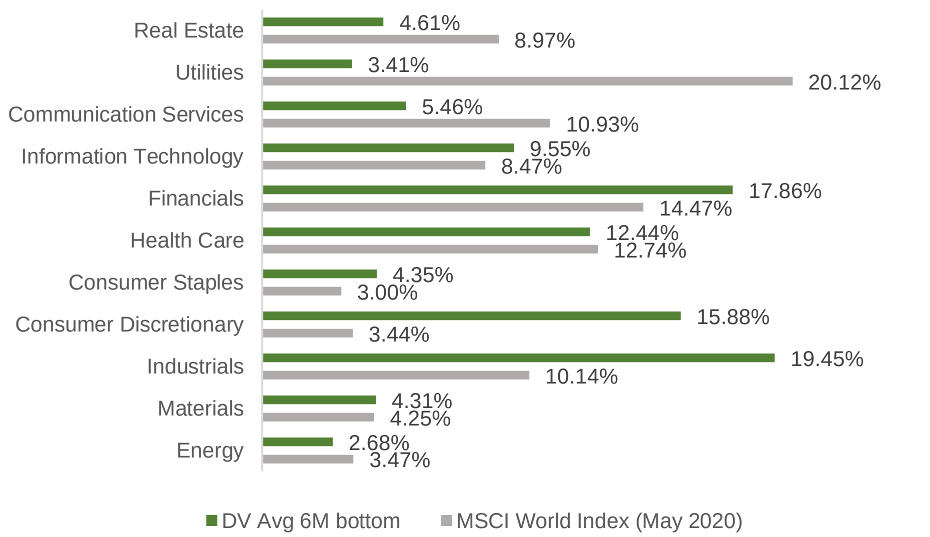




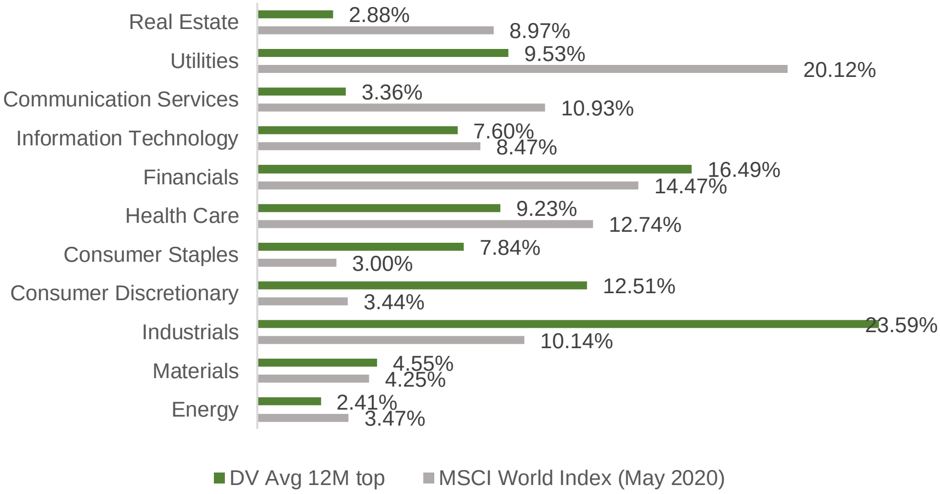
Appendix A5: Developed markets portfolios – Performance group “average” – sector distribution

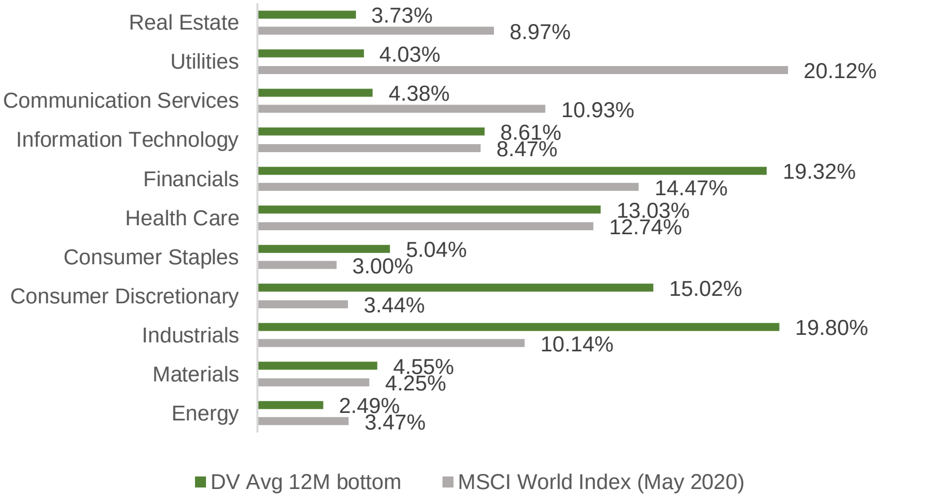
6-month holding period



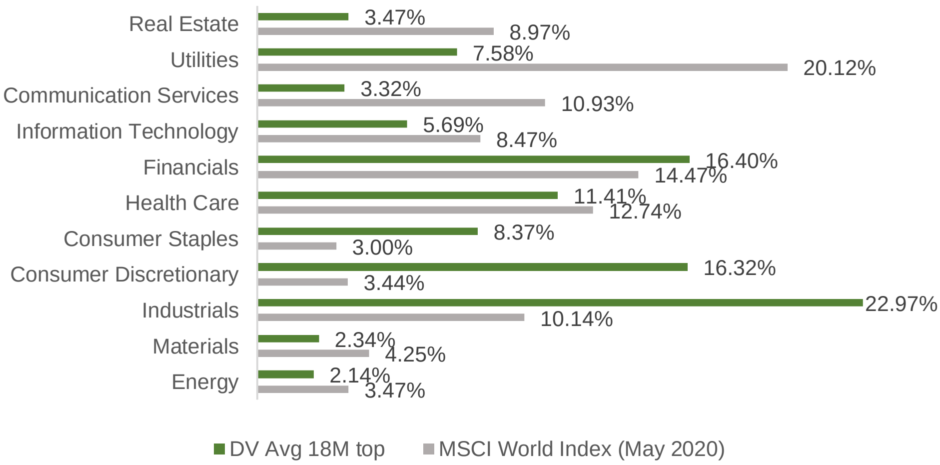


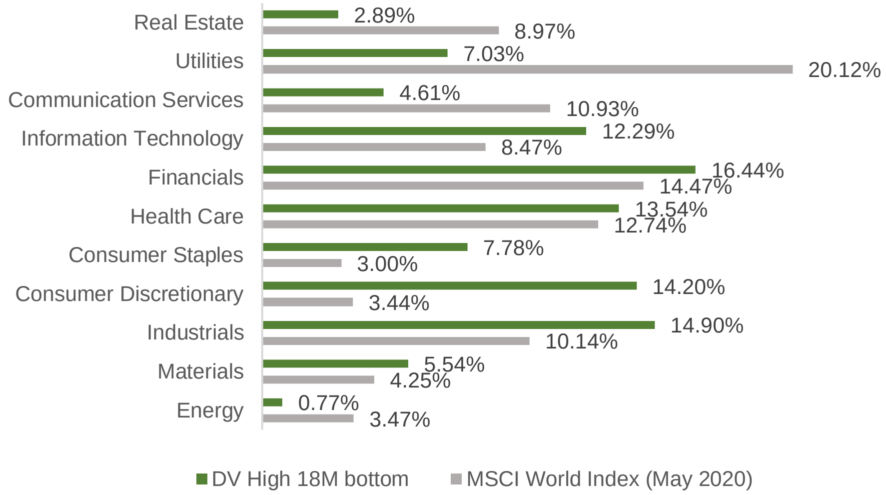
12-month holding period





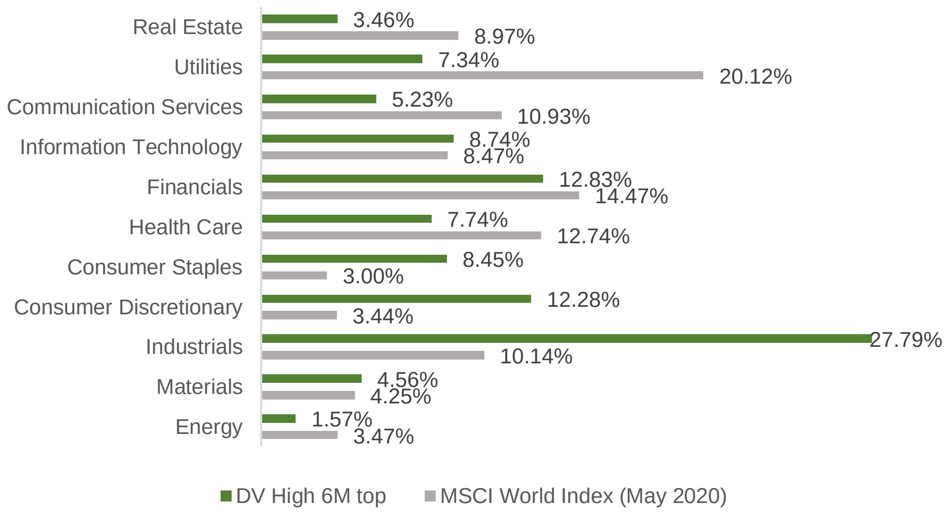
18-month holding period

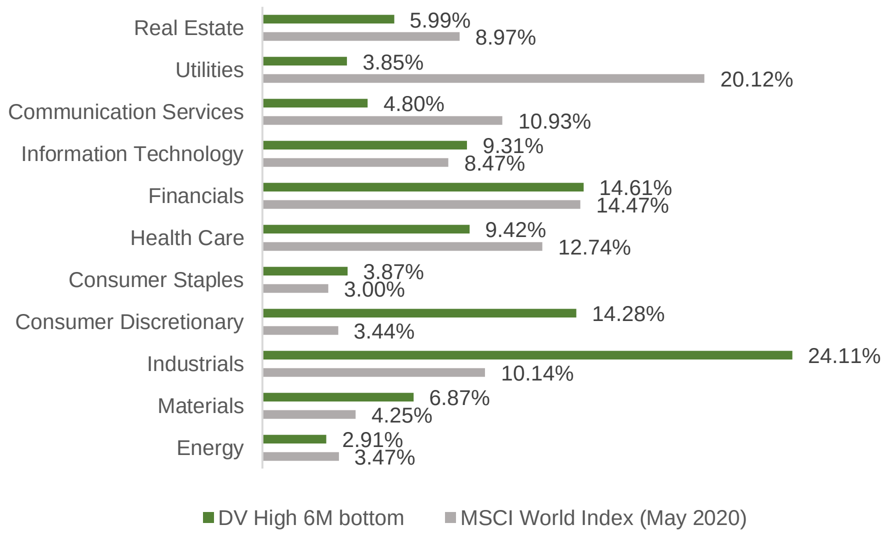




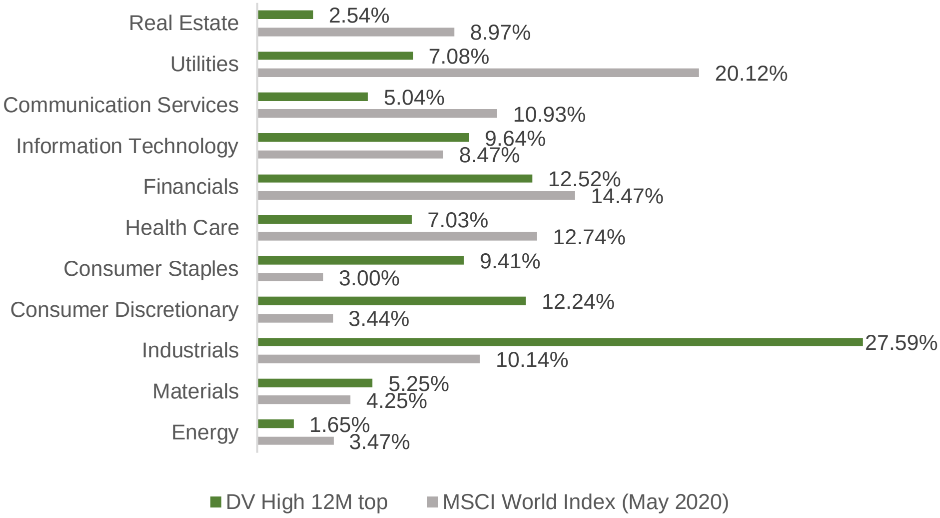
Appendix A6: Developed markets portfolios – Performance group "high" – sector distribution

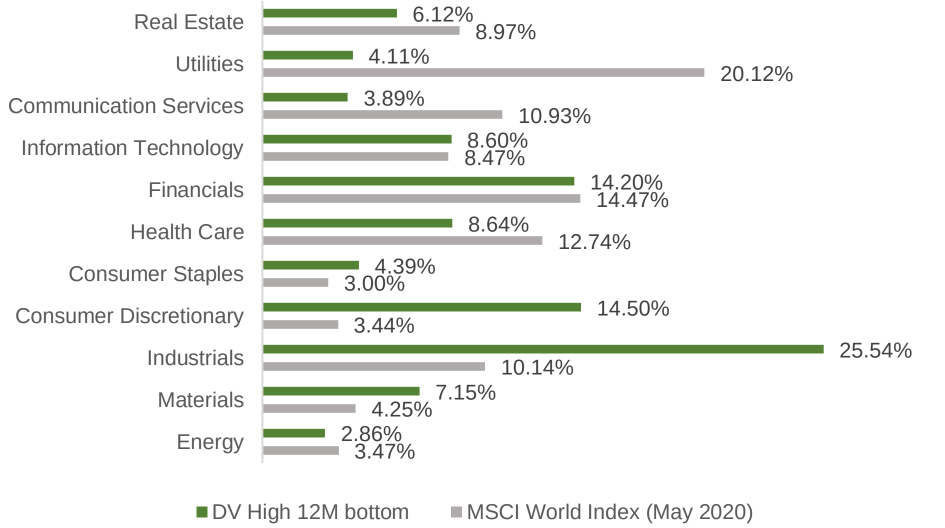
6-month holding period



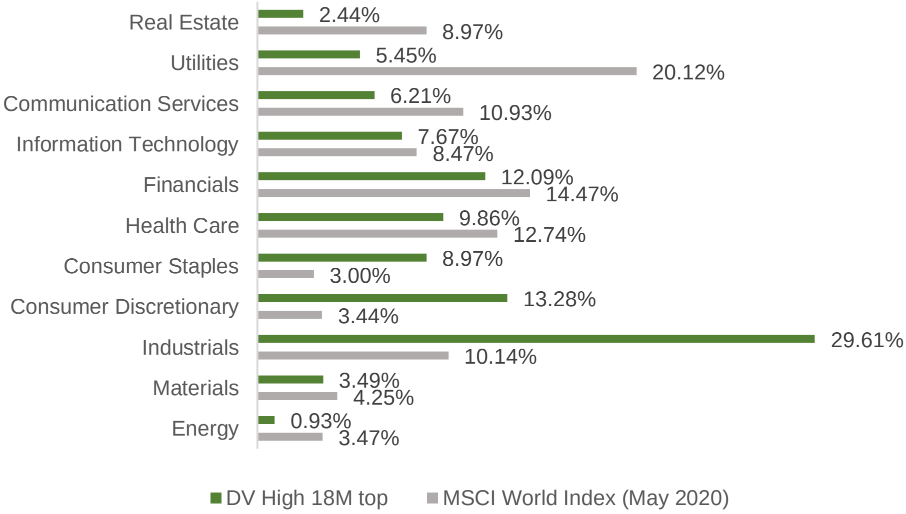


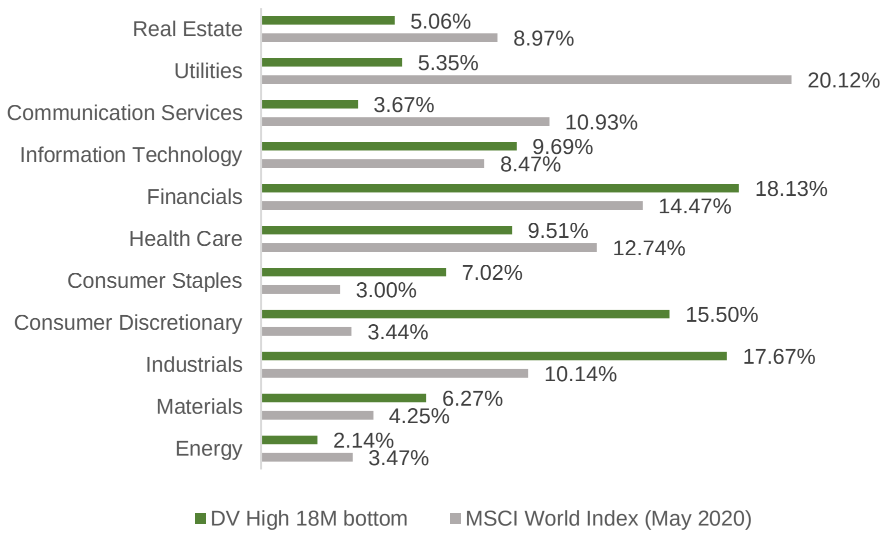
12-month holding period





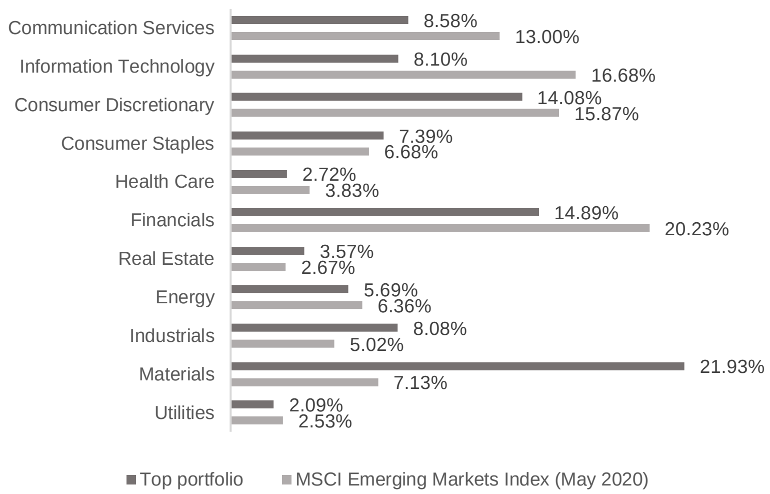
18-month holding period

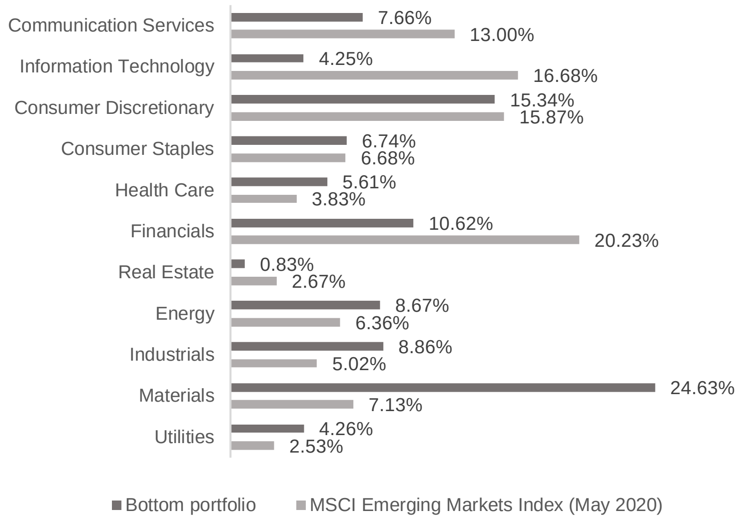




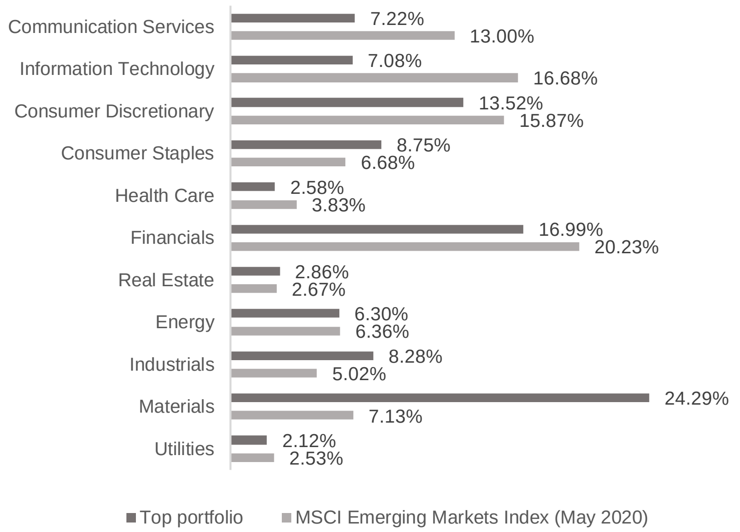
11.4.2.2 Emerging markets

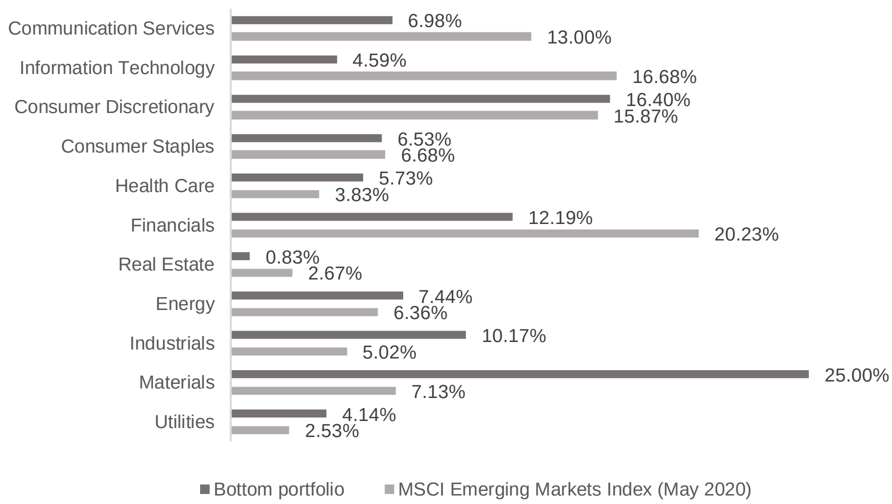
<u>Appendix A7: Emerging markets portfolios – Performance group “low” – sector distribution</u>
6-month holding period



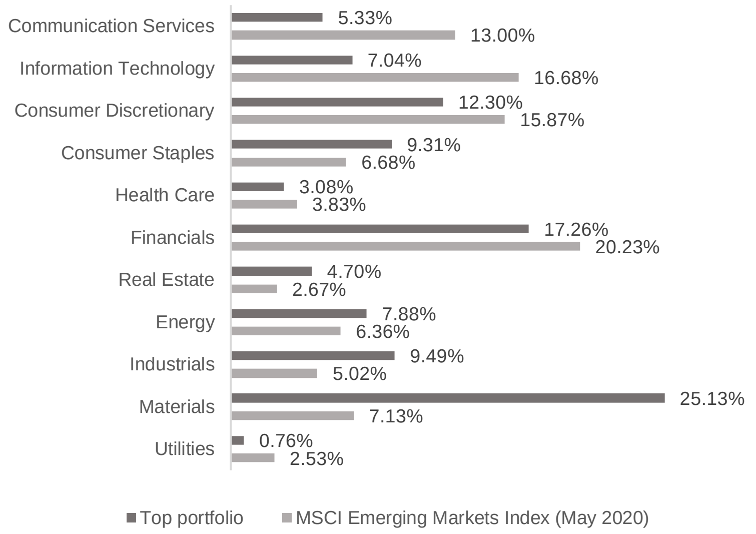


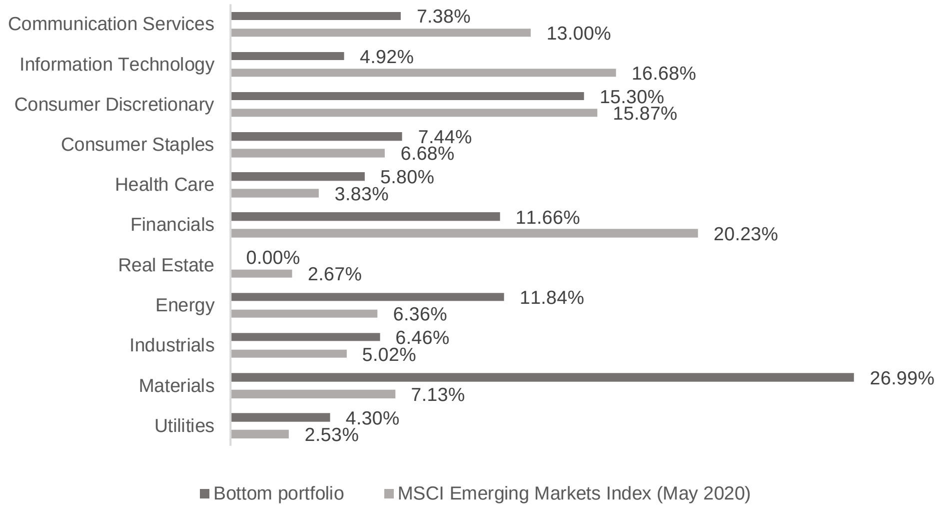
12-month holding period





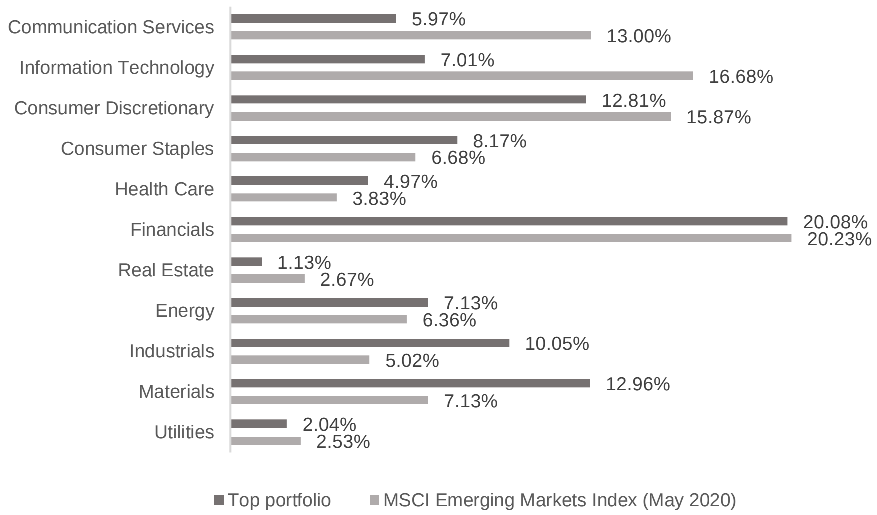
18-month holding period

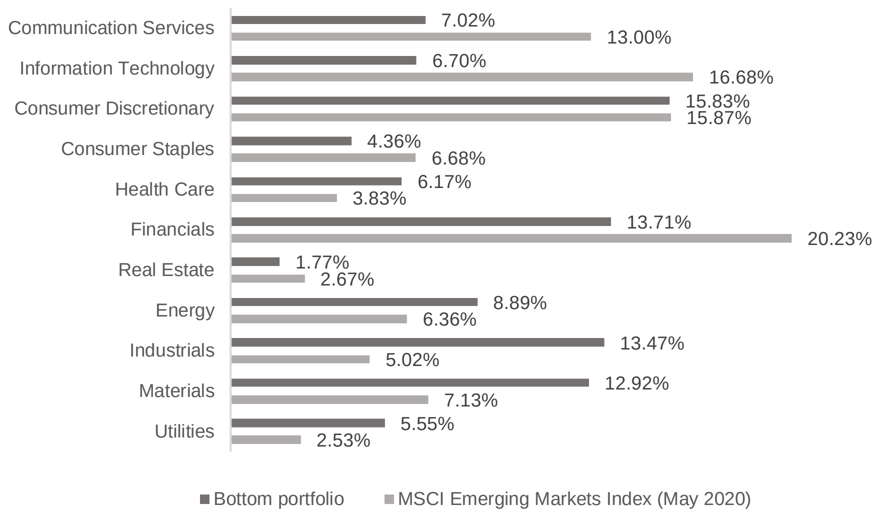




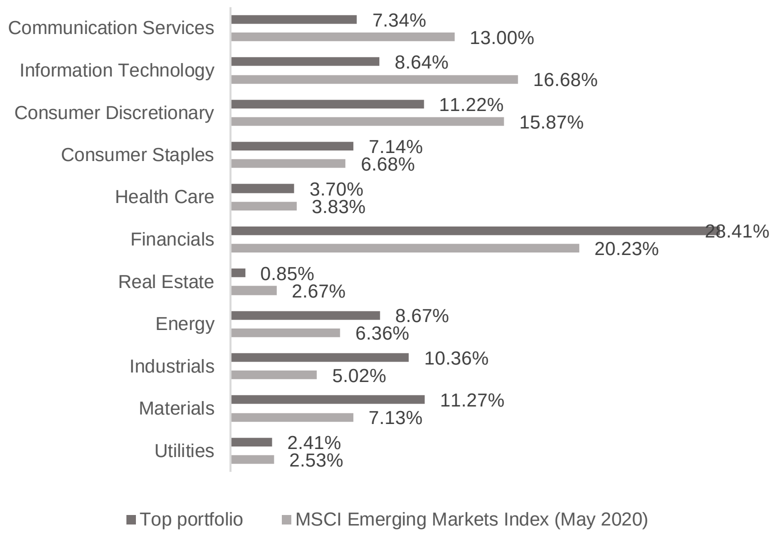
Appendix A8: Emerging markets portfolios – Performance group “average” – sector distribution

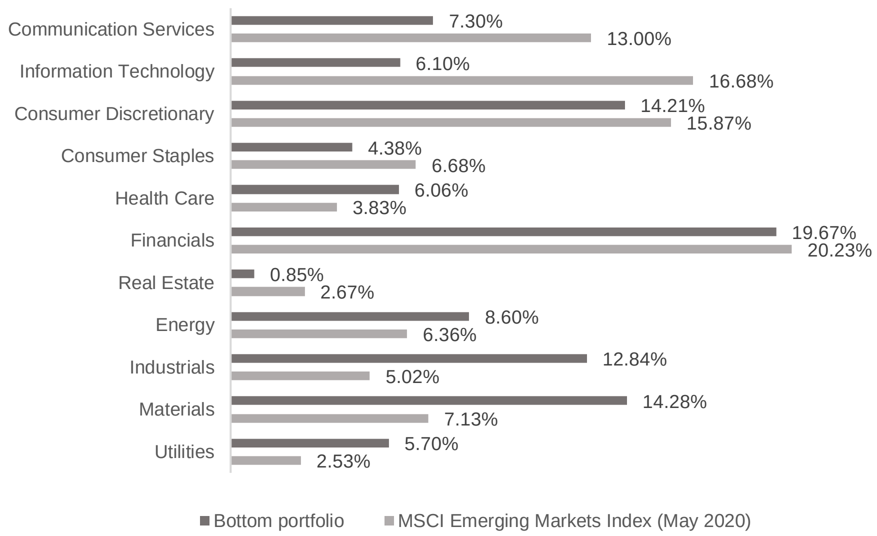
6-month holding period



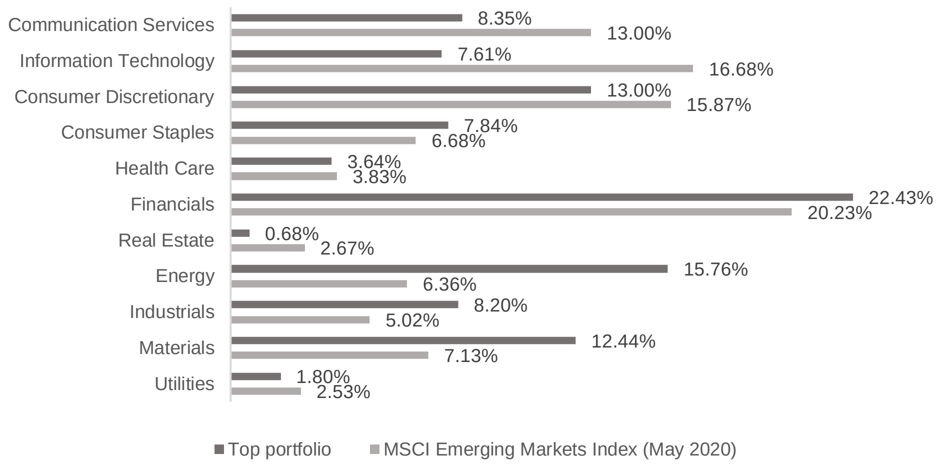


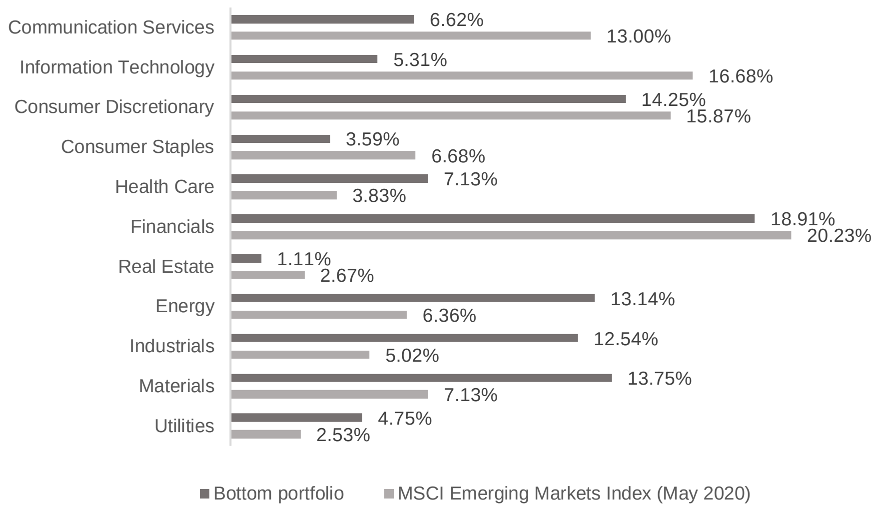
12-month holding period





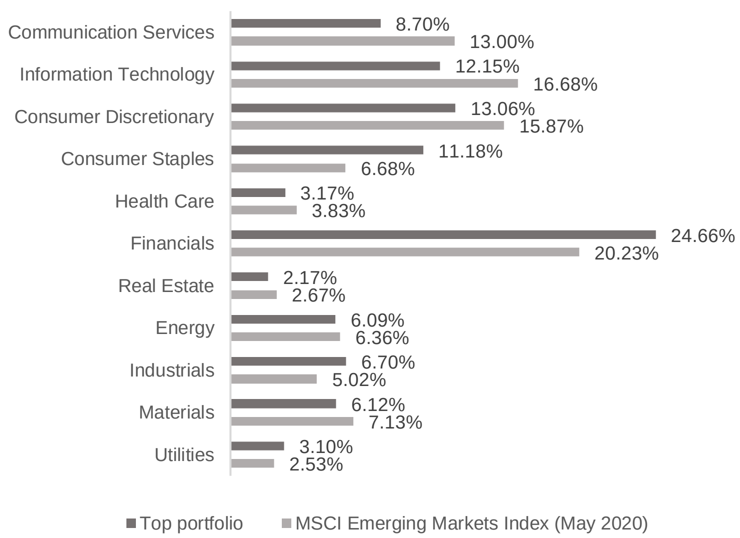
18-month holding period

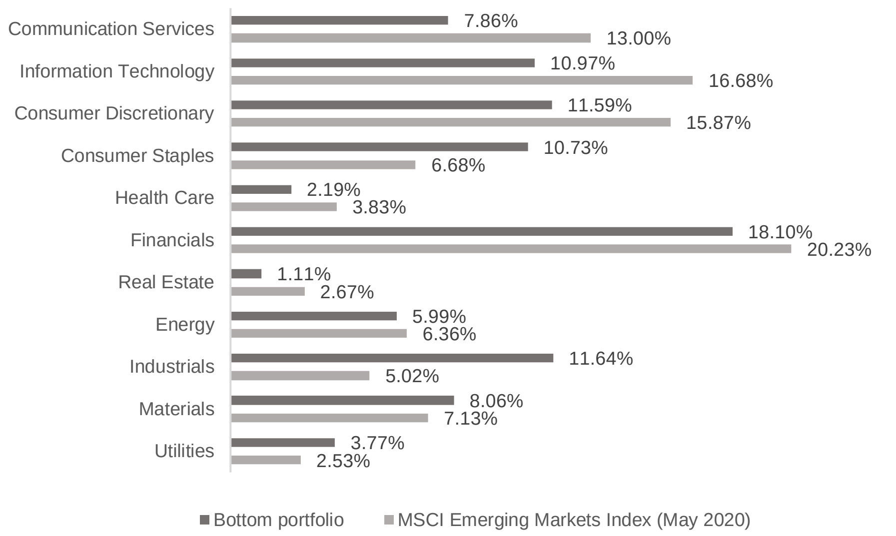




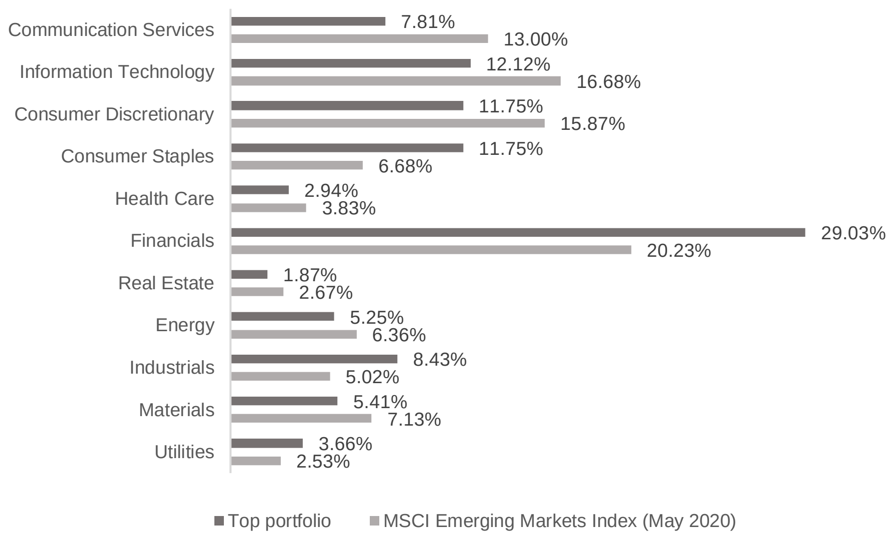
<u>Appendix A9: Emerging markets portfolios – Performance group “high” – sector distribution</u>

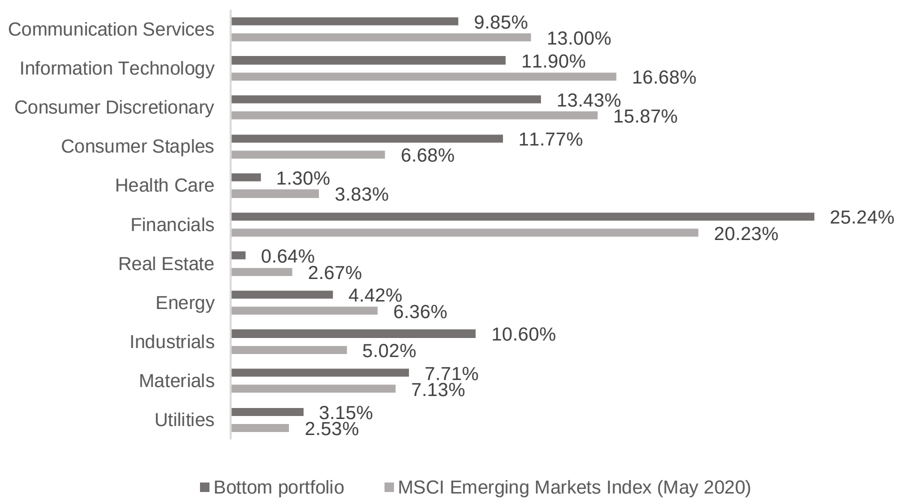
6-month holding period





12-month holding period





18-month holding period