# The Implementation of the ESG Momentum in Factor Investing

*Theoretical and Empirical Approach*

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## Preface and Acknowledgement

We want to express our graditude to those who have contributed to the foundation of this academic research. When we started our thesis in January, we did not expect the outbreak of a global pandemic causing us to write under these extraordinary circumstances. Due to this particular situation, we want to mention a few people who have been valuable to us during this period.

First of all, we want to direct our sincerest thank you to *Mads Stenbo Nielsen* for excellent supervision and contribution to discussions and critical reflections. Moreover, we want to thank our fellow students and the Cand.Oecon class of 2020 for the past two years at Copenhagen Business School, for always being willing to collaborate and lifting our moods. We also want to especially thank *Niklas Ott* and *Jonas Waaben* for their assistance, moral support and for proof reading our final thesis. Lastly, we would like to thank our families for supporting us through our entire study time which we will with the submission of this thesis finally leave behind us.

Enjoy the read!

Johanne & Catharina

## Abstract

As the global assets under management considering sustainable investment criteria steadily increases, new ESG investment strategies emerge aiming for the generation of alpha and outperforming the benchmark. One of these strategies is the ESG Momentum strategy, building on the assumption of a positive relationship between the improvement of a firm's ESG profile and its financial performance. Based on ESG data from MSCI, we are empirically testing the performance of a long-short portfolio in the highest and lowest ESG Momentum firms respectively for the U.S. and Europe. We further develop a factor for the integration into the Carhart 4-factor model to account for a potential systematic outperformance. While we are estimating a cumulative performance of this long-short strategy of 23% above the risk-free rate over a time horizon of 8 years, the constructed factor portfolio yields only a small and insignificant outperformance. By integrating this ESG Momentum factor as an additional explanatory variable, we find a performance-enhancing effect of the factor on portfolio performance in Europe, while only insignificant and negative loadings in U.S. portfolios. We thereby develop a first approach for the integration of the ESG Momentum into factor investing and build a solid foundation for future research due to partly insignificant results and data limitations.

# Contents

# 1 Introduction

As the global awareness of sustainability increases, the consideration of Environmental, Social and Governance (ESG) matters for companies and investors are no longer optional but essential. For companies, the incentives for ESG efforts clearly shifted from ethical to financial motivations. By that ESG became a responsibility of firm managers towards the society, their shareholders and employees in order to ensure the firm's financial health, employee satisfaction as well as its reputational capital (Glossner, 2018).

For investors ESG metrics are accordingly a strong predictor of earnings and operational risks thereby functioning as a performance differentiator (Bank of America, 2019a). A better ESG profile is not only associated with less negative earnings surprises due to recurring ESG incidents (Glossner, 2018), but also with lower systematic as well as idiosyncratic risk measures (Dunn *et al.*, 2018). In particular, we find by means of our data, that high ESG-ranked firms systematically exhibit lower betas and stock price volatility compared to poorly ranked firms. Similar findings are provided by Verheyden *et al.* (2016) which estimate larger drawdowns and tail risks for low ESG firms indicating that ESG constitutes a risk factor which traditional models do not capture yet. Considering ESG information in the investment and portfolio construction process thereby helps investors increase risk-adjusted returns making the investors' incentives of integrating ESG into equity models clearly performance-based (Dunn *et al.* (2018), Verheyden *et al.* (2016)).

This increasing investor awareness of the informative and predictive power of ESG data is reflected by the strong increase in both the number of investment funds considering ESG information in their investment process as well as the assets under management. While the assets under management at the initiation of the UN Principles of Responsible Investing in 2006 only amounted to USD 6 trillion, they have increased to over USD 85 trillion by 2019 (PRI, 2019). Similarly, sustainability focused funds and ETFs covered around USD 20.6 billion in assets in 2019 representing a nearly 4 times increase from 2018. Overall, ESG mandates which so far (2018) represent 26% of actively managed funds is expected to rise to 50% by 2025 (Cowen, 2020). The strategies most used by investors are hereby screening approaches or tilt strategies which are boosting risk-adjusted returns and are often an effective signal of alpha (Bank of America, 2019b).

While most of these investment strategies are build upon the relationship between the ESG score of a firm and its financial performance, only little empirical research has been made with regard to the financial impact of the ESG Momentum. The ESG Momentum describes the financial value of changes in a company's ESG profile thereby representing a dynamic measure which is more predictive of a firm's financial performance than the static ESG score. In particular, the hypothesis of an investment strategy based on ESG Momentum is, that firms with the most improvement in their ESG profile outperform their counterpart with the lowest ESG Momentum. Based on the research by Giese & Nagy (2018), we are developing a modified version of their ESG Momentum investment strategy which we test empirically by means of our MSCI data for the two most mature and ESG-aware markets, the U.S. and Europe. Furthermore, we are delivering a first approach to the integration of the ESG Momentum factor into a factor investing framework based on the suggested systematic outperformance of high relative to low ESG Momentum firms which is not explained by the traditional Carhart (1997) 4-factor model. Our research question therefore investigates whether this systematic outperformance based on the ESG Momentum exists and how much the ESG Momentum factor is able to contribute to explaining differences in portfolio returns in a Fama French factor model.

With respect to the outlined research question, our results provide supporting evidence, albeit economically small and partially insignificant. While we do find a higher monthly excess return for a portfolio consisting of high ESG Momentum firms in comparison to one with low ESG Momentum firms, the difference between the two is not statistically significant. Furthermore, for both of the two portfolios, we find a significant positive abnormal return not explained by other factors in the model indicating a positive impact associated with both high and low ESG Momentum. Integrating the ESG Momentum factor as an additional explanatory variable in our Carhart framework, yields positive and significant results for the European market, while only insignificant and mostly negative coefficients for the U.S. counterpart. Even though the ESG Momentum factor does not seem to be the main driver of performance differences across portfolios, it seems to signal systematic regional differences in awareness and performance effects of ESG, thereby entailing relevant implications for the use of ESG data in different geographies (Amel Zadeh & Serafeim (2018); Bank of America (2019a)). Further breaking down the analysis to industries and the three ESG pillars separately, provides valuable insight into the dimensions of ESG as well as the importance of the industry's material pillar for its performance.

While our thesis is able to provide important results with respect to the performance implications of the ESG Momentum factor, it still lacks some significance and distinctness in return patterns associated with the ESG Momentum. These gaps could be traced back to details of our analytical approach as well as the investigated time horizon but also to qualitative factors of the investment strategy. Considering the contribution along with the shortcomings of our thesis, it serves as a successful first approach to the integration of the ESG Momentum factor into a factor investing framework as well as a valuable foundation for further research.

The remainder of this paper is structured as followed: Section 2 describes the fundamentals of ESG investing, covering an explanation of the three pillars, the scoring methodology of MSCI as well as the incentives for including ESG information into the investment processes. This part of the thesis introduces the financially material dimensions of ESG which beyond the ethical considerations have a tangible impact on a firm's financials, risk and performance.
After briefly explaining traditional investment strategies and asset pricing models relevant for this thesis, section 3 further focuses on the risk dimension of ESG and introduces ESG-related investment strategies and their performance. The section thereby functions as a literature review on the integration of ESG data into investment processes and the corresponding performance implications, building the foundation of our research question and contribution outlined in the last part of section 3. Section 4 subsequently covers the data set used for our analysis including our sample selection approach and relevant descriptive statistics. Section 5 describes the methodological approach used to test our hypotheses.
Following our methodology, section 6 then presents our main results with respect to our conducted analysis on the ESG Momentum factor as well as our regressions. While the first part of the section especially focuses on the factor's basic properties, its distribution and performance patterns, the second part exhibits the results of our full sample and industry-related regressions. The outcome of these results will be discussed in the subsequent section 7 and evaluated critically. We hereby consider our methodological approach and research philosophy as well as limitations due to data availability and quality. Furthermore, we will discuss the shortcomings and opportunities of our thesis providing an outlook on future potential research. Section 8 eventually summarises our findings within the paper.

## 2 Theoretical Background of ESG Investing

The growing interest in environmental, social and governance (ESG) issues has in recent years found increasing importance in the investing space. This is reflected not only in the increasing assets under management and the number of signatories to the UN Principles of Responsible Investing (PRI) (Goldman Sachs, 2018), but also in the rising number of ESG rating agencies. These are meeting investors' demand to screen companies on their ESG performance and develop ESG scores accordingly. However, markets are still far from establishing a standard in terms of how to define and evaluate ESG exposures and develop a common methodology behind company ratings. Correspondingly, reported ESG is still sparse since the coverage of global firms is poor and only little of the ESG reporting is standardised or mandatory for companies (Bender *et al.*, 2018). Thus, the approaches on how to assess a company's sustainability based on the environmental, social, and governance criteria varies substantially across rating providers, making the results difficult to compare and creates confusion for investors (Berg *et al.*, 2019).

The increasing focus on responsible investing observed in the market is hereby driven by several factors observed in various previous research papers which are summarised further down in this section. These driving forces stem on the one hand from investors' growing awareness of value-destroying risks associated with ESG issues and their importance in determining risks and returns of the asset itself. On the other hand there is an increasing demand by beneficiaries of asset managers towards a more transparent and active investment approach considering environmental, social and responsible dimensions in their investments. In the course of this development, asset managers and investors do not only compete in their performance and returns but also in a broader sense concerning investment products, purpose, and responsibility (PRI, 2019). Before going further into detail about the impact of ESG information on investments and investors, we will start by defining environmental, social and governance factors. As there are still no market standards for how to measure and quantify material ESG information, we will use the definitions provided by MSCI which is the ESG data source used for this thesis. We will subsequently explain the rating methodology used by MSCI to assess companies ESG performance. Afterwards, we will summarise the relevant literature on the impact of ESG information on a company's financial performance as well as the current limitations to the use of ESG data in investment processes.

## 2.1 The ESG Pillars

Companies are exposed to a broad range of ESG issues through their industries and respective business models. ESG criteria can correspondingly be seen as a proxy for a company's financial health and long-term performance by many investors (MSCI ESG Research, 2019). As ESG scores are an aggregation of three individual pillars, it is important to understand how environmental, social and governance factors are defined and how they individually impact a company's performance. Good ESG performance is thus reflected by environmental consciousness, social awareness as well as good corporate governance practices. Table 1 summarises the 37 key ESG issues defined by MSCI and describes both risks and opportunities of each of the ESG dimensions (MSCI ESG Research, 2019). It is crucial, that what is a risk for one company within might represent an opportunity for another company. As an example, a proposed new regulation on reduced carbon emissions could impose a negative risk for the aviation sector, but might open up new opportunities for businesses operating in alternative travel industries. Summarising the issues in Table 1, we see that environmental consciousness is measured by things such as low carbon footprint in the production cycle, reduced water usage as well as innovative opportunities that might emerge from new regulations or changing market demand. The social pillar areas of importance are good treatment of employees as well as various measures increasing the well-being of the community. Furthermore, promotion of health and safety at the workplace and along the supply chain represent important aspects of the social pillar. Lastly, good corporate governance is measured by the protection of shareholders' rights, eradiction of corruption and unfair practices as well as transparency.

Table 1 clearly shows that the three pillars of ESG scores cover many different aspects of a company and therefore enable a broad assessment of its score. This is important to keep in mind when considering these aspects in an investment context. Threats resulting from climate change or the scandals following a discriminatory workplace are rarely disclosed, and it can be difficult to measure these risks and quantify their impact on performance (Berg *et al.*, 2019).

*Table 1: ESG Definition MSCI*

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

The assessment of these key issues on a company level eventually comes down to analysing their potential materiality. By definition, a negative externality facing a company or an industry is considered material when it probably will incur costs of substantial magnitude for either the firms or the industry as a whole. Following this, MSCI measures each industry's material issues by looking at the average values of externalised impacts of metric such as carbon or water intensity and injury rates (MSCI ESG Research, 2019). Looking at the differences in geographical markets, material information on ESG metrics in the U.S. are self-reported and are not based on formal standards Bender *et al.* (2018). In Europe, however, more formal requirements are evolving. With the Accounting Directive on disclosure of non-financial and diversity information in 2014, the European Commission approved a mandate for global establishment. This directive has been transferred into national laws by member states, which push the disclosure of ESG information forward Bender *et al.* (2018). Furthermore, the European Commission published an action plan on Sustainable Finance in March 2018 which is set to embed consideration of ESG issues into legislative standards across the financial sector. The EU's regulatory reforms have the intention to establish a common taxonomy across the market to identify environmentally sustainable activities. These activities in turn contribute to fighting inequality, foster social integration, social cohesion as well as labour relations. Furthermore, they promote sound management structures, employee relations and tax compliance. All of these measures cover the three ESG pillars and eventually will make it easier for rating companies to analyse companies and industries on ESG criteria Baker McKenzie (2019). In the following section we will go further into detail about MSCI's assessment of companies ESG score under consideration of the 37 key issues described in Table 1. Furthermore, we will provide a short descriptive analysis of the ESG data from MSCI, to better understand its potential benefits and limitations.

## 2.2 MSCI Rating Overview

In this section, we will go into depth on the ESG data we use for our analysis by building upon the ESG definitions outlined above and explaining the rating methodology used by MSCI. Following that, we will present some descriptive statistics on the data to get a deeper understanding of its basic properties and its differences across regions and industries. As the integration of ESG information in investment strategies represents a relatively new field of research, there are still many limitations to the use of ESG data which we will explain further down in section 2.5.

*Rating Methodology*

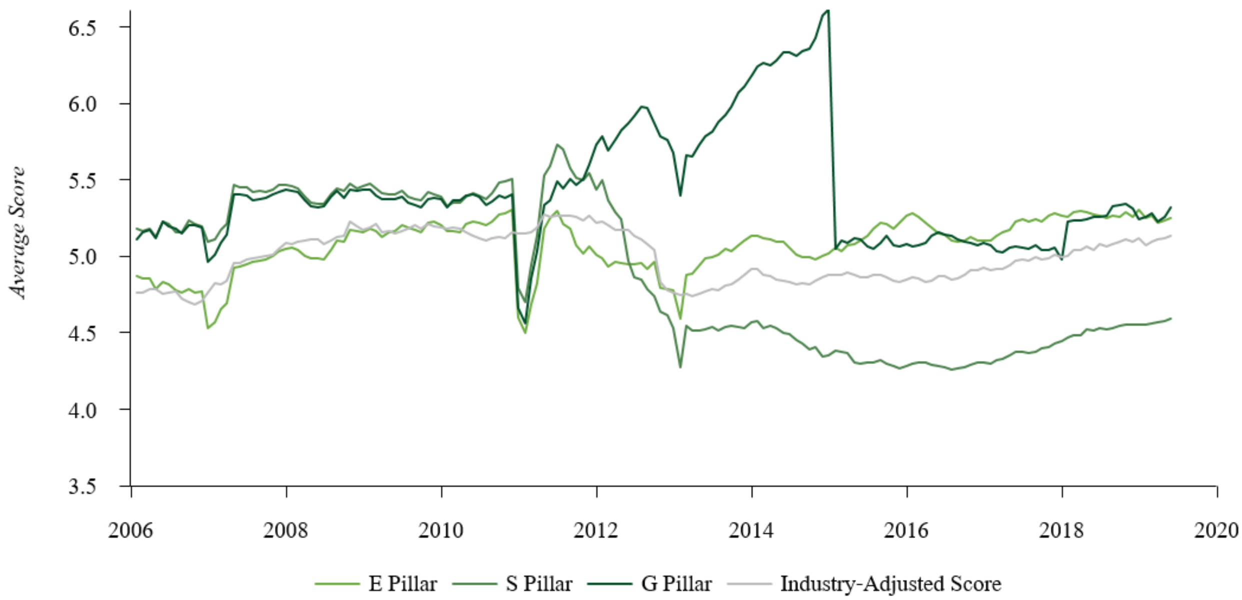
The MSCI ESG ratings are based on individual assessments of the material key issues described in the previous section. The relative importance of the relevant risk factors are applied to each industry by assigning weights to them accordingly. Each company is then given a score on each of the three pillars ranging from 0 to 10 based on how much exposure it has to the relevant key issues and how well they are managed. The individual score on each pillar is subsequently aggregated to the final ESG score as a weighted average. The rating model thus attempts to capture the most significant risks and opportunities a company and its industry face, how exposed they are to these and how well they succeed at limiting the possibility of them materialising. Consequently, a company with high ESG risk exposure might still have a good ESG score if it succeeds at adequately mitigating these risks. The aggregated ESG score is then adjusted by industry to describe each company's ESG performance relative to its industry peers. This is done by normalising the score on a global industry basis, so that the highest rated companies within an industry in general will receive a rating of 10 and the worst a rating of 0 (MSCI ESG Research, 2019). This facilitates the inclusion of ESG information in the investment process, as it enables the comparison of company scores across industries and avoids a bias of investments towards better rated industries due to unadjusted scores (Credit Suisse, 2015).

To be able to present a holistic assessment of companies' ESG risk including industry, geographical and business elements, the data quality needs to be high. For this, MSCI uses a range of sources and documents including company reports, government data, news as well as input from relevant organisations and professionals (Dunn *et al.*, 2018). Referring to the above presented information on the regulation of material ESG issue disclosure, the quality of ESG information has improved over the recent years. Following this process, MSCI has also updated its methodology. In 2013 they expanded the assessed key issues from the same seven for all companies, to three to five main issues selected from the 37 presented in Table 1 (Credit Suisse, 2015). This likely represent an upgrade in terms of data quality, that might be observed in the data. Thus, before we are introducing the impact and materiality of the ESG scores, we will look at some basic properties of the data in the paragraph below.

*ESG Characteristics*

Figure 1 plots the average monthly scores of the individual pillars as well as the aggregated ESG score between 2006, when MSCI first started rating companies, and May 2019. As depicted in Figure 1, we can see that the pillars are mostly stable over time but exhibit time frames of high volatility. Especially in the period between 2011 and 2015, there seem to be a few structural breaks with a large impact on average scores but also on pillar correlations. While the three pillars show a high degree of correlation up until 2012, in the range of 83% -94%, the correlations afterwards are even turning negative at times. In particular, the governance pillar exhibits an increasing pattern up until February 2015, before it decreasing rapidly. This development suggests an investigation of the underlying raw data concerning firms entering the data set but also provides evidence for the above raised question on data quality. Looking at the data set from MSCI more closely reveals a large number of firms entering the data set at once thereby possibly explaining the described fluctuations. In the beginning of 2012, over 2000 new firms with an overall lower rating entered the data set consequently pulling down the average score significantly. Besides the governance pillar, the environment and social score are both more consistent in their development after 2013, when the new methodology was introduced.

*Figure 1: Average Score of Individual Pillars and Industry-Adjusted Score*




*The figure above depicts the time-series average of scores on the E, S, and G pillar individually as well as the industry-adjusted score. The average scores are calculated of a monthly basis for all firms in our sample. We are hereby covering the global data set for the time frame between January 2006 and May 2019.*

In Table 2 we look further into the characteristics of the individual pillars and present the basic descriptive statistics of their individual as well as the industry adjusted ESG scores. As the pillars are not normalised across industries, we also include the weighted average scores, to ease comparison between the pillars and the final score. The purpose of this table is thus to get a first understanding of the interplay of pillars and their contribution to the overall ESG score. As we can see the mean is naturally quite equal across the pillars but slightly tilted towards the environmental and governance pillar. The overall industry score accordingly seems to be driven to a larger extent by the governance followed by the environmental pillar. In terms of the standard deviation, there does not seem to be any significant differences between the pillars. Overall, the ESG scores have a positive skew, meaning that the majority of firms are placed above the mean on the probability distribution.

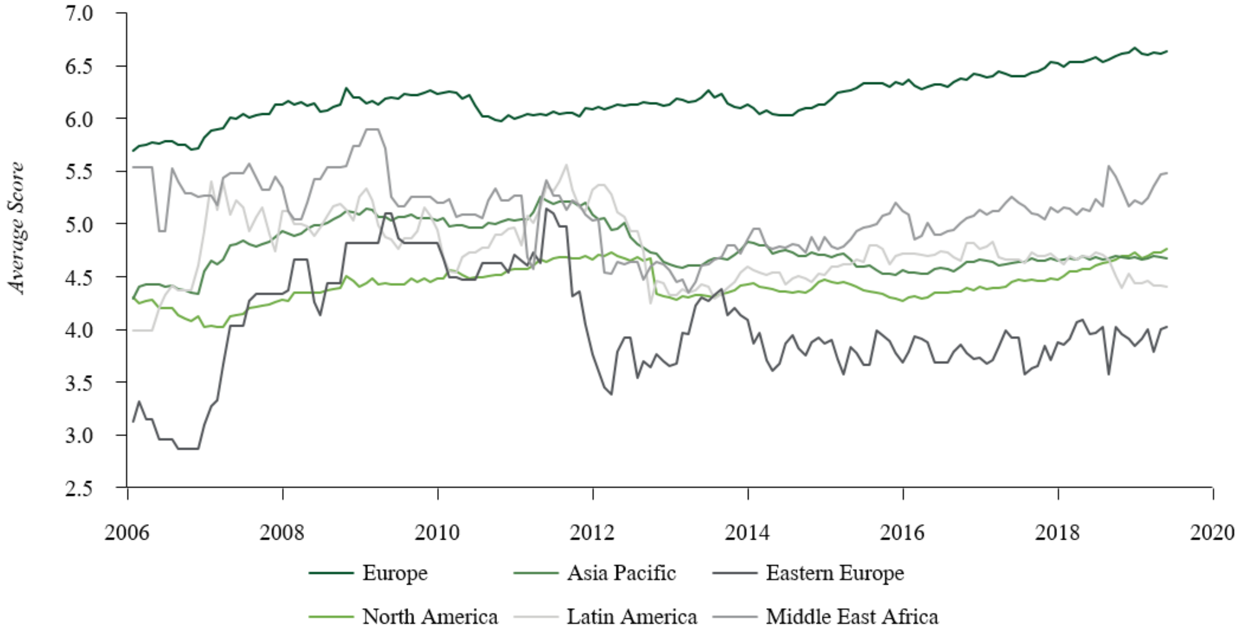
*Table 2: Descriptive Statistics MSCI ESG Data*

| | *Mean* | *Median* | *Skew* | *Std. Dev* |
|---|---|---|---|---|
| Industry-Adj. Score | 4.98 | 4.90 | 0.20 | 2.31 |
| Weighted avg. ESG Score | 4.81 | 4.76 | -0.31 | 1.37 |
| Environmental Pillar | 5.09 | 5.05 | 0.02 | 2.13 |
| Social Pillar | 4.77 | 4.80 | -0.13 | 1.82 |
| Governance Pillar | 5.41 | 4.40 | -0.07 | 2.01 |

*Geographical and Industry Comparison*

In order to better understand how ESG information can be used, we investigate the regional and sectoral differences within the data. As shown in Figure 2 we can see that the average score is quite stable in the European market and the U.S., while appearing to be more volatile across other regions such as Eastern Europe. Compared to other regions, the European average ESG score is also substantially higher indicating that European firms are less exposed to or better at mitigating ESG risks. Furthermore, as outlined above, the regulation on the European market regarding the disclosure of ESG risks has developed more than in other locations providing another explanation for this. In line with these observations, average CO2 emissions in relation to sales in Europe have also historically been significantly lower than other regions which can be seen in Appendix I. This can further be seen as a proxy of the firms' exposure to environmental risks, which again indicates that a higher awareness of European firms for ESG matters.

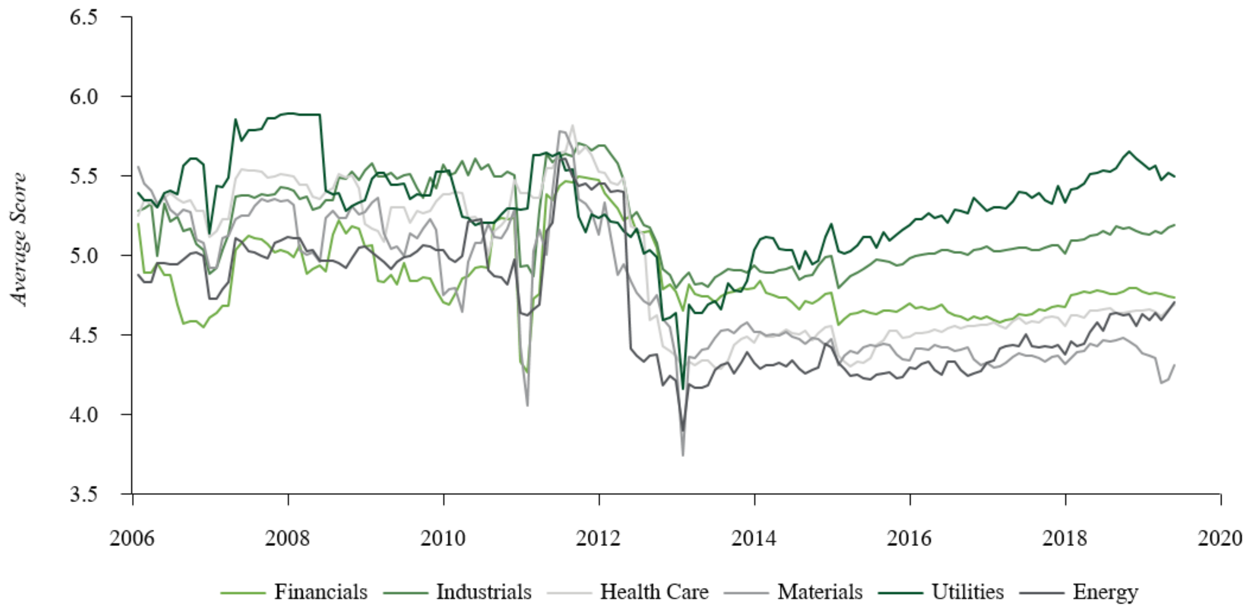
*Figure 2: Industry-Adjusted Score by Geography*




*The figure above depicts the time-series of average industry-adjusted scores of all geographical areas covered in our data set. The industry-adjusted score is hereby calculated on a monthly basis based on all firms active in that region at this point in time. The time frame shown is January 2006 to May 2019.*

Figure 3 provides an overview of the average ESG score by a few selected industries therefore completing the picture on geographical and sectoral differences of firms. The rated companies are categorised based on the Global Industry Classification Standard (GICS), which is an industry taxonomy developed by MSCI and Standard & Poor's (S&P) for use by the global financial community (MSCI ESG Research, 2019). Furthermore, the figure depicts the weighted-average instead of the industry-adjusted scores, as this enables an unbiased comparability between industries. At first glance, it is evident that the average scores across industries appear quite volatile at the beginning of the time frame. This observed volatility, however, is stabilising after 2013 with the establishment of the new methodology regarding the assessment of key material ESG issues within the industries. In the end, most sectors lie within the same range of average ratings, with Industrials and Utilities performing somewhat above average.

*Figure 3: Weighted-Average Score by Selected Industries*




*The figure above depicts the time-series of weighted-average score of selected industries in our data sample. The average score is calculated on a monthly basis using our global sample and including all the geographies. The time frame covered is hereby January 2006 to May 2019.*

We can further see that some of the volatile patterns exhibited in Figure 1, especially with the drop around 2011, can generally be traced back to score developments in emerging markets (Middle East, Africa and Eastern Europe) and industries such as Materials, Utilities and Energy. Based on both Figure 2 and 3, we can also see the significant impact of the changed scoring methodology of MSCI as it seems to stabilise scoring across regions and industries from 2013 on. This again provides some indication and understanding of how quickly the quality of ESG data is developing and how it can lead to more consistent ratings. On the one hand, this is beneficial for the inclusion of MSCI' ESG information in investment decisions as it adds some credibility to the data source. On the other hand, it indicates that there are still limitations to the use and integration of ESG data in the investment process since it is difficult to receive an objective assessment of a company's ESG performance. Before we will go more into detail on the these data limitations in section 2.5, we will first outline which incentives investors have to incorporate ESG information into their decision making and through which channels these ESG matters might be material for the company as well as the investment.

## 2.3 Motivation of Incorporating ESG Information

The general motivation of investors using ESG information in their investment process is summarised in the paper by Amel Zadeh & Serafeim (2018), which presents the results of a global survey including a wide range of asset managers worldwide. The survey investigates not only if and for what reasons investors use ESG information, but also how they integrate it into their decision process. The main share of companies in the survey is located in Europe (40%) and the U.S. (34%) while the remaining 15% and 11% are referring to Asia and the rest of the world respectively. Due to the over-representation of European and North American firms, the authors especially focus on comparing the results of the survey for these two regions. With respect to the use of ESG information in the investment process, the vast majority of investors globally (82%) integrate it in their investment decisions independent of their size, but slightly varying with their share of ESG asset allocations. Comparing the results regionally, the higher statistical penetration with 84% in Europe and only 75% in the U.S. underlines the higher awareness of the importance of ESG within Europe (Amel Zadeh & Serafeim, 2018).

In general this integration of ESG components into investment strategies leads back to two categories of investors' incentives: financial/performance-based incentives and norm-based incentives, also known as ethical investments. The first is the most prominent one, with 63% among investors globally stating to be under the perception that ESG data contains financially material information essential for analysing future performance of investments. This result especially applies to investors with a high asset allocation towards ESG stocks as they in principle might believe in a higher performance of these assets (Amel Zadeh & Serafeim, 2018).

Besides this main incentive of performance enhancement, other strategic-financial motives can be found among investors which are specifically important to large scale investors in contrast to smaller ones. Due to the increased awareness of ESG issues within society, we also observe an increased general demand for more sustainable and responsible investing from clients and beneficiaries. This development in turn forces asset managers not only to expand their usual investment considerations but also to increase their transparency (Amel Zadeh & Serafeim, 2018). The latter is especially crucial for institutional investors such as pension funds which have a high media presence. Sustainable investing can have reputation-enhancing effects for these types of investors while the opposite might harm their social standing. Despite the increase of transparency within the investment process, investors are also motivated to develop innovative new investment products considering ESG data. This incentive is with 47% versus 30% significantly more prominent among US investors compared to European ones (Amel Zadeh & Serafeim, 2018).

Looking at smaller asset managers, they are, similar to European ones, more concerned with the ethical perspective of investing and consider the incorporation of ESG data into their investment process as an ethical responsibility. Furthermore, in particular European investors believe that integrating ESG information into investment decisions might be an effective measure to change s firm's behavior in the long run (Amel Zadeh & Serafeim, 2018).

Overall, the evidence from the survey suggests the relative importance of financial and strategic motives compared to ethical incentives which differs significantly with the geographic location of the investor and its size. We do accordingly observe more consideration of ethical factors within Europe and among smaller investors which also believe that active engagement with these companies might lead to an improvement in addressing ESG issues. In contrast, U.S. investors are more concerned with the financial performance of their assets and even think that using ESG information would violate their fiduciary duty (Amel Zadeh & Serafeim, 2018).

## 2.4 Financial Materiality of ESG Information

As suggested by the previous section, financial motives play a crucial role when incorporating ESG data into the investment process. Accordingly, it makes sense to explain and define the financial impact of material ESG risks outlined by MSCI and summarise related research on this topic. In this section, we will develop the matter of material risks further in order to better understand the relationship between ESG issues and financial performance both, on an aggregate score level and for the individual pillars. This will yield a better understanding of not only investors motivation of including ESG information in their investment strategies, but also of how it should be used. The literature on the impact of ESG on financial performance regarding both, a company's accounting metrics and the returns to shareholders, has so far been inconclusive as described by the overview of previous empirical results below.

In general, most investors (97%) that responded to the survey by Amel Zadeh & Serafeim (2018) consider ESG information as financial material as it has a high impact on the company's reputation and brand, and therefore its value. In close relation to this, 93% of respondents suggest that ESG data contains valuable information about potential litigation and regulatory risks (Amel Zadeh & Serafeim, 2018). These are the two predominant reasons for why investors consider ESG data, which are both addressing the risk dimension of ESG. The risk aspect of ESG will be further discussed in a later section in which we explain why it can have a significant financial impact that could potentially translate into performance losses for the investor. In addition to these two, the survey reveals further indications of how the incorporation of ESG data might materialise. In particular, respondents believe that ESG might serve as a proxy for management quality, signal a long-term approach to value creation or even reveal a competitive strength. As stressed before, all of these factors are associated with a performance-enhancing motive of investors rather than their ethical or social mandates (Amel Zadeh & Serafeim, 2018). The question to be answered though, is whether these motives can be translated into actual financial benefits.

Khan *et al.* (2016) further identified that industry-specific classifications of material ESG information is predictive of firms' future financial performance. Seen from the opposite perspective, ESG factors can also be investigated from the point of view that the lack of ESG efforts and ESG weaknesses can have an assumed negative impact on performance. Furthermore, Khan *et al.* (2016) found that companies that perform well on material ESG issues tend to outperform those with lower scores, while no such relationship can be found on immaterial ESG issues.de Franco (2018) found that the failure of a company to address and mitigate associated risk has a negative effect on European and U.S. stocks, where the market reacts negatively to ESG downgrades. The result was opposite for Asia, where portfolios consisting of ESG controversial stocks outperformed its benchmark. Additionaly, Eccles *et al.* (2014) saw that what they classify as 'High Sustainability companies' outperform their counterparts over the long-term both regarding stock market performance and in relation to accounting metrics.

It has also been suggested that the market does not fully value the benefits of ESG immediately. Deng *et al.* (2013) found that high CSR acquirers realise higher merger announcement returns and larger increases in post-merger long-term operating performance, with long-term positive stock returns.

Despite these results, it is not evident from the existing literature that ESG information impacts financial performance positively. Nollet *et al.* (2016) found that the effect of ESG information on companies' performance is U shaped, which implies that the financial benefits of ESG engagement does not immediately pay off. Rather, it has a negative impact on profitability up until a certain threshold after which the efforts start to pay off. They also investigated the pillars individually, which we will revise and develop further in the subsequent sections. While other literature finds no significant correlation between ESG and financial performance (Garcia *et al.*, 2017), Baron *et al.* (2011) disclose a negative correlation between corporate financial performance and social pressure on the U.S. stock market.

To go further into detail about which ESG issues are financially material and most crucial for the investment process, we are again breaking down ESG into the three pillars. Separating the environmental, social and governance pillars from the aggregated ESG score is in this context useful to understand the entire contribution from ESG to a company's financial performance and risk profile. While several studies have looked at the impact of these individual dimensions, it has been found that the influence of each pillar is dissimilar which further justifies adjustment and customisation of ESG efforts (Jitmaneeroj, 2016). Therefore, besides describing to which extent each ESG issue is financially material, the literature review below also provides insight into the discrepancies between industries and countries regarding the financial impact of each of the three pillars.

*Environmental Pillar*

With climate change as one of the most complex and significant challenges of our time, the environmental pillar does not only refer to the potential impact on society, but also on firms' production decisions that come along with several substantial macroeconomic and financial implications (Barnett, 2019). In general, it has been found that responsible corporate environmental behaviour in the form of reduction of pollution levels or waste prevention measures creates a comparative advantage towards less sustainable competitors and leads to better firm performance. This better firm performance can not only be found in operational measures such as the return on assets, but also in the positive relationship between stakeholder welfare and corporate financial performance. Moreover, mitigating toxic chemicals and accompanying environmental lawsuits will reduce the risk of high litigation costs and thereby further enhance firm value (RBC Wealth Management, 2015).

The above-described issues, which also was touched upon in section 2.1, has received increasing attention with a particular focus on pollution levels. The critical point for most firms dependent on CO2 emissions is the uncertainty regarding the timing and extent of policy changes and regulations which carry risks for the firms' operations. The possible effect of such policy changes in the energy sector has been investigated by Barnett (2019), who models the policy adjustment as a stochastic jump in the energy input share of oil for final output production. This policy adjustment is meant to reflect proposed restrictions and mandates on the use of oil and fossil fuels and should incentivise the switch to green technology. The risk and uncertainty associated with these policies induce the energy giants to avoid their reserves being stranded. Since we in recent years have increasingly observed a movement within the energy sector from fossil fuels to renewables, this transition paired with a decreasing demand in the market will result in substantial oil price reductions and therefore a decline in revenues (Barnett, 2019). Needless to say, this development can also be seen in relation to gas and coal reserves which are as well highly dependent on hydrocarbon assets and are due to the restrictions likely to be stranded. For large energy groups such as Exxon Mobil, BP and Saudi Aramco this stranded fossil fuels naturally translate into a large decrease in firm value and share price valuations. A recent study from the Dutch National Bank on the Dutch financial market also revealed which sectors are particularly vulnerable towards new carbon regulations, by performing a stress test based on four different plausible scenarios. The result focused on the utility, as well as the energy and transportation sector, which in particular are sensitive towards new regulations (DNB Research, 2018).

The above-described issues and risks are especially present within the markets for energy and infrastructure and therefore crucial for geographies whose industrial focus is placed on these sectors. Looking at the Scandinavian market, Dahlberg & Wiklund (2018) confirm this statement and find that the environmental component shows the highest impact on financial performance among the three. With the large oil reserves in Norway and giants within the logistics and infrastructure space such as A.P. Møller Maersk, Scandinavia is particularly exposed to the explained risks. Consequently, also the focus of investors in these areas is placed on predominantly exposed sectors so that their investment performance is highly influenced by their operational performance.

*Social Pillar*

The studies made on the social dimension of ESG relates in large to different aspects of human capital, stakeholder management and workplace practices as described in section 2.1 where we define the individual pillars. Faleye & Trahan (2011) found positive stock price reactions to announcements of the Fortune 500 list including the "100 Best Companies to Work For". Edmans *et al.* (2014) investigate employee satisfaction and stock returns in 14 countries around the world over different time periods and find positive alphas for a portfolio of companies with the highest rate of satisfaction in 11 of the countries. This provides supporting evidence for the positive relation between the social pillar and financial performance, but also that the results are dependent on location. Additionally, Sassen *et al.* (2016) looked at ESG contribution to risk rather than financial performance on a broad sample of European companies, and found that social performance has a significant decreasing effect on companies' risk. Furthermore, Krüger (2015) investigated short-term value effects of environmental and social incidents, and found that disclosure of negative CSR news yields a negative 11-day cumulative abnormal return of 0.88%. For his sample, this negative impact amounts to an average value loss of 60.4 million US dollars per event. Cavaco & Crifo (2014) further investigated the relationship between different ESG dimensions and financial performance and estimated that responsible behaviour toward employees, customers and suppliers appear as complementary inputs of financial performance.

*Governance Pillar*

Many studies have tried to disclose the relationship between stock market performance and corporate governance with conflicting results. The literature on this relationship especially emphasis external governance, level of industry competition and internal dimensions such as the board of directors and executive compensations which are all relating to the material governance issues presented in Table 1. Nollet *et al.* (2016), as well as Velte (2017), found that the corporate governance pillar has the strongest impact of the three ESG categories on financial performance due to the influence it has on shareholders as well as the long tradition on governance reporting. Within the governance pillar, anti-corruption measures are regarded to be especially financially decisive. According to Healy & Serafeim (2015), the disclosure of anti-corruption measures has a double function in predicting both future media coverage of corruption issues as well as sales growth and changes in operating profitability. Other authors, such as Hillman & Dalziel (2003), stress the importance of leadership and the role of the board of directors which evidently have a significant impact on a firm's performance. Similarly, Dunn *et al.* (2018) point out that firms with poor governance might be more likely to experience a scandal or misstate their earnings. While these incidents do not necessarily need to occur in the short-run they have a high probability of increasing long-term risk. In addition, Gompers *et al.* (2003) provides evidence that well-governed firms outperform firms with poor governance by constructing a long-short portfolio of these two firms types assessed based on the adequacy of their shareholder rights. According to Gompers *et al.* (2003) results, this portfolio delivers a risk-adjusted abnormal annual return of 8.5%. However, there is conflicting evidence regarding whether these results are driven by sectoral traits or other firm characteristics. Further adding to this discussion around industry impact, Jitmaneeroj (2016) found the governance pillar to be insignificant for financial performance across all industries.

As is evident from the paragraphs above, there are contradictory results on the contribution of ESG on financial performance. This can be explained partly by differences in countries, industries and sample selection, as well as different methodologies (Iamandi *et al.*, 2019). In line with these findings, Jitmaneeroj (2016) stressed that in addition to the sensitivity to industries, the impact of the pillars also highly depend on geographies, local business conditions, company size and strategies. In conclusion, this means that both systematic and idiosyncratic factors matter and that ESG efforts should be directed towards business units where they are generating the highest value. Thus, these results confirm the need of specialisation and synergies to give the best financial performance. Additionally, all these studies and results show that it is difficult to compare the impact of ESG data across sectors and geographies due to differences in market conditions, reporting practices or the reliability of data sources. These limitations to the use of ESG data will be discussed in the upcoming section which goes further into detail about differences in rating methodologies and the regulatory framework on the disclosure of exposures as well as mitigation of ESG risks across regions.

### 2.5 Limitations to the Use of ESG Data

As mentioned several times in this chapter, a main issue when it comes to integrating ESG data into investment decisions is the lack of standardisation and regulation regarding the disclosure of ESG information. Furthermore, the comparability of rating procedures as well as the assessment of ESG risks from different data providers is due to this lack of standardisation mitigated. This can lead to substantial discrepancies in the approach of using ESG data as well as investment strategies (Bender *et al.*, 2018). Bender *et al.* (2018) broke this issue down further, and recognised some key challenges in the ESG integration process: Defining materiality, normalising materiality of risks across companies, aggregating and weighing of ESG factors and how to estimate ESG risks of unreported companies. All these issues in the end rely on the fact that different rating providers have derived different frameworks for their methodologies, partly due to the absence of clear market standards. The implications of this can be seen in the correlations of ESG scores across rating providers. (Bender *et al.*, 2018) found that ESG scores correlate within a range of 0.47 to 0.76 among the largest rating agencies. In particular, the correlation between MSCI ESG data used in this analysis and Sustainalytics, another market leading provider, is only 53% over their research period. This sheds some additional light upon the issues mentioned above about the objective nature of ESG data available to investors. This lack of market standardisation and regulation on how to assess material ESG risks and opportunities in the market can eventually lead to very different investment strategies (Bender *et al.*, 2018).

This issue has been further confirmed in the survey results by Amel Zadeh & Serafeim (2018) in which they describe the lack of cross-company comparability by the different rating agencies to be the biggest challenge of integrating ESG information. Furthermore, investors face additional difficulties in making use of ESG data since it is not only costly to gather and analyse, but also lacking details making it difficult to quantify. Lastly, some investors consider ESG disclosures too infrequent and even doubt their reliability so that they require external auditing. Even though these responses are assigned with statistically lower importance, they are in line with the lack of reporting standards and underline the rather qualitative approach of ESG disclosures for now (Amel Zadeh & Serafeim, 2018).

It is of course still important to recognise that ESG data has developed a lot over the years, even though the scores differ to a great extent across data providers and the quality in general has been questioned. Rating providers say their systems can only improve if companies are forced to report on sustainability data (Berg *et al.*, 2019). Thus, new regulations such as the new taxonomy from the EU established in the markets, will probably help push the industry towards a new, higher standard.

# 3 Investment Strategies and Asset Pricing Models

Before going into detail about how to incorporate ESG information in the investment process, we first introduce basic investment strategies and asset pricing models relevant to this paper and our ESG integration approach. We thereby focus on the momentum strategy, which in recent years has been the driver of portfolio outperformance, and the Fama French asset pricing model with its extensions which are utilised in nearly every context of asset pricing theory.

## 3.1 Momentum strategy

Momentum trading first introduced by Jegadeesh & Titman (1993) can be understood as an investment strategy aiming at monetising on continuing market trends. Based on the hypothesis that stock prices either tend to over- or underreact to information, Jegadeesh & Titman (1993) investigate strategies of selecting stocks based on their past return to create outperformance. By means of their created decile portfolios based on returns over the past three to 12-months, they showed that the best performing U.S. stocks tend to continue to perform well over the subsequent three to 12 months. Meanwhile, stocks with poor returns over the same period continue to perform poorly. Consequently, a portfolio consisting of a long position in the best performing stocks (*winners*) and a short position in the worst performers (*losers*) earns a positive significant return for any of the tested formation and holding periods. This pattern tends to continue every five year period starting 1965 until 2004 creating consistent outperformance which is even more pronounced when leaving a time gap between formation and holding period to avoid short-term reversals (Jegadeesh & Titman, 2011).

Since the introduction of the momentum strategy in 1993 it has become a well-known and publicised anomaly which continues to generate superior returns in all developed market. As such it might be seen as the strongest evidence against the efficient market hypothesis under which predictable patterns in returns should be exploited by market participants and thereby eliminated quickly (Jegadeesh & Titman, 2011). With the extension of the Fama & French (1993) 3-factor, Carhart (1997) introduced the anomaly of the price momentum as an additional factor making a large contribution to our modern asset pricing theory which is further discussed below.

### 3.2 Asset Pricing Models

*CAPM and the Fama-French 3-Factor Model*

The well known capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) which was long seen as the guideline for the analysis of risk and return, was later questioned due to the significant remaining cross-sectional variation of stock returns that could not be explained by the market beta. In the course of this critique, Fama & French (1992) were the firsts to develop a multifactor model to extend the CAPM with two additional factors. Fama & French (1992) hereby relied on results from Banz (1981), showing that the CAPM beta was misspecified due to the larger average risk-adjusted returns of small firms compared to their larger counterparts. This observed size effect creates a bias in the beta which is estimated as too high for large firms and too low for small firms given the CAPM. On another note, Stattman (1980) and Rosenberg *et al.* (1985) found empirical evidence in the U.S. market for a positive correlation of a firm's stock return to its book-to-market equity ratio (BTM). This value effect which similarly estimates too high betas for growth stock and too low ones for value stock represents the second deficiency of the CAPM according to Fama & French (1992).

In conclusion, Fama & French (1992) found that these two effects can explain cross-sectional variation in returns more efficiently resulting in their inclusion of the two additional factor portfolios as specified in equation 1. These long-short mimicking factor portfolios are created based on the anomaly of the positive excess returns of small compared to large and value compared to growth firms. In the below specified equation the market risk is expressed by *MRKT* and generally approximated by the excess return on a general market index. The size and value factors, *SMB* and *HMB*, represent the excess returns of the long-short portfolios of small firms relative to large firms and high book-to-market firms relative to low book-to-market firms respectively.

$$r_{it} = \alpha_{iT} + \beta_{iT} MRKT_t + \gamma_{iT} SMB_t + \delta_{iT} HML_t \tag{1}$$

The results of Fama & French (1992) show that if used alone, the market beta is not able to explain a large proportion of the cross-sectional variations, which in turn justifies the integration of the two additional factors. These factors, *SMB* and *HML*, and their negative and positive relationship with returns respectively help to improve the explanatory power of the model while being robust to the inclusion of additional controlling factors.

*Carhart's 4-Factor Model*

Building on the foundation of Jegadeesh & Titman (1993) and the one-year momentum effect, Carhart (1997) attempts to explain the persistence in mutual fund performance by adding the price momentum factor to the 3-factor model by Fama & French (1992). The relevant model specification can be seen in equation 2. The factor of the price momentum, *PMOM*, represents the excess return of past year's *winner* stocks in relation to past year's *loser* stocks in a long-short portfolio setup.

$$r_{it} = \alpha_{iT} + \beta_{iT} MRKT_t + \gamma_{iT} SMB_t + \delta_{iT} HML_t + \epsilon_{iT} PMOM_t \tag{2}$$

Looking at the 3-factor model of Fama & French (1992), Carhart (1997) find strong negative model errors for the loser portfolios of the previous year, and positive errors for the winners. By means of his constructed decile portfolios based on their lagged one-year return, he is not only able to provide empirical evidence for the momentum effect, but also significantly improves these pricing errors by including the additional factor. By doing so, he eventually explains most of the spread and patterns in the portfolio.

The main purpose of his portfolio analysis is accordingly the attribution of excess returns to specific factors within the model. Most of the spread in monthly returns between the highest and lowest performing decile is hereby explained by the size and momentum factor with the latter accounting for almost half. While the top decile portfolio seems to hold more small stocks and exhibits a positive correlation, the opposite counts for the bottom decile. This systematic pattern when moving from the highest to lowest decile helps explain the performance differences and additionally emphasizes the economic importance of the price momentum factor. Correspondingly, an investment strategy of going long in last year's top decile and short in the bottom decile mutual fund, yields a yearly return of 8%.

As the 4-factor approach has been widely tested globally, proving the existence of the value and momentum premia and representing a source of outperformance, it has been established as a market standard in asset pricing modelling. It is therefore reasonable to use it as a basis for the empirical structure of our thesis. Based on the investment strategies and their performance implications below we will critically investigate the model and try to find deficiencies with respect to the pricing of ESG information.

## 3.3 The Risk Dimension of ESG

Besides purely ethical and sustainable incentives of incorporating ESG measures into an investment process, there is a broad range of investment strategies focusing on the financial materiality and predictive power of ESG information regarding risk and return. Before describing different investment strategies considered in this paper, we therefore explain how a firm's risk and ESG exposure are related, how we can measure it and through which channels it might impact portfolio returns. Following that, we explain the theoretical foundation for our hypotheses and corresponding methodological approach which will be further outlined in a later section.

### 3.3.1 Risk Assessment of ESG Exposures

Fundamental when developing a strategy of how to include ESG factors in your investment decisions, is to assess the risk of a stock by considering its ESG exposure. This is especially interesting since previous literature largely focused on the impact of ESG issues on returns rather than on risk. As mentioned in section 2.4 on financial materiality of ESG information, there is a wide range of situations in which negative ESG events have a material impact on firm value, even though the timing and the quantitative extent of the issues might be uncertain. The main hypothesis is here that if a firm is failing to manage its ESG exposure it is consequently exposed to this uncertainty and consequently a higher risk level (Dunn *et al.*, 2018).

Dunn *et al.* (2018) are in this context providing an empirical investigation on the potential link between ESG exposures and risk measures leading to portfolio implications of ESG-informed investing which is rather risk- than performance related. Based on MSCI data which assesses how much exposure a company has towards ESG risks and how well it manages it, they empirically analyse the connection between ESG exposure, traditional risk measures and contemporaneous risk forecasts. Looking at the summary statistics comparing various characteristics of firms sorted into quintiles based on ESG score, the first obvious relationship between ESG score and risk can be observed.

Poor firms in the first ESG score quintile hereby reveal higher risk measures in the form of volatility and beta in comparison to firms in the highest ESG quintile. In particular, the average firm in the worst quintile has a total volatility of around 35% and a beta of 1.07 while the average firm in the best scoring quintile exhibits 30% and 1.04 respectively. These findings translate into a consistent pattern when comparing the time series of the two risk variables. Moving from the best to the worst ESG score quintile resulting in a level shift of 15% for volatility and 3% for beta (Dunn *et al.*, 2018).

Even though these patterns are consistent over time they are partially dependent on firm characteristics (e.g. size) which in turn might mitigate the relationship between ESG scores and risk. Smaller stocks hereby tend to reveal higher risk and higher beta but are at the same time associated with a lower ESG score. To account for this bias, Dunn *et al.* (2018) run regressions incorporating control variables for firm characteristics in order to measure the true correlation between ESG scores and statistical risk. This confirms the strong correlation between ESG score and risk not only with statistically significant coefficients, but also with large economic effects. In line with previous results, the total risk, stock-specific volatility as well as the beta increases when moving from the highest ESG scoring percentile to the lowest one. Furthermore, the relationship between ESG scores and statistical risk remains significant and meaningful after controlling for firm characteristics as well as the firm's domicile and sector. The findings still reveal a high negative correlation of risks with ESG score and increase the explanatory power of the regression model (Dunn *et al.*, 2018).

Finally, the authors address the issues mentioned above regarding the timing uncertainty and the difficulty of quantifying ESG risks over a longer time horizon. It is therefore difficult to reliably estimate a rare "ESG event" and its impact with the data available. Instead though, Dunn *et al.* (2018) test whether ESG data contains valuable information for future risks. They hereby use the previously introduced risk measures, total and stock-specific volatility and the beta as dependent variables and regress these measures on ESG scores 1-5 years back as well as the before mentioned control variables on firm characteristics. The results presented in the paper show that ESG data helps predict future risks 3-5 years ahead. Beyond this horizon measures reveal lower statistical significance but still possess the right sign for the coefficient. Since the authors control for the current risk model's output (e.g. volatility or beta) the significant results for the ESG pillars can be interpreted in favour of ESG as an additional risk factor which traditional risk models do not capture yet. While this analysis underlines the high informative value of ESG data and its predictive power of future risks the economic impact of it is still modest. Looking at the difference in risk moving from the highest to the lowest percentile, the discrepancy in ESG score only predicts an increase of around 1%. This could on the one hand be traced back to the noise measured in the ESG data and on the other hand to the short covered time horizon in the paper in which only a few negative ESG events materialise.

Nevertheless, the findings confirm that, even though ESG is not the main driver of risk, it conveys important information on current and future risk which is not accounted for in traditional risk models (Dunn *et al.*, 2018).

Supporting results for the relationship between ESG profiles and risk measures can be found in the research by Verheyden *et al.* (2016) and Giese *et al.* (2019) who besides the traditional risk measures of beta and volatility, further cover drawdowns and tail risks of the underlying stocks. Verheyden *et al.* (2016), therefore, analyse the effects of an ESG screening applied to global indices which removes their 10% and 25% of worst-ranked ESG firms. The result of this screening is therefore a portfolio with a higher average ESG score relative to its unscreened benchmark thereby allowing for a comparison of their risk measures. The risk measures used on a portfolio basis are the volatility of returns, the maximum drawdowns, the 95% conditional value at risk (CVaR) and the 95% conditional drawdown at risk (Verheyden *et al.*, 2016).

While the return volatility is a known risk measure, the others might need further explanation. The maximum drawdown by definition measures the largest percentage loss a hypothetical investor could have incurred if he would have invested at the recent peak and held it to the trough. Alternatively, it can simply be expressed as the maximum difference between the portfolio's cumulative performance at any day and its previous maximum cumulative performance. It is as such a measure of the portfolio's downside risk. The CVaR conversely is a risk assessment that quantifies the amount of tail risk a portfolio possesses by taking the weighted average of the losses in the tail of the distribution beyond the value at risk cutoff point. The 95% CVaR therefore measures the expected monthly return (loss) in the worst 5% of months. Similarly, the related measure of the conditional drawdown at risk measures the average monthly drawdown during the worst 5% of months (Verheyden *et al.*, 2016). The results of the comparison of all of the risk measures across the screened and unscreened portfolios exhibit consistently lower values for the ESG screened portfolios with findings being most significant in Europe and the U.S.

Furthermore, when investigating the downside and tail risks on the individual stock level by applying the *3 $\sigma$ tail* risk measure to each stock's daily returns, the authors find similar risk reducing effects of ESG screening. The *3 $\sigma$ tail* risk describes the set of daily returns which are more than three standard deviations away from the mean and therefore impose increased downside risk. In line with the findings of the 95% CVaR tests the assessment on the individual level also shows slightly lower standard deviations for the daily returns in the tails of the screened universes' distribution. Moreover, the tail of the unscreened portfolio is tilted towards negative returns more than the screened one, reflecting a higher likelihood of experiencing negative daily returns. Correspondingly, the authors conclude that the ESG screening of the portfolio reduces its downside risk therefore confirming the positive impact of ESG scores on risk measures (Verheyden *et al.*, 2016).

Similar results with respect to the idiosyncratic risk comparison between high and low ESG stocks can be found in the study by (Giese *et al.*, 2019). The authors are hereby investigating the differences in the above mentioned risk measures for downside and tail risks across quintiles based on ESG scores. In each of the parameter setups, testing different time periods and drawdown thresholds, companies with a high ESG rating exhibit a significantly lower frequency of harmful ESG incidents compared to poor ESG rating firms. This directly translates into systematically lower idiosyncratic risk especially concerning the stock's tail (Giese *et al.*, 2019).

In sum, in all of the above covered studies a higher ESG profile was associated not only with lower systematic risk in the form of beta but also with lower idiosyncratic risk represented by the stock's price volatility, maximum drawdowns or tail risks. Even though all of them reach the same conclusion regarding the relationship between ESG scores and risks, the channels through which these risk measures might impact valuations and stock performance are still ambiguous and conflicting. The decreased systematic risks in the form of a lower beta, for example, translate into lower cost of equity and accordingly lower cost of capital for a high-ranked ESG firm. In a discounted cashflow framework this lower capital costs would result in a higher valuation and consequently a higher share price of the firm. In contrast, other theories might argue that the higher risk of low ESG score firms should be compensated with a risk premium in the form of higher returns. Similarly, also higher tail and downside risks should require a risk premium. The next section will cover a few of the possible implications of the risk dimension of ESG, building the foundation for the subsequently covered ESG investment strategies.

### 3.3.2 Performance Implications

There is an extensive range of literature covering the question of which performance implications can be drawn from ESG matters and whether stock prices correctly and entirely reflect ESG risk exposures. Some of the papers hereby estimate an underperformance of sustainable firms compared to controversial ones while other papers project a positive relationship between the ESG score and the stock performance of a firm.

A perspective on risks stemming from ESG incidents and their importance in relation to performance and firm value is given by Glossner (2018). As the basis of his analysis he uses the RepRisk score which ranges between 0 and 100 and reflects a company's association with one or more of the 28 negative ESG incidents. A RepRisk score of over 50 hereby classifies a company as controversial which entails certain performance implications investigated below. The aforementioned ESG incidents occur from a firm's business practices and are often a result of unethical or illegal corporate behavior. The impact of these events can either directly flow into firm value due to large penalty fees and litigation costs or indirectly impact firm value by impairing a company's reputational capital (Glossner, 2018). Reputational capital describes an important intangible asset of a company that is composed of a company's economic as well as it's social or ethical dimension. A good corporate reputation resulting from comparative advantages in terms of products, services, jobs or strategies allows a company to charge premium prices, attract high-skilled labour, improve its access to capital markets or attract valuable shareholders. Having a good reputation with respect to social or sustainable aspects further helps to increase stakeholder support, decrease downside risks or even attract opportunities for future growth (Glossner, 2018). This is also closely related to the concept of corporate social responsibility (CSR) which refers to a firm's responsibility to society in form of economic and legal but also ethical and philanthropic factors. It is hereby assumed by the author that weak CSR is one of the components triggering negative ESG incidents thus implying an inferior performance compared to firms with better CSR. Poor CSR is according to Glossner (2018) mostly a result of short-terminism of firm managers or financing restrictions. Reducing costs through e.g. lower environmental standards might then indeed increase short-term profits but also increases the long-term risk of ESG incidents with detrimental effects.

The main analysis of the paper of Glossner (2018) focuses on the impact of exactly these ESG incidents on a firm's stock return which is observed prior to and during the ESG event occurrence. The ESG event is hereby measured by a positive change in the RepRisk index above a certain threshold for severity. By means of a 4-factor Carhart (1997) model and the corresponding 48 industry portfolios by Fama and French (1997) Glossner (2018) estimates the pre-event coefficients which cover a window of 299 to 50 trading days. These estimates are then used to calculate the event's cumulative abnormal return (CAR) during the event window of 21 (to 31) trading days. The results in the paper show that, as expected, all tested ESG incidents with different increases in RepRisk are associated with negative CARs, all significant on the 1% level. In the case of an RepRisk increase of more than 10 points this would translate into a negative CAR of 0.4% (Glossner, 2018). For an average firm in the RepRisk data sample this would amount to a loss in shareholder value of around USD 37.6 million since the average market capitalization within the RepRisk sample is around USD 9.4 billion. In case of an ESG incident increasing the RepRisk by over 30 points the aforementioned loss for shareholders would increase to USD 210.8 million. These results stress the severity of ESG incidents and quantify their strong negative impact on shareholder value (Glossner, 2018).

Following these findings Glossner (2018) goes one step further and investigates whether stock markets are able to correctly integrate the increased risks from ESG incidents into the pricing mechanism. He therefore studies the long-term returns of a portfolio of controversial U.S. stocks that are associated with a many and/or severe ESG incidents and therefore have a two-year peak RepRisk Index of above 50. Since ESG incidents and risks are assumed to be of long-term nature, meaning they do not materialise over a short timeframe, it seems reasonable that the author measures the risk index as well as rebalances the portfolio every two years (Glossner, 2018).
For the analysis to capture the impact of ESG risks on long-term stock returns dissociated with other risk factors, Glossner (2018) estimates the excess portfolio return by means of the Carhart 4-factor model described in section 3.2 which controls for four known risk exposures. The portfolio's $\alpha$ hereby describes the abnormal risk-adjusted return which can not be explained by one of the four risk factors and is according to Glossner (2018) therefore attributable to the company's ESG risks.

The result of the regression reveals a negative annual alpha of around -3.5% on a 1% significance level indicating that the U.S. portfolio of controversial firms largely underperforms it benchmarks. These findings are robust to risk factors, industries and firm characteristics which suggests a causal relationship between the ESG risk exposures and long-term stock returns (Glossner, 2018).

According to Glossner (2018) the negative abnormal returns are traceable back to the inability of the stock markets to fully incorporate ESG information leading to the mispricing of firms associated with large ESG risk exposure. This clearly violates the efficient market hypothesis and explains why controversial firms might be overvalued by the market. Besides the short-sightedness of investors who are ignoring long-term financial risks in relation to ESG, Glossner (2018) stresses the mispricing of a firm's intangible assets and the market's underestimation especially of the above described reputational capital. The negative abnormal returns resulting from this mispricing can be broken down to two channels: First, investors and markets seems unable to simply trade on ESG risks which are difficult to quantify. Instead they react to tangible outcomes from ESG incidents so that they are negatively surprised by new or recurring ESG incidents even though the company revealed a high ESG risk. This channel accounts for -1.08% of the underperformance per year representing around one-third of the impact. Secondly, reputational losses from ESG incidents have significant negative impact on supplier contract, employees' motivation and productivity or customer trust. Since these consequences might not necessarily become public but will most likely result in lower earnings in the future, analysts might overestimate a company's future profits. Based on this markets will be surprised by the negative earnings announcement which in turn leads to negative abnormal returns. This second channel explains around -1.72% per year therefore accounting for around half of the estimated alpha of -3.5% (Glossner, 2018).

In contrast to the view of Glossner (2018) and many other authors, a range of studies predicts different results regarding the performance of low ESG score or controversial firms. By analysing "sin" stocks and their investment environment, Hong & Kacperczyk (2009) are providing evidence for the effect of social norms in a novel setting of the stock market. In particular, they are studying the financial performance and investment implications thereby supporting the opposing view to Glossner (2018) due to their prediction of higher expected returns of sin stocks. The stock market hereby provides a unique and valuable data set concerning the effect of social norms which allows the authors to analyse not only stock pricing but also investor and firm behavior. Based on the data set utilised which covers the period from 1976 to 2006 Hong & Kacperczyk (2009) are able to empirically support their predictions outlined below.

Due to the higher awareness in society for ESG matters, financial markets revealed an increasing tendency to investing in stocks according to a societal norm. This development does not only have consequences for sustainable high score ESG stocks but also for the opposite, the sin stocks represented by the alcohol, tobacco and gambling industry. In this relationship it is especially interesting to look at the clientele engaged in responsible investing. Since institutions such as pension funds, universities or banks have a high exposure to public scrutiny and resulting social norm pressure their investment pool is restricted to non-sin stocks only. Consequently, the proportion of shares in sin stocks held by institutional investors should be smaller compared to other investor classes. Statistics from the Social Investment Forum hereby estimate that roughly 12% per year of total assets under management undergo a social screening process supporting the statement above. Hong & Kacperczyk (2009) further predict less analyst coverage for financial reports and valuations of sin stocks since analysts tend to cater to the needs of institutional investors. In fact, they find only 23% institutional ownership for sin stocks which is approximately 18% less in comparison to normal stocks with a institutional ownership share of 28%. Similarly, the coverage per firm is with 1.3 analysts for sin stocks significantly lower in relation to 1.7 analysts for normal stocks. In addition, Hong & Kacperczyk (2009) also control for the investment share of mutual funds, hedge funds and individual investment advisors in sin companies which are known for being arbitrageurs in the market. According to the underlying data, this class of investors does not invest less in sin stock companies providing evidence for the hypothesis of social norm pressure on public institutions (Hong & Kacperczyk, 2009).

With respect to the performance of sin stocks, Hong & Kacperczyk (2009) consider the Merton (1987) model on neglected stocks as a basis for interpretation. According to Merton (1987) there are two reasons why sin stocks might be priced cheaper and therefore outperform comparable peers even after taking traditional risk factors and other performance predictors into account. First, since institutional investors screen sin stocks out of their portfolio their stock price will be fundamentally lower than their actual value. This price depression can be traced back to the limited risk sharing of these stocks which in turn leads to higher expected returns (Merton, 1987). Second, resulting from the neglection of sin stocks and the limited risk sharing, Merton proves that the CAPM no longer

holds since it only accounts for systematic risk in form of beta. However, when pricing sin stocks, it is important to account for idiosyncratic risk due to sin stock's high litigation risks which are further enhanced by societal norms. In addition to these factors leading to an undervaluation of sin stocks in the market, sin stocks often have other advantages such as decent dividends or conservative accounting measures which further justify their good performance (Hong & Kacperczyk, 2009).
Hong & Kacperczyk (2009) test these predictions regarding sin stock's performance using a time-series regression with data covering the period from 1965 to 2006. They hereby create a portfolio which goes long the sin stocks and short in their comparables and analyse its monthly performance by means of the Carhart (1997) 4-factor model. The result of this regression reveals a monthly outperformance of 26 basis points of the long-short strategy in sin stocks. In a subsequent cross-sectional analysis functioning as a robustness check and controlling for firm characteristics such as book-to-market ratio or size, Hong & Kacperczyk (2009) even find an outperformance of 29 basis points of sin stocks. Both of these findings are economically large and highly statistically significant underlining the sizeable financial benefit of investing in sin stocks. Moreover, comparing sin stocks' valuation ratios (e.g. the book-to-market ratio) to peers from non-sin industries while controlling for various firm characteristics reveals lower valuation ratios of sin stock of 15-20%. Translating these valuation ratios into excess returns via a Gordon Growth Model calibration eventually yields an annual outperformance of sin stocks of around 2% (Hong & Kacperczyk, 2009).

Similar views on the performance of sin stocks can be found in literature of other authors such as Blitz & Fabozzi (2017). Their analysis is based on the widespread hypothesis that sin stocks are systematically underpriced due to their reputational risk to investors which thus should be compensated with a risk premium. By means of a Fama French 5-factor model they however find no evidence for a risk premium associated with sin stocks but instead a strong correlation of their performance with the last two Fama French factors, profitability and investments (Blitz & Fabozzi, 2017). A similar result on the outperformance of sin stocks can be found in an earlier paper by Fabozzi *et al.* (2008). The authors hereby argue that institutional investment policies, that neglect sin stocks due to social common standards, should be reconsidered since their economic consequences and performance implications might be costs that are not worth upholding (Fabozzi *et al.*, 2008). Clearly, this is a consideration that, if applied not only to sin stocks but similar contexts of responsible investing and sustainability, would have a destructive power in our society and our entire environment.

After reading these paragraphs on risk exposure and performance of high ranked ESG stocks, controversial firms as well as sin stocks it becomes apparent that there is no conclusion on whether sustainable investing is performance enhancing or if controversial firms bear too much reputational and operational risk requiring a return premium for investors. Furthermore, sin or controversial stocks which are screened and neglected during the investment process of some investor classes seem to be systematically undervalued therefore suggesting superior returns. In the next section we will under consideration of these findings introduce several different approaches to integrating ESG information into the investment process. While some of the strategies involve using the ESG score as a screening tool others are using them as analytical basis to develop new factors indicating a potential outperformance and alpha creation.

### 3.4 ESG Investment Strategies

While the common method of portfolio creation with ESG integration was the positive and negative screening of sustainable and controversial firms based on their ESG score, strategies like the tilt or momentum strategy introduced a new, more analytical approach of using and modifying the ESG score. The latter two strategies which are initially developed by MSCI, the source of the ESG data used in this paper, recently receive increasing attention due to their suggested generation of significant outperformance. Both of these strategies rely on a connection between ESG score and future stock returns and aim to generate $\alpha$ by allowing for larger active weights and thus more risk. Even though both of these strategies strive for the same goal of outperformance, they implicitly target different time horizons. While the ESG momentum strategy is rather short-term in nature, the ESG tilt strategy aims to influence the portfolio's performance through various channels over the long run. On a another note, the upcoming section explains a novel approach referring to the *ESG-Sharpe Ratio Efficient Frontier.* This frontier by Pedersen *et al.* (2019) introduces a trade-off between the ESG profile and the Sharpe Ratio of a portfolio and uses ESG scores for updating an investor's information set for the portfolio selection process.

Besides giving an overview of existing ESG investment strategies the subsequent paragraphs serve as a foundation to the theoretical approach applied in this thesis.

### 3.4.1 ESG Screening Strategy

The term of negative screening in connection to ESG investing refers to the approach of using ESG as a screening tool for the stock universe considered in the portfolio construction. The approach is similar to the previously introduced screening of sin stocks but instead removes the *worst-in-class* stocks solely based on their ESG score instead of their industry classification. By construction this strategy mainly aims to increase a portfolio's average ESG profile possibly to the detriment of the financial performance. As many studies confirm, the impact of this screening on portfolio performance with respect to its benchmark is slightly negative making incentives rather ethical and sustainable than financial.

As one of the examples, Bender *et al.* (2018) describes the integration of ESG data into active quantitative and fundamental equity strategies as well as passively managed indexed portfolios. For the latter the approach of using negative screening is quite common since it systematically improves the portfolio's ESG profile while keeping the advantages of passive indexing. The in the paper mentioned *Screened and Cap Weighted Equity Core Beta* strategy screens the investment universe and removes the worst 10% of stock according to their ESG score or some other target metric. The remaining stocks are market capitalisation weighted yielding a final portfolio which should similar to an indexed portfolio be broad, liquid and diversified unless a significant part of the stock universe was removed during the screening process. The result of this process is a portfolio that underperforms its benchmark index the MSCI World by 0.4 basis points or 0.004%. While this is of course not a pleasing result for every investor, it is a reasonable price to pay for the improvement in the portfolio's ESG profile (Bender *et al.*, 2018).
Despite the paper of Bender *et al.* (2018) there is literature with contradicting results regarding the performance of negative screening strategies. The paper by Glossner (2018) covered in section 3.3.2 finds that the exclusion of controversial or weak CSR firms positively impacts investment performance. Since Glossner (2018) finds evidence for negative abnormal stock returns of controversial firms which arise from their high risk of recurring ESG incidents and negative earnings surprises, removing them from a portfolio makes a positive contribution to its overall performance (Glossner, 2018).
Similar results predicting performance enhancing impact of ESG screenings are provided by Verheyden *et al.* (2016) who test the hypothesis on a basis of four different investment universes. These

four investment universes, comprised of different combinations of developed and emerging market stocks, are each separately screened for the 10% and 25% worst-ranked ESG companies. In a second step the remaining firms in the four portfolios undergo a further screening filter in which they are checked for compliance with the ten principles of the Global Compact issued by the United Nations. The performance of the resulting four portfolios is in three out of four cases superior compared to the unscreened benchmark over the investment horizon. In particular, Verheyden *et al.* (2016) measure an increased annual performance of 0.16% on average induced by the ESG screening. Further comparing the risk levels of these portfolios on the basis of volatility, drawdowns, CVaR and tail risks yields significantly lower values for the screened compared to the unscreened universe. Overall, these finding therefore suggest an improvement in the portfolio's risk-adjusted excess return that more than offsets the often discussed loss of diversification due to ESG screening (Verheyden *et al.*, 2016).

Since all of the covered papers differ slightly in their results concerning the performance implication of ESG screening, it seems that investors need to find a screening approach which is best integrable into their existing investment strategy. One of the key dimensions to consider is hereby the investment horizon which might differ substantially between investors depending on the nature of their value drivers. As Starks *et al.* (2017) show in their paper, funds with a higher allocation towards higher ESG score firms tend to have a longer investment horizon based on the hypothesis that their advantages materialise over the long run. The presented screening strategies might therefore be appropriate for investors with a long-term value consideration and rather unsuitable for a short-term momentum-oriented investor. It is therefore crucial for investors to find and adapt an ESG integration strategy which complements their existing strategy and is compatible with the primary investment goals and horizon (Bender *et al.*, 2018).

### 3.4.2 The ESG Efficient Frontier

A rather unique and new approach within the ESG investment space is done by Pedersen *et al.* (2019) who are creating an ESG efficient frontier which summarises the trade-off between risk, expected return and ESG. While a range of research is predicting a positive impact of integrating ESG into the investment process other papers argue that ESG hurts performance. By developing a model which allows for both scenarios Pedersen *et al.* (2019) are serving the need for a theoretical framework which provides flexibility in outcomes and thereby closes the gap between the controversial relation of ESG risks to returns. This model gives investors guidance on how to integrate ESG information into their portfolio choice.

Considering the traditional mean-variance model developed by Markowitz (1952) which represents a cornerstone of modern portfolio theory investors maximise their portfolio return for a given level of risk or minimise their risk for a fixed return. The result of this portfolio optimisation problem is the Markowitz (1952) efficient frontier which depicts the best combinations of the maximum return while retaining the lowest possible risk. A rationale investor will consequently always choose a portfolio on this frontier since all portfolios below the frontier yield a lower return with the same level of risk and all portfolios to the right yield the same return for a higher level of risk (Markowitz, 1952). Applying the same framework to the investment process incorporating ESG considerations yields a new efficient frontier which does not only trade-off risk and return but also accounts for ESG scores. Specifically, the frontier displays the highest attainable Sharpe Ratio for every possible ESG score therefore yielding the *'ESG-SR efficient frontier'* (Pedersen *et al.*, 2019). As we can see in Appendix II the frontier is hump shaped. The intention behind this can easily be explained with the standard Markowitz (1952) efficient frontier. According to the mean-variance analysis, the tangency portfolio possesses the highest attainable Sharpe Ratio among all portfolios. The tangency portfolio together with its ESG score must thus represent the peak of the ESG-SR efficient frontier. The tangency portfolio which does not account for ESG information is as depicted below this frontier since it ignores valuable considerations in the portfolio construction. Furthermore, if we move along the curve it is apparent that a restriction of portfolios with respect to their ESG score will eventually yield a lower maximum Sharpe Ratio than of the *ESG tangency portfolio* (Pedersen *et al.*, 2019).

The foundation of the model of Pedersen *et al.* (2019) is built on the assumption of three types of investors: The type U, type A and type M investor. The type U investor is hereby unaware of ESG scores and maximises his unconditional mean-variance utility delivering the same solution as under the traditional Markowitz (1952) theory. Consequently, type U investor chooses the tangency portfolio that ignores ESG information and therefore ends up below the ESG-efficient frontier with a lower Sharpe Ratio. Similarly, type A investor also possesses mean-variance preferences when it comes to portfolio choice. In contrast to U though, investor A updates his views with respect to ESG risk and return implications since he is aware of the informational value of ESG scores. He primarily uses ESG data to create a better forecast of returns but does apart from that not have any non-financial preference for ESG. He might therefore lean towards higher ESG scores but only to the extent that helps him improve his investment performance. The results of his portfolio choice is consequently the *ESG tangency portfolio* which yields the highest possible Sharpe Ratio (Pedersen *et al.*, 2019). The motivated investor type M, however, shows a preference for a high Sharpe Ratio as well as a high ESG score. As a result he is seeking the optimal trade-off between low risk, high returns and high average ESG scores. This trade-off of the three components in the investor's maximisation problem can be narrowed down to a simple trade-off between ESG and the risk-adjusted return. Looking at Appendix II again, type M investor will choose a portfolio which lies to the right of the *ESG tangency portfolio* giving up part of his Sharpe Ratio to satisfy his preference for a higher ESG score. This part of the frontier is called the *ESG-efficient frontier* since it favors higher ESG scores. The choice of portfolio of investor M is accordingly the tangency point of this *ESG-efficient frontier* and his indifference curves which are due to the trade-off between high Sharpe Ratio and high ESG score downward sloping. The resulting portfolio might in the end even reach a Sharpe Ratio below the one of type U (Pedersen *et al.*, 2019).

Testing the model empirically sheds light on the cost and benefits of ESG investing and illustrates the economic trade-offs perceived by investors within the given framework. Comparing the portfolio choice of investor type U and A on the one hand, the Sharpe Ratio of the *ESG tangency portfolio* chosen by A is about 12% higher than the one of U's tangency portfolio ignoring ESG information. This increase in Sharpe Ratio can be interpreted as the benefits from integrating ESG information into the investor's decision making. On the other hand the costs of having non-financial ESG preferences in the case of the type M investor means trading-off a higher ESG score for a lower Sharpe Ratio of around 3%. In conclusion, the generation of the *ESG-SR efficient frontier* actively integrates ESG data into portfolio construction rather than just using it as a screening tool. Pedersen *et al.* (2019) even discovered that screening for and excluding the worst ESG scoring firms detrimentally constraints the investment choice in terms of attainable maximum Sharpe Ratio. When removing the lowest ESG from the portfolio choice the resulting tangency portfolio might even end up with a lower ESG score. This might be due to the fact that unconstrained investors utilise poor-ESG firms to finance larger high ESG-assets or to hedge out their risks (Pedersen *et al.*, 2019). In particular, an investor excluding the worst 10% of firms faces a reduction in the Sharpe Ratio of his portfolio of 5% and thereby a lower expected return. The frontier of an unconstrained investor thus always dominates the one of a restricted one (Pedersen *et al.*, 2019). While this result stands in contrast to Glossner (2018) and Verheyden *et al.* (2016) who predict performance enhancing screening effects the model of Pedersen *et al.* (2019) provides a flexibility in outcomes due to different types of investors closing the gap of the controversial relationship between ESG, risk and return.

### 3.4.3 ESG Tilt Strategy

One of the strategies introduced by MSCI itself is the ESG Tilt strategy which is aiming to improve a portfolio's ESG profile by tilting weight towards better rated companies while minimising the portfolio's active risk. In contrast to previous research papers by MSCI this paper by Nagy *et al.* (2015) builds up on the assumption that ESG data signals the potential to outperformance or the generation of alpha. In the portfolio construction process this implies in turn higher risk strategies with larger active weights. This allowance for higher risk might in turn reveal further relationships of ESG scores with other equity factors which increase the explanatory power of the model (Nagy *et al.*, 2015).

The foundation and driver of the outperformance of this strategy is the assumed positive interrelation between ESG score and future stock performance. As previously discussed in section 3.3, companies that consider ESG factors in their operations are, despite some opposing views, facing lower risks and financial costs with respect to fines, litigation or labor disputes resulting from ESG incidents. Potential comparative advantages, such as the employment of clean technologies, arising from these ESG considerations are hereby expected to be performance enhancing over the long-run explaining the longer time horizon of this strategy (Nagy *et al.*, 2015).

As the investment universe and benchmark Nagy *et al.* (2015) rely on the MSCI World Index creating a global setting with a diverse set of companies. Furthermore, portfolio construction as well as risk and return attribution is done by means of the Barra Global Equity Model (GEM3) which is used in most MSCI research papers. With respect to the portfolio construction the authors decided to impose mild constraints of capping certain tilt bounds which have the purpose of avoiding highly concentrated portfolios.

An important feature of the strategy, however, is the high limit of active risk which eventually is reflected in the difference between the portfolio's and the benchmark's return and a result of the investor's effort to outperform the benchmark index. By allowing such a high active risk the authors are not only able to capture the superior return associated with higher ESG scores but also to explain their interaction with other systematic factors in the risk model (Nagy *et al.*, 2015). Looking at the high-level breakdown of risk and return shown in the paper it becomes apparent that most of the portfolio's active risk (90%) stems from idiosyncratic sources keeping systematic risk minimal. Translating this risk breakdown into returns though, the contribution from stock-specific sources to the yearly active outperformance of 1.06% is with approximately 40% not nearly as high as its share in total active risk. This in turn also implies that the ESG-related contribution to returns which is integrated in stock-specific sources is lower than expected from its risk contribution. Other important return contributors are instead style factors with 72%, followed by country together with currency tilts with 18% and industry tilts with 8%. Industry tilts evidently have the lowest contribution to the active return as most of their impact is already reflected in the industry-adjusted ESG score (Nagy *et al.*, 2015).

In contrast, systematic tilts such as style factors seem to provide a large and consistent contribution to the positive outperformance especially considering the time period after 2012. According to MSCI's Barra Risk Model these style factors can be further subdivided into factor exposures which reveal significant stock characteristics associated with the ESG tilted portfolio. The results of breaking down the individual exposures of the style factor show that tilting the portfolio towards high ESG assets leads to a bias of factor exposures. In particular, the portfolio is biased towards mid-cap stocks, lower idiosyncratic volatility stocks and stocks with a negative exposure towards earnings yield. The latter two factor exposures hereby stayed relatively stable over the observed period with consistent negative exposure towards residual volatility and earnings yield. With respect to size the pattern changes throughout the investment period with decreasing exposure towards size and increasing towards mid-cap. According to Nagy *et al.* (2015) this on the one hand a result of the increasing ESG effort among mid-cap firms catching up with the larger companies in the MSCI World index. On the other hand large-cap firms always have been the center of attention of ESG issues putting larger regulatory pressure on them and mitigating their ratings in the period. Furthermore, the MSCI ESG ratings model steadily improved its methodology over the past years trying to offset the disclosure bias created by the tendency of large cap companies to disclose more ESG information. All these efforts as well as the development of the size factor exposures prove that the ratings become more effective in correcting the market-cap bias we observe in the ESG scores in general (Nagy *et al.*, 2015).

Considering the entire investment horizon from 2007 to 2015 covered in the paper the ESG Tilt strategy generates a cumulative outperformance of 12% compared to its benchmark the MSCI World Index. As discussed in the previous paragraph a significant portion of that outperformance can be attributed to stock-specific factors which indirectly refer to ESG information. Additionally, Nagy *et al.* (2015) found significant systematic contributions which in turn revealed tilts within the created ESG tilt portfolios towards mid-cap, low volatility and lower value stocks. All these findings carry important implications for investors since they suggest an integration of the ESG tilt strategy into existing investment processes which systematically improves the ESG profile of the portfolio but simultaneously still generates outperformance (Nagy *et al.*, 2015).
As J.P. Morgan Asset Management stated in one of the insight and research articles, they use ESG Tilt strategies to enhance portfolio performance through lower drawdowns, reduced volatility and even higher risk-adjusted returns. Furthermore, they stress that ESG scores are additive to traditional credit ratings which do not cover all risks associated with ESG incidents (J.P. Morgan Asset Management, 2019).

#### 3.4.4 ESG Momentum Strategy

Another strategy introduced by the MSCI Research Insight is the so-called ESG Momentum strategy which similarly tries to generate outperformance in form of alpha but based on the link between the *change* in ESG score and future stock returns (Giese & Nagy, 2018). Thus, unlike the ESG Tilt strategy, the ESG Momentum strategy does not tilt towards higher ESG scores but overweights companies within the portfolio that have improved their rating over the past 12 months. It is accordingly based on the assumption that an improvement in the ESG score signals a better management of ESG-related risks which reduces potential future litigation costs that are quickly discounted and priced by market participants(Nagy *et al.*, 2015). By definition this strategy is therefore more short-term oriented since it reacts to the trend in rating development instead of relying on the materialisation of advantages of better rated firms. This in turn also implies that the resulting portfolio from the ESG Momentum strategy is not intended to improve the existing ESG profile since the largest increase in rating is not necessarily associated with the highest rated stocks. Improving the ESG profile of a portfolio is one of the main intentions of the ESG Tilt strategy and thereby constitutes one of the key differences between the two strategies (Nagy *et al.*, 2015). Except for this difference in the source of alpha, the setup with respect portfolio construction and the imposed constraints is identical. Naturally the ESG Momentum strategy covers one year less than the Tilt strategy since the first year of the sample is used for the construction of the Momentum factor (Nagy *et al.*, 2015). The ESG Momentum factor itself, reflecting the financial value of the change in a company's ESG profile, is estimated by MSCI as a simple year-on-year change of the MSCI ESG score (Giese & Nagy, 2018).

Just like for the ESG Tilt strategy, the initial MSCI research paper by Nagy *et al.* (2015) creates a decomposition of active risk and return of the created strategic portfolio to analyse its factor exposures and sources of outperformance. Similar to the results of the breakdown of risk factors of the ESG Tilt strategy, the highest contribution of active risk for the ESG Momentum strategy stems with 80% from stock-specific sources albeit to a less extent. With respect to the estimated active annual return of 2.2% relative to the MSCI World Index, the contribution from stock-specific factors is with approximately 60% larger compared to the ESG Tilt strategy. These idiosyncratic sources are especially predominating in the first part of the investment horizon. In later years of the data sample, however, systematic factors such as industry and style factors gained importance, delivering a consistent contribution to the outperformance (Nagy *et al.*, 2015).
Again, these style factors can be further broken down to individual factor exposures to investigate their contribution to active performance. Hereby the authors particularly stress the tilt towards price momentum stocks which indicates that companies with a positive development of their ESG profile also tend to perform well. The ESG Momentum strategy therefore seems to capture some of the outperformance related to the price momentum factor. Furthermore, a similar pattern compared to the ESG tilt strategy of overweighting mid-cap stocks can be observed, presumably due to the same reasons (Nagy *et al.*, 2015). The positive contribution from industry factors to the overall outperformance can to the largest extent be traced back to the effect of underweighting low momentum firms which at the same time were financially performing poorly. This applies

in particular to the Energy and Materials sector that substantially underperformed during the sample period and whose ESG scores were downgraded disproportionally (Nagy *et al.*, 2015). This development of ESG profiles seems plausible since both of these sectors belong to the most controversial and responsive ones with respect to ESG matters. As their sub-industries consist of the major oil and gas conglomerates as well as the Steel and Aluminium industry which are all highly dependent on hydrocarbon assets, the systematic improvement of a company's ESG is particularly difficult. In the end this underweight induced by the momentum strategy paired with the underperformance of these sectors resulted in a positive contribution to overall performance (Nagy *et al.*, 2015).

While this paper by Nagy *et al.* (2015) only superficially describes the strategy and its decomposition of risk and return, a subsequent paper by MSCI which solely focuses on the ESG Momentum strategy investigates the performance on a deeper level. Giese & Nagy (2018) hereby simulate the performance of a hypothetical monthly rebalanced investment strategy of going long in the upper and short in the lower quintile of calculated ESG Momentum factors. Correspondingly, firms are sorted into one of the quintiles based on their ESG Momentum on a monthly basis yielding a long-short portfolio which by construction allows to control for market movements. Analysing the performance of the created long-short portfolios yields a cumulative outperformance of 12% for the developed markets and 14% for the emerging markets. Considering the shorter sample period of the emerging markets portfolio this results is even more prominent and might suggest a lack of the integration of ESG information into pricing in emerging markets (Nagy *et al.*, 2015).
In addition to the performance analysis Giese & Nagy (2018) construct an ESG valuation curve estimating the ESG Momentum effect on a company's valuation conditional on its initial ESG score. This valuation curve implicitly measures the historical performance of the long-short portfolio separately for three tertiles based on ESG score. It thereby aims to compare the ESG Momentum's implication for company valuations and stock performance depending on the firm's degree of sustainability. By rerunning the analysis for the long-short portfolio for every ESG tertile we can observe the strongest performance for the middle range of ESG scores. Since the average ESG Momentum as well as the realized volatility are approximately the same across all three tertiles the strong performance of the middle one cannot be traced back to up- or downgrades in scores nor to an increased level of risk. The results simply suggest a non-linear link between the MSCI ESG scores and the valuation where valuations and therefore performance reacts stronger in the middle range of ini-

tial ESG scores (steep curve) compared to the tails of the ESG scale (flat curve) (Giese & Nagy, 2018).

In conclusion the analysis historically tests the economic impact of changes in ESG scores on equity prices by means of the valuation curve. As seen in the results, a positive change in the ESG profile of a company is hereby associated with an increase in valuation and therefore in stock price while a negative development of the ESG profile induces a downgrade to lower valuation and performance. The degree of impact this ESG Momentum has on stock prices is especially significant in the middle range of initial ESG scores and rather flat for the top and bottom ends of the ESG scale. Since none of these effects can be traced back to general market or equity factors of traditional risk and pricing models, the ESG Momentum seems to have a causal relation to stock performance adding new insight to the market's pricing mechanism (Giese & Nagy, 2018). Given the novelty of the approach and the limited research and backtesting of the theory aside from MSCI, the ESG momentum strategy is not widely used in investment processes.

## 3.5 Approach and Hypotheses of this Thesis

Under consideration of the before covered literature and findings, we developed our hypotheses about the integration of ESG data into the investment process and its impact on performance. Based on these hypotheses we then developed our methodology and empirical approach, covered in the remainder of this thesis. By means of our analysis we are aiming to uncover current weaknesses in pricing mechanisms of financial markets concerning ESG risks and contribute new methods for the ESG integration.

In a first step of our analysis we are assessing the risk of firms in relation to their ESG profile based on our own data sample. In line with the findings of Dunn *et al.* (2018), Verheyden *et al.* (2016) and Giese *et al.* (2019), we do as well believe that a company with a poor management of its ESG risk exposure, and thus with a low ESG score, also inherits higher statistical risk measures of its equity. By systematically impacting the risk profile of a firm, it is therefore evident that ESG data has an impact on a firm's stock performance, making ESG information essential for the investment process beyond their ethical considerations (Dunn *et al.*, 2018). Establishing this systematic relationship between the ESG profile and the systematic and idiosyncratic risk of the firm consequently builds the foundation of our analysis and justifies the integration of ESG data into the investment decision process. Beyond the risk assessment of our data set, conditional on the ESG score, we decided to focus on the ESG Momentum strategy as our preferred investment approach. As it appears as the most profitable, but at the same time the least covered investment approach in current literature, it serves as an interesting foundation for a range of analysis and for further research. While the novelty of the strategy on the one hand allows us to experiment with our methodology, it on the other hand lacks constructive guidelines or comparison to other approaches.

In the subsequent sections of this paper we will construct, analyse and critically discuss the ESG Momentum factor and its integration into equity models and investment strategies. The construction of the factor is hereby based on the above presented paper by MSCI ESG Research (2019) who first introduced the factor. By applying a slightly different construction method which is more similar to the construction of the stock momentum factor we are hereby critically scrutinising the approach of Giese & Nagy (2018) and opening up new perspectives. After constructing the ESG Momentum factor we investigate its relation to other risk and equity factors, as well as its performance implications by sorting firms into groups of high and low ESG Momentum. Regarding the performance implications of the ESG Momentum, our hypothesis is in line with the findings of Giese & Nagy (2018). Accordingly, we are predicting a significant outperformance of a portfolio containing firms with the highest ESG Momentum which thus improved their ESG profile most in the past, compared to its counterpart consisting of firms from the lowest ESG Momentum quintile.

Based on this hypothesis regarding the connection between the *change* in a company's ESG profile and its stock performance, we develop a strategy of using the ESG Momentum as an additional explanatory variable in a factor investing framework. In a first step we therefore need to detect the anomaly associated with the ESG Momentum factor which cannot be explained by traditional model factors and therefore justifies the integration of our additional factor. We are therefore dividing our data into quintile portfolios based on our constructed ESG Momentum factor and regress them on the four Carhart (1997) factors. In line with our hypothesis, we are hereby expecting a positive abnormal return in form of alpha for the highest quintile portfolio, while a negative one for the lowest quintile portfolio.

Based on this anomaly in returns associated with the ESG Momentum, we are extending the 4-factor

Carhart (1997) framework by our additional ESG Momentum factor, adding explanatory power to the model. Furthermore, the setup of our regression with decile portfolios based on performance will enable us to measure the ESG Momentum factor's contribution to explaining return differences in the portfolios. Similar to the stock momentum, we are hereby expecting a monotonous increasing pattern in factor loadings, indicating an higher concentration of high ESG Momentum firms in well performing portfolios and of low ESG Momentum firms in poorly performing ones.

By further breaking down ESG to the three pillars and relating them to the sectors they are most material for we are providing further insight into the dimension of ESG and the difference in contribution of each pillar. In line with the findings of Khan *et al.* (2016), we are predicting a significant positive impact on performance by a change in the sector's material pillar, while a negative or insignificant one for a change in the immaterial ones. This would not only prove the dissimilar impact of the three pillars on performance but also justify a customisation of ESG efforts to business context and industries (Jitmaneeroj, 2016).

Based on the literature covered in the paragraphs above, we believe that financial markets fail to fully incorporate ESG information and misprice firms by ignoring valuable ESG information. Consequently, our hypothesis is that the above developed strategy of portfolio construction based on the ESG Momentum will generate an anomaly of high ESG Momentum firms outperforming low ones which cannot be explained by the factors in the traditional asset pricing models such as the Carhart (1997) 4-factor model. In response to this lack of explanatory power of the Fama French models and its extensions, we develop an additional factor based on the ESG Momentum. We will then integrate this factor into the model to account for this unexplained outperformance in form of alpha.

In the course of this investigation of our research question we will focus solely on the two most mature and ESG aware markets, Europe and the U.S., to avoid biases with respect to geographical differences. Furthermore, the comparison between the U.S. and Europe might yield substantially different results and entail relevant implications for the use of ESG data (Bank of America, 2019a). A detailed approach and the data used for the analysis will be further outlined in section 4 and 5 under consideration of these hypotheses.

# 4 Data

In this section we will present and describe the data used for the empirical analysis of this thesis. We refer to section 2.2 for a more detailed description of the methodology as well of a descriptive analysis of the ESG data used in this study, as this was essential when defining material ESG issues. In this section we will conversely, focus in more detail on the data used for the main analysis of this thesis.

## 4.1 Data Procurement

The ESG data set used in this thesis, to identify companies' ESG exposure, is provided by MSCI. The MSCI ESG database covers over 7500 companies accounting for 98% of the market cap of the MSCI World Index as of July 2019 (MSCI ESG Research, 2019). The data set provides information on the score of each individual ESG pillar, their relative weight to the overall company score, as well as the aggregated raw score and the industry adjusted ESG score on a monthly basis. In addition, we obtain information on CO2 emission intensity from MSCI which is measured as the total carbon emissions in relation to sales. As companies with higher carbon intensity have a higher exposure to regulatory risk, this intensity ratio serves as a proxy for a company's potential exposure towards climate related risks (MSCI ESG Research, 2019).
For reasons mentioned in section 2.2, we will mainly use the industry-adjusted score for our analysis, as this will prevent the results from being biased towards certain industries. The industries are based on the GICS categorisation, developed partly by MSCI, across which the industry-adjusted score is normalised.

The financial data on a company level, including various accounting, stock market and risk metrics, is obtained from the global S&P Capital IQ database. The use of these in the course of our factor construction and regressions will be further explained in section 5. In our data set, we consider the large and mid-capitalisation segment of publicly listed firms in Europe and U.S. with financial information from January 2006 to May 2019 on a monthly basis. The final data set is correspondingly restricted to firms with a market capitalisation of at least USD 2.5 billion as of the end of 2019 and is adjusted to match variations in market cap over time. While we apply the entire time frame for our initial risk analysis, our regressions are only based on financial information from January 2010 due to data inconsistencies. For the risk analysis, we additionally use the global database S&P Capital IQ through the Excel plug-in to download stock-specific risk measures in form of beta and price volatility. Finally, we download the 1-Month U.S. Treasury Bill from the FRED database as well as the MSCI World Index from the MSCI website which we will use as a proxy for the risk-free rate and the market portfolio respectively.

## 4.2 Sample Selection and Descriptive Statistics

We choose to restrict our analysis to firms in Europe and the U.S. following the observations made in section 2.1 and 2.4, as these markets are the most developed in terms of regulation on disclosure of ESG related issues and awareness amongst investors. This selection can possibly provide a deeper understanding of how investors can use ESG information in general, and the ESG Momentum in particular, in their investment decisions. In terms of the chosen time frame for the analysis, we refer to section 2.5 and the points made around data quality as well as the methodology improvements from MSCI. Choosing a time frame in this setting is essentially a trade-off between data quality and the number of observations. On the one hand, we want to include data of high quality instead of a mass of inconsistent data. However, there is no evidence of MSCI backtesting their early rating with their new methodology. Contrarily, it rather seems, by means of our descriptive analysis, that the scoring underwent a drastic improvement over the years. Data quality is therefore an issue we need to further consider in the limitations of our thesis. On the other hand, excluding observations makes it more difficult to obtain significant results from regressions which we will further outline in our methodology. As a middle way, to avoid outliers in the data set caused by the financial crisis and to include data of high quality without excluding too many observations, we choose to restrict our sample from January 2010 to May 2019. As the empirical research made by Fama & French (1992) and Carhart (1997), which we to a large degree replicate, covers a longer time frame, our time horizon might influence the quality of our results. We will discuss these and other limitation of this thesis at a later stage and critically question our approach. As explained in the section above, we still include observations back to 2006 for the initial risk analysis, as will be outlined in the upcoming section on methodology.

*Table 3: Descriptive statistics European and U.S. Sample*

***Panel A: European Sample***

| | *Q1 (low ESG)* | *Q2* | *Q3* | *Q4* | *Q5 (high ESG)* | *Q5-Q1* |
|---|---|---|---|---|---|---|
| Industry-Adj. ESG score | 3.16 | 5.25 | 6.56 | 7.83 | 9.40 | 6.24 (189) |
| Min | 0.37 | 4.52 | 5.92 | 7.20 | 8.51 | 8.14 (386) |
| Max | 4.45 | 5.85 | 7.14 | 8.44 | 10 | 5.55 (238) |
| Standard Deviation | 0.99 | 0.41 | 0.37 | 0.39 | 0.58 | -0.44 (-48.9) |
| Annualised Return | 8.75% | 8.19% | 7.47% | 7.94% | 9.51% | 0.76 (1.09) |
| Market cap | 15,439 | 19,971 | 20,022 | 19,410 | 23,843 | 8,404 (15.2) |

***Panel B: U.S. Sample***

| | *Q1 (low ESG)* | *Q2* | *Q3* | *Q4* | *Q5 (high ESG)* | *Q5-Q1* |
|---|---|---|---|---|---|---|
| Industry-Adj. ESG score | 1.85 | 3.46 | 4.70 | 5.98 | 7.98 | 1.85 (173) |
| Min | 0.22 | 2.82 | 4.16 | 5.35 | 6.81 | 0.95 (274) |
| Max | 2.74 | 4.09 | 5.28 | 6.73 | 10 | 7.26 (565) |
| Standard Deviation | 0.59 | 0.41 | 0.35 | 0.43 | 0.97 | 0.38 (52.6) |
| Annualised Return | 13.9% | 15.9% | 14.0% | 13.6% | 12.4% | -1.5 (-0.21) |
| Market Cap | 17,568 | 19,290 | 20,878 | 24,814 | 34,753 | 17,185 (29.5) |

*Panel A present descriptive statistics on the European sample divided into quintiles based on industry adjusted ESG scores, as well as the spread between the highest and lowest quintile and corresponding t-statistic in parenthesis from January 2010 to May 2019. Panel B presents the equivalent measures for the U.S.*

We finally merge the ESG data set from MSCI with the financial company data based on the Company IDs and dates, and get a final unbalanced sample of 3,080 firms from January 2010 to end-of-May 2019. Firms with a continuous rating of zero are hereby entirely removed from the sample as they have not been rated by MSCI. Firms with a temporarily score of zero, which might be an indication of a lack of data quality, are accordingly removed for these points in time only. Leaving them in the data set, would create extreme ESG Momentum factors potentially biasing our portfolio construction, distribution and eventually results. However, the result of this procedure is an unbalanced panel which does not contain the same firms at every point in time of the analysis.

In Table 3 we present descriptive statistics for the European and U.S sample respectively, divided into quintiles based on their industry-adjusted ESG score. The goal of this is to get a better understanding of how the data behaves within the two markets. Furthermore, we receive an impression of the relationship between the level of ESG scores and financial performance of high and low rated firms. For each quintile, we calculate the average industry-adjusted ESG score, standard deviation, annualised return as well as the average market cap. In summary, data overall counts 181,833 observations over the time frame described. The average firm in the sample has an average annual return of 3.7%, an industry-adjusted ESG score of 5.64 and a market cap of USD 23,756 billion. However, looking at the tables more closely, we can see that the European market has on average higher rated ESG firms than the U.S., but forfeits with lower returns compared to the U.S. market. It can also be observed that companies rated within the mid-range of ESG scores have the highest returns. In the last column we look at the spread between the upper and lower quintile of the ESG score. It is hereby interesting to observe, that there is a positive spread between the highest and lowest quintile in the European market over the period, whereas the same is not true for the U.S sample. Another observation is that the returns are consistently increasing with the ESG score for the European market. The same pattern can not be observed across the U.S market. This gives an indication of the correlation between financial performance and ESG scores which seems to be higher in Europe than in the U.S. In addition, from both markets we can observe that larger firms tend to have a higher ESG score than smaller firms. Furthermore, the volatility of the ESG score is decreasing with better scores in Europe, while no such clear pattern can be seen in the U.S.. Thus, we can see that firms in Europe in general perform better on ESG related issues. American firms, in contrast, are in general larger and obtain higher average annual returns, in line with previous empirical observations (see section 2).

# 5 Methodology

This section of our thesis will provide an overview of the methodologies used for the stated hypotheses and prediction in part 3.5. Our entire analysis is hereby focused on two regions, the U.S. and Europe, which represent the two most mature but also ESG-aware markets. Due to these characteristics we are expecting the most distinct patterns and valuable results by looking exclusively at these

two regions. Furthermore, the difference between these two large markets might suggest additional implications for the integration of ESG data into equity models.
This section is structured as followed: After describing the risk assessment of companies with respect to their ESG profile we focus on the construction and characteristics of our ESG Momentum factor. In a subsequent step we are then explaining the setup pf various regression analysis to investigate the ESG Momentum's influence on stock performance. Based on these findings we outline the integration of the factor into existing equity models underlining its importance in investments decisions.

## 5.1 Assessing ESG Risk

As outlined in our approach and hypotheses the first step in our analysis is an assessment of the relationship between risk and ESG scores suggested by other authors in section 3.3. By applying a similar approach to the one of Dunn *et al.* (2018) to our data set, we are trying to investigate if there is a systematic pattern in risk measures when comparing companies with different ESG profiles. As described in section 4, our ESG data is obtained from MSCI, and thus we are expecting similar findings to the paper of Dunn *et al.* (2018).

Just as Dunn *et al.* (2018), we split the total risk of a firm into two separate measures of systematic and stock-specific risk. The systematic risk is hereby represented by the stock's beta while the idiosyncratic risk is assessed from the stock's price volatility. Both of these metrics are obtained for each of our observations in the data set from the global database S&P Capital IQ through the Excel plug-in.
For the stock's price volatility we decided to use a one-year historical figure which measures the stock's price fluctuations within the past year. The metric is hereby constructed as the one-year backward looking volatility which is annualised based on the stock's daily standard deviation. The corresponding formula can be found below where $\sigma$ represents the standard deviation of the stock price and T the timeframe. In this case, since we are looking at the annualised volatility, the T

corresponds to the 252 trading days the daily volatility is based on.

$$\begin{aligned} \sigma_{Daily} &= \sqrt{\frac{\sum(P_{av} - P_i)^2}{n}} \\ \sigma_{Annualised} &= \sigma_{Daily} * \sqrt{T} \end{aligned} \tag{3}$$

The beta used for the systematic risk assessment refers to the sensitivity of an asset's share price with respect to a benchmark index and measures its relative movement to it. It is estimated as the coefficient of the traditional CAPM regression which regresses the excess return of a stock on the excess return of the chosen benchmark index. The result of this regression hereby depends to some extent on the parameters utilised, such as the duration of the period and the frequency of estimating the beta. In our framework we decided for a 5-year time span with a monthly frequency which is a standard approach when trying to obtain a comparable metric across firms. As the benchmark we decided to apply two different approaches to compare and test for robustness. As both regions, the U.S. and Europe represent major markets with a global footprint, it seems reasonable to use a global benchmark index to achieve comparability. On the one hand, we therefore decided to use the MSCI World Index as the global benchmark consistent with our ESG data source. On the other hand, for a more accurate assessment of each firm's risk exposure, it might be preferable to estimate the beta of each company with respect to its local index. Our risk analysis will correspondingly compare both approaches to investigate if patterns systematically deviate according to the benchmark used. For the U.S. we hereby apply the S&P 500 Index while for Europe the Euro Stoxx Index consisting of 500 and 300 constituents respectively. Just like the historical price volatility, a firm's beta is obtainable from S&P Capital IQ with the above described estimation approach. For each firm in our data set we therefore download the corresponding 5-year monthly beta for every month it occurs in the sample.

Applying these methods to our entire data set, limited to Europe and the U.S., yields a panel data frame of monthly rolling one-year windows for each stock's price volatility as well as 5-year windows for the beta, on the local and global index. By means of this panel data frame, we are then able to conduct our main risk analysis assessing the influence of the ESG score on the risk measures of a company. We hereby cover both geographies together since we expect a pattern which is applicable globally and not specific to one region. For this purpose, we first divide the universe of firms into quintiles based on their ESG score on a monthly basis. This is similar to a portfolio construction process using the ESG score as a monthly rebalancing criterion. For each of these quintiles separately, we then calculate an average on each of the risk metrics, leaving us with a time-series of company averages on price volatility and beta. Finally, we compare these time-series trying to obtain systematical risk patterns dependent on the ESG quintile classification of firms.

For the visualisation of the patterns we are again using the Dunn *et al.* (2018) paper as an inspiration. We accordingly plot our time-series of the average price volatility and beta for the highest and lowest quintile. Furthermore, we create a graph which represents the percentage difference for each of the two risk measures, between the highest and the lowest ESG score quintile. We can thereby see if the highest ESG score quintile has systematically lower or higher risk values compared to the poor ESG score quintile. In addition, all of the in the graph observed patterns are summarised in a table which as well is inspired by the work of Dunn *et al.* (2018). Based on the ESG score quintiles we compute a time-series average on selected metrics such as the risk measures, the annualised return as well as firm and quality characteristics. Furthermore, we add a column with the difference between the highest and lowest quintile and the relevant t-statistics of these differences. Comparing these additional summary statistics gives further insight into the firm characteristics and performance associated with each of the score quintiles.

## 5.2 The ESG Momentum Factor

The main part of our analysis is, as mentioned in section 3.5, based on the ESG Momentum factor first introduced by Giese & Nagy (2018). For the construction of the factor we limit our data sample geographically on Europe and the U.S. as outlined in our data section 4 since these two represent the most developed markets and possess the highest ESG data quality. We accordingly construct our ESG momentum factor and also conduct all subsequent analysis separately for the two regions.

*ESG Momentum Factor Construction*

To construct our ESG Momentum factor we establish an approach inspired by the MSCI Research Insight from Giese & Nagy (2018), which we slightly modify based on several grounds. Giese & Nagy (2018) define the ESG Momentum as a simple year-on-year change in the ESG score. This amount of 12 months lookback period was chosen by the authors after consideration of a range of time frames between 6 to 24 months. Using a time frame of only 6 months yields very noisy and rather flat performance results of the introduced long-short portfolio since a lot of firm ratings are not updated within that period. Since Giese & Nagy (2018) exclude firms with a zero ESG Momentum these firms with an updated score are falling through the filter. Since MSCI updates their scores once a year and on a industry-by-industry basis, a horizon below 12 months seems intuitively not reasonable, even though simulations covering 9-month and 12-month periods yield the strongest and most persistent outperformance (Giese & Nagy, 2018). Furthermore, the authors find that the longer the time horizon towards 24 months, the weaker the outperformance signal of the factor. A middle ground between these two periods therefore seems ideal.

Considering our data set we tested two approaches of a 12-month and 15-month Momentum and compared the results. Eventually, we decided to apply a time horizon of 15 months to cover changes in ESG scores broadly and effectively. By that, we also avoid having a lot of firms in the sample with a zero Momentum due to the shifted update of scores. Furthermore, instead of computing a simple year-on-year change of the ESG score we calculate the ESG Momentum as a cumulative return based on the ESG score inspired by the traditional price momentum method. In contrast to the price momentum though, we do not expect a last month's reversal effect, so that we include it in the calculation.

*ESG Momentum Characteristics*

After constructing our ESG Momentum factor in the described manner we are interested in the basic properties of the constructed factor in order to get a better insight into how the factor could be used in financial models. For all of these basic properties and analyses, the MSCI Research Insight by Giese & Nagy (2018) served as inspiration and analytical basis for our approach. The outcome of some of the properties are in this context crucial since they might suggest some additional modification of the factor to better implement it into equity models.

The first step of our fundamental analysis is the distribution of the ESG Momentum factor which we have calculated for all firms on a monthly basis. When integrating ESG Momentum into the portfolio construction process it is important to be aware of the distribution's mean, standard deviation as well as its skew and kurtosis. Having too many outliers which are creating a large dispersion in the factors, might for example justify a capping of these outliers. Furthermore, the specific shape

of the distribution and its skew might suggest a trend of development of ESG scores and entail implications and interpretations of the ESG Momentum factor. We therefore plot a histogram of the computed ESG Momentum factors, alongside a table with the basic properties of the distribution to investigate these patterns.
Secondly, we are interested in the correlations of the ESG score and ESG Momentum factor with traditional factors included in risk and equity models. When using the ESG Momentum factor as basis for the portfolio construction, we have to rule out factor biases due to correlations. Seeing large correlations between the ESG Momentum and the other equity factors would pose a problem for the incorporation of the ESG Momentum into equity models due to multicollinearity.

*ESG Momentum Performance*

The most important feature of the ESG Momentum factor is its influence on stock performance. Since our goal is to integrate the factor in existing equity strategies and asset pricing models it is important to investigate whether there is abnormal positive or negative returns associated with the ESG Momentum of firms.
As presented in section 3.4.4 the MSCI study on the ESG Momentum strategy by Giese & Nagy (2018) provides evidence for a positive relationship between the change in a firm's ESG score and its financial performance. With a hypothetical zero-cost investment strategy of going long in the highest quintile of ESG Momentum scores and short in the lowest quintile the authors create a long-short portfolio which yields a significant cumulative outperformance over the sample period (Giese & Nagy, 2018). Following these findings, we are replicating the approach with our data for the U.S. and Europe.

In order to plot the cumulative performance of the long-short portfolio, we first need to divide our set of firms into quintiles based on the monthly ESG Momentum score, like outlined above. We subsequently calculate the return for the two quintile portfolios with the highest and lowest momentum over our entire time frame. Since the long-short strategy is a zero-cost strategy it does not need an outlay of money in the beginning. By definition the proceeds of the short sales are used to fund the long purchases meaning that the short position finances the long one. This in turn implies that the cumulative performance of the long-short strategy is just the cumulative sum of the differences in monthly net return of the upper and lower quintile portfolio. Plotting this cumulative performance will eventually provide insight into the either positive or negative impact of ESG Momentum on performance. Furthermore, we can infer from the performance graph if there is a consistent impact of the ESG Momentum on stock performance over our time frame or if the pattern systematically changes with respect to certain periods analysed.

### 5.3 Fama French Factor Creation

As outlined in section 3.5 our goal within this thesis is to integrate the ESG Momentum as an additional factor in the traditional Fama French model and its extensions. Besides the ESG Momentum factor, we thus also have to create the relevant Fama French factors based on our data sample. A basic guide to how the factors are constructed can be found on the website of Kenneth R. French (2020) in cooperation with the Tuck School of Business of Dartmouth university. In addition to this factor construction process, the website also offers to download the relevant factors specifically tailored to the model set-up (i.e. 3-factor, 4-factor model etc.), specific geographies or industries.

On the basis of the instructions we are outlining our construction approach for each of the included factors in the subsequent paragraphs. The factors needed for our analysis can be inferred from equation 4 below which represents the comprehensive framework of our hypothesis including all factors.

$$r_{it} = \alpha_{iT} + \beta_{iT} MRKT_t + \gamma_{iT} SMB_t + \delta_{iT} HML_t + \epsilon_{iT} PMOM_t + \phi_{iT} ESGMOM_t \tag{4}$$

The first four factors as well as the dependent variable are here identical to the framework of the Carhart (1997) 4-factor model. $r_{it}$ on the left-hand side stands for the monthly excess return on an asset or portfolio $i$ at time $t$. The index $i$ can therefore in the entire framework refer to an single asset, in most of the cases though it represents a portfolio. The factors on the right-hand side represent the typical Fama French 3-factors as well as Carhart's additional price momentum. All of the factors have an index of time $t$ since they do not vary across firms or portfolios but are computed for each month in the sample. The coefficients of the factors all possess the index $iT$ since their value is varying across asset or portfolio $i$, but represent a time-series average over $T$. Same counts for our ESG Momentum factor which we include as the fifth factor in addition to the four Carhart (1997).

*The Market Excess Return*

The market risk premium is the initial factor introduced under the CAPM framework which covers the return of the market portfolio in excess of the risk-free rate specified in the model. The $\beta$ coefficient in front of it measures, as mentioned in earlier parts of this paper, the relative movement of the stock's or portfolio's return with the return of the market and thereby serves as a proxy for its systematic risk. While the risk-free rate is in most of the literature represented by the one-month U.S. Treasury Bill rate the choice of market portfolio is a bit more elaborated. Since the market portfolio should cover the entire universe of stocks investigated in the portfolio it is often a large market proxy with either global or geographical focus.

Since our data samples cover on the one hand the European and on the other hand the U.S. market, we choose our proxies for our regressions according to these geographical constraints. Since our utilised ESG data set does not include any small cap firms, as described in the data section 4, we can limit our choice of market proxy to large indices as well. As the relevant market portfolio for the two regions we therefore choose the MSCI World Index which cover large and mid-cap stocks from 23 developed countries. Accordingly, the factor for the market excess return is computed by deducting the risk-free rate from the monthly return of each of the indeces at any point in time. In both cases we hereby use the one-month U.S. T-Bill as the risk-free rate for better comparability of the results.

*SMB and HML*

The following two factors $SMB$ and $HML$ are the extension of the traditional CAPM to the Fama French 3-factor model introduced in section 3.2. These factors are created based on the discovered anomaly in returns when comparing small and big firms as well as value and growth firms. In particular, as Fama & French (1992) tested the CAPM, they found significant and high alphas for small compared to large firms and high book-to-market (BTM) compared to low book-to-market firms. As a result, Fama & French (1993) created the two indicated factors accounting for the small cap and value bias in returns based on six portfolios formed on size and BTM.

Following this approach of Fama & French (1993), we are constructing the six value-weighted factor portfolios based on our data sets and for each of the two regions separately. The portfolios are created on a monthly basis by classifying stocks as small or big and value, neutral or growth firm based on their market capitalisation and BTM respectively. In contrast to the methodology of Fama & French (1993), who rebalance their portfolios according to size and BTM once a year, we decided to apply a monthly rebalancing approach. By that we are able to capture all fluctuations in the data and accurately measure each portfolio's performance with respect to the underlying construction parameters. We therefore define breakpoints for market cap and BTM in every month $t$ and sort our universe of stocks into these clusters. While the size breakpoint is just the median of market caps in every month, the BTM is divided into three categories. The lowest 30% of values hereby refer to growth firms, the middle 40% to neutral ones and the upper 30% to value firms. After sorting each firm into one of the combinations of size and value portfolio we calculate the monthly value-weighted return on each of the portfolios based on the firms in it. The result is a time-series of average returns of these six portfolios from which we calculate the relevant $SMB$ and $HML$ factors by means of the following equations:

$$\begin{aligned} SMB \; &= \frac{1}{3}\,(Small\ Value\ +\ Small\ Neutral\ +\ Small\ Growth) \\ &- \frac{1}{3}\,(Big\ Value\ +\ Big\ Neutral\ +\ Big\ Growth) \end{aligned} \tag{5}$$

$$\begin{aligned} HML \; &= \frac{1}{2}\,(Small\ Value\ +\ Big\ Value) \\ &- \frac{1}{2}\,(Small\ Growth\ +\ Big\ Growth) \end{aligned} \tag{6}$$

As can be inferred from equation 5 the $SMB$ factor is derived by subtracting the average return on the three big portfolios from the average return on the three small ones. Similarly, equation 6 depicts the $HML$ factor as the difference in average returns of the two value and the two growth portfolios. The two factors therefore simply represent a time-series of the average excess return of portfolios constructed by means of size and value parameters in each month of the sample.

*Price Momentum*

The $PMOM$ factor included in equation 4 leads back to the introduced momentum strategy by Jegadeesh & Titman (1993) who predict superior returns for firms with a strong past performance relative to firms with the opposite. The factor therefore measures the difference in average returns of a portfolio including firms with a high momentum compared to one constructed based on low momentum firms.

The price momentum itself is computed based on the common methodology of Jegadeesh & Titman (1993). It defined as the stock's past year's cumulative return excluding the most recent month, thereby covering a period of 11 months. The last month is hereby excluded due to the reversal effect we observe when analysing the trend of stock returns. Based on this stock-specific price momentum factor we are then able to create six portfolios in a similar manner to the $SMB$ and $HML$ portfolio construction. For the size classification of stocks we use the same monthly breakpoint of the median of market capitalisation to either sort companies in the small or big portfolios. Subsequently, instead of sorting stocks by BTM, we now use the 30th and 70th percentile of the calculated price momentum as monthly breakpoints for the portfolio construction. Stocks are therefore categorise as either high, medium or low momentum stocks depending on their specific value each month. Following the portfolio construction, we can then compute the value-weighted average monthly return on each of the six resulting portfolios and compute the $PMOM$ factor with the adjacent equation:

$$PMOM \ = \ \frac{1}{2} \ (Small \ High \ + \ Big \ High) \ - \ \frac{1}{2} \ (Small \ Low \ + \ Big \ Low) \tag{7}$$

As equation 7 illustrates, the monthly calculated $PMOM$ again generates a time-series of average excess returns of stocks with a high momentum compared to those with a low one. Including this factor in the regression model will therefore account for the anomaly associated with this momentum factor.

*ESG Momentum*

Similar to the intuition of the price momentum and inspired by the MSCI Research by Giese & Nagy (2018), we believe that there is a positive abnormal return associated with firms that experienced an increase in their ESG score compared to firms with a downward trend in ESG score. This ESG Momentum is measured in a similar way to the price momentum by calculating the past year's change in ESG score per firm and month. Since we do not expect a reversal effect of the score trend within the most recent month, we are not applying the price momentum rule of excluding the last month from the ESG Momentum calculation. Instead we simply consider a 15-month lookback period and compute the cumulative return on the ESG score for each firm on a monthly basis.

Note that, we are hereby revising the 12-month lookback period of Giese & Nagy (2018). Since scores

are not updated at a specific date each year but on a industry-by-industry basis, our calculated Momentum factor is likely to contain a lot of zeros due to unchanged scores. As a result it might be difficult to calculate the respective breakpoints for the portfolio construction in case they are not unique or different from zero. At this point, we therefore decided to adjust the lookback period to 15 months to avoid too many zeros in the data and ensure unique portfolio breakpoints.
The main contribution of our paper is the integration of the ESG momentum factor into the Fama French framework outlined above. Due to the similarity of the factors' intentions we are closely following the factor construction process of the price momentum outlined above. In contrast to the price momentum, however, we use different breakpoints for our portfolio construction which are in line with our outperformance analysis. Accordingly, we are constructing monthly quintile breakpoints based on the calculated ESG Momentum, thereby creating five portfolios on the ESG Momentum criterion. The firms sorted into the top and bottom quintile with the highest and lowest ESG Momentum scores respectively, are the ones included in the factor construction. Combining their affiliation with either top or bottom quintile with the classification of size yields ten portfolios for which we can compute the monthly value-weighted return.

$$ESGMOM \; = \; \frac{1}{2} \left(Small\ Top \; + \; Big\ Top\right) \; - \; \frac{1}{2} \left(Small\ Bottom \; + \; Big\ Bottom\right) \tag{8}$$

As depicted in equation 8 above the $ESGMOM$ factor is derived by deducting the average return of the two bottom ESG Momentum portfolios from the two top ones. The resulting factor can therefore, similar to the ones above, be interpreted as the monthly excess return of a high ESG momentum portfolio compared to a low one, representing the anomaly associated with the ESG factor.

### 5.4 Regressions

The main contribution in this paper is the integration of the ESG Momentum into the Fama French framework as an additional factor. As we try to illustrate in our cumulative performance analysis of an ESG Momentum long-short portfolio, the change in a company's ESG profile has significant impact on its performance. If that is the case, then ESG data might be a source of outperformance which is not captured by traditional asset pricing models. In particular this means, that in a Fama

French framework there would be a significant alpha which the initial factors cannot explain. In order to test this hypothesis, we are creating a regression model based on the Fama French framework resembling the one of Carhart (1997) which includes his four factors: *Market Excess Return, SMB, HML and Price Momentum*. After using the above mentioned models to test the ESG Momentum strategy for outperformance or significant alpha we implement the ESG Momentum factor into the 4-factor framework of Carhart.

### 5.4.1 ESG Momentum Quintile Portfolios

In a first step we are recalling our analysis from above referring to the cumulative outperformance associated with a long-short portfolio based on ESG Momentum. To test this hypothesis of outperformance not cumulatively but on a monthly basis, we are applying our ESG Momentum strategy to a traditional asset pricing model like the Carhart (1997) 4-factor model. As explained in section 3.2 the Carhart model is one of many extensions of the CAPM and includes four risk factors which help explain portfolio returns.

$$r_{it} = \alpha_{iT} + \beta_{iT} MRKT_t + \gamma_{iT} SMB_t + \delta_{iT} HML_t + \epsilon_{iT} PMOM_t \tag{9}$$

By means of the model equation above we are running regressions on our five quintile portfolios based on the ESG Momentum. By running the regression on all the portfolios separately we can, on the one hand, observe if there is a higher monthly excess return associated with a higher ESG momentum portfolio. On the other hand, we can determine if there is a significant outperformance in the form of alpha in any of the portfolio which is not explained by the four factors of the model. Since we are trying to discover an anomaly with respect to ESG Momentum, we are hereby expecting a significant positive alpha for the top quintile and correspondingly a negative alpha for the bottom quintile, indicating a lack of explanatory power of the model. In this case the ESG Momentum strategy would be a profitable strategy to use for investors signaling a potential to outperformance.

### 5.4.2 Return-Sorted Portfolios

In a subsequent step we are testing the implementation of our constructed ESG Momentum factor in the above outlined regression framework. We are hereby referring back to our result from above which serves as the basis of this step of the analysis. Under ideal results we would observe the significant positive and negative alpha for our top and bottom quintile respectively, thereby justifying the integration of our ESG Momentum factor to account for the anomaly. In case the results will be not as expected we will still run the regression including the ESG Momentum factor for the sake of completeness. Our goal in this regression setup is therefore to test our ESG Momentum factor for significance and assess whether it helps improve the explanatory power of the model. For this purpose we are estimating the regression model in two modifications. The first one is simply the 4-factor model as represented by equation 9. The second one, however, additionally includes our ESG Momentum factor as explanatory variable for the excess returns of the portfolios on the left hand side, leading to equation 10.

$$r_{it} = \alpha_{iT} + \beta_{iT}MRKT_t + \gamma_{iT}SMB_t + \delta_{iT}HML_t + \epsilon_{iT}PMOM_t + \phi_{iT}ESGMOM_t \tag{10}$$

The second purpose of this regression setup is to create a performance attribution model explaining the construction of portfolios on the left hand side. Inspired again by the 4-factor model of Carhart (1997), we are constructing ten monthly rebalanced decile portfolios formed on the past year's return. The highest decile therefore by definition includes the firms with the highest performance over the past year, while the ones with the worst performance are sorted into the lowest decile. By means of the ten separate regressions we are accordingly able to measure each factor's contribution to the out- and underperformance of each of the ten portfolios. Overall, we therefore not only test our ESG Momentum factor for statistical significance, but also observe if its coefficient systematically changes across performance portfolios indicating varying exposures to the factor.

To assess whether our additional ESG Momentum increases the regression model's explanatory power of the portfolios' excess returns, we compare the adjusted $R^2$ and the mean absolute errors (MAE) of the 4- and 5-factor model specifications. While the adjusted $R^2$ hereby measures the share of by the model explained residuals, adjusted by the number of predictors, the MAE estimates the size of errors in a set of predictions.

#### 5.4.3 Industry Breakdown

In order to further investigate the potential of the ESG Momentum as an additional factor in the model we are breaking down the data set to different sectors again. As addressed in section 2.4, the impacts of each pillar on performance are dissimilar when analysing them with respect to a certain industry or business context. According to Khan *et al.* (2016) each industry possesses a pillar which is most material for its operations and therefore has the evidently highest impact on performance. Based on this statement, we want to repeat our conducted analysis from above specified to a certain industry and with respect to the ESG pillar they are most exposed to. For simplicity and due to the scope of this thesis, we will replicate the analysis for two industries in Europe where we expect the most distinct results and patterns regarding their material pillar. On the one hand, we decided to use the Utilities sector since it is by nature highly dependent on carbon emissions and therefore exposed to the environmental pillar. On the other hand, we are investigating the Financial sector which, among all industries, is most exposed to the governance pillar. Comparing these two industries and the impact of each pillar separately will provide insight into whether there are systematical differences between industries and if performance can be attributed to one specific pillar improvement within each sector.

$$\begin{aligned} r_{it} \; = \; & \alpha_{iT} \; + \; \beta_{iT} MRKT_t \; + \; \gamma_{iT} SMB_t \; + \; \delta_{iT} HML_t \; + \; \epsilon_{iT} PMOM_t \\ & + \; \phi_{iT} EMOM_t \; + \; \pi_{iT} SMOM_t \; + \; \rho_{iT} GMOM_t \end{aligned} \tag{11}$$

For this purpose we are in a first step replicating the analysis from equation 9 which regresses the Momentum quintile portfolios on the four Carhart (1997) factors. In contrast to before, we are at this point creating the Momentum portfolios based on the material pillar for the sector investigated. In case of Utilities, we therefore employ the E Momentum factor for portfolio construction, while for the Financial sector we use the G Momentum. We can correspondingly compare if the outperformance of the portfolios, based on the change in the material pillar, deviates from the one we observed under our initial full sample analysis.

In a second step, we are similar to section 5.4.2, creating decile portfolio based on the lagged one-year return which we regress on our factor portfolios. We are hereby again implementing our Momentum factor as an additional explanatory variable but in this case decomposed into its pillars. As equation 11 shows, each of the pillars now has its own factor portfolio which we will test for significance across the decile portfolios. Employing this approach therefore enables us to assess whether each pillar has the same impact on return within the portfolios or if the material pillar of the specific industry will be more significant in contributing to portfolio returns.

### 5.5 Robustness Checks and Econometric Considerations

We perform several robustness checks to validate our results, as we want to avoid biases in our regression results stemming from misspecified factor models. These checks refer, on the one hand, to empirical tests and, on the other other hand, to parameters and restrictions used in our analytical approach.

We start out by looking into whether our results are robust towards some simple changes in terms of the chosen methodology. We restrict this part of the analysis to the main contribution of this thesis, which is the 5-factor model including the ESG Momentum factor, as it is mainly the impact of this additional factor we want to validate. In our main analysis we have constructed value-weighted decile portfolios. To see whether this choice of portfolio construction impacts our results, we replicate our regression analysis with equal-weighted portfolios. In addition, we investigate whether the results are robust against different time frames and restrictions with respect to firm size. As we are covering a rather short time horizon compared to similar empirical factor analyses (see Fama & French (1992) and Carhart (1997)), we understand that our choice of time frame might impact our results. As MSCI does not offer ESG ratings before 2006, this naturally limits the possible time frame. At the same time, the updated methodology of the ESG data could affect the quality of our results, as previously discussed. Thus, we try to both adjustments of including the whole time frame with available ESG data from MSCI but also restricting the sample to only the period after the methodology update in 2013. The results of this robustness check might give an indication on whether the chosen time frame is driving our results.
Additionally, we test whether the firm size has any important implications, by restricting our sample

to the 200 largest firms within each market. Through this restriction, we can see whether returns within the largest segment of the sample react differently to the ESG Momentum factor.

Moving on to the econometric challenges of running standard linear regressions, there are some essential considerations with regard to the assumptions that are needed for a model to produce unbiased and consistent estimators. For these tests we extend the analysis to include both the 4- and 5-factor model. We first address the issue of autocorrelation, which is the notion of time dependence in the data and refers to the correlation of an explanatory variable with its past values. We further test the models for heteroskedasticity, which means that the variance of the error terms is not constant. Neither the presence of autocorrelation, nor of heteroskedasticity lead to an unbiased estimator, but make the model inefficient and the derived standard error unusable for inference. There are a number of ways to test for autocorrelation in the error terms, where the Durbin Watson test and the Breusch-Godfrey test are the most widely used (Wooldridge, Jeffrey M., 2012). We decided to apply the Breusch-Godfrey test, as it is more flexible with respect to the order of lags it can detect compared to the Durbin Watson test. The null hypothesis of the Breusch-Godfrey test is no serial autocorrelation. Additionally, the presence of heteroskedasticity will be analysed by the Breusch-Pagan test, which has a null hypothesis of homoskedastic error terms. In case we find a wide-spread heteroskedasticity and autocorrelation in the time-series data, we will in response use Newey-West standard errors in our regressions. These will correspondingly account for heteroskedasticity and autocorrelation in the error terms and ensure an efficient estimation. This procedure is a standard approach within the research of asset pricing models (Wooldridge, Jeffrey M., 2012).

$$VIF_i = \frac{1}{(1 - R_i^2)} \tag{12}$$

We also test for multicollinearity, which occurs whenever the explanatory variables are correlated with each other. The presence of multicollinearity will cause the regressions to have difficulties in distinguishing which of the explanatory variables are driving the results. As we in our research apply models which are widely used within the academic theory, we find it reasonable to assume that the models do not contain a high degree of multicollinearity. However, since we are including an additional factor in this paper, we still find it necessary to investigate the matter. As explained above in this chapter, we will look into the cross-correlations between the constructed factor portfolios which gives a first indication of the degree of multicollinearity the models contain. As an additional robustness, we will further run a variance inflation factor (VIF) test. The VIF-test hereby runs regressions for each of our five factors as dependent variable, using the remaining factors in the model as explanatory variables. It therefore rules out biases through too high correlations between the factors, in addition to our initial check of cross-correlations. The VIF-factor is then calculated as follows from Equation 12 Wooldridge, Jeffrey M. (2012).

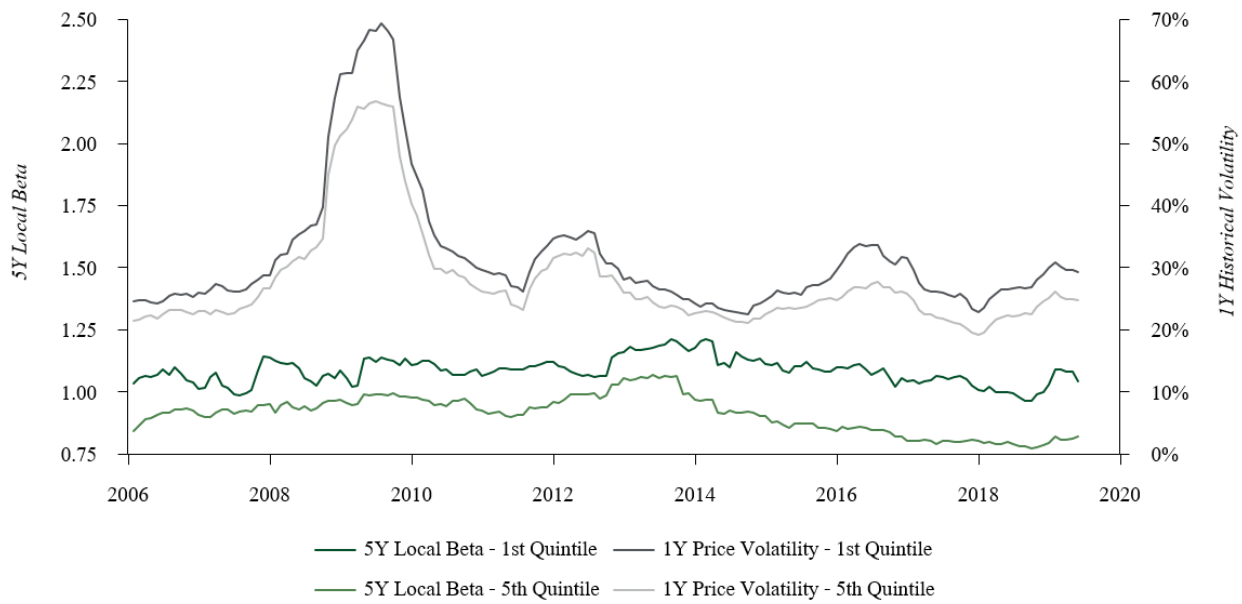
# 6 Results

The upcoming section summarises our findings with respect outlined analysis in the methodology section. We are covering each results section in the same manner as the structure of section 5. We are therefore starting with our general risk analysis before we go into detail on the constructed ESG Momentum and its factor characteristics. The results to our main analysis and regressions will then be found in the last part of this section providing the main contribution of our thesis.

## 6.1 ESG Risks

As delineated in section 5.1, we are conducting an analysis of the individual risk exposure of firms dependent on their ESG profile and based on European and U.S. firms combined. In particular, we are measuring systematic and idiosyncratic risk in the form of beta and price volatility respectively for each of our five quintiles based on the industry-adjusted ESG score. We are hereby expecting a consistent time independent pattern of a systematically higher risk exposure for firms within the poor versus in the high quintile. Figure 4 below depicts the time-series average of the firms' 5Y backward looking local beta and the 1Y historical price volatility for the best (Q5) and worst (Q1) ESG score quintile. The upper two grey lines hereby show the average price volatility with reference to the right percentage scale axis. The lower two green lines conversely, illustrate the beta scaled on the left-side axis. For illustration purposes we only plotted the risk curves for these two extreme ESG profiles. The pattern of the relationship between ESG and risk profile for all of the quintiles, however, will be picked up at a later stage in this section.

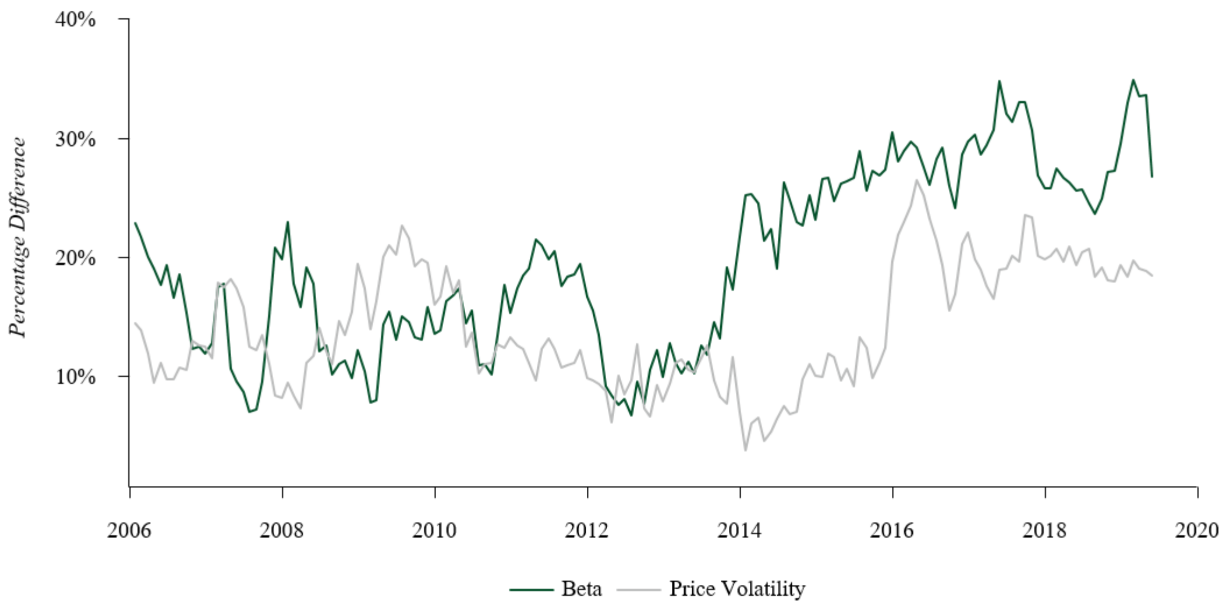
*Figure 4: Beta and Price Volatility of Best (Q5) and Worst (Q1) ESG Quintile*




*The figure above depicts the plotted 5Y Beta as well as the 1Y historical price volatility for the 1st and 5th quintile separately. The metrics are extracted on a monthly basis form the S&P Capital IQ platform for each firm in the sample and averaged after. The geography covered is hereby Europe and the U.S. over a time frame from January 2006 until May 2019.*

As we can see on the basis of Figure 4, there is a consistent pattern over time showing systematically higher risk metrics of firms in the poor ESG quintile compared to the high one. With respect to the stock-specific risk, an average firm in the worst quintile possesses a stock price volatility of around 32% while the average firm in the best quintile only has about 28%. More precisely, the idiosyncratic risk of a firm with a poor ESG profile is substantially higher and above the one of a high-ranked ESG firm at every point in time. The price volatility is hereby relatively stable throughout the entire timeframe except for the period after the Great Financial Crisis, in which volatility peaked around 70% and 60% for the poor and high ESG quintile respectively. This consequently increases the overall average across the entire time-series making the price volatility in general quite high compared to the volatility of the MSCI World or S&P 500. In general this curve progression with a peak around 2009/2010 is very similar to our baseline paper from Dunn *et al.* (2018), even though their volatility levels are not as high as ours. Looking at the beta curves, we can as well observe a significantly higher level of systematic risk in the form of beta at every point in time.

*Figure 5: Percentage Difference of Beta and Price Volatility between Best (Q5) and Worst (Q1) ESG Quintile*




*The figure above depicts the plotted percentage difference in betas and price volatility between the 1st and 5th quintile based on the ESG score. The betas and price volatility are extracted from S&P Capital IQ on a monthly basis for each firm in the sample. The geography covered is hereby Europe and the U.S. over a time frame from January 2006 until May 2019.*

Throughout the entire observation period we can observe a consistent gap for both risk measures, volatility and beta, between the lowest and the highest ESG score quintile. This confirms the negative relationship between a firm's ESG profile and its risk exposures. Looking at Figure 5, which plots the percentage difference between the best and worst ESG quintile for both of the risk metrics, this observation becomes even more apparent. The graph depicts a continuously positive spread of volatility as well as beta moving from the lowest-ranked to the highest-ranked firms. More specifically, the volatility of the lowest ESG score firms is on average 14% higher, whereas the beta even reaches an average difference of 20%. While the overall observation of the analysis is similar to the findings of Dunn *et al.* (2018), the extent to which lower ESG firms show a higher risk profile is substantially larger in our results. Dunn *et al.* (2018) correspondingly estimate an average difference of around 15% for the volatility and only 3% for the beta. These differences in findings, especially with respect to the beta, are quite substantial but might be traceable back to the differences in the parameters and the estimation approach.

*Table 4: Summary Statistics on Risk Measures*

| | *Q1 (poor ESG)* | *Q2* | *Q3* | *Q4* | *Q5 (high ESG)* | *Q5-Q1* |
|---|---|---|---|---|---|---|
| Industry-Adj. ESG Score | 1.99 | 3.71 | 5.04 | 6.50 | 8.59 | 6.6 (209.8) |
| | | | | **Risk Metrics** | | |
| Stock Volatility | 31.82% | 31.28% | 30.73% | 30.06% | 27.82% | -4.0% (-3.7) |
| Local Beta | 1.09 | 1.08 | 1.04 | 0.99 | 0.91 | -0.17 (-24.0) |
| MSCI World Beta | 1.03 | 1.02 | 1.01 | 0.97 | 0.92 | -0.12 (-13.8) |
| | | | | **Performance** | | |
| Annualised Return | 8.77% | 11.36% | 6.99% | 6.63% | 5.15% | -3.62% (-11.1) |
| | | | | **Characteristics** | | |
| Market Cap (USD m) | 14,940 | 16,717 | 19,091 | 23,531 | 28,210 | 13,270 (24.3) |
| Book-to-Market | 0.57 | 0.60 | 0.55 | 0.52 | 0.51 | -0.06 (-1.7) |
| Price Momentum | 8.05% | 10.05% | 6.36% | 6.05% | 4.69% | -3.36% (-10.9) |
| Profitability | 0.25 | 0.26 | 0.26 | 0.26 | 0.27 | 0.02 (11.9) |

*The table above shows the risk metrics as well as the firm characteristics for each quintile. The quintiles are based on the ESG scores for the entire data sample for the U.S. and Europe between January 2006 and May 2019. The last column represents the difference between the highest (Q5) and lowest (Q1) quintile with t-statistics in parentheses. The profitability measure is defined as the Gross Profit over Total Assets.*

All of the above mentioned findings are summarised in Table 4, which covers all of the five ESG quintiles. In addition, the table provides an overview of firm characteristics and performance indicators, which gives further insight into the companies sorted into each of the quintiles respectively. The last column describes the spread between the highest and lowest quintile.

The top row of the table shows the average industry adjusted ESG score. Looking at the two extreme ones, it is obvious that the spread between the score levels is quite significant which further implies large differences in the companies itself. Below this score overview, Table 4 summarises the risk measures depicted in Figure 4 and 5 above. For all of the three metrics there is a constantly decreasing pattern in risk measures moving from the lowest quintile (Q1) to the highest (Q5) confirming the hypothesis that larger ESG scores induces lower systematic as well as idiosyncratic risk. While the beta of the graphs above refer to its local index measure, Table 4 also exhibits the MSCI World beta which appears slightly lower but shows the same trend when moving from the poor to the high ESG quintile. The last column of the table further displays the difference between the two extreme quintiles alongside their t-statistic in parentheses. As can be seen from the high t-statistics of the risk measures, the difference between Q5 and Q1 is statistically significant on the 1% level for all of them.

Besides the risk measures, Table 4 also reports performance and firm characteristics providing further insight into which companies are sorted into each of the five quintiles. The most obvious pattern is hereby the market capitalisation which steadily increases towards the higher ESG quintile. Similarly, a firm's profitability measured as the ratio of gross profit to total assets appears to be higher for firms in the high ESG quintile with a statistically significant difference. The book-to-market ratio in turn, categorising a firm as growth or value firm, is decreasing moving from the poor to the high ESG quintile. The price momentum does not show any distinct pattern across quintiles.
Looking at the annualised return across quintiles there is no clear pattern identifiable moving from the lowest to the highest quintile. However, comparing again the two extremes we find a statistically significant higher annualised return of the low ESG quintile compared to the high one. Recalling our analysis of Hong & Kacperczyk (2009), this superior performance of poorly ranked firms might on the one hand be subject to the neglect premium stemming from the lower investors demand and therefore lower prices of these assets. On the other hand though, in line with Dunn *et al.* (2018) and our results of the risk assessment above, the higher return might also include a compensation for the additional risk that low ESG score firms carry. This intuition is further supported by the patterns of stock characteristics discussed above. Since low ESG scores tend to be smaller in size, exhibit a higher book-to-market ratio and are therefore cheaper, the market in turn assigns them with lower valuations. Part of the Q1 outperformance might therefore be a result of a small cap premium paired with cheap valuations of low-ranked ESG stocks (Dunn *et al.*, 2018).

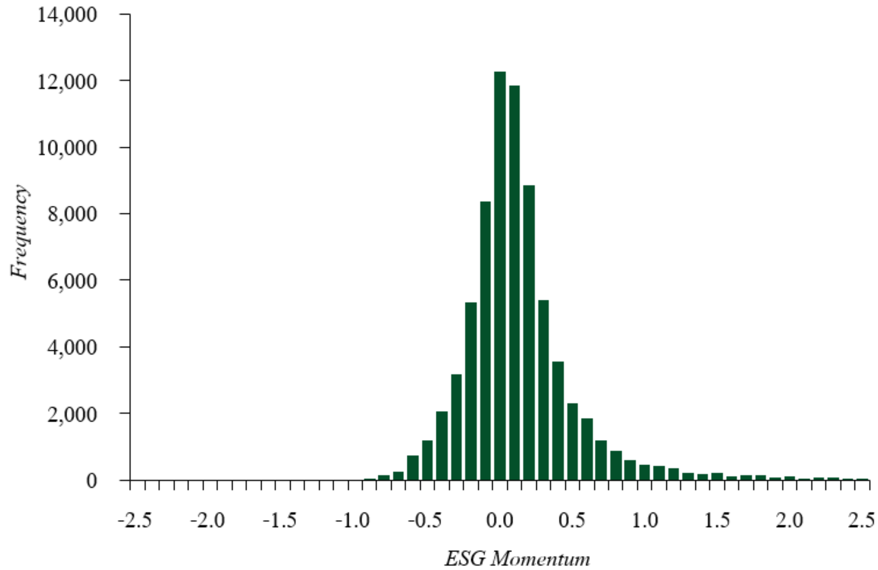
In conclusion, all of our results are in line with our reference paper by Dunn *et al.* (2018) which served as the methodological foundation of this analysis. The pattern of systematically higher risk for low ESG score firms compared to high-ranked firms is time consistent and with 14% for the volatility and 20% for the beta also quite drastic. Note at this point that we acknowledge that this is a baseline risk assessment which does not control for additional company characteristics. Expanding the analysis by control measures for firm characteristics and quality measures as presented in Table 4 might yield a less strong difference in risk exposures between the highest and lowest ESG quintile. Due to the scope and limit of this thesis, however, we will not cover these additional analysis but only focus on our main hypothesis. Since we have demonstrated that ESG data contains information on a firm's risk profile which complement traditional risk models, it is evident that the consideration of ESG in the investment process has financial incentives beyond ethical ones.

### 6.2 The ESG Momentum Factor

As outlined in section 5 on our methodology, our ESG Momentum factor is constructed based on the approach by Giese & Nagy (2018) for our two samples, the U.S. and Europe. Even though the foundation of our approaches is the same, our methodology contains a few key differences which might be the reason for discrepancies between the results of Giese & Nagy (2018) and ours presented below. As explained in section 5 we are computing a cumulative return of the past 15 months instead of calculating the simple year-on-year return. This is similar to the initial price momentum methodology and decreases the number of zero Momentum factors due to not yet updated scores. In addition, unlike Giese & Nagy (2018), we are neither capping our Momentum factor nor deleting zeros from the sample as this did not impact our results significantly.

The result of our ESG Momentum factor construction is visualised in Figure 6 representing the histogram with the frequency of the underlying Momentum factors. For illustration purposes, we hereby only plotted the factors in the range of -2.5 to 2.5, omitting some outliers in the highly positive range of the scale. Moreover, we summarised the statistics of the ESG Momentum distribution in Table 5 beneath the histogram. Looking at Figure 6 we can see that most of the observations are concentrated in the middle of the histogram around the mean of 0.115. Having a mean of 0.115 here means that the average firm in our two samples improves it's ESG score by 11.5% within the past 15 months. Furthermore, we can infer from the positive mean as well as the large positive skew that our data set is largely tilted towards score upgrades mainly due to our large positive outliers. Note, that this might further entail important implications for performance since portfolios based on ESG Momentum are likewise tilted towards firms with an upward trend in ESG scores (Giese & Nagy, 2018).

*Figure 6: Histogram of ESG Momentum Factors*




*The figure above presents the histogram of the constructed ESG Momentum factor for a range from -2.5 to 2.5. The ESG Momentum factor is calculated based on a 15-month lookback period for the time frame between January 2006 and May 2019.*

*Table 5: Statistics of ESG Momentum Distribution*

| *Mean* | *Std. Dev.* | *Skew* | *Kurtosis* |
|---|---|---|---|
| 0.115 | 0.6261 | 8.4213 | 120.4346 |

Even though the histogram reveals a nice frequency with concentration around the mean, the distribution is not that well behaved which is further reflected in its kurtosis of 120.4. While the normal distribution has a kurtosis of around 3 and the logistic distribution of around 4.2, our results are far away from that. Our results are thereby not only in strong contrast to these standard distributions but also to the findings of Giese & Nagy (2018) whose distribution resembles a logistic one. As mentioned above, these discrepancies in statistics on the distribution might stem from differences in the methodology used to calculate the ESG Momentum. In addition to the different lookback horizons and return calculation applied, Giese & Nagy (2018) delete all zero ESG Momentum factors from their sample which we do not consider reasonable. Furthermore, there is no indication in their paper of how they treat large outliers as we experience them in our data sample. The implications of these differences will be picked up and tested at a later point in this section.

For the remainder of this paper we are dividing our data sample not only into the two geographical areas, Europe and the U.S., but also into quintiles based on the ESG Momentum score which are the basis of our main analysis. Furthermore, due to data inconsistencies and a lack of quality, we use data from 2010 on to construct our factors. Table 6 including Panel A and B below summarises the basic descriptive statistics of these five portfolios for each of the two regions. Looking at the distribution of characteristics across the quintiles it is notable that many of the factor development resemble a U- or inverted U-shape with their extreme values in the middle range. We can accordingly find the firms with the lowest BTM, highest profitability, highest average ESG score and thus also with the lowest beta and volatility in Q3. For the U.S., we can further find the largest firms, measured by market cap, in quintile 3. These characteristics therefore apply for the firms which are associated with the most neutral change in their ESG score (Q3).

*Table 6: ESG Momentum Descriptive Statistics*

***Panel A: European Sample***

| | *Q1 (low)* | *Q2* | *Q3* | *Q4* | *Q5 (high)* | *Q5-Q1* |
|---|---|---|---|---|---|---|
| Ind-Adj. ESG Score | 3.03 | 4.79 | 5.49 | 5.41 | 4.65 | 1.66 (37.6) |
| Market Cap | 20,954 | 21,218 | 20,649 | 19,888 | 16,184 | -4,771 (-9.39) |
| Book-to-Market | 1.01 | 0.65 | 0.60 | 0.66 | 0.67 | -0.34 (-3.66) |
| Beta | 0.99 | 0.91 | 0.90 | 0.91 | 0.99 | 0.00 (0.13) |
| Volatility | 32.6% | 29.9% | 27.5% | 30.3% | 31.0% | -1.63% (-1.41) |
| Price Momentum | 7.5% | 2.6% | 6.1% | 3.2% | 4.4% | -3.1% (-0.94) |
| Profitability | 0.23 | 0.26 | 0.26 | 0.26 | 0.24 | 0.01 (4.30) |

***Panel B: U.S. Sample***

| | *Q1 (low)* | *Q2* | *Q3* | *Q4* | *Q5 (high)* | *Q5-Q1* |
|---|---|---|---|---|---|---|
| Ind-Adj. ESG Score | 4.92 | 6.75 | 7.06 | 7.04 | 6.34 | 1.42 (11.2) |
| Market Cap | 22,629 | 23,308 | 27,049 | 25,348 | 21,199 | -1,429 (-2.07) |
| Book-to-Market | 0.51 | 0.46 | 0.43 | 0.46 | 0.45 | -0.05 (-3.79) |
| Beta | 1.00 | 0.98 | 0.98 | 0.95 | 1.00 | 0.00 (-0.51) |
| Volatility | 31.2% | 30.2% | 27.0% | 29.1% | 30.7% | -0.49% (-0.34) |
| Price Momentum | 8.2% | 8.6% | 10.0% | 7.9% | 9.9% | 1.7% (0.72) |
| Profitability | 0.25 | 0.26 | 0.27 | 0.28 | 0.26 | 0.01 (2.32) |

*The table describes the value of average factors values as well as the industry-adjusted ESG scores across quintile portfolios created on our 15-month ESG Momentum. Panel A describes the European sample, whereas Panel B covers the U.S. sample over the period between January 2010 to May 2019. The last column represents the difference between the highest (Q5) and lowest (Q1) quintile with t-statistics in parentheses. The profitability measure is defined as the Gross Profit over Total Assets.*

On the extreme sides of the quintiles, in Q1 and Q5, we can observe statistically significant differences in the factor values for most of the variables presented in the right column. The high ESG Momentum quintile consists of smaller firms which possess a higher average ESG as well as a lower BTM. Especially in Europe the score and small cap bias is highly significant implying a high exposure towards these factors in an equity model. In general, these characteristics indicate that we expect smaller and growth firms to experience the highest ESG profile improvements, while larger value firms rather exhibit a modest or negative development of scores.

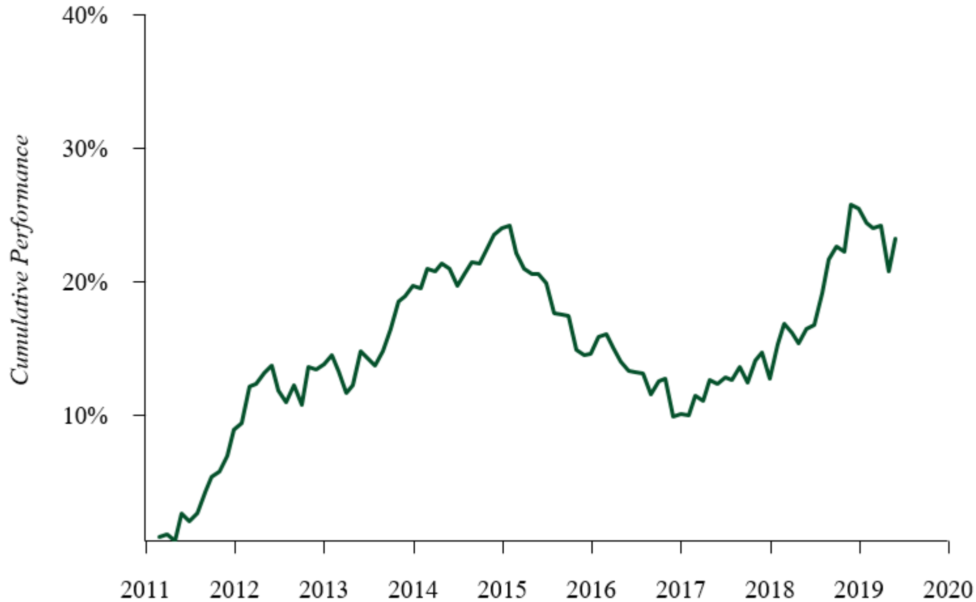
With respect to the price momentum it is notable that there is no clear pattern or a statistically significant difference between the two extreme quintiles. Overall it is obvious that there does not seem to be a high correlation between the ESG Momentum and specific firm characteristics or quality factor which is further supported by Appendix III.

In order to find the optimal strategy of integrating ESG data, and specifically our ESG Momentum factor into existing equity models, it is further crucial to understand its relation to standard equity style factors of these models. To follow up on the descriptive statistics of companies in each ESG Momentum quintile, we calculate the correlations between the ESG Momentum and essential equity style factors. Appendix III summarises these correlations and contrasts them with the correlations of the industry adjusted ESG scores. This gives us an initial understanding of how ESG ratings and their Momentum are connected to typical equity factors and which implications we can draw from these correlations of their integration into these models. High correlations between equity factors and one of the ESG factors could potentially bias our results due to multicollinearity in a regression setup. As we saw in our risk assessment, as well as in Appendix III, ESG scores have significant negative correlations with volatility and beta as well as a positive correlation with company size. The ESG Momentum factor in contrast, appears uncorrelated with all of the factors reducing the risk of large factor biases in equity models or portfolio construction to a minimum.

Since this fundamental hypothesis of our paper is that higher ESG Momentum firms experience a better stock performance in compared to a low ESG Momentum, we are creating a hypothetical portfolio with a long position in the high ESG Momentum quintile (Q5) and a short position in the lower one (Q1). The performance of this long-short portfolio is plotted in Figure 7 representing a high-level analysis of performance implications of our suggested ESG Momentum strategy. For simplicity we hereby plot the U.S. and Europe together since their development is similar. Furthermore, due to data inconsistency which lead to a very volatile and often negative cumulative performance, we decided to use only data from 2010 onwards. Since our ESG Momentum factor is constructed based on a 15-month lookback period, the plot shows the cumulative performance after 2011. Since our time frame in general is quite short, we decided to exclude this time of the financial crisis as it is not representative of the general pattern and biases results.

As can be seen in Figure 7 the graph has an overall positive trend indicating an outperformance associated with the long-short strategy based on the ESG Momentum. The cumulative performance of this monthly balanced hypothetical portfolio ends up with a cumulative outperformance of 23% after a holding period of a bit over eight years. These findings are in terms of trend in line with Giese & Nagy (2018), but overall larger in size. This can, on the one hand, be traced back to our sample only covering European and U.S. firms and, on the other hand, to the larger time frame covered. However, the biggest anomaly which we do not observe in the research by Giese & Nagy (2018) is the significant unexplained negative performance of the long-short portfolio between 2015 and 2017. Due to our small period covered this is an anomaly which might impact our results largely with a view to our subsequent analysis.

*Figure 7: Cumulative Performance of Long-Short Portfolio in Q5 and Q1 of ESG Momentum Quintiles*




*The figure above represents the cumulative performance of the long-short portfolio constructed based on the highest (Q5) and lowest (Q1) ESG Momentum quintiles. The graph covers the time frame between January 2011 and May 2019 and is plotted combined for Europe and the U.S.*

## 6.3 Regressions

Based on the findings for the cumulative outperformance of the high ESG Momentum versus the low ESG Momentum quintile, we are presenting the main part of our analysis in the subsequent paragraphs. As indicated in our hypothesis in section 3.5, our goal and main contribution is to integrate the ESG Momentum as an additional factor into the Fama French framework alongside the four factors of the Carhart (1997) paper. We are hereby aiming to add explanatory power to the model by including a statistically significant ESG Momentum factor which helps explain the performance attribution to each of the factors. All of the analyses and regressions below are conducted for Europe and the U.S. separately and with factors constructed over the time frame of 2010 until 2019 in line with our cumulative performance analysis in Figure 7.

For this purpose, it is essential to first look at the summary statistics of the created five factor portfolios created based on the methodology outlined in 5.3. This summary statistics include monthly excess returns of each of the factor portfolios as well as cross-sectional correlations between them. While the first one helps estimating each factor's possible impact on explaining portfolio returns in the main regression, the latter ensures we are not exposed to any kind of biases due to multicollinearity. This issue will be further addressed below in Section 6.4. Table 7 and Appendix IV present these summary statistics for the factor portfolios of the European and the U.S. market respectively.

*Table 7: Cross-Correlations on Factor Portfolios Europe*

| *Factor* | *Monthly* | *Std.* | *Cross-Correlations* | | | | |
|---|---|---|---|---|---|---|---|
| *Portfolio* | *Excess Return* | *Dev.* | *MRKT Excess* | *SMB* | *HML* | *PMOM* | *ESGMOM* |
| Mrkt Excess Return | 0.98% | 3.26% | 1.00 | | | | |
| SMB | 0.37% | 1.16% | 0.31 | 1.00 | | | |
| HML | -1.42% | 3.03% | 0.29 | 0.24 | 1.00 | | |
| Price Momentum | 0.43% | 3.27% | -0.36 | -0.27 | -0.68 | 1.00 | |
| ESG Momentum | 0.02% | 1.18% | -0.02 | -0.04 | -0.20 | 0.29 | 1.00 |

*The table above exhibits the average excess return as well as the standard deviation for each of the factor portfolios created for the 4- and 5-factor regressions. Additionally, the table shows the cross-correlation matrix of the factors.*

The low cross-correlations between the factors and the market proxy depicted in Table 7 for Europe indicate that multicollinearity does not have a large effect on models containing these factors. In particular it is striking that especially the ESG Momentum exhibits imperceptible correlations of below 12% with all of the factors. The only exception from all low cross-correlations is the relationship between the HML and price momentum factor which is largely negative. Similar observations can be made when looking at Appendix IV and the corresponding factor correlations for the U.S.. While all the cross-correlations between the factor portfolios are sufficiently small, especially for the ESG Momentum factor, there is the same high negative outlier for the cross-correlation of the HML and Price Momentum factor.

With respect to the monthly excess returns on the factor portfolios in Europe we can observe that all of the initial four Carhart (1997) factors are large in size. Correspondingly, they seem to account for a lot of the cross-sectional variations in the mean of portfolio returns. The ESG Momentum factor portfolio's monthly excess return, in contrast, is with 0.02% quite small. Looking at the outperformance graph in Figure 7 once again, this small monthly return might be a result of the negative period between 2015 and 2017 which presses down the return close to zero on a monthly basis. However, with respect to the standard deviation, all four factors seem to have a quite large variance compared to the ESG Momentum factor portfolio. This means that, even though the ESG Momentum factor does not account for a lot of variation in mean portfolio returns, it might still contribute with an economically small but stable and on average positive effect on portfolios. Looking at the U.S. table in Appendix IV the pattern is once again quite similar. While all of the initial four Carhart (1997) factors might be able to explain a large share of the cross-sectional variations in mean portfolio returns, they also show substantially higher variances. In this case, the price momentum factor, however, has a surprisingly low average monthly excess return. The ESG Momentum factor conversely, seems to have, with an average monthly excess return of high ESG Momentum firms of 0.13%, a larger economic impact compared to Europe. In both regions though, the monthly excess return of the ESG Momentum factor portfolio therefore indicates the tendency of high ESG Momentum firms outperforming low ones.

### 6.3.1 ESG Momentum Quintile Portfolios

Our first part of the regression analysis consists of the regression of the five quintiles based on ESG Momentum on our Carhart (1997) four factors. As we tested the cumulative performance of a long-short portfolio in the highest and lowest ESG Momentum quintile depicted in Figure 7, the purpose of this regression is to replicate this outperformance hypothesis on a monthly basis. We therefore estimate the difference in monthly excess return of the highest and lowest ESG Momentum quintile to assess whether there is a significant positive excess return associated with a high ESG Momentum factor.

In addition, we are further testing whether this outperformance is explained by the four model factors or whether there is significant alpha in one or more of the ESG Momentum quintile portfolios. As explained in section 5.4.1 and in line with our hypothesis, we would hereby expect the lowest ESG Momentum quintile (Q1) to show a significant negative alpha whereas the highest quintile should exhibit a significant positive alpha. This pattern would indicate a negative abnormal return associated with the worst ESG score development and a positive abnormal return for the highest ESG score improvement which is not explained by our four factors in the model. This in turn would suggest the ESG Momentum as the source of outperformance justifying its integration as an additional factor, accounting for this anomaly and explaining the abnormal returns. Furthermore, by means of this regression we are able to compare factor exposures across quintiles which gives further insight into the composition of the ESG Momentum portfolios.

*Table 8: 4-Factor Regression On ESG Momentum Quintiles Europe*

| *Decile* | *Monthly Excess Return* | *Std. Dev.* | *Alpha* | *Market Excess Return* | *SMB* | *HML* | *Price Momentum* | *Adj. $R^2$* |
|---|---|---|---|---|---|---|---|---|
| 1 (low) | 0.42% | 4.69% | 0.51%* | 0.862*** | -0.003 | 0.599*** | 0.062 | 79.3% |
| | | | (1.69) | (10.28) | (-0.02) | (5.33) | (0.57) | |
| 2 | 0.36% | 4.37% | 0.16% | 0.891*** | 0.031 | 0.426*** | 0.114 | 74.9% |
| | | | (0.55) | (10.62) | (0.15) | (3.8) | (1.06) | |
| 3 | 0.46% | 4.30% | 0.32% | 0.81*** | -0.096 | 0.417*** | -0.019 | 70.7% |
| | | | (1.07) | (9.67) | (-0.45) | (3.71) | (-0.17) | |
| 4 | 0.39% | 4.58% | 0.33% | 0.826*** | -0.102 | 0.413*** | -0.063 | 73.5% |
| | | | (1.09) | (9.85) | (-0.48) | (3.68) | (-0.58) | |
| 5 (high) | 0.48% | 4.76% | 0.49%* | 0.895*** | 0.134 | 0.63*** | 0.147 | 76.7% |
| | | | (1.70) | (10.68) | (0.63) | (5.61) | (1.37) | |
| 5-1 | 0.06% | 1.25% | -0.02% | 0.033 | 0.138 | 0.031 | 0.086 | 5.0% |
| | (0.0412) | | (-0.53) | (0.79) | (1.24) | (0.56) | (1.55) | |

*The table above presents the regression of the monthly excess return of five quintile portfolios based on the ESG Momentum factor regressed on the traditional four Carhart factors. The regression covers the data frame from 2010 to May 2019 and includes data for the European market. T-statistics are given in parenthesis below the coefficient. The asterisks behind the coefficients indicate the significance level:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 8 presents the actual result with respect to our above explained approach for the European sample. As we can see from the last row of the table, depicting the long-short portfolio consisting of the highest and lowest ESG Momentum quintile, there is no significant monthly excess return associated with our ESG Momentum strategy. In contrast to the observation in our outperformance graph, the return pattern on a monthly basis does not appear equally strong. In line with the monthly excess return of the ESG Momentum factor portfolio in Table 7, the difference in monthly excess return of the quintile portfolios is with a spread of 0.06% economically small and statistically

insignificant. Likewise, against our expectations, we do not estimate a significant alpha for our long-short strategy since both of the quintiles exhibit a similar positive alpha of 0.5% on the 10% significance level. This observation of an unexplained positive outperformance in both portfolios could possibly be traced back to the composition of the quintiles. The lowest quintile might for example contain a lot of sin stocks which are according to Hong & Kacperczyk (2009) carrying a neglect or risk premium in returns. Furthermore, the higher return could stem from well performing high ESG score stocks which have difficulties further improving their ESG profile and are therefore sorted into the lowest quintile. For the highest quintile, we could similarly argue that it only contains the prime ESG Momentum stocks which indeed have a higher performance and therefore trigger the positive alpha. These explanations are of course just a presumption and would need more investigation in order to be confirmed with certainty.
Looking at the U.S. output in Appendix V, we do estimate a larger difference in monthly excess return of Q5 and Q1 compared to Europe. With a spread of 26 basis points the highest ESG Momentum quintile outperforms the lower quintile, even though this difference is insignificant as well. Just as in Europe both extreme quintile portfolios hereby exhibit a positive significant alpha which stands in contrast to our initial hypothesis. As explained above there might be several plausible reasons for this unexplained performance in these portfolios such as the sin stock premium in the lower quintile and the superior ESG performance in the upper one.

With respect to the factor exposures in each of the two samples, we can come to similar conclusions for both regions. First, in both cases the market excess return represents the most significant factor in the model with consistently large coefficients across the quintile portfolios. Each quintile of the ESG Momentum strategy therefore has approximately the same positive exposure to market movements, which explain a large portion of the variation in returns across the portfolios. Apart from that we observe a mixed and inconsistent pattern for the other factors. While the stock momentum and the SMB are statistically insignificant for almost all of the quintile portfolios in the U.S. and Europe, the HML factor at least indicatse some explanatory power of the portfolios' returns in Europe. Here the portfolios exhibit a highly significant positive loading on the HML factor which paired with its monthly excess return of -1.72% depicted in Table 7 explains some downward pressure on the portfolios' overall monthly returns. Since all of the coefficients are quite similar across the five portfolios, however, it is not the reason for the difference in performance between Q5 and Q1 in

Europe. In the U.S. sample conversely, none of the three additional factors, with the exception of a few coefficients, seems to contribute to the performance of the ESG Momentum portfolios. The main driver of returns is here the market excess return which potentially might incorporate other omitted variables like the ESG Momentum itself.

Overall, the results for both regions suggest that most of the performance of each quintile is driven by the market excess return, since the other factors are mostly statistically insignificant except for the European HML factor. Furthermore, we can not observe any systematic pattern with respect to the factor loadings of the ESG Momentum portfolios which would help us understand varying exposures to certain type of stocks and thereby the composition of each of the portfolios. This in turn further implies that none of the four factors are able to explain the spread in the monthly excess returns of the two extreme quintiles. Since the $R^2$ are with 5% for the European sample and 8.6% for the U.S. sample remarkably low, there seems to be a lot of potential for increasing the model's explanatory power with an additional factor.

For this reason we will in the subsequent regressions still test the implementation of our ESG Momentum factor as an additional explanatory variable. Even though the outperformance of the long-short portfolio in both markets is not significant, we still see a positive abnormal return in the highest and lowest ESG Momentum quintile. This indicates that some part of the performance of the extreme quintile portfolios cannot be explained by the traditional factors and might correspondingly be traced back to the ESG dimension. Generally speaking, the analysis above has demonstrated the complexity and difficulty of explaining the performance patterns of the ESG Momentum investment strategy. The complexity of the ESG topic in a whole will be addressed in the discussion part of our results considering all the possible factors impacting and driving the results above.

### 6.3.2 Return-Sorted Portfolios

As outlined above for the sake of completeness, we will in this part of our analysis test the implementation of our ESG Momentum factor into the 4-factor model. As outlined in our methodology, we are creating ten decile portfolios based on the stocks' lagged one-year return whose monthly excess return is used as the dependent variable. Our output therefore compares the regression of the performance decile portfolios on the four Carhart (1997) as well as the five factors including our ESG Momentum. We thereby hope, by integrating the additional factor, to increase the explanatory power of the model in form of an increased adjusted $R^2$ and lower mean absolute errors (MAE).

*Table 9: 4-Factor Regression On Lagged One-Year Return Europe*

| *Decile* | *Monthly Excess Return* | *Std. Dev.* | *Alpha* | *Market Excess Return* | *SMB* | *HML* | *Price Momentum* | *Adj. $R^2$* |
|---|---|---|---|---|---|---|---|---|
| 1 | 0.24% | 7.11% | 1.03%*** | 0.927*** | 0.079 | 0.749*** | -0.748*** | 83.5% |
| | | | (3.3) | (11.8) | (0.39) | (6.97) | (-7.32) | |
| 2 | 0.16% | 6.17% | 0.61%* | 0.952*** | -0.061 | 0.662*** | -0.5*** | 83.5% |
| | | | (1.95) | (12.12) | (-0.3) | (6.16) | (-4.89) | |
| 3 | 0.26% | 5.07% | 0.19% | 0.894*** | -0.197 | 0.37*** | -0.418*** | 79.8% |
| | | | (0.62) | (11.38) | (-0.96) | (3.45) | (-4.09) | |
| 4 | 0.31% | 4.72% | 0.07% | 0.935*** | -0.153 | 0.351*** | -0.166 | 74.2% |
| | | | (0.21) | (11.9) | (-0.74) | (3.27) | (-1.63) | |
| 5 | 0.35% | 4.69% | 0.36% | 0.882*** | -0.24 | 0.535*** | -0.017 | 71.3% |
| | | | (1.14) | (11.23) | (-1.17) | (4.98) | (-0.17) | |
| 6 | 0.50% | 4.39% | 0.18% | 0.943*** | -0.255 | 0.41*** | 0.097 | 71.0% |
| | | | (0.58) | (12.0) | (-1.24) | (3.82) | (0.95) | |
| 7 | 0.49% | 4.21% | 0.22% | 0.913*** | -0.221 | 0.447*** | 0.197* | 70.5% |
| | | | (0.70) | (11.62) | (-1.07) | (4.16) | (1.93) | |
| 8 | 0.52% | 3.99% | 0.24% | 0.879*** | -0.123 | 0.439*** | 0.319*** | 68.0% |
| | | | (0.77) | (11.19) | (-0.60) | (4.09) | (3.12) | |
| 9 | 0.73% | 4.33% | 0.34% | 1.005*** | -0.113 | 0.489*** | 0.486*** | 71.1% |
| | | | (1.08) | (12.79) | (-0.55) | (4.55) | (4.75) | |
| 10 | 0.53% | 4.39% | 0.47% | 0.96*** | 0.205 | 0.65*** | 0.65*** | 73.0% |
| | | | (1.52) | (12.21) | (1.00) | (6.05) | (6.36) | |
| 10-1 | 0.29% | 5.27% | -0.62%** | 0.034 | 0.129 | -0.099 | 1.400*** | 71.2% |
| | (0.595) | | (-2.22) | (0.49) | (0.70) | (-1.04) | (15.35) | |

*The table above describes the regression of the monthly excess returns of ten decile portfolios based on lagged one-year performance on the traditional four Carhart factors as well as the ESG Momentum factor. The regression covers the data frame from 2010 to May 2019 and includes data for the European market. T-statistics are given in parenthesis below the coefficient. Asterisks behind the coefficients indicate the significance level: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.*

Table 9 depicts our 4-factor results for Europe while the outcome for the U.S. market is shown in Appendix VI. As can be seen in the first column both of the sample's monthly excess return of the portfolios have by construction an increasing pattern with the rank of the decile portfolio. However,

this pattern is not entirely monotonic but has a few outliers. For Europe, in Table 9, we can observe that the first and thereby worst performing decile portfolio is higher than expected by construction. In accordance with that it exhibits a positive significant alpha of 1.03% on a 1% significance level. We similarly observe a lower than by portfolio rank indicated monthly excess return for the highest decile portfolio, which similar to decile 1 has an unexplained, albeit insignificant, abnormal return of 0.47%. Looking at the long-short portfolio consisting of these two tail portfolios, we still observe an outperformance of the highest decile of 0.29% but also measure a difference of -0.62% between the two alphas on a 1% significance level. This result therefore indicates that there is an abnormal negative return on this long-short portfolio which is not explained by the model.
Similar observations can be made for the U.S. sample in Appendix VI in which we as well find a positive alpha for decile 1 on a 1% significance level. Looking at decile 10 we can in this case even observe a negative, albeit insignificant, abnormal return of the portfolio. Translating this into our long-short portfolio though, in fact yields an outperformance of 0.21% but also a negative and on the 1% level significant alpha of -0.91%. Consequently, we estimate a by the model unexplained return on the long-short portfolio consisting of the highest and lowest performing decile for both, the U.S. and Europe.

As suggested by Carhart (1997), we can use the remaining factor exposures to investigate each factor's contribution to the portfolio's performance and the spread between decile 10 and 1. For Europe, most of the spread between the two portfolios, depicted in Table 9, seems to be explained by the stock momentum factor indicated by the high t-statistics of its factor in the long-short portfolio. Similar to the pattern we can observe in the Carhart (1997) paper, the loading of the momentum factor systematically changes with the rank of the decile portfolio. While the lowest one has a large negative loading on the stock momentum, the highest decile exhibits a large positive exposure towards the factor. This in turn means that the lower deciles are exposed to past winner stocks performing poorly over the holding period, whereas for the upper deciles the usual stock momentum hypothesis counts. This pattern across the deciles is hereby not surprising since by construction the lowest deciles are the worst performing ones and thereby contain the worst stocks. As the monthly return on the momentum factor portfolio is 0.43% as depicted in Table 7 the spread between the highest and lowest decile coefficients of 1.4 explains a large portion of the performance of the long-short portfolio.

For the other factors in the European sample we cannot observe any systematic exposures of the decile portfolios. While the market excess return is, as usual, highly statistically significant with coefficients close to 1, none of the coefficients of the SMB factor are significant. As a result the difference in return between large and small firms does not impact portfolio returns. In our data sample this is not particularly surprising since, as described in our data section 4, our data set excludes small cap firms. We therefore do not expect a particular size effect across portfolios. Besides the market excess return, the HML factor exhibits statistically significant coefficients on the 1% level. All portfolios hereby exhibit a positive loading on the HML factor indicating they are behaving as value portfolios. Even though the coefficients are highly statistically significant, there is no systematic pattern observable across portfolios. In general, none of the factors besides the momentum factor shows a significant difference of coefficients in the long-short portfolio implying that they are not able to explain the spread in return between the highest and lowest decile.

For the U.S. the picture in Appendix VI looks slightly different. Here all factors seem to contribute to the outperformance of the long-short portfolio since they exhibit highly significant differences in coefficients between decile 10 and 1. The most prominent factor is hereby again the price momentum which is negative for the lower deciles and positive for the higher ones, in line with the findings of Carhart (1997). In general though its economical impact is rather small since the average monthly excess return on the factor portfolio is only 0.07% according to Appendix IV. Considering the market excess return coefficients which are very consistent across portfolios in Europe, we can recognise an increasing pattern with the portfolio rank in the U.S. sample. While the beta in decile 1 is only 0.95, it is 1.10 in decile 10 indicating a larger share of high beta and thus riskier stocks in the upper decile.

For the SMB and HML factor many of the coefficients of the decile portfolios are insignificant on the 10% level thereby not contributing much to the portfolios' performance. Nevertheless, we can observe a significant difference in coefficients for the long-short portfolio in decile 10 and 1. With respect to size, decile 10 seems to have, compared to decile 1, less exposure to small stocks which over the investment period were outperformed by large firms by on average -0.37% per month (Appendix IV). Similarly, decile 10 exhibits a negative loading on the value factor, meaning it's behaved like a growth portfolio, in contrast to decile 1 whose loading is positive. Since the average monthly excess return on the value factor portfolio is -1.45%, the difference in factor loadings of the two components of the long-short portfolio explain a considerable part of its outperformance.

*Table 10: 5-Factor Regression On Lagged One-Year Return Europe*

| *Decile* | *Monthly Excess Return* | *Std. Dev.* | *Alpha* | *Market Excess Return* | *SMB* | *HML* | *Price Momentum* | *ESG Momentum* | *Adj. $R^2$* |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.24% | 7.11% | 1.03%*** | 0.927*** | 0.080 | 0.750*** | -0.749*** | 0.018 | 83.5% |
| | | | (3.35) | (11.9) | (0.39) | (7.01) | (-7.40) | (0.08) | |
| 2 | 0.16% | 6.17% | 0.63%** | 0.935*** | -0.056 | 0.692*** | -0.52*** | 0.421* | 84.1% |
| | | | (2.05) | (12.01) | (-0.27) | (6.47) | (-5.14) | (1.95) | |
| 3 | 0.26% | 5.07% | 0.22% | 0.874*** | -0.191 | 0.405*** | -0.441*** | 0.49** | 81.0% |
| | | | (0.71) | (11.23) | (-0.94) | (3.79) | (-4.36) | (2.27) | |
| 4 | 0.31% | 4.72% | 0.09% | 0.915*** | -0.146 | 0.387*** | -0.19* | 0.507** | 75.5% |
| | | | (0.30) | (11.74) | (-0.72) | (3.62) | (-1.88) | (2.35) | |
| 5 | 0.35% | 4.69% | 0.38% | 0.864*** | -0.234 | 0.569*** | -0.039 | 0.467** | 72.5% |
| | | | (1.23) | (11.09) | (-1.15) | (5.32) | (-0.38) | (2.17) | |
| 6 | 0.50% | 4.39% | 0.21% | 0.923*** | -0.249 | 0.444*** | 0.075 | 0.478** | 72.5% |
| | | | (0.67) | (11.86) | (-1.23) | (4.15) | (0.74) | (2.21) | |
| 7 | 0.49% | 4.21% | 0.25% | 0.889*** | -0.213 | 0.491*** | 0.169* | 0.617*** | 73.2% |
| | | | (0.81) | (11.41) | (-1.05) | (4.59) | (1.67) | (2.86) | |
| 8 | 0.52% | 3.99% | 0.25% | 0.868*** | -0.120 | 0.458*** | 0.307*** | 0.266 | 68.6% |
| | | | (0.82) | (11.15) | (-0.59) | (4.29) | (3.03) | (1.23) | |
| 9 | 0.73% | 4.33% | 0.36% | 0.988*** | -0.107 | 0.52*** | 0.466*** | 0.431** | 72.3% |
| | | | (1.17) | (12.68) | (-0.53) | (4.86) | (4.6) | (2.0) | |
| 10 | 0.53% | 4.39% | 0.49% | 0.95*** | 0.208 | 0.667*** | 0.639*** | 0.241 | 73.4% |
| | | | (1.58) | (12.20) | (1.03) | (6.24) | (6.31) | (1.12) | |
| 10-1 | 0.29% | 5.27% | -0.60%** | 0.026 | 0.132 | -0.083 | 1.390*** | 0.223 | 82.6% |
| | (0.595) | | (-2.19) | (0.36) | (0.72) | (-0.86) | (15.19) | (1.14) | |

*The table above describes the regression of the monthly excess returns of ten decile portfolios based on lagged one-year performance on the traditional four Carhart factors as well as the ESG Momentum factor. The regression covers the data frame from 2010 to May 2019 and includes data for the European market. T-statistics are given in parenthesis below the coefficient. Asterisks behind the coefficients indicate the significance level: *$p<0.1$; **$p<0.05$; ***$p<0.01$.*

Even though part of the outperformance of the long-short portfolio in decile 10 and 1 can be explained by the factor exposures of the model, we still remain with a significant alpha for both samples. By integrating our additional factor, the ESG Momentum, we hope to explain part of the alpha and add explanatory power to the model. The latter point can easily be evaluated by comparing the 4-factor and 5-factor ESG Momentum model's error measure metrics. We hereby use, on the one hand, the common measure of the adjusted $R^2$ which measures the proportion of the variation in our portfolio returns which can be explained by the model parameters. On the other hand, we apply the metric of the mean absolute error (MAE) which measures the average size of the errors in the model. As we can observe by comparing Table 9 and 10 as well as Appendix VI and Appendix VII, the adjusted $R^2$ increases in both sample from the 4- to the 5-factor model specification. In particular, the average value in Europe increases from 74.6% to 76.3%, while in the U.S. from 88.6% to 89.7%. Similarly, the MAE metric for both of the regions significantly decreased from an average of 1.87% and 1.34% for the 4-factor to 1.31% and 1.02% for the 5-factor model in Europe and the U.S. respectively.

Looking at the factor exposures more closely, it is apparent that most of the 4-factor coefficients did not change when we added the fifth factor, our ESG Momentum. This is also in line with our findings in Table 7 and Appendix IV in which the ESG Momentum factor shows only small cross-correlations with the remaining 4 factor portfolios. Evidently, the integration of the additional factor did not bias their coefficient estimates.

In general, the effect of the integration of the ESG Momentum factor in Europe is larger compared to the U.S. with seven out of ten significant coefficients depicted in Table 10. All of these factors are significant at least on the 5% level and are condensed in the middle range of the decile portfolios, in line with the largest increases in the adjusted $R^2$. With the exception of some outliers most of the coefficients range between 0.42 to 0.5, thereby delivering a consistent contribution to the portfolios' returns. Since the monthly excess return of the ESG Momentum factor portfolio is only 0.02% though, the size of the impact is economically notably small. Nevertheless, the result shows that the decile portfolios seem to have approximately the same positive loading on our ESG Momentum factor underlining its consistent positive, albeit small, contribution to all of the portfolios. Correspondingly, since the ESG Momentum does not show a particular pattern across portfolios, it is not the main driver of performance and cannot explain large variations in returns. With respect to the spread between the coefficients of decile 10 and 1 we can further see that even though the highest decile has a larger loading on the ESG Momentum factor, the difference is not statistically significant. As a result, the alpha of the lowest decile portfolio as well as the one of the long-short portfolio is persistent and significant and not explainable with our implemented factor.

Looking at the U.S. sample in Appendix VII, we can make similar observations of the persisting significant alphas in the highest and lowest decile as well as the long-short portfolio. Consequently, the ESG Momentum factor is here as well not able to explain this abnormal return. Even though the implementation of the ESG Momentum factor increases the adjusted $R^2$ and improves other error metrics, it does not seem to add any explanatory power. In contrast to Europe, the coefficients appear way less significant with only two out of ten above the 10% and 5% significance threshold. The striking thing, however, is that the most significant coefficient can be found in the highest decile 10, contributing a positive amount to the overall return of the portfolio.
Interpreting the coefficient on the ESG Momentum, it says that for every 1% of high ESG Momentum firms outperforming low ones, the factor adds 30 basis points to the performance. Since the monthly excess return on the ESG Momentum factor portfolio is 0.13% on average, around 4 basis points of the 1.56% portfolio return can be attributable to the ESG Momentum factor. This is of course a small contribution of our ESG Momentum factor, but it might in turn reflect the composition and significant exposure to high ESG Momentum firms of the highest performing portfolio in the U.S.. Despite this positive impact, it is notable that compared to the European sample there are many negative coefficients across the portfolios indicating that low ESG Momentum firms might be predominating in those portfolios. Put differently, with the exception of the best performing decile portfolio, the loading on the ESG Momentum is in most cases negative indicating these portfolios behave like low ESG Momentum funds.

Following this train of thought, our regression analysis of the two separate samples might suggest systematic differences in implications of our ESG Momentum factor for the two geographical regions. Considering the results, Europe seems more responsive to our factor by exhibiting consistent positive loadings on the factor and many significant estimates. The U.S., in contrast, shows only little significance or positive impact of our ESG Momentum factor with the exception of the highest performing portfolio. Consequently, this might indicate a lack of awareness for the performance enhancing impact of an improvement in ESG scores in the U.S. market, in line with predictions from Amel Zadeh & Serafeim (2018). Likewise, the on average positive monthly excess return on the ESG Momentum factor portfolio does not add but subtract value from most of the portfolio's return.
For Europe, conversely, our findings might have important implications with respect to the ESG Momentum investment strategy. Even though the ESG Momentum factor is not the main driver of

portfolio performance, the regression results suggest a positive impact of using the ESG Momentum as an additional screening tool in portfolio construction.

### 6.3.3 Industry Breakdown

To go further into detail regarding our positive findings in the European market, we are now breaking down our entire analysis to two specific industries in that region. In this relation we are investigating, if the results substantially differ when analysing a single industry with respect to its material pillar. As suggested by Khan *et al.* (2016) the impact of the pillars on the performance of firms within a specific industry is dissimilar and highly depends on the importance of the pillar for the sector. Similarly, we do believe that an improvement in the score of the industry's material pillar will have a larger impact on performance than an increase in the other two. To test this hypothesis we decided, as outlined in our methodology, to replicate our analysis for the Utilities and the Financial sector which are most exposed to the environmental and governance pillar respectively.

Appendix VIII and Appendix IX first depict our 4-factor model regression with respect to the Momentum quintile portfolios as dependent variable. The quintile portfolios are in contrast to before now constructed based on the material pillar's change in ESG score. For Utilities we therefore use the E Momentum, while for Financials the G Momentum as basis for portfolio construction. Compared to our initial results for the European market, we can now observe a relatively high outperformance of the highest quintile in the Utilities sector, but a considerably low one with respect to the highest quintile in the Financial sector. The E Momentum factor therefore seems to have an a lot larger impact compared to the G Momentum in their respective industry. This is further reflected by the average monthly excess return on the factor portfolio which is 0.29% for the E and 0.13% for the G Momentum. The impact of integrating the additional Momentum factors for the three pillars might accordingly be way more significant for the Utilities than for the Financial sector.

Looking at the output of our ESG-integrating model specifications, provides insight on the differences between the two sectors and the relevancy of the pillars for predicting returns. In particular, it is striking that the adjusted $R^2$ in the Financial sector is much higher than in the Utilities sector for the quintile as well as the decile regressions. This in turn suggests that the financial performance of firms within Utilities is dependent on more aspects than covered by the four initial Carhart (1997) factors and therefore appears more complex. This is also reflected by the systematically lower betas for this sector since the returns of the portfolios move with the market to a less extent compared to the Financial sector. This is a common observation of the Utilities or Energy sector, since their industries are less dependent on overall market movements.

The main focus of this analysis, however, are the coefficients on the three pillars and their impact on performance of the decile portfolios depicted in Appendix X and Appendix XI. By means of the Utilities sector, we can confirm our hypothesis of a larger impact of the environmental pillar compared to the other two. While the coefficients for the E Momentum pillar are all positive and in some case even statistically significant, the coefficients on the S or G Momentum are either considerably small or even negative. This means that the portfolio performance within the sector positively depends on the outperformance of high E Momentum firms and the related improvement in the environmental pillar. Similarly, the portfolio's performance is mostly negatively correlated with an outperformance of firms due to improvements in their social or governance pillar. In other words, the portfolio performance within the Utilities sector increases in case low S and G Momentum firms are outperforming their peers which highly improved their score in this pillar. This result consequently underlines the importance of the environmental pillar for the Utilities sector and the financial performance of its constituents since firms with a higher return due to a high E Momentum exhibit performance-enhancing effects on the decile portfolio return.

For the Financial sector the result of the regression is not that distinct and obvious. While the social pillar still has an either low or negative insignificant impact, the other two pillars both show some positive, as well as significant influence on portfolio performance. Even though the coefficients are small in size they, in the majority of cases, predict a positive impact of firms with a high E or G Momentum outperforming peers with a low degree of improvement in these pillars.

Considering the explained results above, we can conclude that the material pillar of a sector seems to have a higher influence on the financial performance of the sector's constituents compared to the other two pillars. This interpretation is especially plausible when looking at the distinct results of the Utilities sector and the environmental pillar. While the decile portfolio returns are increasing with high E Momentum firms outperforming low ones, there is a negative impact of the same outperformance of firms associated with a high G or S Momentum. The Utilities sector which is highly dependent on carbon emissions and therefore exposed to environmental risks and regulatory changes, values an improvement of the environmental pillar score and related performance enhancements. For the Financial sector the result for the material pillar is not that significant and distinct. However, due to the extensive impact of climate change on every industry, we can expect a positive effect of a score improvement in the environmental pillar for almost all sectors. Since banks are increasingly offering solutions for environmental friendly investing, such as green bonds, the positive loadings on the E Momentum in the Financial sector still seems reasonable.

Note, that we do not find many significant estimates but rather interpret the loadings on the three pillar factors in the regression. The lack of significance could hereby be traced back to our rather small sample sizes, since we are only looking at a specific industry within the European market. This and other aspects influencing our results are further addressed in the upcoming discussion section.

### 6.4 Robustness Checks

To validate the above presented results, we perform several robustness checks as outlined in section 5.5. First, we want to check if our results are robust towards small changes in methodology such as portfolio construction and our chosen time frame. This analysis focuses on the 5-factor regression where we extend the Carhart (1997) 4-factor model to include our constructed ESG momentum factor for the European and U.S. market. We subsequently report on the econometric tests performed on our models, where we further investigate the 4-factor model. In relation to these tests, we have provided a few output tables in the Appendix for illustration.

A first confirmation of our results is that the choice between value- or equal-weighted portfolios does not appear to have an impact on the regressions in our analysis, as the significance of the coefficients are robust against this change in methodology. For Europe, we still have significant coefficients for the ESG Momentum in the mid-range of return portfolios, while the other factors behave similar as well. Similarly, the coefficients for the U.S. behave as described in the above-outlined sections. This provides some evidence of the portfolio construction not driving the results.

In terms of the chosen time frame, the significance observed across the decile portfolios for the ESG momentum factor in the European sample disappears when restricting the included observations to start in 2013. However, the sign of the coefficient remain positive. These changes in coefficients might be a result of the smaller sample size due to the limited time frame that causes the factor to become insignificant for all portfolios. Furthermore, the coefficients seem more similar in size in response to the test, all ranging between 0.39 and 0.59 across portfolios. The reduced predictiveness of the model can further be traced back to the loss of significance in the coefficients of the market excess return as well as the HML factor. With regard to the price momentum factor, four of the middle decile portfolios now have a p-value above 10%. When we instead increase the sample to contain all observations back to 2006, the signs of the coefficients are similar to those of our main analysis, with slightly stronger significance for all factors in the model. However, for the ESG Momentum factor, coefficients decreased in significance confirming our choice of time frame in the main analysis.

Similarly, for the regressions based on the U.S. sample, the ESG Momentum receive ambiguous results when including observations starting from 2013. The remaining factors exhibit the same direction, as the signs remains constant, but the significance has decreased. When extending the timeframe back to 2006, the ESG Momentum coefficients turn negative for nine out of ten decile portfolios, though only decile 1 and 9 are significant. Decile 10, on the other hand, returns a positive significant coefficient. Even though the signs of the coefficients are hereby similar to the main analysis again, their significance decreased as in the European sample.

Thus, it is not evident that our chosen time frame does not impact our results in any way, but without clearer indications of changes in the results, we still find our choice reasonable given the data available. One explanation might be that with improved data quality, we can see a more homogeneous ESG Momentum effect across the portfolios after 2013. Furthermore, it is reasonable to assume that the financial crisis of 2008 impacts the ESG Momentum pattern to a large extent and permanently affected the way ESG information translate into returns.

However, what can be observed, is that when we perform the analysis on the largest 200 firms in terms of market cap, in both of the two markets some of the significance disappears. This might suggest that size effects are driving parts of the results. Since larger firms are also associated with a higher ESG profile, their ESG Momentum might be accordingly low due to the difficulty of improving their high rating. As a result the factor portfolios might be even less significant in their outperformance than before. In general, however, it is difficult to make these assumptions based on results from regression with such a restricted sample size.

For the econometric and model technical aspects, we perform a few tests to make sure the assumptions needed for unbiased and efficient results hold. We test for the presence of autocorrelated error terms in the models using the Breusch-Godfrey test up to 12 lags. The p-value is above the 10% level for all the regressions for all decile portfolios in both Europe and the U.S., as can be seen in Appendix Appendix XII and Appendix XIII. We thus fail to reject the null hypothesis of no autocorrelation and proceed with looking for heteroskedasticity by performing the Breusch-Pagan test. Besides a few exceptions, which include the lowest decile portfolio for Europe and decile 5 of the U.S. sample, all p-values are above 10%, and we fail to reject the null hypothesis of homoskedastic error terms in our models. These results are reported in Appendix Appendix XIV and Appendix XV. Based on this, we find fairly good grounds to assume that we do not need to worry about autocorrelation and heteroskedasticity biasing our results. As a last check point, we compute the VIF for all portfolios which can be found in Appendix Appendix XVI and **??**. We find all factors to be between 1 and 2 for the variables in our regressions. The level of multicollinearity does therefore not appear to be a concern, as further confirmed by the factor correlations presented in Table 7 and Appendix IV.

# 7 Discussion, Caveats and Further Research

The centre of our research question is the investigation of the ESG Momentum factor and its implementation in a factor investing framework. While the previous section presented our main results on the analysis, this section will reflect upon our approach as well as discuss the implications of our findings in the light of our chosen research philosophy. Furthermore, under consideration of data availability and further limitations to our study, we will outline the shortcomings of this thesis and propose possible extensions of our research.

## 7.1 Discussion of Results

While the results in the first part of section 6 represent replications of findings from other papers, the second part builds our main contribution to integrating ESG and its Momentum into the investment processes. Since we are using previous literature as guidelines for the first part and customise the methodology to our research questions, we critically question our approach and discuss potential impacts on results in our robustness analysis in section 6.4. Albeit these details on our analytical setup are crucial and might to some extent be decisive of our results, we further need to make a more qualitative evaluation of our approach with respect to the second part of our results. The next paragraphs therefore discuss some general aspects regarding the investigation of the ESG Momentum strategy which make a holistic assessment of the impact of all its dimensions on investment decisions difficult.

The first aspect concerns the intuition behind the ESG Momentum factor that measures a firms efforts to improve its ESG profile and which is used as the analytical basis for classifying a firm within the high or low performance range. As our ESG Momentum investment strategy predicts, firms with a high ESG Momentum, meaning they have a significant increase in their ESG profile, will outperform firms with low ESG Momentum values. This hypothesis though, refers only to the influence a *change* in ESG score has on returns, while ignoring the positive impact of the raw ESG score on financial performance as estimated by []. For clarification of this point, it makes sense to think about what types of firms portfolios of high and low ESG Momentum respectively would be composed of. The low ESG Momentum portfolio, on the one hand, consists of controversial firms or even sin stocks which do not invest any efforts to reach a higher rating. On the other hand, however, it might also include sustainability pioneers with an ESG score close to 10 for which it is increasingly difficult to improve their ESG profile even more. As a result, both of these types of firms might contribute to the lower ESG Momentum portfolio having a higher return than initially expected by the hypothesis of the investment strategy. While the high ESG score firms might boost returns in line with the prediction of [], sin stocks in this portfolio could earn a positive neglect or risk premium (Hong & Kacperczyk, 2009). Looking at the high ESG Momentum portfolio, it is furthermore likely to be comprised of initially low or middle range ESG score companies for which it is comparatively easy to achieve a better rating. Consequently, since high ESG Momentum is not necessarily associated with high ESG score firms but rather with middle or even low ranked companies, our investment strategy might sort firms mistakenly into one performance portfolio without considering all its ESG dimensions.

Similarly, there might exist substantial differences across industries and how their efforts are translated into score improvements. While for low rated energy companies a small adjustment in their business model in response to regulatory changes might yield a significant increase in their ESG rating, the efforts for other industries might be considerably larger to achieve the same increase. This might in turn lead to industry tilts within a certain ESG Momentum portfolio, biasing its returns and impacting our outcome with respect to the predicted outperformance of high versus low ESG Momentum firms.

As a result of these possible biases, there might be opposing forces on returns within the portfolios leading to less distinct performance patterns. Applying this to our results in section 6, this statement might provide explanation for the positive abnormal return in form of alpha we found for both, the highest and lowest ESG Momentum quintiles, which mitigate the outperformance associated with the ESG Momentum strategy. In general, however, to be sure which of these biases apply, it is necessary to analyse the portfolios' composition in more detail with respect to firm characteristics, industries and ESG profiles.

The second aspect addresses our main analysis and the integration of the ESG Momentum as an additional factor in the Carhart (1997) 4-factor equity model, for which we use the stock momentum as a close inspiration for the construction methodology of the factor portfolio. Similar to the setup of Carhart (1997), we analyse the implementation of our ESG Momentum factor by means of the decile portfolios on lagged one-year returns to be able to compare the contribution of each factor to each decile portfolio's return. Due to our regression setup, we expected to observe a similar systematic pattern in our ESG Momentum as in the stock momentum across portfolios making an attribution of portfolio performance possible.

Comparing our results presented in section 6 with respect to the coefficients of the two factors, however, does not yield the same explanatory power of estimated coefficients. While the price momentum monotonically increases its coefficients from the worst to the best performing portfolio, thereby contributing to each portfolio's performance by its different loadings, the coefficients of the ESG Momentum are rather flat across portfolios and insignificant at times. Considering the complexity of the two factors though, this result is not surprising. As the price momentum only reflects the trend in past returns, the dimensions that ESG, and in this case the ESG Momentum, covers are far more extensive. As we have seen above, the returns within the ESG factor portfolio do not only depend on the change in ESG score but also on the firm and industry composition of the quintiles used to construct the factor. The crucial point is hereby that while the relationship between past and current return is way more obvious, the link between ESG and performance is ambiguous. Therefore, even though the setup is intuitively easy and comparable to the stock momentum factor, the ESG Momentum is far more complex and less intuitive due to its multiple dimensions. As a result, systematic patterns, as we see them for the stock momentum, are harder to spot and interpret.

Nevertheless, we are still able to contribute a valuable result with respect to the geographical differences of our two samples. The use of and reliance on good ESG measures as a signal of superior performance seems to be particularly promising and successful in the European market in which the awareness for the financial materiality of ESG and ESG score improving efforts is positively incorporated in equity factor models. In the U.S. sample, however, the coefficients are mostly negative and insignificant indicating systematic differences between the two markets and a lack of awareness of the performance-enhancing effect of ESG in the U.S. (Amel Zadeh & Serafeim, 2018). Of course, for an accurate comparison of the two markets it would hereby again be beneficial to analyse the individual portfolio composition and drivers of these results.

An insight into the dimensions of ESG and the ESG Momentum factor is given by the last part of our analysis in section 6.3.3, in which we replicate our approach for two industries and construct our Momentum factor for each of the pillars separately. By means of this industry breakdown, we are trying to provide evidence for the dissimilar impact of the three pillars dependent on the sector they are material for. In line with the findings of Khan *et al.* (2016), we hereby expect to see a higher and more significant impact of the industry's material pillar indicating it as the main contributor among the three to the portfolio's performance. As outlined in section 6.3.3, we do find supporting evidence for this statement, especially with respect to the Utilities sector and the environmental pillar, albeit coefficients are mostly insignificant.

The split of industries and pillars therefore introduces some of the dimensions of ESG and suggest industries and their material pillar as the main driver of the ESG Momentum factor's contribution to portfolio performance. Due to our limited sample size resulting from the industry breakdown, however, it is difficult to provide significant evidence for our hypotheses. Therefore, this analysis might serve as a foundation for further research including more observations and covering different industries as well as regions.

Overall, for all of the analyses conducted, we can observe a lack of significant findings with respect to the hypothesised outperformance of high ESG Momentum firms. While we provide some qualitative explanations for our results above we can, however, also trace back the lack of significance to our time frame investigated. Considering the work of Fama & French (1993) or Jegadeesh & Titman (1993), they are analysing historical periods covering 30 or 40 years to test their hypothesis and unveil their patterns on the size, value or momentum effect. Comparing this to the time frame investigated in our analyses, a period of 8 years can be considered as too short to find the same significant patterns. As we can see in Figure 7 in which we plot the cumulative outperformance of the long-short portfolio in the highest and lowest ESG Momentum firms, despite the overall positive tendency, there is still a period between 2015 and 2017 in which the relationship appears to be negative. While these opposing relations are smoothed out over a long time frame, they might mitigate the overall significance and size of our performance results over our short time horizon. Furthermore, it is unclear which influence the changing scoring methodology, as well as the constantly increasing firm base, might have on our constructed ESG Momentum factor and associated analyses. Consequently, as the novelty and scoring inconsistency of the ESG data inhibits the analysis of a longer time horizon at this point, it might be an interesting opportunity for future research.

In the end, the question remains to which degree our analysis in section 6 contributes to the understanding of the ESG Momentum strategy, its integration into the investment process and its performance implications. As the ESG Momentum and ESG itself is comprised of multiple dimensions which enter the performance equation over several channels, this unambiguous effect on the investment's return is difficult to measure. Based on our findings, it is therefore apparent that the ESG Momentum is not suitable to use as the main driver of investment decisions and performance. Our results rather suggest that the ESG Momentum factor should be applied as a complementary tool for choosing the right stocks in your portfolio construction. Similar to the ESG score, the ESG Momentum could therefore serve as an additional screening tool in portfolio construction to exploit the positive alpha associated with the highest ESG Momentum quintile.
Our thesis therefore not only provides a deeper understanding of the dimensions of ESG and its momentum but also through which channels these might impact performance. Furthermore, it gives an indication of how the ESG Momentum can be used in investment decisions and contribute to a portfolio's performance. As we are delivering a first approach to the integration of the ESG Momentum in factor investing which at certain points lacks significance and distinct patterns it

further builds a theoretical foundation and starting point for future research.

## 7.2 Research Philosophy

When conducting any type of research, it is important to reflect upon the choice of methodology as well as the development of data and knowledge. Research philosophy is based on the beliefs and on the assumptions made around the perception of reality which naturally affects how the research process is developing and how the results are interpreted (Saunders *et al.*, 2019). When deciding upon a specific methodology, one should have this in mind throughout the process to make sure the research is carried out in a trustworthy manner.
Financial empirical research has almost exclusively belonged to the functionalist positivist paradigm, as it is founded on a positivist tradition which draws a hard line between values and facts (Lagoarde-Segot, 2015). Positivist studies focus on observable and quantifiable findings and there should be no provisions for any human interests within these studies. As a general notion, positivist research leans on a deductive approach to data, which means that general conclusions are drawn from particular observations (Saunders *et al.*, 2019). Put differently, studies with positivist paradigm are based on facts and consider the world to be external and objective, and it is within this research tradition that we find our thesis.

To elaborate further on this, the methodology this thesis applies is based on standard approaches within the literature, such as see Fama & French (1992) and Carhart (1997). Our cross-sectional data is collected from one of the largest and most frequently used ESG data providers available and a global company data platform. This should give the reader some assurance of the derived results of our study, as the choice of data should not drive the results. Thus, both the setup and choice of data are in line with conducting the research and results according to the positivist approach chosen. To further ensure objectivity, we have in our literature review in section 2 and 3.4.4 referred to widely cited papers within the research area that makes use of ESG data both from a risk and investment perspective. Furthermore, we have tried to find existing literature that both support and that can help disprove our hypothesis, to make sure the interpretation of results are made in an objective manner. Furthermore, we have throughout this study focused on addressing the quality of data, sample size and possible biases that stems from the choice of methodology and how the data is derived (see Section 2.5 for data limitations and section 6.4 for robustness checks).

Interestingly observed though, is that this objective nature of financial empirical analyses can be a naive point of view, as it hangs on the distinction between the financial reality, that is based on facts and neutrally describe the world, and values (Lagoarde-Segot, 2015). For this thesis, when including non-financial dimensions, such as environmental impact, social well-being and promotion of good corporate governance, value and facts are not necessarily that easy to distinguish. When conducting tests on ESG data, and in order to draw conclusions, it is therefore crucial to keep the objectivistic and positivist approach when analysing the results. At the same time, one should be careful to draw too general conclusions made from a few observations. When performing research based on these non-financial dimensions of firms' performances, it is important to keep in mind that many different factors can drive the results. We will further discuss these limitations in the upcoming section.

### 7.3 Data Quality and Limitations

With growing data availability, the possibility of integrating ESG in equity portfolios has emerged. ESG represents a source of possibly valuable information for investors with an impact on both return and risk. But as shown by Bender *et al.* (2018), the attribution of ESG comes with variation across data sources and can thus both add and subtract from investment returns depending on data source and different metrics used. As seen from several studies, the discrepancies in between data providers has resulted in surprisingly low correlations, leading to confusion amongst investors and question the results of empirical research conducted on ESG data (Bender *et al.*, 2018; Berg *et al.*, 2019). Thus, as already stated in Section 2.5 about data limitations, the use of ESG information in the investment process does not come without challenges. In the upcoming discussion, we will further look at the implications of these issues and limitations in the light of our above-presented findings.

As already stressed, our chosen methodology for this analysis follows standard procedures within the literature (see (Carhart, 1997) and (Fama & French, 1992)). Looking at our output from the regressions in Table 9, 10 as well as Appendix VI and Appendix VII, the coefficient resemble to a large extent the ones of traditional literature. This is true in terms of market return, both the

SMB and HML factor as well as the price momentum. Furthermore, as confirmed by the conducted robustness checks, the choice of methods does not appear to drive the results, as they do not change in response to the applied variations. What could be questioned, however, when adding our additional ESG Momentum factor to the pricing model, is the quality of the data we build the factor upon.

Our results indicate that the integration of the ESG momentum factor into classical factor models does not necessarily have a large economic impact. And for the U.S. sample, the direction of the impact is not completely clear. It is of course reasonable to question if we would find stronger or different results if we could obtain data of higher quality, or even used a different data provider considering the rather low correlation that has been found between different rating agencies (Bender *et al.*, 2018; Berg *et al.*, 2019). We will avoid speculating too much into these matters, but we find that the ESG criteria should not be disregarded on the basis of its rather low economic influence. When comparing the results from Europe and the U.S., we can see that markets (here Europe) with more developed reporting standards show a higher responsiveness to ESG information and furthermore, improvements in ESG performance. This could imply that with the coming regulatory developments, the research field of ESG in general, and ESG Momentum in particular, should still deserve some increasing attention.

As emphasised in Section 2 and further throughout this thesis with regard to our choice of time frame, the data quality of MSCI's ESG data seemingly improved with their updated methodology. This result is further depicted in Figure 5, where we can see that the risk profile of high performing ESG firms in relation to low ESG firms becomes clearer after 2013. This result gives some additional indication of the impact and benefits of considering material ESG issues in the assessment which also has been confirmed by Khan *et al.* (2016). As they document, investment decisions with respect to sustainable aspects can only be successful if materiality is accounted for on an industry-by-industry basis building the foundation for the rating structure outlined by MSCI.
Another point to emphasize with respect to the data, is the low rating frequency which also was mentioned in the survey study by Amel Zadeh & Serafeim (2018). As financial data is available at a much more frequent basis, the market can already have absorbed effects stemming from controversies or improved risk mitigation that the ESG scores are not yet including. Consequently, this will mean that the data used to construct the ESG Momentum factor does not fully work as a proxy for a firm's

improvement in ESG performance. Moreover, it is also not clear, how fast markets are absorbing and evaluating ESG information.
At the same time, in the absence of clear reporting standards, rating companies often estimate data for unreported companies based on similarities within industry and company characteristics. This adds a certain amount of subjectivity and potential noise into the ESG data employed in the investment process Bender *et al.* (2018). This is also an aspect which needs to be taken into consideration when analysing the results from the previous section.

As increasing ESG awareness and regulation to some extent appear to yield higher returns on high ESG momentum portfolios, this is still a research field that deserves increasing attention as the markets further develop a more streamlined standard on how to assess ESG exposures. Deriving clear investment strategies based on the available ESG data is thus still difficult at this stage, as the convergence in data quality makes empirical research hard to compare. This raises questions about the trustworthiness of the results from both this thesis, and others before us. At this point though, the indication that the results give are interesting to build further upon.

## 7.4 Future Research

As indicated by our discussion of results, the ESG Momentum is still a largely uncovered topic with respect to its financial implications and its integration into investment strategies. While there are many possibilities for analysing and interpreting the dimensions of ESG, the results presented in this thesis and discussed above offer clear suggestions for future research.

The main point to consider in the ESG Momentum strategy is the intuition behind the factor itself which due to its multiple dimensions can impact performance over various channels. As presented in the discussion, the ESG Momentum strategy is based on the proposition that the firms with the highest Momentum will outperform the ones with the lowest one. Intuitively, however, the firms with the highest change in ESG score are not associated with the highest initial scores but rather with low- or middle-ranked firms. Due to the composition of portfolios which might have a further impact on performance, there might be opposing forces within the portfolios biasing our results. Since we find a positive outperformance of both, the highest and the lowest quintile portfolio, we could assume that the lower quintile is characterised by controversial as well as high-ranked firms boosting the returns of the portfolio. Similarly, the upper quintile might contain the largest improvements in ESG scores which as well, have a positive impact on returns.

Considering this bias in our results suggest analysing the composition of the constructed ESG Momentum quintile portfolios further, especially to find the source of positive alpha within the highest and lowest quintile portfolio. Furthermore, using the analysis of Giese & Nagy (2018), who measure the largest effect of the ESG Momentum in the middle range of initial ESG scores, might further help understanding the driver of performance in our analysis. Accordingly, it might be useful to repeat our conducted analysis but conditional on ranges of initial ESG scores. This might provide insight into how changes in ESG scores translate into returns for different levels of firm sustainability and might further suggest new methods of integrating the ESG Momentum into the investment process.

Furthermore, as our industry analysis shows, there are some discrepancies between industries on how they perform on their material ESG pillars. It would be interesting to further uncover how ESG Momentum translates into financial performance on a sectoral level. This would be useful for investors, to better understand how to make use of ESG information and in order to shift their ESG strategies towards businesses that generate the highest value.

Besides these analyses going deeper into our investigated research question, there are some aspects of our analytical setup which are worth criticising. For example, above-raised issues relating to rating frequency and the time horizon of markets pricing ESG information might entail valuable implications portfolio construction. Accordingly, instead of a monthly rebalancing approach it could be useful to look at yearly rebalanced portfolios to see if results significantly change. This, in turn, could indicate a longer time needed for markets to process ESG information.

Furthermore, as discussed above, the intuitive nature of the ESG Momentum is evidently more complex than that of the price momentum. As estimated by Jegadeesh & Titman (2011) leaving a time gap between formation and holding period of their portfolios, they avoided short-term reversals, and the stock momentum effect became more pronounced. Consequently, it could be reasonable to expect the same effect with respect to ESG information, as it is said to capture long term performance (MSCI ESG Research, 2019). A similar setup of leaving a time gap between portfolio formation and holding period could further improve the significance and distinctness of results.

Furthermore, it might be useful to address the issue of reverse causality in the analytical approach. In all of our performance analyses of this thesis, it is thereby not clear, whether an improved ESG profile of a firm enhances its financial performance or, if in turn, higher returns create financial resources and incentives within the firm to improve its ESG score. By means of a simple Granger-causality test, the researcher could therefore test whether the relationship of ESG score and financial performance is only one-sided or if reverse causality might pose a problem.

So far MSCI is the only research provider on the ESG Momentum factor. As it at the same time functions as the source of data, there might be a bias within the analysis to reach a certain result. Furthermore, as described above the correlations between individual ratings provider are surprisingly low posing a problem of comparability. Consequently, future research could replicate our analysis for data of a different provider, such as Sustainalytics, to validate or discard our results.

# 8 Conclusion

This thesis has presented a theoretical background as well as a methodological approach and empirical analysis on ESG investing, providing insight into the many dimensions of ESG and its implementation in investment processes. The centre of our research and analysis is hereby the ESG Momentum strategy representing a novel investment approach which due to is scarce coverage by previous literature and empirical analyses offers broad research opportunities. The ESG Momentum strategy is based on the hypothesis of a positive relationship between the *change* in a firms ESG score and its financial performance, thereby representing a dynamic measure to predict the financial materiality of ESG. The corresponding alpha-generating strategy refers to the construction of a portfolio going long in the highest ESG Momentum firms while shorting the ones with the lowest ESG Momentum. It accordingly exploits the relative outperformance of firms significantly improving their ESG profile. By testing this hypothesis for a consistent pattern in historical returns, we are eventually creating a factor portfolio, similar to the stock momentum, for the integration in the Carhart (1997) 4-factor model.

Before going into our main analysis, however, we first of all concentrate on replicating findings from previous literature to provide evidence for the relevance of ESG and its Momentum for an investment's performance. We thereby further aim to build grounds for our subsequent analysis. Just as Dunn *et al.* (2018), we find a similar outcome on the negative relationship between the ESG profile of a company and its risk metrics, by conducting a basic risk analysis of firms dependent on their ESG score. In particular, we estimate a systematically lower level of systematic as well as idiosyncratic risk for firms with higher ESG scores. This in turn confirms the importance of ESG information for a holistic assessment of an investment's risk and return.

After constructing our ESG Momentum factor and analysing its distribution and basic properties, we are plotting the performance of the ESG Momentum strategy first on a cumulative basis. Over the period from 2011 to May 2019 the above described long-short portfolio based on the highest and lowest ESG Momentum quintiles yields a cumulative outperformance of 23%. This is not only in line with our baseline paper by Giese & Nagy (2018), but also confirms the hypothesis of a superior relative performance of firms significantly improving their ESG profile.

Comparing this cumulative outperformance with the monthly excess return of the created ESG Momentum factor portfolio, however, yields a less significant result. While in the European market high ESG Momentum firms outperform low ones by 0.02% on a monthly basis, the same analysis for the U.S. market yields 0.13% outperformance. Similarly, when regressing the ESG Momentum quintiles on the Carhart (1997) 4-factors for Europe and the U.S., we not only obtain an overall insignificant difference between the highest and lowest portfolios' monthly excess returns, but also a positive significant alpha for both of them. This in turn indicates a positive abnormal return and impact associated with both, high and low ESG Momentum firms, which is not explainable by any of the traditional four factors and contradicts our initial hypothesis.

By extending the model to our 5-factor ESG framework, we estimate the ESG Momentum factor's contribution to explain the difference in the performance of ten portfolios based on their lagged one-year return. While we were expecting a similar pattern to the stock momentum, the loadings on the ESG Momentum factor are rather consistent across portfolios and do not appear to drive the differences in the portfolios' performances. However, the positive and mainly significant coefficients of the European sample compared to the mostly negative and insignificant ones of the U.S., reveal systematic discrepancies between the two markets which entail relevant implications for their use of ESG data. Consequently, while the European market demonstrates more awareness of ESG matters with a performance-enhancing effect of the ESG Momentum, the U.S. market does not seem to positively incorporate improvements in ESG ratings.

By further breaking the analysis down to the three pillars and specific industries, we additionally provide evidence for the dissimilar impact of each pillar, depending on its materiality for the sector (Khan *et al.*, 2016). Our results are hereby particularly evident for the Utilities sector in which the outperformance of firms improving their environmental score positively, albeit insignificantly, affects the portfolio's return, whereas an improvement in the other two pillars is not rewarded.

With the above-outlined analysis we are not only providing a deeper insight into the ESG Momentum factor and its characteristics but also deliver a first approach to its integration into a factor investing framework. Even though we do not find the expected systematic and significant patterns in returns, the tendency of our estimated monthly excess return on the quintile portfolios, give an indication of the superior performance of high ESG Momentum firms. Furthermore, in the European market, the ESG Momentum factor exhibits a significant positive, albeit economically small, contribution to the portfolio's return proving it's relevance in investment decisions.

This suggests on the one hand that, even though the ESG Momentum is not the main driver of performance differences across portfolios in our setup, it might serve as a useful complementary tool for stock selection in the portfolio construction process. On the other hand, it further indicates the complexity of the ESG Momentum factor which, although it is constructed similar to the stock momentum, is composed of multiple dimensions impacting performance through various channels. While our thesis provides insight into some of these dimensions, there are still some gaps in our research which might be the source of our partially insignificant results. For one thing, the portfolio construction based on the ESG Momentum ignores important dimensions of ESG, which in turn create potential biases in return patterns through the resulting composition of firms within the ESG Momentum quintiles. On another note, the short time horizon covered in our analysis might make it difficult to detect systematic patterns as Fama & French (1993) or Jegadeesh & Titman (1993) did. Furthermore, as outlined in our data limitations, our concerns about data quality as well as the lack of a standardised ratings methodology make the reliance on results of previous research as well as the prediction of results for other data providers difficult.
Considering the novelty of the ESG Momentum itself as well as its scarce empirical coverage, our thesis provides a valuable first approach to integrating ESG Momentum into factor investing as well as a solid foundation for future research.

## References


Amel Zadeh, Amir, & Serafeim, George. 2018. Why and how investors use ESG information: Evidence from a global survey. *Financial Analysts Journal*, **74**(3), 87–103.

Baker McKenzie. 2019. ESG Regulatory Reform: Impact on Asset Managers. *Baker McKenzie, Published: July 2019.*

Bank of America. 2019a. ESG Matters: 10 reasons you should care about ESG. *Bank of America Equity and Quant Strategy, Published: 23 September 2019.*

Bank of America. 2019b. ESG Matters: Global ESG from A to Z. *Bank of America Equity and Quant Strategy, 25 November 2019.*

Banz, R.W. 1981. The relationship between return and market value of common stocks. *Journal of Financial Economics*, **9**(1), 3–18.

Barnett, Michael. 2019. *A Run on Oil: Climate Policy, Stranded Assets, and Asset Prices*. Ph.D. thesis, University of Chicago.

Baron, David P., Agus Harjoto, Maretno, & Jo, Hoje. 2011. The economics and politics of corporate social performance. *Business and Politics*, **13**(2).

Bender, Jennifer, Bridges, Todd, He, Chen, Lester, Anna, & Sun, Xiaole. 2018. A Blueprint for Integrating ESG Into Equity Portfolios. *Journal Of Investment Management*, **16**(1), 44–58.

Berg, Florian, Koelbel, Julian F, Rigobon, Roberto, Berg, Florian, Koelbel, Julian F, & Rigobon, Roberto. 2019. Aggregate Confusion: The Divergence of ESG Ratings. *MIT Sloan School Working Paper 5822-19*, 0–42.

Blitz, David, & Fabozzi, Frank J. 2017. Sin Stocks Revisited: Resolving the Sin Stock Anomaly. *The Journal of Portfolio Management*, **44**(1), 105 111.

Carhart, Mark M. 1997. On persistence in mutual fund performance. *Journal of Finance*, **52**(1), 57–82.

Cavaco, Sandra, & Crifo, Patricia. 2014. CSR and financial performance: Complementarity between environmental, social and business behaviours. *Applied Economics*, **46**(27), 3323–3338.

Cowen. 2020. Cowen's Best ESG Investment Ideas for 2020. *Cowen Equity Research, Published: 3. March 2020*.

Credit Suisse. 2015. ESG- $\alpha$ Series: Finding Alpha in ESG. *Credit Suisse Equity Research, Published: 19 June 2015*.

Dahlberg, Linnea, & Wiklund, Frida. 2018. *ESG Investing In Nordic Countries: An analysis of the Shareholder view of creating value*. Ph.D. thesis, Umeå University.

de Franco, Carmine. 2018. ESG Controversies and Their Impact on Performance. *Ossiam Research*, **29**(2), 33–45.

Deng, Xin, koo Kang, Jun, & Low, Buen Sin. 2013. Corporate social responsibility and stakeholder value maximization: Evidence from mergers. *Journal of Financial Economics*, **110**(1), 87–109.

DNB Research. 2018. An energy transition risk stress test for the financial system of the Netherlands. *De Nederlandsche Bank*.

Dunn, Jeff, Fitzgibbons, Shaun, & Pomorski, Lukasz. 2018. Assessing risk through environmental, social and governance exposures. *Journal Of Investment Management*, **16**(1), 4–17.

Eccles, Robert G., Ioannou, Ioannis, & Serafeim, George. 2014. The impact of corporate sustainability on organizational processes and performance. *Management Science*, **60**(11), 2835–2857.

Edmans, Alex, Li, Lucius, & Zhang, Chendi. 2014. Employee Satisfaction, Labor Market Flexibility, and Stock Returns Around the World. *European Corporate Governance Institute (ECGI) - Finance Working Paper No. 433/2014*.

Fabozzi, Frank J, Ma, K C, & Oliphant, Becky J. 2008. Sin Stock Returns. *The Journal of Portfolio Management*, **35**(1), 82 – 94.

Faleye, Olubunmi, & Trahan, Emery A. 2011. Labor-Friendly Corporate Practices: Is What is Good for Employees Good for Shareholders? *Journal of Business Ethics*, **101**(1), 1–27.

Fama, Eugene F., & French, Kenneth R. 1992. The Cross-Section of Expected Stock Returns. *The Journal of Finance*, **47**(2), 427–465.

Fama, Eugene F., & French, Kenneth R. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, **33**(1), 3–56.

French, Kenneth R. 2020. *Kenneth R. French Data Library.*

Garcia, Alexandre Sanches, Mendes-Da-Silva, Wesley, & Orsato, Renato. 2017. Sensitive industries produce better ESG performance: Evidence from emerging markets. *Journal of Cleaner Production*, **150**, 135–147.

Giese, Guido, & Nagy, Zoltan. 2018. How markets price ESG: Have Changes in ESG Scores Affected Stock Prices? *MSCI Research, Published: November 2018.*

Giese, Guido, Lee, Linda-Eling, Melas, Dimitris, Nagy, Zoltán, & Nishikawa, Laura. 2019. Foundations of ESG Investing: How ESG Affects Equity Valuation, Risk, and Performance. *The Journal of Portfolio Management*, **45**(5), 69–83.

Glossner, Simon. 2018. The Price of Ignoring ESG Risks. *SSRN Electronic Journal.*

Goldman Sachs. 2018. Integrating ESG in Equity Factor Investing. *STS Academic Review Issue 3.*

Gompers, Paul, Ishii, Joy, & Metrick, Andrew. 2003. Corporate governance and equity prices. *Corporate Governance and Corporate Finance: A European Perspective*, **118**(February), 523–556.

Healy, Paul M, & Serafeim, George. 2015. An Analysis of Firms' Self-Reported Anticorruption Efforts. *The Accounting Review*, **91**(2), 489–511.

Hillman, Amy J, & Dalziel, Thomas. 2003. Boards of Directors and Firm Performance: Integrating Agency and Resource Dependence Perspectives. *The Academy of Management Review*, **28**(3), 383–396.

Hong, Harrison, & Kacperczyk, Marcin. 2009. The price of sin: The effects of social norms on markets $. *Journal of Financial Economics*, **93**(1), 15–36.

Iamandi, Irina Eugenia, Constantin, Laura Gabriela, Munteanu, Sebastian Madalin, & Cernat-Gruici, Bogdan. 2019. Mapping the ESG behavior of European companies. A holistic Kohonen approach. *Sustainability*, **11**(12), 3276.

Jegadeesh, Narasimhan, & Titman, Sheridan. 1993. American Finance Association Returns to Buying Winners and Selling Losers : Implications for Stock Market Efficiency. *The Journal of Finance*, **48**(1), 65–91.

Jegadeesh, Narasimhan, & Titman, Sheridan. 2011. Momentum. *SSRN Electronic Journal*.

Jitmaneeroj, Boonlert. 2016. Reform priorities for corporate sustainability: Environmental, social, governance, or economic performance? *Management Decision*, **54**(6), 1497–1521.

J.P. Morgan Asset Management. 2019. Does an ESG tilt improve corporate bond portfolio outcomes? A systematic back-test of MSCI ESG ratings. *Available at: https://am.jpmorgan.com/au/en/asset-management/adv/insights/portfolio-insights/does-an-esg-tilt-improve-corporate-bond-portfolio-outcomes/, Accessed: 25 March 2020.*

Khan, Mozaffar, Serafeim, George, & Yoon, Aaron. 2016. Corporate sustainability: First evidence on materiality. *Accounting Review*, **91**(6), 1697–1724.

Krüger, Philipp. 2015. Corporate goodness and shareholder wealth. *Journal of Financial Economics*, **115**(2), 304–329.

Lagoarde-Segot, Thomas. 2015. Diversifying finance research: From financialization to sustainability. *International Review of Financial Analysis*, **39**, 1–6.

Lintner, John. 1965. The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets: A Reply. *The Review of Economics and Statistics*, **51**(2), 222.

Markowitz, Harry. 1952. Portfolio Selection. *Journal of Finance*, **7**(1), 77–91.

Merton, Robert C. 1987. A Simple Model of Capital Market Equilibrium with Incomplete Information. *Journal of Finance*, **42**(3), 483–510.

MSCI ESG Research. 2019. MSCI ESG Ratings Methodology. *MSCI Research, Published: September 2020.*

Nagy, Zoltán, Kassam, Altaf, & Lee, Linda-Eling. 2015. Can ESG add alpha? *MSCI Research*.

Nollet, Joscha, Filis, George, & Mitrokostas, Evangelos. 2016. Corporate social responsibility and financial performance: A non-linear and disaggregated approach. *Economic Modelling*, **52**, 400–407.

Pedersen, Lasse Heje, Fitzgibbons, Shaun, & Pomorski, Lukasz. 2019. Responsible Investing: The ESG-Efficient Frontier. *NYU Stern School of Business*.

PRI. 2019. Annual Report Principles for Responsible Invesment. *Principles for Responsible Investment*.

RBC Wealth Management. 2015. Will ESG investing hurt my returns? Debunking the myths. *Available at: https://www.rbcwealthmanagement.com/sg/en/research-insights/will-esg-investing-hurt-my-returns-debunking-the-myths/detail/, Accessed: 04 April 2020*.

Rosenberg, Barr, Reid, Kenneth, & Lanstein, Ronald. 1985. Persuasive evidence of market inefficiency. *The Journal of Portfolio Management*, **11**(3), 9–16.

Sassen, Remmer, Hinze, Anne Kathrin, & Hardeck, Inga. 2016. Impact of ESG factors on firm risk in Europe. *Journal of Business Economics*, **86**(8), 867–904.

Saunders, Mark N K, Thornhill, Adrian, & Lewis, Philip. 2019. *Research methods for business students*. 8. ed. edn. New York: Pearson.

Sharpe, William F. 1964. Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk. *The Journal of Finance*, **XIX**, 425–442.

Starks, Laura T., Venkat, Parth, & Zhu, Qifei. 2017. Corporate ESG Profiles and Investor Horizons. *SSRN Electronic Journal*.

Stattman, Daniel. 1980. Book values and stock returns. *The Chicago MBA: A Journal of Selected Papers*, **4**, 25–45.

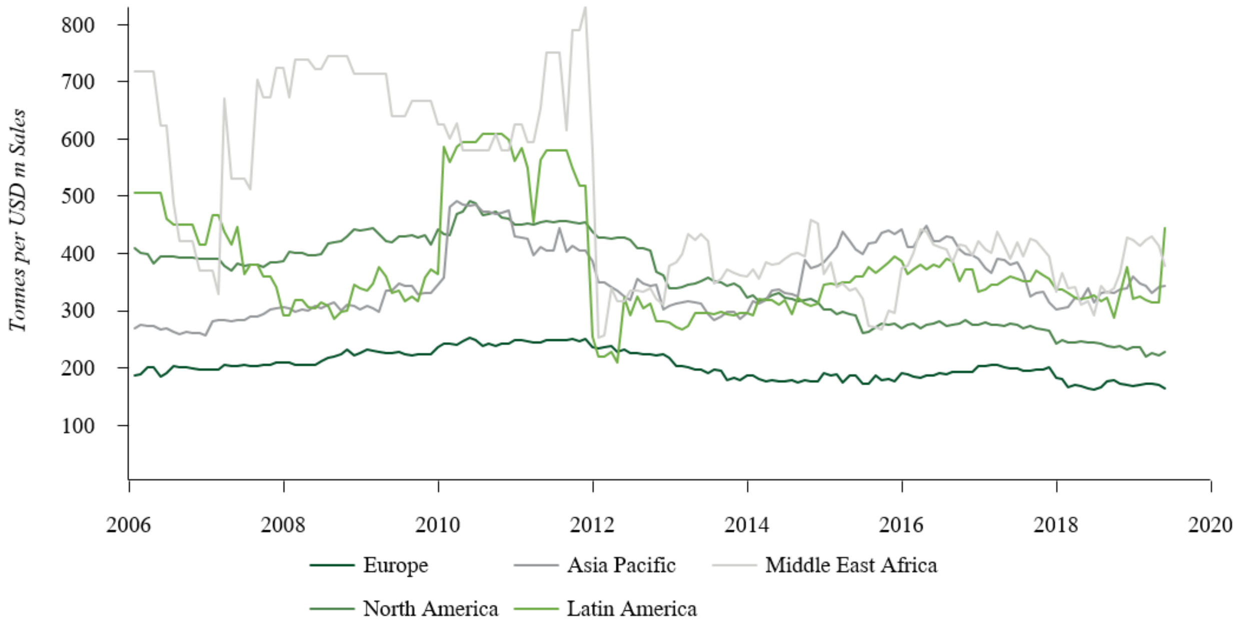
Velte, Patrick. 2017. Does ESG performance have an impact on financial performance? Evidence from Germany. *Journal of Global Responsibility*.

Verheyden, Tim, Eccles, Robert G., & Feiner, Andreas. 2016. ESG for All? The Impact of ESG Screening on Return, Risk, and Diversification. *Journal of Applied Corporate Finance*, **28**(2), 47–55.

Wooldridge, Jeffrey M. 2012. *Introductory Econometrics A modern Approach*. 8 edn. Pearson.

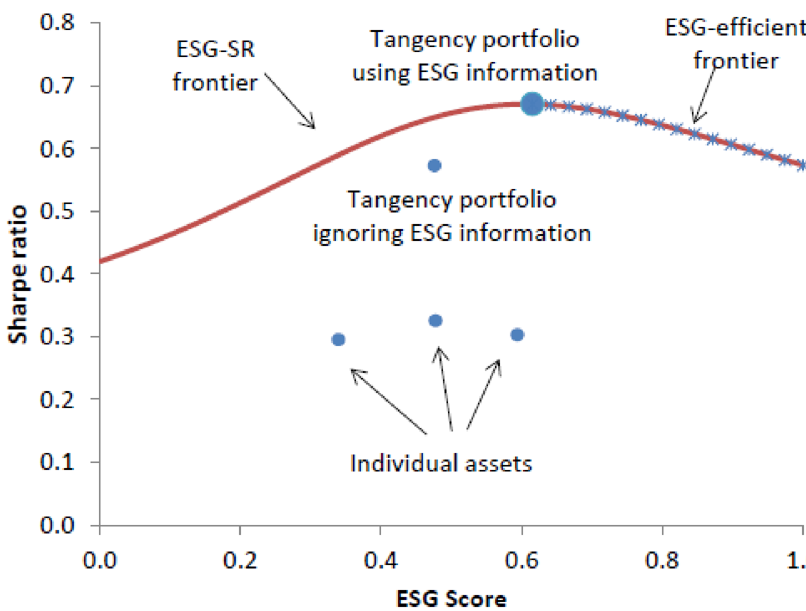
# Appendix

*Appendix I: Average CO2 Emissions by Region*




*The figure above depicts the average CO2 Emissions by geographic area. The amount of CO2 emitted is hereby measured on a monthly basis as tonnes per million USD sales within the region. Due to inconsistent data, we have hereby excluded the Eastern Europe region. The time frame covered is January 2006 until May 2019.*

*Appendix II: The ESG-SR Efficient Frontier (Pedersen* et al.*, 2019)*



*Appendix III: ESG and Equity Factor Correlations*

| | *ESG Score* | *ESG Momentum* |
|---|---|---|
| Market Cap | 0.079 | -0.006 |
| BTM | -0.005 | -0.002 |
| Volatility | -0.078 | 0.007 |
| Liquidity | -0.001 | -0.001 |
| Leverage Ratio | -0.004 | -0.002 |
| Beta | -0.081 | 0.007 |
| Profitability | -0.015 | 0.000 |
| Dividend Yield | 0.003 | -0.002 |

*This table provides an overview of the correlation of the raw ESG scores and the ESG Momentum factor with traditional equity factors.*

*Appendix IV: Cross-Correlations of Factor Portfolios U.S.*

| *Factor* | *Monthly* | *Std.* | *Cross-Correlations* | | | | |
|---|---|---|---|---|---|---|---|
| *Portfolio* | *Excess Return* | *Dev.* | *MRKT Excess* | *SMB* | *HML* | *PMOM* | *ESGMOM* |
| Mrkt Excess Return | 0.99% | 3.27% | 1.00 | | | | |
| SMB | -0.37% | 1.28% | 0.19 | 1.00 | | | |
| HML | -1.45% | 2.23% | 0.09 | 0.28 | 1.00 | | |
| Price Momentum | 0.07% | 3.09% | -0.24 | -0.32 | -0.70 | 1.00 | |
| ESG Momentum | 0.13% | 0.98% | -0.18 | -0.05 | -0.07 | 0.08 | 1.00 |

*The table above exhibits the average excess return as well as the standard deviation for each of the factor portfolios created for the 4- and 5-factor regressions. Additionally, the table shows their cross-correlation matrix of the factors.*

*Appendix V: 4-Factor Regression On ESG Momentum Quintiles U.S.*

| *Decile* | *Monthly Excess Return* | *Std. Dev.* | *Alpha* | *Market Excess Return* | *SMB* | *HML* | *Price Momentum* | *Adj. $R^2$* |
|---|---|---|---|---|---|---|---|---|
| 1 (low) | 1.10% | 3.57% | 0.21%* | 0.978*** | -0.073 | 0.068 | -0.067 | 91.6% |
| | | | (1.65) | (31.47) | (-0.89) | (1.08) | (-1.44) | |
| 2 | 1.12% | 3.54% | 0.01% | 1*** | -0.317*** | -0.026 | -0.108** | 95.0% |
| | | | (0.1) | (32.21) | (-3.9) | (-0.42) | (-2.32) | |
| 3 | 1.04% | 3.34% | 0.06% | 0.927*** | -0.118 | -0.024 | -0.061 | 92.8% |
| | | | (0.47) | (29.83) | (-1.45) | (-0.38) | (-1.32) | |
| 4 | 0.88% | 3.47% | -0.11% | 0.956*** | 0.04 | -0.047 | -0.048 | 94.9% |
| | | | (-0.82) | (30.78) | (0.49) | (-0.76) | (-1.02) | |
| 5 (high) | 1.36% | 3.38% | 0.38%*** | 0.916*** | -0.108 | -0.03 | -0.017 | 92.0% |
| | | | (2.92) | (29.49) | (-1.32) | (-0.47) | (-0.36) | |
| 5-1 | 0.26% | 1.51% | 0.17% | -0.062 | -0.035 | -0.097 | 0.05 | 8.6% |
| | (0.521) | | (0.78) | (-1.22) | (-0.27) | (-0.95) | (0.66) | |

*The table above presents the regression of the monthly excess return of 5 quintile portfolios based on the ESG Momentum factor regressed on the traditional four Carhart factors. The regression covers the data frame from 2010 to May 2019 and includes data for the U.S. market. T-statistics are given in parenthesis below the coefficient. The asterisks behind the coefficients indicate the significance level:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

*Appendix VI: 4-Factor Regression On Lagged One-Year Return U.S.*

| *Decile* | *Monthly Excess Return* | *Std. Dev.* | *Alpha* | *Market Excess Return* | *SMB* | *HML* | *Price Momentum* | *Adj.* $R^2$ |
|---|---|---|---|---|---|---|---|---|
| 1 | 1.35% | 5.3% | 0.663%*** | 0.951*** | 0.211* | 0.039 | -0.982*** | 87.1% |
| | | | (3.523) | (21.091) | (1.791) | (0.425) | (-14.487) | |
| 2 | 0.85% | 4.4% | 0.124% | 0.978*** | -0.142 | 0.139 | -0.657*** | 93.3% |
| | | | (0.661) | (21.706) | (-1.204) | (1.534) | (-9.695) | |
| 3 | 1.04% | 3.8% | 0.284% | 0.925*** | -0.092 | 0.102 | -0.386*** | 86.9% |
| | | | (1.509) | (20.541) | (-0.779) | (1.117) | (-5.698) | |
| 4 | 0.84% | 3.7% | 0.062% | 1.004*** | -0.171 | 0.167* | -0.208*** | 92.4% |
| | | | (0.328) | (22.278) | (-1.443) | (1.833) | (-3.061) | |
| 5 | 0.95% | 3.6% | 0.025% | 1.015*** | -0.337*** | 0.118 | -0.113* | 90.2% |
| | | | (0.131) | (22.528) | (-2.853) | (1.301) | (-1.669) | |
| 6 | 1.04% | 3.1% | 0.215% | 0.912*** | -0.201* | 0.097 | -0.014 | 90.3% |
| | | | (1.141) | (20.252) | (-1.705) | (1.061) | (-0.206) | |
| 7 | 1.08% | 3.1% | -0.025% | 0.929*** | -0.121 | -0.095 | 0.13** | 91.0% |
| | | | (-0.131) | (20.612) | (-1.028) | (-1.04) | (1.919) | |
| 8 | 1.02% | 3.2% | -0.139% | 0.941*** | 0.001 | -0.149 | 0.207*** | 87.1% |
| | | | (-0.739) | (20.867) | (0.014) | (-1.64) | (3.058) | |
| 9 | 1.11% | 3.0% | 0.143% | 0.860*** | -0.003 | -0.062 | 0.252*** | 83.5% |
| | | | (0.761) | (19.096) | (-0.024) | (-0.677) | (3.722) | |
| 10 | 1.56% | 4.0% | -0.145% | 1.106*** | 0.023 | -0.429*** | 0.236*** | 83.9% |
| | | | (-0.769) | (24.542) | (0.194) | (-4.722) | (3.479) | |
| 10-1 | 0.21% | 5.1% | -0.909%*** | 0.152*** | -0.469 | -0.523*** | 1.111*** | 79.3% |
| | (0.14) | | (-2.715) | (2.09) | (-2.447) | (-3.835) | (11.418) | |

*The table above describes the regression of the monthly excess return of ten deciles based on lagged one-year performance on the traditional four Carhart factors. The regression covers the data frame from 2010 to May 2019 and includes data for the U.S. market. T-statistics are given in parenthesis below the coefficient. Asterisks behind the coefficient indicate the significance level:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

*Appendix VII: 5-Factor Regression On Lagged One-Year Return U.S.*

| *Decile* | *Monthly Excess Return* | *Std. Dev.* | *Alpha* | *Market Excess Return* | *SMB* | *HML* | *Price Momentum* | *ESG Momentum* | *Adj. $R^2$* |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.35% | 5.32% | 0.66%*** | 0.949*** | 0.211* | 0.035 | -0.982*** | -0.056 | 87.2% |
| | | | (3.5) | (21.05) | (1.79) | (0.38) | (-14.51) | (-0.38) | |
| 2 | 0.85% | 4.40% | 0.11% | 0.974*** | -0.143 | 0.127 | -0.66*** | -0.198 | 93.4% |
| | | | (0.58) | (21.6) | (-1.21) | (1.39) | (-9.74) | (-1.36) | |
| 3 | 1.04% | 3.80% | 0.28% | 0.925*** | -0.092 | 0.098 | -0.387*** | -0.051 | 87.0% |
| | | | (1.49) | (20.5) | (-0.78) | (1.08) | (-5.71) | (-0.35) | |
| 4 | 0.84% | 3.68% | 0.05% | 1.002*** | -0.171 | 0.159* | -0.209*** | -0.113 | 92.5% |
| | | | (0.28) | (22.21) | (-1.45) | (1.74) | (-3.08) | (-0.78) | |
| 5 | 0.95% | 3.57% | 0.01% | 1.01*** | -0.339*** | 0.102 | -0.116* | -0.245* | 90.6% |
| | | | (0.03) | (22.4) | (-2.87) | (1.12) | (-1.72) | (-1.68) | |
| 6 | 1.04% | 3.13% | 0.22% | 0.913*** | -0.201* | 0.099 | -0.014 | 0.033 | 90.2% |
| | | | (1.15) | (20.25) | (-1.7) | (1.08) | (-0.2) | (0.23) | |
| 7 | 1.08% | 3.10% | -0.03% | 0.927*** | -0.122 | -0.099 | 0.129* | -0.064 | 91.0% |
| | | | (-0.16) | (20.56) | (-1.03) | (-1.08) | (1.91) | (-0.44) | |
| 8 | 1.02% | 3.24% | -0.14% | 0.941*** | 0.002 | -0.148 | 0.207*** | 0.014 | 87.1% |
| | | | (-0.73) | (20.85) | (0.01) | (-1.62) | (3.06) | (0.1) | |
| 9 | 1.11% | 3.01% | 0.13% | 0.856*** | -0.004 | -0.075 | 0.25*** | -0.202 | 93.9% |
| | | | (0.68) | (18.98) | (-0.04) | (-0.82) | (3.69) | (-1.39) | |
| 10 | 1.56% | 4.03% | -0.12% | 1.112*** | 0.025 | -0.41*** | 0.24*** | 0.295** | 84.4% |
| | | | (-0.65) | (24.65) | (0.21) | (-4.49) | (3.54) | (2.02) | |
| 10-1 | 0.21% | 5.11% | -0.90%*** | 0.159** | -0.464** | -0.503*** | 1.115*** | 0.243 | 79.5% |
| | (0.14) | | (-2.7) | (2.17) | (-2.45) | (-3.65) | (11.45) | (0.98) | |

*The table above describes the regression of the monthly excess returns of ten decile portfolios based on lagged one-year performance on the traditional four Carhart factors as well as the ESG Momentum factor. The regression covers the data frame from 2010 to May 2019 and includes data for the U.S. market. T-statistics are given in parenthesis below the coefficient. Asterisks behind the coefficient indicate the significance level: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.*

*Appendix VIII: 4-Factor Regression on E Momentum Quintiles - Utilities Sector*

| *Decile* | *Monthly Excess Return* | *Std. Dev.* | *Alpha* | *Market Excess Return* | *SMB* | *HML* | *Price Momentum* | *Adj. $R^2$* |
|---|---|---|---|---|---|---|---|---|
| 1 (low) | 0.21% | 3.46% | -0.006% | 0.395*** | -0.412* | 0.315** | 0.082 | 30.1% |
| | | | (-0.01) | (3.80) | (-1.84) | (2.22) | (0.76) | |
| 2 | 0.33% | 3.95% | 0.209% | 0.508*** | -0.829*** | 0.244* | 0.042 | 30.2% |
| | | | (0.55) | (4.88) | (-3.71) | (1.72) | (0.39) | |
| 3 | 0.34% | 3.78% | 0.569% | 0.434*** | -0.343 | 0.392*** | -0.027 | 32.1% |
| | | | (1.51) | (4.16) | (-1.52) | (2.71) | (-0.25) | |
| 4 | 0.44% | 4.13% | 0.334% | 0.410*** | -0.544** | 0.482*** | 0.091 | 31.5% |
| | | | (0.88) | (3.94) | (-2.43) | (3.40) | (0.84) | |
| 5 (high) | 0.66% | 3.95% | -0.135% | 0.693*** | -0.776*** | 0.277** | 0.036 | 30.3% |
| | | | (-0.35) | (6.67) | (-3.47) | (1.96) | (0.33) | |
| 5-1 | 0.45% | 0.49% | -0.128% | 0.298*** | -0.364* | -0.037 | -0.046 | 10.4% |
| | (0.34) | | (-0.35) | (3.00) | (-1.70) | (-0.27) | (-0.44) | |

*The table above presents the regression of the monthly excess return of 5 quintile portfolios based on the E Momentum factor for the Utilities sector regressed on the traditional four Carhart factors. The regression covers the data frame from 2010 to May 2019 and includes data for the European market. T-statistics are given in parenthesis below the coefficient. The asterisks behind the coefficients indicate the significance level:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

*Appendix IX: 4-Factor Regression on G Momentum Quintiles - Financial Sector*

| *Decile* | *Monthly Excess Return* | *Std. Dev.* | *Alpha* | *Market Excess Return* | *SMB* | *HML* | *Price Momentum* | *Adj.* $R^2$ |
|---|---|---|---|---|---|---|---|---|
| 1 (low) | 1.27% | 6.79% | 0.168% | 0.875*** | -0.692*** | 0.325*** | -0.056 | 81.2% |
| | | | (0.59) | (11.6) | (-3.24) | (3.1) | (-0.58) | |
| 2 | 0.84% | 6.31% | -0.181% | 0.939*** | -0.451** | 0.426*** | -0.112 | 84.3% |
| | | | (-0.64) | (12.44) | (-2.11) | (4.05) | (-1.15) | |
| 3 | 1.28% | 6.25% | -0.274% | 0.978*** | -0.608*** | 0.463*** | -0.168* | 84.1% |
| | | | (-0.96) | (12.96) | (-2.84) | (4.41) | (-1.74) | |
| 4 | 0.99% | 6.07% | -0.308% | 0.974*** | -0.989*** | 0.307*** | -0.281*** | 85.9% |
| | | | (-1.08) | (12.91) | (-4.62) | (2.92) | (-2.91) | |
| 5 (high) | 1.31% | 6.12% | -0.099% | 0.911*** | -1.068*** | 0.489*** | -0.363*** | 81.3% |
| | | | (-0.35) | (12.07) | (-4.99) | (4.65) | (-3.76) | |
| 5-1 | 0.04% | 2.66% | -0.267% | 0.035 | -0.375 | 0.164 | -0.307*** | 33.5% |
| | 0.452 | | (-0.8) | (0.4) | (-1.51) | (1.34) | (-2.73) | |

*The table above presents the regression of the monthly excess return of 5 quintile portfolios based on the G Momentum factor for the Financials sector regressed on the traditional four Carhart factors. The regression covers the data frame from 2010 to May 2019 and includes data for the European market. T-statistics are given in parenthesis below the coefficient. The asterisks behind the coefficients indicate the significance level:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

*Appendix X: Industry Regression on Separate Pillars - Utilities Sector*

| *Decile* | *Monthly Excess Return* | *Std. Dev.* | *Alpha* | *Market Excess Return* | *SMB* | *HML* | *Price Momentum* | *E Mom* | *S Mom* | *G Mom* | *Adj.* $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | -0.39% | 6.28% | 0.23% | 0.511*** | -0.587* | 0.633*** | -0.592*** | 0.051 | 0.035 | -0.248 | 54.5% |
| | | | (0.48) | (3.91) | (-1.84) | (3.23) | (-4.07) | (0.25) | (0.2) | (-1.64) | |
| 2 | -0.14% | 4.93% | -0.29% | 0.589*** | -0.863*** | 0.367* | -0.511*** | 0.134 | 0.052 | -0.238 | 49.9% |
| | | | (-0.61) | (4.51) | (-2.71) | (1.87) | (-3.52) | (0.65) | (0.31) | (-1.58) | |
| 3 | -0.06% | 5.10% | 0.05% | 0.448*** | -0.593* | 0.263 | -0.433*** | 0.274 | -0.001 | -0.087 | 38.9% |
| | | | (0.1) | (3.43) | (-1.86) | (1.34) | (-2.98) | (1.32) | (-0.01) | (-0.57) | |
| 4 | 0.82% | 4.21% | 0.16% | 0.573*** | -0.916*** | -0.088 | -0.196 | -0.013 | 0.014 | -0.383** | 29.9% |
| | | | (0.35) | (4.38) | (-2.87) | (-0.45) | (-1.35) | (-0.06) | (0.08) | (-2.54) | |
| 5 | 0.46% | 3.17% | 0.43% | 0.431*** | -0.515 | 0.249 | 0.048 | 0.12 | -0.024 | -0.26* | 23.6% |
| | | | (0.9) | (3.3) | (-1.62) | (1.27) | (0.33) | (0.58) | (-0.14) | (-1.72) | |
| 6 | 0.75% | 3.97% | 0.26% | 0.46*** | -0.606* | 0.345* | 0.109 | 0.467** | -0.074 | -0.142 | 26.9% |
| | | | (0.54) | (3.52) | (-1.9) | (1.76) | (0.75) | (2.26) | (-0.44) | (-0.94) | |
| 7 | 0.67% | 3.75% | 0.59% | 0.419*** | -0.614* | 0.377* | 0.294** | 0.233 | -0.027 | -0.192 | 24.0% |
| | | | (1.25) | (3.21) | (-1.92) | (1.92) | (2.03) | (1.13) | (-0.16) | (-1.27) | |
| 8 | 0.76% | 3.61% | 0.46% | 0.439*** | -0.582* | 0.174 | 0.277* | 0.37* | 0.032 | -0.26* | 31.9% |
| | | | (0.97) | (3.36) | (-1.82) | (0.89) | (1.91) | (1.79) | (0.19) | (-1.72) | |
| 9 | 0.69% | 3.58% | 0.48% | 0.432*** | -0.65** | 0.409** | 0.483*** | 0.196 | -0.047 | -0.15 | 32.2% |
| | | | (1) | (3.3) | (-2.04) | (2.09) | (3.32) | (0.95) | (-0.27) | (-0.99) | |
| 10 | 0.04% | 3.79% | -0.34% | 0.44*** | -0.733** | 0.379* | 0.339** | 0.229 | 0.139 | -0.235 | 29.7% |
| | | | (-0.71) | (3.37) | (-2.3) | (1.93) | (2.33) | (1.1) | (0.82) | (-1.56) | |
| 10-1 | 0.44% | 6.03% | -0.57% | -0.071 | -0.146 | -0.254 | 0.931 | 0.177 | 0.105 | 0.013 | 70.3% |
| | (0.595) | | (-1.52) | (-0.69) | (-0.58) | (-1.65) | (8.14) | (1.09) | (0.78) | (0.11) | |

*The table depicts the industry based regression of the monthly excess return on the decile portfolios on using the four Carhart factors as well as the Momentum factor on each separate pillar. The regression covers the data frame from 2010 to May 2019 and includes data for the European Utilities sector. T-statistics are given in parenthesis below the coefficient. Asterisks behind the coefficient indicate the significance level:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

*Appendix XI: Industry Regression on Separate Pillars - Financial Sector*

| *Decile* | *Monthly Excess Return* | *Std. Dev.* | *Alpha* | *Market Excess Return* | *SMB* | *HML* | *Price Momentum* | *E Mom* | *S Mom* | *G Mom* | *Adj.* $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.30% | 8.11% | 0.03% | 0.935*** | -0.697*** | 0.75*** | -0.84*** | 0.144 | -0.145 | 0.065 | 88.7% |
| | | | (0.1) | (10.62) | (-2.83) | (6.04) | (-6.7) | (0.79) | (-0.72) | (0.38) | |
| 2 | 0.82% | 7.50% | 0.19% | 0.875*** | -1.01*** | 0.344*** | -0.623*** | 0.179 | 0.013 | 0.157 | 86.9% |
| | | | (0.58) | (9.94) | (-4.1) | (2.77) | (-4.97) | (0.98) | (0.07) | (0.93) | |
| 3 | 0.34% | 6.10% | 0.27% | 0.842*** | -0.608** | 0.684*** | -0.324*** | 0.36** | 0.014 | 0.05 | 84.9% |
| | | | (0.8) | (9.56) | (-2.47) | (5.51) | (-2.58) | (1.96) | (0.07) | (0.29) | |
| 4 | 0.60% | 5.43% | -0.02% | 0.827*** | -0.673*** | 0.435*** | -0.376*** | -0.1 | 0.016 | 0.15 | 92.5% |
| | | | (-0.06) | (9.4) | (-2.73) | (3.5) | (-3) | (-0.55) | (0.08) | (0.88) | |
| 5 | 0.74% | 5.31% | -0.06% | 0.92*** | -0.934*** | 0.432*** | -0.312** | 0.183 | -0.007 | -0.076 | 78.5% |
| | | | (-0.18) | (10.45) | (-3.79) | (3.48) | (-2.49) | (1) | (-0.03) | (-0.45) | |
| 6 | 0.77% | 4.86% | 0.21% | 0.959*** | -0.763*** | 0.407*** | -0.055 | 0.188 | 0.096 | 0.143 | 78.8% |
| | | | (0.64) | (10.89) | (-3.1) | (3.28) | (-0.44) | (1.03) | (0.48) | (0.84) | |
| 7 | 0.71% | 4.91% | -0.08% | 1.017*** | -1.131*** | 0.431*** | 0.075 | -0.194 | -0.348* | 0.057 | 86.6% |
| | | | (-0.25) | (11.55) | (-4.59) | (3.48) | (0.6) | (-1.06) | (-1.72) | (0.33) | |
| 8 | 0.71% | 4.64% | -0.01% | 1.04*** | -1.024*** | 0.267** | 0.012 | 0.239 | -0.022 | 0.095 | 81.7% |
| | | | (-0.02) | (11.81) | (-4.16) | (2.15) | (0.1) | (1.3) | (-0.11) | (0.56) | |
| 9 | 0.41% | 4.41% | 0.09% | 0.869*** | -0.548** | 0.557*** | 0.369*** | 0.349* | 0.025 | 0.146 | 73.9% |
| | | | (0.28) | (9.87) | (-2.23) | (4.49) | (2.95) | (1.9) | (0.12) | (0.86) | |
| 10 | 0.21% | 4.23% | -0.48% | 0.86*** | -0.259 | 0.197 | 0.473*** | 0.049 | -0.16 | 0.324* | 73.7% |
| | | | (-1.46) | (9.77) | (-1.05) | (1.59) | (3.78) | (0.27) | (-0.79) | (1.91) | |
| 10-1 | -0.16% | 6.53% | -0.52% | -0.752 | 0.438 | -0.553 | 1.313 | -0.096 | -0.015 | 0.259 | 88.4% |
| | (-0.232) | | (-1.56) | (-0.86) | (1.78) | (-4.47) | (10.51) | (-0.52) | (-0.07) | (1.53) | |

*The table depicts the industry based regression of the monthly excess return on the decile portfolios on using the four Carhart factors as well as the Momentum factor on each separate pillar. The regression covers the data frame from 2010 to May 2019 and includes data for the European Financial sector. T-statistics are given in parenthesis below the coefficient. Asterisks behind the coefficient indicate the significance level:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

*Appendix XII: Breusch-Godfrey Test Europe*

| | *4-factor* | | *5-factor* | |
|---|---|---|---|---|
| | *LM* | *p-value* | *LM* | *p-value* |
| Decile 1 | 14.343 | 0.279 | 13.343 | 0.279 |
| Decile 2 | 13.384 | 0.343 | 11.838 | 0.459 |
| Decile 3 | 10.336 | 0.587 | 9.5468 | 0.656 |
| Decile 4 | 16.857 | 0.105 | 17.689 | 0.113 |
| Decile 5 | 15.086 | 0.237 | 14.838 | 0.251 |
| Decile 6 | 10.665 | 0.558 | 10.684 | 0.556 |
| Decile 7 | 17.979 | 0.102 | 17.877 | 0.119 |
| Decile 8 | 10.776 | 0.548 | 9.515 | 0.658 |
| Decile 9 | 22.028 | 0.037 | 16.543 | 0.168 |
| Decile 10 | 11.547 | 0.483 | 11.433 | 0.492 |

*The table depicts the results from the Breusch-Godfrey test performed on all 4- and 5-factor regressions with each decile portfolios sorted on 1-year lagged return for the European sample as independent variable. A p-value over 0.10 indicates fails to reject of the null hypothesis of no autocorrelation.*

*Appendix XIII: Breusch-Godfrey Test U.S.*

| | *4-factor* | | *5-factor* | |
|---|---|---|---|---|
| | *LM* | *p-value* | *LM* | *p-value* |
| Decile 1 | 12.781 | 0.385 | 13.663 | 0.323 |
| Decile 2 | 16.884 | 0.154 | 16.076 | 0.188 |
| Decile 3 | 10.978 | 0.531 | 13.250 | 0.351 |
| Decile 4 | 3.820 | 0.987 | 3.561 | 0.990 |
| Decile 5 | 9.704 | 0.642 | 9.789 | 0.635 |
| Decile 6 | 9.753 | 0.638 | 10.581 | 0.565 |
| Decile 7 | 6.554 | 0.886 | 6.066 | 0.913 |
| Decile 8 | 7.566 | 0.818 | 7.779 | 0.802 |
| Decile 9 | 15.800 | 0.201 | 15.104 | 0.236 |

*The table depicts the results from the Breusch-Godfrey test performed on all 4- and 5-factor regressions with each of the decile portfolios sorted on 1-year lagged return for the European sample as independent variable. A p-value over 0.10 indicates fails to reject of the null hypothesis of no autocorrelation.*

*Appendix XIV: Breusch-Pagan Test Europe*

| | *4-factor* | | *5-factor* | |
|---|---|---|---|---|
| | *LM* | *p-value* | *LM* | *p-value* |
| Decile 1 | 8.230 | 0.080 | 2.209 | 0.530 |
| Decile 2 | 5.507 | 0.239 | 2.961 | 0.398 |
| Decile 3 | 5.731 | 0.220 | 4.733 | 0.192 |
| Decile 4 | 3.307 | 0.508 | 1.853 | 0.660 |
| Decile 5 | 4.674 | 0.322 | 3.266 | 0.352 |
| Decile 6 | 2.782 | 0.595 | 1.773 | 0.621 |
| Decile 7 | 3.553 | 0.470 | 1.401 | 0.705 |
| Decile 8 | 5.825 | 0.213 | 1.507 | 0.681 |
| Decile 9 | 3.638 | 0.457 | 2.555 | 0.466 |
| Decile 10 | 7.564 | 0.120 | 3.549 | 0.314 |

*The table depicts the results from the Breusch-Pagan test performed on all 4- and 5-factor regressions with each of the decile portfolios sorted on 1-year lagged returns for the European sample as dependent variable. A p-value over 0.10 fails to reject the null hypothesis of homoskedastic error terms in the model.*

*Appendix XV: Breusch-Pagan Test U.S.*

| | *4-factor* | | *5-factor* | |
|---|---|---|---|---|
| | *LM* | *p-value* | *LM* | *p-value* |
| Decile 1 | 6.005 | 0.306 | 6.605 | 0.148 |
| Decile 2 | 4.603 | 0.331 | 6.034 | 0.303 |
| Decile 3 | 6.928 | 0.140 | 6.674 | 0.246 |
| Decile 4 | 2.938 | 0.568 | 3.154 | 0.676 |
| Decile 5 | 9.778 | 0.044 | 14.413 | 0.013 |
| Decile 6 | 6.002 | 0.298 | 7.921 | 0.161 |
| Decile 7 | 1.844 | 0.764 | 7.021 | 0.219 |
| Decile 8 | 3.104 | 0.541 | 3.203 | 0.669 |
| Decile 9 | 5.579 | 0.233 | 6.971 | 0.223 |
| Decile 10 | 1.435 | 0.838 | 10.075 | 0.073 |

*The table depicts the results from the Breusch-Pagan test performed on all 4- and 5-factor regressions with each decile portfolio sorted on 1-year lagged returns for the U.S. sample as dependent variable. A p-value over 0.10 fails to reject the null hypothesis of homoskedastic error terms in the model.*

*Appendix XVI: VIF Europe*

| | *4-Factor* | *5-Factor* |
|---|---|---|
| Market Excess | 1.224 | 1.240 |
| SMB | 1.136 | 1.136 |
| HML | 1.842 | 1.881 |
| Price Momentum | 1.901 | 1.920 |
| ESG Momentum | - | 1.080 |

*The table depicts the results from the VIF tests performed on the factors used for the 4- and 5-factor regressions on the European sample.*

*Appendix XVII: VIF U.S.*

| | *4-Factor* | *5-Factor* |
|---|---|---|
| Market Excess | 1.198 | 1.250 |
| SMB | 1.272 | 1.287 |
| HML | 1.798 | 1.715 |
| Price Momentum | 1.843 | 1.855 |
| ESG Momentum | - | 1.098 |

*The table depicts the results from the VIF tests performed on the factors used for the 4- and 5-factor regressions on the U.S. sample.*