COPENHAGEN BUSINESS SCHOOL

MASTER'S THESIS

Impact of ESG ratings on stock performance & resiliency:

A comparative study of European, Asian and Oceanian stocks

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May 17, 2021

Characters incl. spaces: 217,394

Tables and figures: 37

Normal pages: 96

ABSTRACT

This thesis sat out to measure the long-term returns and short-term resiliency of socially responsible stocks in Europe, Asia and Oceania. To test the long-term returns, we used ten value-weighted decile portfolios and a long-short portfolio sorted on an overall- and "pillar specific" Environmental-, Social-, and Governance score. We primarily focused on Jensen's alpha measure in our adaption of the Fama and French three-and-five factor model and Carhart's four factor model. For the European and Oceanian region, our Jensen's alpha coefficients did not differ significantly from zero. With this, we conclude that both the overall- and the pillar-specific ESG portfolios showed neither sign of outperformance nor underperformance. For the Asian region, our Jensen's alpha coefficient for the long-short portfolio showed negative and significant results at the 5% level. With this, we conclude that an investment strategy that shorts "brown"-tilted portfolios to fund an investment in "green"-tilted portfolios would produce a negative alpha. We analyzed the long-term returns from January 2007 through 2020.

To test the resiliency of stocks, we undertook a multiple regression analysis of the buy-and-hold abnormal returns on the company's overall – and "pillar specific" scores, after controlling for multiple other factors such as sector affiliation, market-based measures of risk and accounting-based measures of financial performance. To further substantiate our findings, we undertook an Owen-Shapley decomposition of R^2. We analyzed the resiliency of socially responsible stocks in a COVID crisis period from January through March 2020. For the European and Oceanian region, we presented robust evidence that neither the overall- nor the pillar-specific scores offered significant resiliency or strong explanatory power for returns. For the Asian region, we showed that the overall ESG score and the Environmental- and Social-pillar offered negative explanatory power for returns and did not provide investors with short-term resiliency.

To the best of our knowledge, this thesis represents the first tri-regional, ESG-pillar-specific performance and resilience study, using an identical methodological approach across regions. Our findings from Europe and Oceania support the group of previous studies finding non-negative links between ESG and financial performance and resiliency. Oppositely, our findings from Asia indicates that there exist inter-regional differences and that socially responsible performance is negatively associated with long-term returns and short-term resiliency in Asia.

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KEYWORDS

CSR: Corporate Social Responsibility

SRI: Socially responsible investing

GFC: Global financial crisis

ESG: Environmental, Social and Governance

E: Environmental pillar

S: Social pillar

G: Governance pillar

Green stocks: Those stocks in the top five portfolios

Brown stocks: Those stocks in the bottom five portfolios

CFP: Corporate financial performance

CAPM: Capital Asset Pricing Model

FF3: Fama French 3-factor model

C4: Carhart 4-factor model

FF5: Fama French 5-factor model

HML: Value factor

SMB: Size factor

MKT: Market factor

MOM: Momentum factor

CMA: investment-style factor

RMW: Profitability factor

OSD: Owen-Shapley decomposition

OLS: Ordinary Least Square

MLR: Multiple linear regression

BHAR: Buy-and-hold excess return

SR: Sharpe ratio

VW: Value weighted

EW: Equally weighted

Part I

INTRODUCTION

OUTLINING THE PROBLEM 1

1.1 ESG AS A SOURCE OF ALPHA AN RESILIENCY

In 2021, Larry Fink, CEO of BlackRock, wrote a letter to the CEOs of the companies in which BlackRock holds shares. In this letter, Fink sought out to highlight the issues that are pivotal to creating long-term return advantages, one of which is sustainability. Specifically, Fink wrote *"The more your company can show its purpose in delivering value to its customers, its employees, and its communities, the better able you will be to compete and deliver long-term, durable profits for shareholders."* (Fink, 2021).

Fink mentions that we are currently seeing a divergence: companies with better ESG profiles are performing better than their peers, enjoying a "*sustainability premium*". Secondly, he argues that the sustainability premium was even more noticeable during the first quarter of 2020, a period that revealed the sustainable funds' resilience to a downturn in the market (Fink, 2021). Fink's view is to a large extend shared by Environmental, Social and Governance (ESG) data purveyors and asset managers. EY's 2020 Global Survey on ESG portfolios reports that a large majority of asset managers agree that COVID-19 has reinforced the narrative that sustainable strategies do not require a return tradeoff and have important resilient properties.

By examining Q1 of 2020 and the COVID-19 pandemics impact on the economy and financial markets we find that the narrative, at first glance, is well-supported. In Q1 of 2020, MSCI world index dropped 14.5% in March. However, 62% of large-cap ESG funds outperformed this index (Darbyshire, 2020)[1]. In total, MSCI reported that 15 out of 17 of their sustainable indices outperformed broad market counterparts, while Blackrock reported that 94% of a globally

[1] For more examples see Mckinsey's "Institutional investing in the time of COVID-19", Fortune's "The coronavirus pandemic may be a turning point for responsible business", European capital markets institute "ESG resilience during the COVID crisis, is green the new gold"

representative selection of widely analyzed sustainable indices outperformed their parent benchmark[2]. However, despite of the apparent outperformance, skepticism is beginning to emerge[3]. The opponents argue that claims of ESG outperformance and resiliency is a mirage and will disappear when adjusted for risk, sector bias and firm-specific quality factors (Bruno, Esakia, & Goltz, 2021).

Together, we believe the conflict described above and the COVID-19 pandemic provides a unique opportunity to test the opposing views by first studying the long-term performance of ESG leaders and laggards and secondly their short-term resiliency to a shock like COVID-19. A particular reason for this circumstance is that COVID-19 separates itself from previous shocks to the market. According to Bodnár, Le Reux, Lopez-Garcia, & Szorfi (2020), this can be explained by the nature of the shock which is described as partly exogenous.

A partly exogenous shock creates a valuable opportunity to gain insights into the true drivers of value creation before and during a market downturn. Moreover, previous studies that focus on value creation and the resiliency of ESG factors examine the Global Financial Crisis (hereafter GFC). Such an analysis may under-, or overestimate crisis impacts in unknown ways due to the distinguishing feature of the crisis (Ramelli & Wagner, 2020). Specifically, the 2008 GFC was not independent but originated from past regulatory frameworks that distorted and created poor incentives for market participants (Danielsson, Macrae, Vayanos, & Vayanos, 2020). On the contrary, the COVID-19 crisis – a global pandemic – provides a new opportunity for researchers, as it to a large extend is exogeneous to global financial systems. As such, our paper capitalizes on the exogeneity of the COVID-19 pandemic and will provide new indications of the role of ESG on alpha and resiliency.

In this thesis we strive to investigate two things. First, we investigate if an investment strategy that goes long in "green" stocks and short in "brown stocks" delivers long-term, durable profits for an investor[4]. According to portfolio theory, such a strategy should, at best, perform on par with conventionally screened portfolios, but is that what we observe in practice? Secondly, our study

[2] https://www.blackrock.com/corporate/literature/investor-education/sustainable-investing-resilience.pdf
[3] See for example that of the Wall Street Journal "ESG investing in the Pandemic shows Power of Luck"
[4] Throughout this thesis we will refer to "green" stocks as companies with a high ESG score that are positioned in the top five ESG-performing portfolios. "Brown" stocks, are those companies with a low ESG score that are positioned in the bottom five ESG-performing portfolios.

undertakes an extensive set of analyses in order to shed light on the debate about sustainable investing's resiliency during a downturn. Are companies managed with a focus on sustainability better positioned to weather adverse financial conditions? Both of these questions have been at the heart of much academic research, and our thesis joins these ranks with a unique contribution by collectively investigating if 1) a company's overall- and "pillar-specific Environmental-, Social-, and Governance activities contribute to producing alpha and 2) if the overall and/or pillar specific factors create crisis-period resiliency.

1.2 OBJECTIVE AND RESEARCH QUESTION

Today's investor is increasingly concerned with integration Environmental, Social and Governance (ESG) factors into their investment strategy (BlackRock, 2020). By interviewing industry experts, we discovered that the typical investor possesses four central motivations for adopting a sustainable approach:

I. Aligning investment strategy with values and norms
II. Making a social impact by pressuring corporations to incorporate ethical strategies
III. Reducing risk exposure to climate and litigation risk by excluding ESG laggards
IV. Generating performance benefits by favoring more socially responsible companies

Our main objective is to assess whether there is support in Europe, Asia, and Oceania for the last-mentioned motivation and secondarily if ESG acts as a resilience factor during COVID-19 in these regions. To assess this, we undertake a series of analyses designed to uncover whether there exist signs of a significant relation between value creation and ESG. Our extensive analysis will help us answer the main research question and the underlying sub-questions stated below.

Main research questions

Can a sustainable investment strategy produce alpha and did ESG performance carry important resilient properties during the first quarter of 2020?

1.2.1 Sub-Question one: *is there a green-to-brown premium?*

The first sub-question is specifically related to the first part of the main research question. The focal aim of this sub-question is to investigate if an investment strategy that goes long in "green" stocks and short in "brown stocks" delivers long-term, durable profits for an investor. We base the majority of our analysis on Fama and French's acknowledged three factor model (FF3), Carhart's four factor model (C4), and Fama and French's five factor model (FF5). Moreover, to mobilize the analyses, we have decided to focus on alpha for which we create the following hypothesis. The null hypothesis states a relation that can either be positive or negative and reflects the portfolio performance of ten decile portfolios, rated on their ESG score:

$$H_0: a_{long\ minus\ short} = 0$$

$$H_1: a_{long\ minus\ short} \neq 0$$

Where α is Jensen's alpha measure of excess risk-adjusted return for the portfolios.

1.2.2 Sub-Question two: *Are high performing ESG, Environmental, Social and Governance companies more resilient to a partly exogenous shock like COVID-19?*

To add to existing literature and to analyze the performance of green and brown stocks during a downturn in the market, the second sub-question aims to investigate if ESG is an "equity vaccine" that contributes to stock price resiliency during a partly exogenous shock. Specifically, we perform a multiple regression analysis to examine the movements of buy-and-hold abnormal returns of green and brown stocks in Q1 of 2020. Furthermore, to assess the relative explanatory power of the overall ESG score and pillar-specific scores as individual regressors and resilience factors, we also undertake an Owen-Shapley decomposition of the R-squared (Huettner & Sunder, 2012).

The purpose of such an analysis is two-fold. Firstly, investigating the relationship between ESG and stock prices is an aspect that is closely related to sub-question one. In majority of cases, stock prices are argued to be positively influenced by a strong ESG proposition (Bassen, Busch, & Friede, 2015). Therefore, when analyzing the influence of ESG performance on buy-and-hold abnormal returns during an exogenous shock, it becomes essential to also examine the underlying explanatory power of the variables in question. Does ESG offer an "insurance-like effect" during COVID-19 and as such act as a positive explanatory power for returns? Or do other variables such as market-based measures of risk and traditional company-specific measures explain returns? These are some of the questions this sub-question seeks to answer. We set up the following hypothesis:

Hypothesis I: ESG score

$$H_0: X_{ESG} = 0$$

$$H_1: X_{ESG} \neq 0$$

Where X_{ESG} is the coefficient for the independent variable, ESG, for the January-March 2020 COVID-19 crisis period buy-and-hold excess returns. Furthermore, to fully answer sub-question two, this thesis also aims to uncover the individual influence of the three pillars that constitute the aggregated ESG score. Therefore, in strong contrast to previous literature, covering the link between ESG and crisis-period resiliency, the pillar-specific scores as well as the overall ESG score will be analyzed in detail. Performing such an analyzes, will allow us to uncover whether any of the disaggregated elements of ESG are more material to investors and thus stock market returns during Q1 of 2020. It is believed that such a distinction is especially important for the COVID-19 period returns, as investor sentiment took an acute shift towards the social pillar[5]. We mobilize this analysis through the following hypotheses:

Hypothesis II: Environmental score

$$H_0: X_E = 0$$

$$H_1: X_E \neq 0$$

Hypothesis III: Social score

$$H_0: X_S = 0$$

$$H_1: X_S \neq 0$$

[5] https://www.forbes.com/sites/bhaktimirchandani/2020/11/03/what-matters-most-in-esg-investing-how-to-spot-opportunities-across-market-cycles-and-the-capital-structure/?sh=2243fd0dc1b9

Hypothesis IV: Governance score

$$H_0: X_G = 0$$

$$H_1: X_G \neq 0$$

Only a few studies have analyzed a version of sub-question one and sub-question two collectively, with most of the studies focusing on US equity markets. This thesis seeks to broaden the geographical scope of current studies focusing on ESG and corporate financial performance (hereafter CFP) by analyzing three different regions, namely Europe, Asia, and Oceania.

1.3 SCOPE AND DELIMITATIONS

We restrict our geographical scope to Europe, Asia, and Oceania. Moreover, the study is delimited to listed companies with an operating revenue above USD 50 million in Oceania, USD 500 million in Europe and USD 1.000 million in Asia. As a result, companies with an operating revenue below the outlined threshold will not be considered in this thesis.

Furthermore, the thesis will assess these companies in two specific periods, named "Full period" and "outbreak". The first period is between January 2007 and December 2020 and is related to sub-question one. We have chosen this period to ensure sufficient and correct ESG and company specific data. The second period focuses on the first quarter of 2020 (January through March 2020) and is thus related to sub-question two. The period is characterized by the dramatic COVID-19 infused selloff where Asian (-18%), European (-25%) and Oceanian (-19%) benchmark indexes fell drastically (MSCI, 2021)[6]. For both sub-question one and sub-question two, we assume that the hypothetical investments are held for the periods specified above. We acknowledge that a delimitation of the investment horizon is not an ideal reflection of reality where the holding period can vary from short to long term investments. However, for simplicity reasons we delimit the study to assume a holding period that is equal to the length of the time periods described. We also restrict our ESG ranking and ESG index methodology to Refinitiv. This results in a lack of diversity in ESG scores. Therefore, we rely heavily on Refinitiv's ability to accurately collect and

[6] Benchmarks indexes: MSCI AC Asia, MSCI AC Europe and MSCI AC Asia ex Japan. Daily end-of-day data from 31/12/2019 to 31/03/2020

process ESG-related data to calculate the individual ESG score for all the companies in our sample.

1.4 STRUCTURE OF THESIS

The remainder of this thesis is divided into six chapters (chapter two through seven). **Chapter two** defines the concept of Socially Responsible Investment (hereafter SRI) and its connectiveness with ESG and describes how both concepts have evolved. **Chapter three**, the literature review, highlights a fraction of existing literature within the field of ESG and CFP. Armed with an understanding of the existing body of literature, **Chapter four** presents the theoretical foundation for our thesis, including the efficient market hypothesis, factor models, multiple regression analysis and Owen-Shapley's decomposition of R-squared.

Chapter five outlines the methodology we use to examine our main research question and following two sub-questions. The chapter also presents our data preparation process and data validation process before finally presenting the portfolio mathematics behind the value weighted portfolio approach, which are constructed based on the ESG-scores and market capitalization of the individual companies. In **Chapter six**, we present our empirical findings and interpretations thereof. Finally, **Chapter seven** discusses and concludes the thesis by outlining the implications of our approach, contribution to existing literature and the limitations with it.

2.1 SOCIALLY REPONSIBLE INVESTING: AN INTRODUCTION

The origins and continued evolution of socially responsible investing (hereafter SRI) reflects a large group of investing terms such as, value-based investing, green-investing, sustainable investing and responsible investing (Blaine Townsend, 2020). However, a lack of standardization in terminology has made a universally accepted single definition of what SRI is practically impossible. Academics and financial institutions provide a good starting point with Button (1988) defining SRI as *"Putting your money into investments which will yield a financial return for you, but which do not support areas of business interest that you disapprove of, such as arms, tobacco, alcohol, apartheid, violation of human rights".*[7]

Horst, Renneboog, & Zhang (2008) extends this definition further, by arguing that the investment screens to select or exclude assets is based on three focal pillars – ethical, social, and corporate governance. As such, SRI is directly tied to the ESG criteria. According to Townsend (2020), ESG has done what traditional socially responsible investing failed to accomplish, which is to breach the gap between the ill-defined SRI term and socially minded investors. It has done so by creating two camps, 1) value-based investing that resembles traditional SRI and 2) a proactive sustainability-focused analysis, which strives to assess the materiality of non-traditional data to determine which companies are best prepared to compete in a global world that faces global problems (Townsend, 2020).

By the mid-2000s, a trifecta of catalyst bolstered the demand for the second camp. The first catalyst focused on the relationship between fiduciary duty and issues of sustainability. The second was a global focus on climate change. The third was the epic corporate governance and ethical failings that defined the subprime market crash in 2008-2009 and sooner led to the revitalization that the largest asset owners needed a better framework to assess risks in the market. Today, investors call for companies to provide more sustainability disclosures that are material to long-

[7] Quote was found in "Ethical Investment Processes and mechanisms of institutionalisation" by Céline Louche (2004)

term performance of a stock (Bernow, 2020). Furthermore, investors need a lens in which they can assess environmental, lower investor trust, and litigation related risks. Traditional Wall Street analysis did not provide this lens, but maybe ESG will (Townsend, 2020).

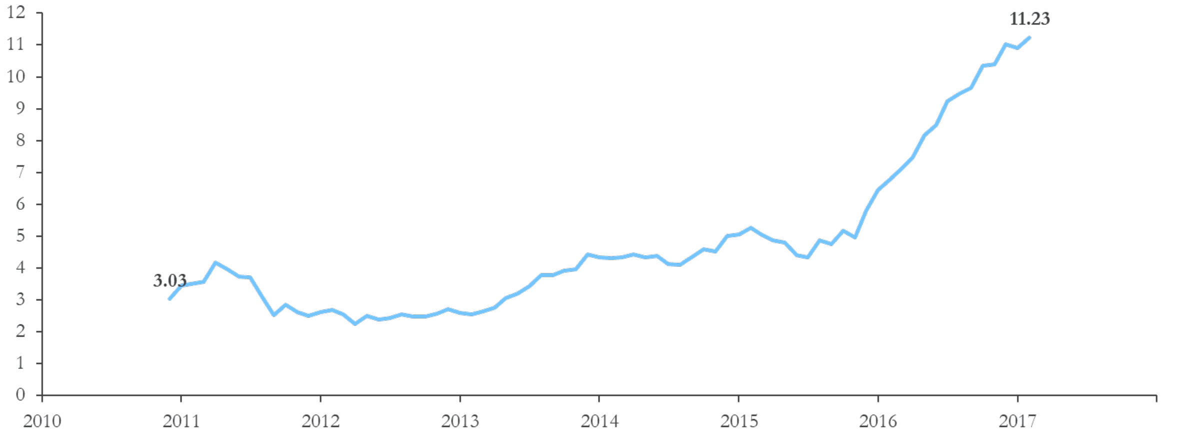
2.2 THE DEVELOPMENT OF ESG

Traditionally, the financial performance of an investment is evaluated based on the relationship between expected risk and return, with investors seeking to find the most attractive risk-return tradeoff. Academia have written an extensive number of theories and financial models within this field. Some of these theories and models include but are not limited to the Random Walk Theory, Modern Portfolio Theory, and the Efficient Market Hypothesis. However, as global financial markets change, new trends emanate, and different aspects may need to be considered when evaluating investments and performance. A huge trend that has caught the eye of experts and academia over the last 20 years is sustainable finance, a segment that is primarily driven by global climate issues, environmental disasters and social and governance related scandals (Hill, 2020).

The practical field of sustainable investing has grown immensely and continues to expand across money markets. At the start of 2016, the Global Sustainable Investment Alliance (hereafter, GSIA) estimated that sustainable investments constituted 26% of assets that are professionally managed in Europe, Asia, Australia, New Zealand, Canada and the United States – amounting to USD 22.89 trillion (GSIA, 2018). However, the scale of investing varies greatly from region to region. The proportion of sustainably managed assets from European asset managers is 52.6%, followed by Australia and New Zealand (50.6%) and Canada (37.8%). The proportion of sustainable investing from the United States (21.6%), Japan (3.4%) and Asian countries other than Japan (0.8%) is less prevalent (Bernow, 2017).

Within the USD 22.89 trillion invested in sustainable investing, approximately 47% of the market are invested in ESG-themed exchange-traded funds (JPMorgan, 2018). Figure 1 illustrates how the value of ESG-themed ETFs has risen with >200% between 2010-2017.

Figure 1: Growth of total assets under management in ESG ETFs between 2010 and 2017
Numbers in USD, trillions.



Source: Self-developed graph based on J.P Morgan (2018)

In sum, SRI has grown from a niche to a global phenomenon, and the trend is showing no signs of slowing down. Fueled by the pressure of consumers and investors, corporations are embracing sustainability and are incorporating ethical strategies that proactively prioritize the three pillars of ESG (Interview, ATP).

2.3 ESG SCORE METHODOLOGY AND SCREENING STRATEGIES

ESG consist of three individual pillars, Environmental, Social and Governance, that are used by investors to analyze how much, and if, a company's strategy integrates sustainable practices with the aim of achieving corporate sustainability. Lozano (2015) defines corporate sustainability as *"Corporate activities that proactively seek to contribute to sustainability equilibria, including the economic, environmental, and social dimensions of today, as well as their inter-relations within and throughout the time dimension (i.e. the short-, long-, and longer-term), while addressing the company's systems, i.e. operations and production, management and strategy, organizational systems, procurement and marketing, and assessment and communication; as well as with its stakeholders".*

However, a huge drawback of corporate sustainability is the lack of transparent and reliable corporate sustainability disclosures (Danica Pension and ATP). In the search of such quality data, investors turn to ESG rating agencies. In the last decade, the presence of ESG rating agencies has grown considerable and is now undergoing a phase of consolidation driven by mergers and acquisitions (Escrig-Olmedo, Fernandez-Izquierdo, Ferrero-Ferrero, & Rivera-Lirio, 2019). The consolidation process from 2008-2018 has allowed ESG rating agencies to integrate specialized actors that have collectively allowed the rating agencies to develop wider and integral assessments of a company's corporate sustainability profile and has extended their geographic and sectorial reach (Escrig-Olmedo, Fernandez-Izquierdo, Ferrero-Ferrero, & Rivera-Lirio, 2019). Today, the rating agencies market primarily consist of five dominant actors - Morgan Stanley Capital International (MSCI), RobecoSAM, Bloomberg, Sustainalytics, and Thomson-Reuters Refinitiv (hereafter TRR).

As an example of how the rating agencies rate individual companies, we can look at how TRR develop ESG scores[8]. TRR collects data from more than 70% of the global market cap (nearly 9,000 companies), across more than 500 different ESG metrics and has done so since 2002 (Refinitiv, 2021). North America and Europe represent the most substantial fractions of the nearly 9,000 companies with 41% and 25%, respectively, while Asia represents 15% (Refinitiv, 2021). Refinitiv rate each company on a scale from 0-100, as well as letter grades from D- to A+. The rating process starts with the collection of over 500 company-level ESG measures from independent audits, annual reports, company websites, stock exchange filings, news sources and CSR reports. Out of the 500 ESG measures, 186 industry-specific metrics are used to power the next steps in the overall scoring process. Next, the 186 industry specific metrics are grouped into ten categories relative to the category weights. The pillar weights are then normalized into a percentage ranging from 0-100 (Refinitiv, 2021). An illustration of the rating process can be found in Appendix (1).

ESG scores, such as those provided by TRR, have made it possible for socially responsible investors to construct and manage portfolios based on different approaches – integration, screening and thematic. Integrational investors seek to systematically include ESG factors into their investment analysis to enhance risk adjusted returns. Investors using the screening strategy, do so by applying filters to list potential investments based on ethics and investor values. The third approach, thematic investing, seeks to combine attractive risk return profiles with the intention of

[8] Thomson Reuters will be the only ESG data source throughout this assignment

supporting a specific environmental or social outcome (Boffo & Patalano, 2020). Additionally, the GSIA list seven fundamental screening strategies (GSIA, 2018):

1. Negative/exclusionary screening,
2. Positive/best-in-class screening,
3. Norm-based screening,
4. ESG integration,
5. Sustainability themed investing,
6. Impact/community investing, and
7. Corporate engagement and shareholder action

According to the report, the top three largest sustainable investment strategies are ranked as I) negative/exclusionary screening, II) ESG integration and III) Corporate engagement and shareholder action. Negative/exclusionary screening is the predominant strategy in Europe while ESG integration is more prevalent in US, Canada, Australia, and New Zealand in asset-weighted terms. In Asia, corporate engagement and shareholder action is the dominant strategy (GSIA, 2018).

3.1 PREVIOUS RESEARCH

In the following section, we provide insights and perspectives from the literature that governs the field of socially responsible investing. We specifically examine how investments in the realm of ESG are believed to enhance shareholder value and how ESG is perceived as an insurance-like protection against downside risk. We structure the section as follows: Initially, an overview of the conflict between portfolio theory and the growth of socially responsible investing will be discussed. Secondly, an overview of studies focusing on the ESG-CFP relationship will be presented, showing both a positive and a negative relationship. Afterwards, the focus will turn towards academic literature that support and oppose the case for ESG as a mitigator of downside risk. Each of these three subsections will highlight only a fraction of existing literature as an exhaustive analysis of all previous academic papers is deemed to be outside the scope of this thesis. Finally, the last section will summarize and highlight the most important key takeaways from this section whilst finding and mobilizing the variables and regression models used.

3.1.1 *The conflict between portfolio theory and the growth of Socially Responsible Investing*

In 1952, Harry Markowitz pioneered modern portfolio theory in his paper "portfolio selection" that was published in *The Journal of Finance* in 1952. Later in 1990, Harry Markowitz shared the Nobel Prize in Economics with William F. Sharpe and Merton Miller.

Harry Markowitz hypothesizes that a utility-maximizing and thus rational investor is risk-averse and will construct a well-diversified portfolio through investing in different assets (Markowitz, 1952). According to this theory, the optimal portfolio with respect to risk and expected return cannot be improved by imposing constraints that, for example, discriminate between socially responsible and non-socially responsible assets. Accordingly, by excluding certain assets an investor will diminish the investment universe from which the investor can construct their portfolio by deselecting certain assets.

Additionally, The Capital Asset Pricing Model (CAPM) provided by Sharpe (1964), Lintner (1965) and Mossin (1996) argues that the single company-specific factor relevant to the expected return on an asset is its systematic risk, also known as the non-diversifiable risk. The measure was created to calculate the required rate of return of a portfolio and thus describes the relationship between expected return and risk of investing in a specific portfolio (Bodie, Kane, & Marcus, 2014). If the CAPM holds, then it implies that no excess expected return from socially responsible investing exists, and risk-reduction is maximized by not diminishing the investment universe through a deselection of "sin stocks" (Easton & Pinder, 2018).

The conflict between portfolio theory, the CAPM and the growth of SRI raises some questions. Specifically, how does a portfolio consisting of socially responsible assets perform on a risk-adjusted basis? According to portfolio theory they should at best perform on par to non-screened portfolios, but what do academic studies find? Are ESG factors reflected in stock prices or not? Do they create a resilience like factor when shocks occur in the market? These questions have been at the heart of much academic research, all of which we will discuss in the coming sections.

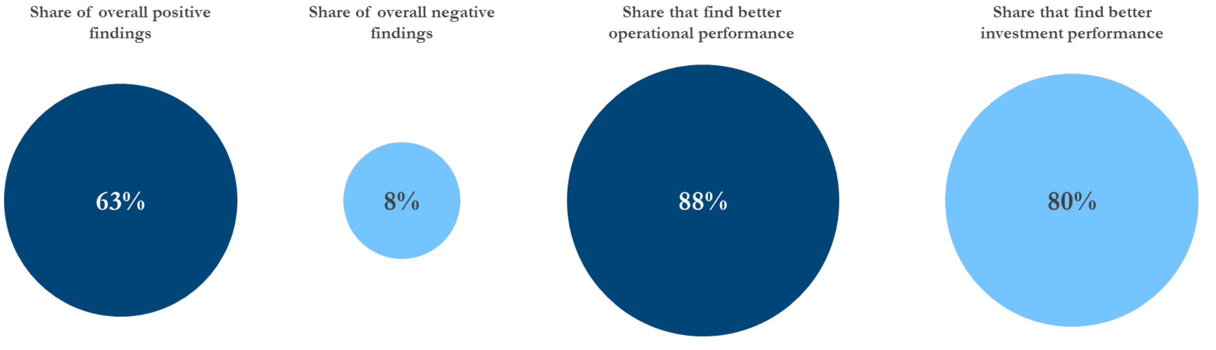
3.1.2 *Socially responsible investing – Learnings from meta studies*

Ever since Bragdon & Marling (1972) wrote the first empirical study about the relationship between corporate social performance and corporate financial performance, academic literature has increasingly explored ESG factors and the impact of corporate social responsibility on market-based and financial statement measures of performance (Boffo & Patalano, 2020).

Capelle-Blanchard & Monjon (2012) actively demonstrates that the number of academic articles and newspaper publications alike have significantly increased since the beginning of the 1980's. For example, Bassen, Busch & Friede (2015) analyzed the link between corporate social performance and corporate financial performance across 2,000 academic review studies. The findings from their research tells us that 90% of these studies find a nonnegative ESG-CFP relationship while 63% of all published academic papers actively demonstrate a mildly positive relationship between ESG scores on one hand and financial returns on the other, whether measured by equity returns or profitability or valuation multiples.

The positive relationship is substantiated by Clark, Feiner, & Viehs (2015). In their meta-study of more than 200 sources, they find a correlation between diligent sustainability business practices and economic performance. As shown in Figure 2, the meta-study specifically finds that 88% of the reviewed sources conclude that companies with strong sustainability practices yield better operational performance. Secondly, the study finds that 80% of the reviewed sources demonstrate that strong sustainability practices yield positive influence on investment performance i.e., more sustainable companies generally outperform less sustainable companies.

Figure 2: Results from >2.000 studies concerning the impact of ESG on Corporate Financial Performance



Source: Gunnar Friede, et al. (2015) and Gordon clark, et al. (2015)

3.1.3 *Positive ESG and CFP link from a theoretical point of view*

According to Berry & Junkus (2015), SRI is dominated by two schools of thoughts: "*Doing good by doing well*" and "*Do good but not well*". In this section we will look at the first relationship, namely *"Doing good by doing well"*, or otherwise specified as a positive link between ESG and corporate financial performance.

Outperformance can happen when the market produces and underreaction to certain ESG related information. In his model, Merton (1987) demonstrates this concept and proves the extent to which corporate disclosure affects company value. Accordingly, Bauer, Derwall, Guenster, & Koedijk (2004) found that high-ranked ESG portfolios showed higher excess risk-adjusted returns. The particular reason for this circumstance was argued to be caused by the market mispricing these stocks in their short horizon evaluation, namely the market's underreaction to ESG.

In line with this, Borgers, Derwall, Koedijk, & Horst (2013) showed that high-ranked ESG stocks typically achieve actual earnings announcements above earnings estimations. One reason for this may be that ESG investments create information asymmetry because it is difficult for corporations to communicate the strategic value of ESG activities (Berry & Junkus, 2015). Secondly, ESG activities are more often than not intangible and do not appear directly on a company's balance sheet which makes them complicated to price for investors (Hvidkjær, 2017).

Other studies focus on more broad defined measures of company performance. Cheng, Ioannou, & Serafeim (2013) found that ESG leads to better access to finance because these companies face lower capital constraints due to reduced agency costs. Secondly, companies with a better governance are often perceived at less risky which may result in increased valuations. Finally, Albuquerque, Koskinen, & Zhang (2018) argue that corporations' investments into CSR activities is beneficially perceived as it allows companies to benefit from relatively less price elastic demand, resulting in higher profit margins and product prices, ceteris paribus. Furthermore, their model predicts that CSR decreases systematic risk and increases overall company value.

3.1.4 *Negative ESG and CFP link from a theoretical point of view*

Contrary to the positive association between ESG activities and company value, is the notion of *"doing good, but not well"* – or underperformance. As mentioned, restricting the investment universe to those assets that qualify on some ESG criteria should according to portfolio theory result in lower return per unit of risk and reduce the diversification effect which implies a suboptimal risk-return profile (Berry & Junkus, 2015). From a solely theoretical and mathematical standpoint, such constrained optimizations will never be more efficient than unconstrained optimizations as investors may under-expose their portfolios to some high-performing industries (Markowitz 1952). Secondly, the implementation of such additional screening strategies is labor-intensive and can be costly for both investors and companies and should therefore reap suboptimal performance compared to an efficient diversified portfolio (Berry & Junkus, 2015).

Thirdly, in some cases, investors may act against the traditional neoclassical view of the rational investors and be willing to trade returns to express their social, political, or environmental values through their investment decisions. This example, which foundation is discussed in behavioral corporate finance, is shown by Pastor, Stambaugh, & Taylor (2019) in their paper called "sustainable investing in equilibrium". The authors analyze both financial and real effects of "green" and "brown" stocks in an equilibrium mode[9]. The authors find that agents' taste for green holdings affect asset prices. Specifically, they show that investors are willing to pay more for greener companies which in turn lowers the company's cost of capital. The model's prediction for alphas also show that Green assets have negative CAPM alphas, whereas brown assets have positive alphas. Finally, the study concludes that greener investors who hold an overweight of green assets earn lower expected returns, but that these investors are not unhappy because their motives are primarily driven by the notion of "doing good".

Fourth and finally, an alternative view propose that executives may choose to improve the companies ESG proposition, at the expense of increasing shareholder value, in order to enhance their own personal reputations (Demers, Hendrikse, Joos, & Lev, 2020). This managerial entrenchment combined with the implementation of socially responsible actions have particularly negative effects on a company's financial performance (Surroca & Tribó, 2008). According to the agency theory problem, ESG investments are wasteful and harmful to shareholder value and negatively associated with share prices. Furthermore, Demers, Hendrikse, Joos, & Lev (2020) argue that such motives could be a hindrance of a company's resilience during times of crisis.

3.2 EMPIRICAL EVIDENCE

3.2.1 *The relationship between ESG and CFP*

To our knowledge, the study of Bragdon & Marling (1972) is the first empirical study that investigates the relationship between corporate social performance and corporate financial performance. The pair found a positive relationship and pioneered the field of empirical studies relating to corporate social performance and corporate financial performance.

Newer studies, such as that of Connolly & Cheung (2011), have investigated the relationship between sustainability index inclusion vs exclusion and the effect on stock prices. The author shows that index inclusion for companies operating in the manufacturing industry have a positive

[9] Green stock refers to companies that generate positive externalities for the society. Brown stocks companies expose negative externalities

effect of their stock price performance while index exclusion has a significantly negative impact of stock prices. Evidence from other studies show that companies with a "high sustainability" profile deliver higher returns than "low sustainability" profile companies. This view is demonstrated in a newer study by Eccles, Ioannou, & Serafeim (2014) who investigates this relationship across 180 U.S companies. By dividing a matched sample of 180 U.S. companies into two separate quartiles, a "high-sustainability" portfolio and a "low sustainability" portfolio, the paper show that the annual excess performance for the "high-sustainability" portfolio outperforms the latter by 4.8% on a value-weighted base (2.3% on an equal-weighted base). The author also find that the outperformances hold true in 11 of the 19 years of the sample period.

Against the overall view that "*good deeds foster good business*", scholars and practitioners claim that most positive ESG-CFP relations are ambiguous, inconclusive, or contradictory and that the general effect is disputable (Revelli & Viviani, 2015).

In their study from 2015, Borgers, Derwall, Horst, & Koedijk (2015) consider the economic significance of social dimensions in investment decisions by analyzing the holdings of U.S. equity mutual funds over the period January 2004 to December 2012. By dividing portfolio weights in sin stocks, weak-ESG and strong-ESG companies, the study finds that the estimated payoff per fraction invested in socially sensitive stocks is positive and statistically significant. Secondly, the authors do not find robust evidence that exposure to a broader set of strong-ESG stocks influences risk-adjusted mutual fund returns.

Another study by Lys, Naughton, & Wang (2013) supports this non-positive conclusion. The study focuses on companies in 9 different industries in the Russel 1000 index and examines whether CSR expenditures are related to long-term financial performance. Their results show that the positive association between CSR expenditures and financial performance is more likely due to the signaling value of CSR expenditures. Specifically, ESG investments is used as a channel through which companies management communicates an anticipated future stronger performance. Finally, the study concludes that ESG expenditures generally generate insufficient returns and reduces shareholder value.

3.2.2 *ESG as a resilient factor doing times of crisis*

Whether high ESG scores offer a positive explanatory power for returns during adverse economic environments, such as Global Financial Crisis (GFC) and the current COVID-19 pandemic, remains a topic of considerable debate.

In their study of the financial crisis, Lins, Servaes, & Tamayo (2017) present such a positive explanatory power doing a downturn in the market. The authors examine the sample performance of 1,673 US based non-financial companies, with CSR data available on the MSCI ESG Stats database, from August 2008 to March 2009. In their regression, which controls for a wide variety of factors and company fixed effect, the authors present evidence that higher social capital companies had 4-7 percentage points higher crisis-period stock returns compared to those with lower social capital. In summary, the paper concludes that a company with high company-specific social capital will build an insurance policy that will pay of when the economy faces a time of crisis.

However, the nature of the COVID-19 crisis is much different from the financial crisis. As mentioned in previous sections, the GFC was largely fueled by financial imbalances and risks that accumulated over many years, while the COVID-19 crisis occurred at a much faster rate and constricted global economic activity from one day to the next. The fast-moving and unknown variables of a crisis like COVID-19 forces us to investigate what new academic studies concludes about the relationship between ESG and CFP during the current COVID-19 crisis.

According to the study by Ding, Levine, Lin, & Xie (2020) the nature of the COVID-19 crisis did nothing but strengthen the hypothesis that high ESG scores positively affect companies' stock price resilience during times of crisis. To evaluate how corporate characteristics (such as financial conditions, international supply chain, CSR activities, corporate governance systems and ownership structures) shape stock price movements in response to the COVID-19 pandemic, the authors use a global sample of more than 6,000 companies from 56 different economies. They found that companies with stronger CSR policies, prior to the pandemic, experienced superior stock price performance during the first quarter of 2020. However, as pointed out by Demers, Hendrikse, Joos, & Lev (2020) their regression model does not control for traditional marked-based measures of risk and may suffer from correlated omitted variable bias.

Another analysis of the COVID-19 pandemic is that of Albuquerque, Koskinen, Yang, & Zhang (2020). Opposite to that of Ding, Levine, Lin, & Xie (2020) this paper includes accounting-based control variables and include additional company and industry fixed effects that are suggested to be highly correlated with returns and companies' ESG scores. The paper uses Thomson Reuters' Refinitiv ESG database to estimate cross-sectional regressions of cumulative excess returns of U.S. listed companies. The authors conclude that stock prices for companies with high ESG scores perform better than stock prices for companies with low scores. However, the study assumes that only two of the three ESG pillars are relevant for COVID-19 crisis period resilience – the environmental and social pillars.

A repeated study that only includes the aggregated ESG score, conducted by Demers, Hendrikse, Joos, & Lev (2020), show opposite conclusions regarding the role of ESG as a share price resilience factor during the COVID crisis. The study uses a sample of 1,652 U.S. based companies to investigate the claim laid forth in that of Albuquerque, Koskinen, Yang, & Zhang (2020). The authors undertake a series of analyses to uncover whether ESG is an important determinant of COVID period returns. By performing a multiple regression analysis of stock returns during the first quarter of COVID-19 – i.e., January through March 2021, that controls for numerous other known determinants of return such as company characteristics and accounting-based measures of financial performance (leverage, liquidity, total assets, company age, market share and more), the authors conclude that ESG scores offer no such positive explanatory power for returns during COVID-19. Instead, the authors argue that market-based measures of risk and accounting-based measures together dominate the explanatory power of COVID-19 returns. As a final remark it is concluded by the study that celebrations of ESG as an important resilience factor in times of crisis are, at best, premature.

3.3 SUMMARY AND CONNECTION OF PREVIOUS RESEARCH

The previous literature indicates that there exists extensive research on the relationship between corporate social responsibility and corporate financial performance, also doing times of crisis (Table 1). Most of the previous research concludes that there is a positive ESG-CFP relation and that ESG can act as a mitigator of downside risk doing times of crisis. What is clear to the authors of this thesis is that the time horizon, selection of ESG pillars, controlling variables, weighting scheme used and the relationship between the simulated portfolios have a significant effect on the outcome of the analysis. Thus, previous studies have been helpful for narrowing down which measurement to use, including ESG-ratings and company specific and accounting-based characteristics.

Table 1: Summary of previous studies and their findings

For sub-question one, positive is defined as a relationship where ESG positively affects corporate financial performance, i.e., generates a higher return than "sin" stocks. For sub-question two, positive is defined as a relationship where ESG is a mitigator of downside risk doing times of crisis.

				Sub-question one (1)	Sub-question two (2)
Authors and year	Geographic focus	Time period	# of observations	ESG-CFP relatedness (findings)	ESG as a mitigator of downside risk doing times of crisis
Bauer and Hann (2010)	USA	1995-2006	582	Positive	N/A
Jiraporn et al., (2014)	USA	1995-2007	2,516	Positive	
Godfrey et al., (2005)	USA	1991-2002	160	Positive	Positive
Tim Verheyden et al., (2015)	Global	2010-2015	<5,000	Positive	Positive
Cheung (2011)	Hong Kong	2002-2005	510	Positive	N/A
Eccles et al., (2013)	USA	1993-2010	180	Positive	
Arian Borgers et al., (2015)	USA	2004-2012	6,443	Non-significant (negative)	
Thomas Lys et al., (2015)	USA	2002-2010	5,928	Non-significant (negative)	
Karl V. Lins et al., (2016)	USA	2008-2009 (GFC)	1,673	Positive	Positive
Wenzhi Ding et al., (2020)	Global	2020 (COVID-19)	6,000	Positive	Positive
Albuquerque, et al. (2020)	USA	2020 (COVID-19)	2,171	Positive	Positive
Elizabeth Demers et al. (2020)	USA	2020 (COVID-19)	1,652	Non-significant (negative)	Non-significant (negative)

GFC – Global financial crisis

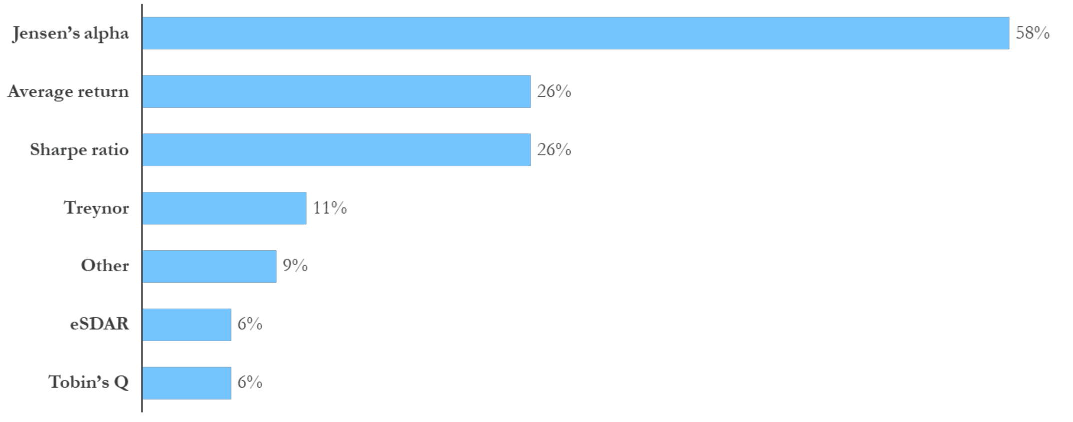
ESG – Environmental, social and governance

CFP – Corporate financial performance

3.4 MOBILIZING COMPANY CHARACTERISTICS AND FINANCIAL PERFORMANCE

To investigate the relationship between ESG and CFP, researchers must decide what analysis to conduct, which variables to include and how extensive the sample. The landscape of CFP metrics in academic studies is illustrated in the study of Klein & Wallis (2015). Their research show that most studies tend to focus on risk-adjusted returns by applying certain factor models. As highlighted in Figure 3 below, Jensen's alpha is the most frequently used metric in the 58 analyzed papers.

Figure 3: Summary of previous studies and the most used financial metrics
Academic studies investigating the relationship between ESG and CFP



Source: Self-developed graph based on von Wallis and Klein (2015)
Note: The graph sums to >100% as some studies use multiple financial metrics

Jensen's alpha was introduced by Jensen (1967, 1969) and is closely tied to the Capital Asset Pricing Model (CAPM) by Treynor (1961) and Sharpe (1964) as it measures the risk-adjusted return of a stock or a portfolio relative to the expected return in the Capital Asset Pricing Model (Le, Kim, & Su, 2018). The CAPM was later extended by Fama and French (1993) with the FF3 that added two additional explanatory variables aside from the market factor – a size risk factor and a value risk factor. Later, Carhart (1997) further extended the model to a four-factor model by an additional variable – the "momentum" factor. We will elaborate more on these factor models and their relevance in part II.

In addition to the financial metrics, Klein & Wallis (2015) also assess the sample size of most academic studies analyzing the ESG-CFP relationship. The studies examine a variety of sample sizes and time periods and finds that the average sample size is between 0-100 observations (Appendix 2), a number we deem relatively small. The small sample size reduces the confidence level and suppresses the power of the statistical tests. Thus, we find that this area, though thoroughly investigated by over 2,000 articles, is still interesting to investigate further.

Part II
UNDERSTANDING OF THEORETICAL PRINCIPLES

THEORY 4

This thesis has now defined how SRI is becoming a popular alternative to conventional investing and presented the existing body of knowledge supporting it. In the following section, we will move on to the theoretical methods and models we apply throughout this thesis to answer the main research question. Section 4.1 will describe the Efficient Market Hypothesis and the Random Walk theory and its relatedness to SRI. Section 4.2 will present the Capital Asset Pricing Model (CAPM). Section 4.3 will present Jensen's alpha measure which will be the preferred financial performance metric in this thesis. Section 4.4 will present three well-known factor models and how they will be deployed to investigate if known risk factors explains the return of 10 decile portfolios and a long-short ESG portfolio. Section 4.5 will present the basic assumptions for conducting a multiple regression analysis. Finally, section 4.6 will present the Owen Shapley decomposition procedure which will be used to test whether ESG, market-based measure of risk and/or company specific factors can explain returns during the first quarter of 2020.

4.1 EFFICIENT MARKET HYPOTHESIS AND THE RANDOM WALK

Discounted cash flow analysis (DCF) is widely used to estimate the value of a particular asset. The method states that the value of an asset is equal to the sum of the discounted expected future cash flows. Intuitively, this relationship holds that a change in the price of an asset will be caused by new information that changes the expectations of the particular asset's future cash flow. Based on this relationship, Fama (1970) build the theory of efficient capital markets. The hypothesis states that the stock market is extremely efficient at reflecting information about stocks and the financial market as a whole. The general assumption of the theory suggests that new information spreads extremely fast and is quickly incorporated into the prices of stocks. The theory of efficient capital markets is closely linked to the Random Walk Hypothesis which states that news is by definition unpredictable and, thus, resulting price changes in an asset must be unpredictable or "random" (Burton, 2003). As a result, prices fully reflect all known information and future movement in the underlying value of the stock is related to new information, which in nature cannot be predicted. This entails that an investor is not able to profit from trading strategies, such as a long-short ESG strategy.

4.2 CAPM

The Capital Market Asset Pricing Model (CAPM) was developed by Sharpe (1964), Treynor (1962), Lintner (1965a, b) and Jan Mossin (1966) and builds on Markowitz's (1959) Modern Portfolio Theory.

CAPM is based on the idea that not all risks should affect asset prices. In practice, the model is used to estimate the cost of capital for a company or to evaluate the performance of stocks or portfolios (Fama & French, 2004). Fama & French (2004) argues that the popularity of CAPM derives from its powerful and intuitively pleasing predictions about how to measure risk and its relation to expected return. Unfortunately, the model is empirically flawed due to many simplifying and unrealistic assumptions. The assumptions of the CAPM are outlined below.

Assumptions:

I. Investors are risk-averse and evaluate their investment portfolios solely in terms of expected return and standard deviation of return measured over the same single holding period.
II. Capital markets are perfect in several senses: all assets are infinitely divisible; there are no transactions costs, short selling restrictions or taxes; information is costless and available to everyone; all investors can borrow and lend at the risk-free rate
III. All investors have access to the same investment opportunities
IV. All investors make the same estimates of an individual asset expected returns, standard deviations of return and the correlations among asset returns (Perold, 2004).

Overall, these assumptions characterize a highly simplified and idealized world (Fama & French, 2004). The formula of the Capital Asset Pricing Model is shown below:

$$E[R_i] = R_F + \beta_i (R_M + R_F) \tag{1}$$

Where $E[R_i]$ is the expected return of stock i, R_F is the risk-free rate, β_i is the beta value of stock i and (R_M-R_F) is the market risk premium (Kenton, 2021).

The model implies that the expected return of an asset can be estimated by the risk-free rate plus the asset's beta value times the market risk premium.

The risk-free rate is the rate of return for an investment with zero risk of loss. One of the most applied risk-free rates in financial markets is the US Treasury Bill, which is considered to be nearly free of default risk (Chen, 2021). The market risk premium is the expected return above the risk-free rate. Beta is a measure of the volatility (systematic risk) of a stock compared to the market as whole. The beta value of a stock is calculated using the following formula.

$$\beta_i = \frac{COV(R_i, R_M)}{\sigma_M^2} \qquad (2)$$

4.3 JENSEN'S ALPHA

Jensen's alpha is a measure that is used to determine the abnormal return of a stock or a portfolio of stocks. The metric has been used as a proxy for financial performance by the majority of SRI and ESG studies (Figure 3). Jensen's alpha measure is used to determine the outperformance or underperformance of a stock/portfolio compared to how it is expected to perform, given a level of systematic risk (Jensen, 1968). As we can observe from the CAPM and beta in section 4.2, these change over time. The interpretation of Jensen's Alpha measure must acknowledge that a significant or an insignificant alpha value can signal either outperformance or incorrect benchmarking (Gregory, Matatko, & Luther, 2003). Gregory, Matatko, & Luther (2003) note that Jensen's alpha is likely to be affected by small firm effects, creating a biased alpha estimate. In order to account for the potential bias, we use a multifactor model, which controls for exactly small firm effects (SMB factor) along value risk (HML factor). We will explain the Fama-French multifactor model in greater detail in section 4.5. In the empirical analysis part of this thesis, Jensen's (1968) alpha will be employed to investigate the performance of our decile portfolios and long-short portfolio.

4.4 SHARPE RATIO

As outlined in the literature review, Jensen's alpha is by far the most commonly used performance metric. However, the central limitation of Jensen's alpha is that it only adjusts for systematic risk (Mossin, 1966). To account for the total risk, we follow that of Modigliani & Modigliani (1997) and combine the use of Jensen's alpha with the Sharpe ratio (Sharpe, 1966).

The Sharpe Ratio (hereafter SR) was developed by William Sharpe and is a ratio that helps investors understand the return of an asset compared to its total risk. The SR can be calculated using the following formula:

$$Sharp\ Ratio = \frac{R_i - R_F}{\sigma_i} \tag{3}$$

Where R_i is the return of a stock, R_I is risk-free rate and σ_i is the standard deviation of the stock or the portfolio of stocks excess return. The greater the value of SR, the more attractive the risk-adjusted return.

4.5 FACTOR MODELS

The following section will present the three chosen factor models - Fama French 3-factor model (1992), the Carhart 4-factor model (1997) and the Fama French 5-factor model (2015).

4.5.1 *Fama and French 3 factor model (FF3)*

In extension to CAPM, Fama & French (1992) developed the Fama French 3-factor model, in which they added size risk (SMB) and value risk (HML) factors to the market risk factor in CAPM. In the 1990's Eugene Fama and Kenneth French attempted to better explain market returns. In their research, they prove that value stocks historically showed a tendency to outperform growth stocks. Similarly, they found that small-cap stocks historically showed a tendency to outperform large-cap stocks. Based on this, they found that a size factor "small-minus-big" (SMB) and the book-to-market equity ratio factor "high-minus-low" (HML) had a significant ability to explain the cross-section of average return. Furthermore, by including the SMB the HML factors, the model adjusts for this outperforming tendency, which is thought to make it a better tool for estimating the expected stock return. The formula for the Fama French 3-factor model is shown below (Hayes, 2020):

$$R_i - R_F = a_i + b_i MKT + s_i SMB + h_i HML + \varepsilon_i \tag{4}$$

Where $(R_i - R_F)$ is the excess return of stock i, α_i is the intercept i, b_i, s_i, and h_i are the factor coefficients, *MKT* is the market risk premium, *SMB* is the size premium and *HML* is the value premium.

The *market risk premium* is the value-weighted return of the market portfolio minus the risk-free return. Coefficient b_i is the beta value of the stock and is estimated the same way as in CAPM. The size premium and value premium factors are constructed using 6 value-weight portfolios formed on size and book-to-market equity ratios. This is done by a high minus low procedure, where several portfolios are created based on their exposure to a risk factor, by buying the portfolios with high exposure to the risk factor and short selling the portfolios with a low exposure to the risk factor (French, 2020).

4.5.2 *Carhart 4-factor model (C4)*

The Carhart 4-factor model is an extension of the FF3 from 1993 and is a popular multifactor model used to price stocks. The additional factor is a "cross-sectional momentum" factor discovered by Jegadeesh and Titman (1993). In 1997 Mark Carhart decided to extend the FF3 with the momentum factor, which builds on a momentum effect that exist when the return of a stock is positively correlated with the return from previous periods. In their paper from 1993, Jegadeesh and Titman showed that this correlation exists. They documented that strategies which buy stocks that have performed well in the past and sell stocks that have performed poorly, generated significant positive return over 3- to 12 months holding periods (Jegadeesh & Titman, 1993). By combining the momentum strategy from Jegadeesh & Titman (1993) and the FF3, Carhart (1997) created the Carhart 4-factor model. The formula for the Carhart 4-factor model is shown below:

$$R_i - R_F = a_i + b_i MKT + s_i SMB + h_i HML + m_i MOM + \varepsilon_i \tag{5}$$

Where $(R_i - R_F)$ is the excess return of stock i, α_i is intercept i, b_i , s_i ,h_i and m_i is the factor coefficients, *MKT* is the market risk premium, *SMB* is the size premium, *HML* is the value premium and MOM is momentum factor calculated as the equal weight average return for two winner portfolios minus the average return of the returns for two loser portfolios (French, 2021).

$$MOM = \frac{1}{2}(Small\ High + Big\ High) - \frac{1}{2}(Small\ Low + Big\ Low) \tag{6}$$

To construct the momentum factor, six portfolios are developed each month. To be included in one of these portfolios in month t (formed at the end of the month t-1), a stock must have a price for the end of month t-13 and a good return for t-2 (French, 2021).

4.5.3 *Fama French 5-factor model (FF5)*

The final factor model we use to test for risk-adjusted excess returns is the Fama French 5-factor model (Fama & French, 2015). In their paper about the five-factor asset pricing model, Fama & French (2015) argues that the average stock return is correlated with the book-to-market equity ratio (B/M). Additionally, they find evidence that profitability and investments add to the description of expected returns. The relation between these variables and the expected return is explained by the dividend discount model. The model states that the market value of a company equals the sum of all its future dividend payments, discounted back to their present value:

$$m_t = \sum_{\tau=1}^{\infty} E(d_{t+\tau})/(1+r)^{\tau} \tag{7}$$

Where m_t is the share price at time t, $E(d_{t+\tau})$ is the expected dividend for period $(t + \tau)$ and r is the internal rate of return on expected dividends.

Equation (7) states that if two companies have the same expected dividends at time t, but are traded at two different prices, the company with the lower price would have a higher (long-term average) expected return than the company with a higher price. With a bit of manipulation, Fama

& French (2015) describe the relations between expected return, expected profitability, expected investments and B/M as follows:

$$m_t = \sum_{\tau=1}^{\infty} E(Y_{t+\tau}\text{-}dB_{t+\tau})/(1+r)^{\tau} \tag{8}$$

Where $Y_{t+\tau}$ is the total equity earnings for period $(t + \tau)$ and $dB_{t+\tau} = B_{t+\tau} - B_{t+\tau-1}$ is the change in total book equity. Dividing this by the book equity in time t gives:

$$\frac{M_t}{B_t} = \frac{\sum_{\tau=1}^{\infty} E(Y_{t+\tau} - dB_{t+\tau}) \,/\, (1+r)^{\tau}}{B_t} \tag{9}$$

Fama & French (2015) describe that this equation makes three interesting statements about expected stock returns.

1. A higher book-to-market equity ratio $\frac{M_t}{B_t}$ implies a higher expected stock return (r).
2. Higher expected earnings $Y_{t+\tau}$ imply a higher expected stock return.
3. Higher expected growth in book equity (Investments) implies a lower expected stock return.

Furthermore, Fama & French (2015) explains that Equation (9) made it challenging to identify proxies for expected earnings and investments. A proxy for the expected profitability was provided by Novy-Marx (2012) who found a strong relation between profitability and average stock return, while a proxy for investment was provided by Aharoni, Grundy, & Zeng (2013), who found a statistically reliable, but weaker, relation between investments and average stock return (Fama & French, 2015).

Lastly, Fama & French (2015) acknowledged that the above-mentioned evidence suggested that a lot of the variation in average stock returns was related to profitability and investments, something that was left unexplained by FF3. This led to the development of the Fama & French 5-factor model, which add profitability and investment factors to the original market, size, and value factors in the FF3. The equation of the Fama & French 5-factor model is shown below.

$$R_i - R_f = a_i + b_i MKT + s_i SMB + h_i HML + r_i RMW + c_i CMA + \varepsilon_i \qquad (10)$$

Where $(R_i - R_F)$ is the return of stock *i*, α_i is the intercept *i*, b_i, s_i, h_i r_i and c_i is the factor coefficients, *MKT* is the market risk premium, *SMB* is the size premium, *HML* is the value premium, *RMW* is the equity profitability premium and *CMA* is the equity investment-style premium. The RMW factor is calculated as the difference between returns on diversified portfolios of stocks with robust and weak profitability, hence the name RMW, which stands for "robust-*minus-weak*". The CMA factor is calculated as the difference between returns on diversified portfolios of stocks with a conservative and aggressive investment-styles, hence the name CMA, which stands for *"conservative-minus-aggressive"*. Lastly, it is worth mentioning that if the exposure to all five factors b_i, s_i, h_i r_i and c_i explain all the variation in expected returns, alpha (α_i), is equal to zero for all stocks *i* (Fama & French, 2015). Alpha is a measure of performance used in finance, and indicates if a strategy, trader or portfolio manager has managed to beat the market return over a given period (Chen, 2021). A positive alpha indicates that a portfolio has managed to beat the market and vice versa. Later, in this thesis we will investigate if the decile portfolios result in positive alphas.

We have now presented three different factor models with a total of six different risk factors, the market risk (MKT), size (SMB), book-to-market equity ratio (HML), momentum (MOM), profitability (RMW) and investments (CMA). These factor models will specifically be used to answer sub-question one.

4.6 MULTIPLE LINEAR REGRESSION (MLR)

In this thesis, we will use Multiple Linear Regression (Hereafter MLR) to investigate the relation between a dependent variable and multiple independent variables. The following section will describe the statistical technique and its assumptions.

MLR is an extension to Simple Linear Regression which is used to model the relation between two continuous variables (JMP, 2021). The objective of Simple Linear Regression is to predict the value of the dependent variable based on the value of an independent variable.

Linear Regression models apply the method of Ordinary Least Squares (OLS) which finds the intercept and slope coefficients that minimize the sum of the squared errors. According to the OLS regression, there are five main assumptions which must be satisfied in order to make a correct interpretation of the model estimates.

I. Linearity (the true relation is linear)

II. Normality (errors are normally distributed)

III. Homoskedasticity (constant variance in residuals)

IV. Autocorrelation (independence of the observations)

V. No Multicollinearity (or perfect collinearity)

I. Linearity

When we use MLR, we fit a linear model and assumes that the relationship between the dependent variable and the independent variables is in fact linear. This is not always the case, which leads to the fact that other models, such as non-linear regression, might be a better fit. On the other hand, it is possible to use transformations to correct problems of non-linearity or unequal variances. A common transformation technique to apply is to take the logarithms of some of the sample variables.

II. Normality

The normality assumption states that the errors (residuals) are normally distributed. This assumption is not required for validity of the OLS method, but if the errors are far from normal, or has an obvious pattern, this could potentially be a problem (JMP, 2021).

III. Homoskedasticity

Homoskedasticity assumes constant variances in the error term, meaning that the relationship between the independent variables and the dependent variable is the same across all values of the independent variables (StatisticsSolutions, 2021).

If this assumption is not fulfilled, heteroskedasticity is assumed. Heteroskedasticity suggests that the size of the error term differs across the value for the independent variable. Heteroskedasticity can be problematic in regression models because OLS regressions seeks to minimize residuals. OLS regressions contributes equal weights to all observations, but when heteroskedasticity is present, this results in observations with larger disturbances have more "pull" than other observations. If heteroskedasticity is present, a weighted least squared regression would be more suitable because it "down-weights" observations with larger disturbances. Lastly, heteroskedasticity might lead to standard errors being biased (StatisticsSolutions, 2021).

IV. Autocorrelation

By using OLS, we assume that the observations are independent of one another. The assumption of autocorrelation can be an issue when dealing with time series data (JMP, 2021). Additionally, the assumptions argue that the sample taken for the linear regression model must be drawn randomly from the population. The number of observations taken in the data sample should be greater than the number of independent variables being estimated.

V. Multicollinearity

The OLS assumptions of no multicollinearity states that there should not be a linear relationship between the independent variables applied in the regression model. In a situation with multicollinearity, a strong correlation between independent variables, it is recommended that some of the variables are removed, because it can potentially cause problems in OLS estimators (Albert, 2021). The main consequences of multicollinearity in regression are according to Ghosh (2017) that (1) OLS estimators (coefficients) have large variances and covariance making precise estimation difficult (2) confidence intervals tends to be wider (3) t ratios and more coefficients tends to be statistically insignificant (4) the R^2 might be too high (5) the OLS estimators, and (6) their standard errors can be sensitive to small changes in the data.

In section 5.8, Data Validation, these assumptions will be tested using different econometric test such as the Breusch-Pagan (1979) test for Homoskedasticity, the Breusch-Godfrey (1978) test for Autocorrelation, the Jarque-Bera (1980) test for Normality. Additionally, a VIF test will be made to check for multicollinearity. Lastly, "Residual vs Fitted" plots will be presented to test for linearity.

4.7 OWEN SHAPLEY DECOMPOSITION OF R-SQUARE

One of the unwritten conventions in applied econometrics and multiple regression analysis is that the authors of a given academic paper provide the reader with some sort of goodness-of-fit measure (Hereafter GOF). However, it is rare that the GOF is allocated to individual regressor variables (Huettner and Sunder, 2012). A decomposition of GOF, provides the author with a comprehensive diagnostic tool for identifying the relative importance of individual and/or groups of regression variables in a given regression model (Huettner & Sunder, 2012). Specifically, the term of relative importance refers to the quantification of an individual regressor's contribution to a multiple regression model and is a topic that has seen a lot of interest in recent years (Grömping, 2006). The Owen Shapley decomposition procedure is based upon the marginal effect of each variable in the model. It assumes that the marginal effect of a specific variable is equal to the contribution of that specific variable. Therefore, the approach is a way to calculate, for a linear regression, the exact contribution of each independent variable to the total R-squared. The contribution of each individual variable to the R-square is expressed as a percentage to the variance of the dependent variable (Antweiler, 2014).

In this thesis, we adopt the Owen Shapley decomposition to investigate the contribution of ESG and numerous other independent variables such as market-based measures of risk, sector affiliation and company-specific metrics, on the dependent variable buy-and-hold excess returns for Q1 of 2020.

Mathematically, the procedure can be described as follows, using an ordinary least squares (OLS) regression for an equation:

$$y_i = \beta_0 + \sum_{j=1}^{p} \beta_j x_i + \varepsilon_i \tag{11}$$

In this example, we wish to identify how much a particular regressor x_i contributes to the overall explanation of variation in the regression model, also called R^2 (R-square). Using the framework of Huettner and Sunder, (2012) we can decompose the models total R-squared into partial R_j^2 so that $R^2 = \sum_j R_j^2$. Equivalently, for each regressor j (j = 1, 2, 3,…,k), the expected contribution R_j^2 is defined as:

$$R_j^2 = \sum_{T \subseteq Z \setminus \{x_j\}} \frac{K!*(p - k - 1)!}{p!} [R^2(T \cup \{x_j\}) - R^2(T)] \tag{12}$$

Where T is the model with k regressors without the regressor x_j and $(T \cup \{x_j\})$ is a sub-model of the full model that includes the regressor x_j. Finally, the Z contains all model specifications with combinations of the regressors. R_j^2 can be computed by iterating over each regressor and summing the weighted marginal contributions (Antweiler, 2014).

Part III

METHODOLOGICAL APPROACH

DATA COLLECTION AND METHODOLOGY 5

This chapter outlines the key considerations the authors of this assignment have made to collect the most representative data. The chapter consist of two sections – I) data description and II) portfolio methodology. We will start by describing three subsections for the data description section. First, we start by describing the rationale for our geographical focus and sample time horizons. Second, we describe the cleaning procedure. Third, the selection of dependent and independent variables for our regressions are explained, starting with stock market data. Fourth, in the portfolio methodology section, we will elaborate on how we have sorted the data and constructed ten dynamic and yearly re-balancing ESG decile portfolios. Finally, the thesis will address the topics of data validation and sample selection bias.

5.1 GEOGRAPHICAL SCOPE

The integration of ESG into the investment universe varies from region to region. Currently, the U.S. is considered a laggard with ESG being in the top three investment considerations for only 11% of US investors (JPMorgan, 2020). The same survey, conducted by JPMorgan, found that 46% of European investors said ESG was in their top three considerations while Australian investors reported 25%.

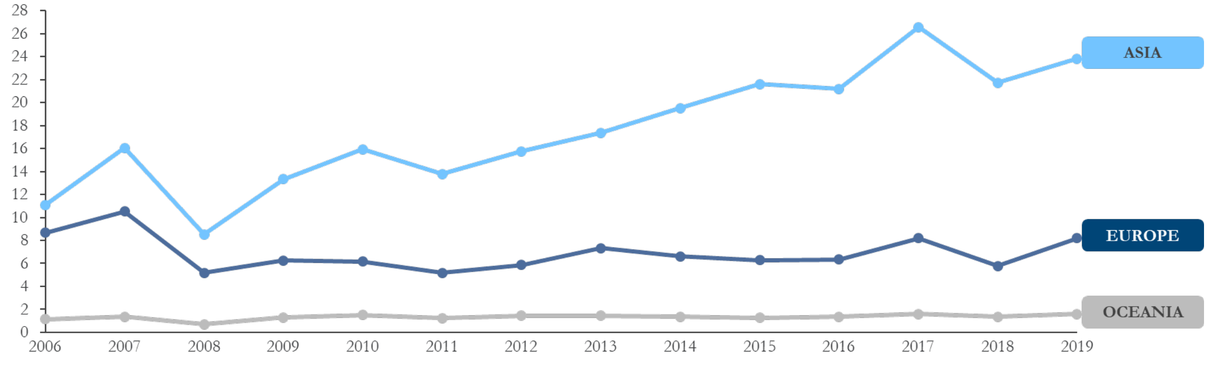
Another quantifiable way of measuring the growth in regional sustainability concerns is through the degree of SDG-alignment. SDG-alignment is a framework that measures a portfolio's impact and sustainability-driven goals. According to Emelianova (2020), U.S. companies are the least aligned (8%) compared to Asia (19%), Europe (17%) and Australia and New Zealand (15%). Relating these findings to the two objectives of our study, which is I) to investigate the if ESG create long term returns and II) to investigate the relation between ESG scores and stock price resilience during the current COVID crisis, we find that Europe, Asia, and Oceania are the most interesting regions to analyze.

Furthermore, most of the studies we have encountered are primarily focused on U.S. Jurisdictions, i.e., a market in which there is much talk of, but less practical emphasis on the implementation of ESG into corporate strategies and investment strategies. Thus, to achieve the most generalizable results, we have decided to collect company specific information from a total of 4.415 listed companies across Europe, Asia, and Oceania. We have used the company database Orbis to find the largest companies, measured on operating revenue. The reason why we have filtered on operating revenue is because our main parameter is ESG scores, and we expect that more reliable ESG-related data are available for the largest companies.

In Asia, we have filtered on an operating revenue of at least 1.000 million USD. In doing so, we have identified 2,740 relevant companies. In Europe we have filtered on an operating revenue of at least 500 million USD, resulting in 1,115 companies. In Oceania we have filtered on an operating revenue of at least 50 million USD, resulting in 560 companies.

We have filtered on distinct operating revenues due to the difference in regional business demography. With a market capitalization of listed domestic companies in Asia of 23.82 Trillion USD, we found it most appropriate to filter on the highest operating revenue (Figure 4). Accordingly, with a market capitalization of listed domestic companies in Oceania of USD 1.59 Trillion, we found it most appropriate to filter on the lowest operating revenue (World Bank, 2021).

Figure 4: Market capitalization of all listed domestic companies in Asia, Europe, Oceania
Values are in *USD, trillions* (period from 2006 to 2019).



Source: Self-developed graph based on The World Bank (2021)

5.2 SAMPLE TIME PERIODS

We organize our primary analysis along two periods, which we label "full period" which covers a 14-year period (January 2007 to December 2020), and "outbreak period" (Monday, January 1st, 2020 – Thursday, March 31st, 2020).

The decision to choose the "full period" is based on the availability of reliable ESG-scores which first became available from around 2007 (interview, Danica Pension). Secondly, the period covers the long-term stock performance, including the financial crisis and subsequent recovery period where ESG principles rapidly became an integral part of investment strategies.

It would not be wrong to call the "full period" anything else but *"the decade of the bull"*[10]. The period saw incremental progress and steady volatility which was supported by favorable monetary policies that stimulated the economy. One must therefore keep in mind that the financial performance of a variety of high and low performance ESG portfolios is measured in a bull market and not a full economic cycle. Intuitively, such an analysis is not incorrect. However, to be able to generalize our findings and the performance of each portfolio, one must capture returns and ESG measures over a full business cycle. Hence, one of the reasons for including the full year of 2020 which includes the COVID-19 downturn.

For the outbreak period, we analyze the first quarter of 2020. The period is characterized by the global COVID-19 pandemic that triggered a market-wide financial crisis where investors suffered significant loses in just a few days due to dramatic market movements (Ji & Zhang, 2020). Although stock markets in Q3 of 2020 began rebounding, a great deal of uncertainty remains as the pandemic continues globally. The COVID-19 pandemic was first brought to the world's attention in January 2020 when China shared the genetic sequence of the virus. On 23 January 2020, Wuhan city, the epicenter for the virus, was locked down. A week later the World Health Organization (WHO) declared the outbreak of the coronavirus a public health emergency of international concern[11]. As of 25 March 2020, all EU/EEA countries and more than 150 countries worldwide had been affected.

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[10] https://money.usnews.com/investing/stock-market-news/articles/2019-11-29/decade-in-review-2010s-was-the-decade-of-the-bull?fbclid=IwAR3iKWgCVqDteObeqz3rXO5rG_nJk5_wW5n9PWifFLGKuSb3aAjDRBg-lnw
[11] https://www.ecdc.europa.eu/en/COVID-19/timeline-ecdc-response

5.3 CLEANING

The dataset that is used in this thesis decreased in size due to a thorough cleaning process. It is important to note that a majority of the cleaning process was performed manually. Therefore, we expect small, yet insignificant, errors that potentially could have small implications for the empirical findings.

All company specific financial data, stock prices and ESG scores has been collected from Thomson Reuters Refinitiv (TRR). The data we collect from TRR is commonly known to provide several issues for the researcher, such as instances of errors in the return data. The effect of such problems needs to be considered before performing the analysis (Ince & Porter, 2006). In order to test for such inconveniences in our data, we perform a series of test in R to screen and correct the data. The process of collecting the data is described below.

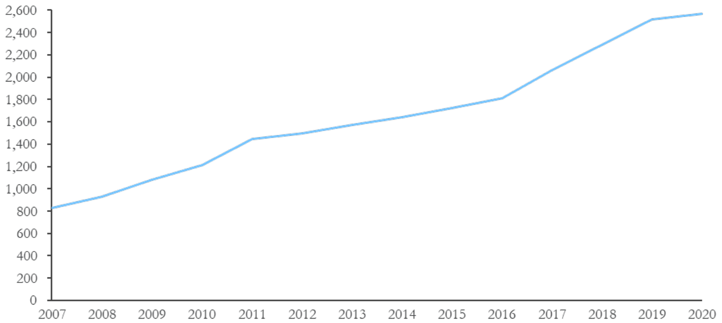
First, the dataset was collected from TRR with the most important variables for this study being ISIN code, Sector, ESG score and Environmental-, Social-, and Governance scores. The data was collected for every company for each year between January 2007 and December 2020. Secondly, all company specific financial data was combined in one large dataset using R (Appendix 31). Before dividing each observation into our decile portfolios, we conducted a thorough cleaning process to secure the reliability of the data and the results. The original data set consisted of 4,415 companies distributed across three regions: Oceania (560), Europe (1,115) and Asia (2,740). Because we collected data from 14 years, our data set consist of 7.840 (560*14) observations for Oceania, 15,610 observations for Europe and 38,360 observations for Asia. In the analysis related to sub-question one, we removed all observations that did not have an ESG-score or market capitalization. Accordingly, these observations were removed from the dataset. Lastly, we checked the stock return for outliers and duplicates. The cleaning process resulted in 3,069 observations for the Oceanian dataset, 7,254 observations for the European dataset and 12,852 observations for the Asian dataset (Appendix 3).

Thirdly, the observations were divided into ten decile portfolios and matched with the companies' monthly stock return. We value-weight (hereafter VW) each stock based on its market capitalization for the previous year. Based on these steps, it has been made possible to calculate the average VW monthly return for all the decile portfolios throughout the specified period. The cleaning process results in 331 observations for the Oceanian dataset, 691 observations for the European dataset and 1,350 for the Asian dataset.

5.3.1 *Individual companies throughout the period*

As mentioned above, we have collected data from a total of 4,415 companies across the three regions Europe, Oceania, and Asia. Figure 5 below show the development of companies with an ESG score in the period from January 2007 to December 2020. In 2007, only 930 companies were given an ESG-score from TTR, while this number had increased to 2,367 in 2020, corresponding to an increase of about 150%.

Figure 5: Development in number of firms in our dataset from January 2007 to December 2020
List below the graph show the actual number of individual stocks covered on an annual basis.



# of firms	930	1.081	1.213	1.444	1.494	1.569	1.643	1.721	1.809	2.065	2.290	2.519	2.567

Source: Self-developed table

5.4 STOCK MARKET DATA

We use monthly adjusted closing price data from Thomson Reuters Refinitiv. Specifically, we use the data code TR.ClosePrice in the formula builder which supports the adjusted parameter for dividends and splits. Thus, monthly adjusted return data will ensure that the prices we use have taken intermediate dividends and stock splits into account which is necessary for a quantitative analysis of this magnitude. We have decided to use Thomson Reuters Refinitiv, since their database includes an unrivalled amount of historical data and because it covers global stocks, including the biggest companies in Europe, Asia, and Oceania. We first calculate the monthly holding period return during the 14-year period using the following equation:

$$R_t = \frac{P_t - P_{t-1}}{P_t} \tag{14}$$

Where Rt denotes the holding period return, P_t denotes the beginning price and P_{t-1} denotes the price of the asset at the end of the holding period (Bodie, Kane, & Marcus., 2018). In order to receive the excess market returns, the monthly risk-free rate is subtracted from the market returns. We have selected the United States 1-month treasure yield, which have been collected from Kenneth French Data Library (French, 2021). The rationale behind using this rate is two-fold. First, as the data collected on all stocks are based on monthly returns, the risk-free rate for comparison should also be monthly. Second, treasury bills are considered nearly free of default risk because they are fully backed by the U.S. government and are thus a common rate to use in academic papers with a financial focus[12].

5.5 ESG SCORES

In this study, we use ESG data from TTR which is one of the largest financial data providers with 40,000 customers and 400,000 end users across 190 countries[13]. The business is partially owned by Thomson Reuters who retains a 45% stake and Blackstone which holds the remaining 55%. Refinitiv delivers its data through products such as Thomson Reuters Eikon. Other providers of ESG data include but is not limited to MSCI which cover 8,500 companies, Sustainalytics which covers 12,000 companies and Bloomberg which covers 11,500 companies.

As briefly touched upon in previous sections, TTR's ESG score measures the performance of nearly 9,000 companies across three pillars – Environmental, Social and Governance. TTR calculates a controversy score, ESG combined score and a basic score. This thesis will use the basic score. The value of the score ranges from 0 to 100 with 0 being the worst and 100 being the best. The score per category is calculated based on a percentile-rank scoring approach for each of the ten indicators mentioned in Appendix (1). Afterwards, these categories are weighted into a pillar score for E, S and G. The weights for the environmental and social pillar varies across industries, but the governance pillar remains fixed. The reason for this circumstance is that E and S is benchmarked against sector peers while G is benchmarked against companies that operate within the same country. Thus, we can conclude that the final basic ESG scores are sector-

[12] https://www.investopedia.com/ask/answers/040915/how-riskfree-rate-determined-when-calculating-market-risk-premium.asp

[13] https://www.refinitiv.com/en/about-us

adjusted. The weights for each pillar can be found in Table 2 which shows the composition of the aggregated ESG score in accordance with the framework laid forth by TTR (as of April 2021).

Table 2: ESG methodology of Thomson Reuters Refinitiv (TRR)

Table 2 shows the indicators and weights for the induvial pillars; Environmental, Social and Governance. All percentages rounded to the nearest integer.

Pillar	Indicators	Weights
Environmental	68	37%
Social	62	33%
Governance	56	30%

5.5.1 *ESG scores in more detail*

To get a more detailed notion of how the ESG scores work in combination for all observations in our dataset, we have investigated the correlations between the aggregated ESG score and each of the three individual pillars. Due to the aggregated ESG scores composition and its weighing, we find it very improbable that the various pillars are perfectly correlated – that is, knowing the value of one variable exactly predicts the value of the other variable

The correlation matrixes in Table 3 show that all individual pillars are highly correlated with the aggregated ESG score. However, this is not the case when we analyze the correlation between the individual pillars. Table 2 reveals that while the environmental and social pillar are moderately correlated with 70%, their correlation with the governance pillar is significantly lower. The correlation of the governance pillar with the environmental pillar is 55% and 53% with the social pillar. These findings support our decision to investigate the explanatory power of the overall and pillar specific Environmental, Social and Governance scores.

The correlation differences might be explained by the history of CSR and ESG. CSR was first introduced around the 1950s and 1960s, while ESG is considered a modern concept of the 21st century (Agudelo, Davidsdottir, & Johannsdottir, 2019). Thus, the focus on corporate behavior and governance-aware companies have existed for much longer, compared to the two other pillars in the ESG framework (Horst, Renneboog, & Zhang, 2008). Another way of explaining the poor correlation between the G pillar and the S and E pillar is the focus on shareholder and external stakeholders. While governance practices focus on shareholder value, social and environmental practices are benefiting external stakeholders, such as the environment, communities, or employees. This reverse relation is clearly reflected in the individual scores and their correlation (Table 3).

Table 3: Correlations between the aggregated ESG score and the decomposed pillars
Data from Thomson Reuters Refinitiv - E stands for environmental, S stands for Social and G stands for Governance.

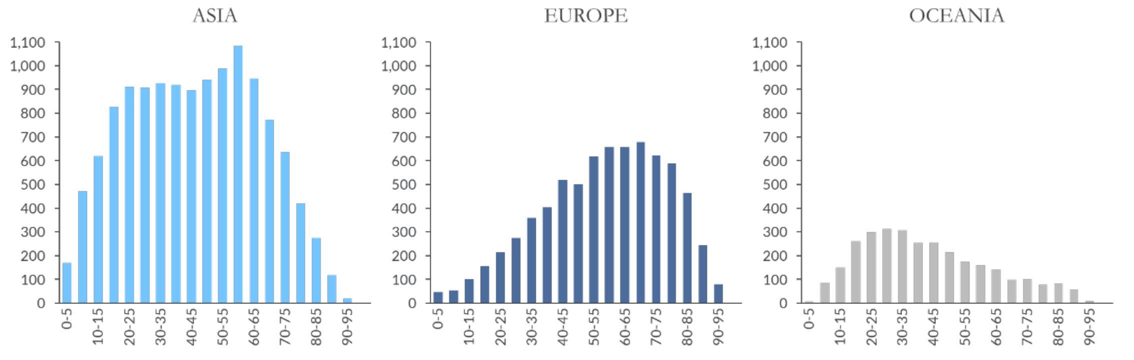
	ESG	E	S	G
ESG	1.00	0.84	0.89	0.65
E	0.84	1.00	0.72	0.37
S	0.89	0.89	1.00	0.40
G	0.65	0.65	0.40	1.00

5.5.2 *Summary statistics for ESG scores (stock level)*

Figure 6 presents the distribution of the weighted ESG scores from Refinitiv for Oceania, Europe, and Asia. In Oceania, the ESG score ranges from 1.03 to 91.81 with a mean of 40.24 (median) and a standard deviation of 20.29. Additionally, the ESG scores have a positive skewness of 0.53. Skewness is a measure of the asymmetry that deviates from symmetry, or the normal distribution. In other words, skewness can be quantified as how far the distribution departs from symmetry (Sharma, 2020). A symmetrical distribution such as the normal distribution has a skewness of 0.

A skewness of 0.53 indicates that the size of the right-handed tail is larger than the left-handed tail, which is illustrated in Figure 6 for Oceania. In Europe, the ESG scores varies from 0.53 to 95.03 with a mean of 55.91 (median) and a standard deviation of 19.80. The ESG scores have a negative skewness of -0.40 indicating that the size of the left-handed tail is larger than the right-handed tail. Lastly, in Asia, the ESG score range from 0.40 to 92.37 with a mean of 43.41 (median) and a standard deviation of 20.89. The skewness is 0.02 indicating a much more symmetric distribution compared to Oceania and Europe. The statistic for each market illustrates that companies in Europe between January 2007 and December 2020 have the highest average ESG score, while companies in Oceania have the lowest. Additionally, Figure 6 indicates that high and low ESG scores in Asia are more equally distributed among the companies, suggesting a relatively more symmetrical distribution.

Figure 6: Distribution of the weighted ESG scores from Thomson Reuters Refinitiv (TTR)
Left plot shows distribution for Asia, middle plot Europe and right plot Oceania. Period is from January 2007 to December 2020



Source: Self-developed table

5.5.3 *Summary statistics for ESG scores (Portfolio level)*

The mean TTR weighted ESG score for each pillar and the mean aggregated ESG score, in each portfolio, is summarized in Table 4. We observe that the relation is similar to that in Figure 6.

In Europe, the mean individual pillars and the mean aggregated ESG score ranges from 11.01 to 85.54, showing a generally higher mean score in each pillar and each portfolio compared to Asia and Oceania. In Oceania, the mean score for each individual pillar and the aggregated ESG is generally lowest, ranging from 2.13 to 81.38. In Asia, the mean score for each individual pillar and the aggregated ESG score ranges from 4.76 to 77.41.

It is clear from Table 4 that the E, S, G and overall ESG score is highest in Europe. Furthermore, we observe a clear increasing pattern in Market capitalization, cash, and earnings for all pillars in all regions, i.e., the higher the ESG score the higher the market capitalization, cash, and earnings. In summary, our data shows that larger companies dominate the high-rated deciles. According to Banz (1981), stocks with a smaller market capitalization generally experience a higher average return than larger stocks. Accordingly, we should expect that these portfolios perform worse than the low-rated portfolios. If the size effect is present, it will be captured by the SMB factor in part IV.

Table 4: Portfolio characteristics and mean Refinitiv weighted ESG score

This table displays the mean of Market capitalization, debt-to-equity ratio, return on assets, cash holdings, and the single scores per ESG decile for Europe (top), Asia (middle) and Oceania (bottom), based on the overall sample from January 2007 to December 2020.

EUROPE

ESG Portfolios	E	S	G	ESG	Market Cap.	D/E ratio	ROA	Cash
PF1	11.01	23.34	24.35	19.93	3.900.454.507	122%	5%	256.457.562
PF2	26.81	35.65	37.44	33.65	4.518.476.426	130%	5%	261.073.885
PF3	37.70	45.27	41.40	42.26	5.034.636.762	102%	5%	297.829.134
PF4	45.63	52.39	45.51	48.88	6.579.443.220	112%	5%	360.817.460
PF5	53.78	58.06	48.40	54.83	9.377.327.495	110%	5%	530.710.273
PF6	62.24	66.42	49.62	60.66	10.748.138.807	448%	5%	591.672.758
PF7	68.57	70.04	55.86	66.00	13.484.747.722	164%	4%	771.292.161
PF8	73.66	75.79	62.02	71.45	16.980.755.174	153%	4%	1.034.922.936
PF9	78.16	80.49	69.59	77.28	20.175.256.494	139%	4%	1.319.374.052
PF10	85.54	87.75	78.99	85.14	40.283.762.425	128%	4%	2.527.084.281

ASIA

ESG Portfolios	E	S	G	ESG	Market Cap.	D/E ratio	ROA	Cash
PF1	4.76	7.20	19.73	9.82	4.800.325.448	80%	6%	114.027.424
PF2	11.90	13.81	35.33	19.59	5.774.745.469	91%	5%	174.689.915
PF3	19.28	20.88	41.40	26.78	6.856.542.439	108%	5%	395.979.155
PF4	27.13	28.01	43.55	33.53	8.371.854.376	107%	5%	356.930.190
PF5	35.67	35.81	47.56	40.29	10.627.234.779	109%	5%	772.583.660
PF6	45.16	41.38	52.00	47.13	12.543.400.813	99%	5%	758.603.267
PF7	52.98	49.25	55.30	53.45	13.206.208.150	97%	5%	705.643.238
PF8	59.67	57.52	59.07	59.84	13.772.536.970	111%	5%	1.029.770.605
PF9	67.18	63.93	66.88	66.94	16.174.185.229	95%	4%	956.644.062
PF10	76.49	75.07	76.85	77.41	21.025.675.001	103%	5%	970.523.165

OCEANIA

ESG Portfolios	E	S	G	ESG	Market Cap.	D/E ratio	ROA	Cash
PF1	2.13	14.32	21.29	12.30	855.809.624	68%	2%	56.450.204
PF2	5.00	20.16	31.38	18.82	840.118.146	164%	5%	55.559.244
PF3	8.36	23.55	41.50	24.24	1.213.751.326	55%	7%	54.973.635
PF4	12.20	28.79	44.31	29.12	1.448.480.422	58%	5%	55.798.526
PF5	17.61	33.93	47.67	34.09	1.582.368.227	69%	4%	73.052.443
PF6	24.76	36.21	54.64	39.38	2.081.333.797	71%	6%	96.898.383
PF7	28.85	42.05	61.54	45.44	3.739.394.907	111%	4%	116.904.459
PF8	41.04	49.51	65.12	53.29	4.076.022.409	72%	5%	250.127.257
PF9	55.29	61.26	72.68	63.94	8.791.704.286	86%	5%	266.331.286
PF10	73.38	80.44	81.38	79.73	29.809.201.575	169%	6%	462.069.454

5.5.4 D*ata representativity*

By talking to ESG-specialist from Danica Pension[14], ATP[15] and Pensam[16] we learned that ESG-related disclosures, from individual companies, are limited, unverified, and non-standardized. In connection to this, we learned that a very sought-after toll from investors is a common, transparent ESG reporting standard. These findings are in line with a survey conducted by CFA institute. In their survey they asked 1.110 portfolio managers and analysts worldwide about ESG-scores and their representativity. All stated that it would be beneficial to agree upon a single ESG reporting standard that could streamline the data-collection process and produce more quality data (CFA institute, 2019). The push towards more transparent and standardized ESG ratings is no surprise. A review study by Huber and Comstock (2017), finds that the top ESG rating providers use vastly different methodologies and rating systems in their evaluation of international and domestic public companies, resulting in different ESG ratings. Furthermore, a time-series correlation analysis of MSCI, Bloomberg and Refinitiv by Elefsen & Glintborg (2020) found that the three different rating agencies rate high as well as low ESG performing companies vastly different. They conclude that there is no clear consensus in the ESG ratings between these tree different providers.

These findings raise some warning questions in terms of creating generalizable results. It is reasonable to assume that by conducting the same analysis as we do, with ESG scores from Bloomberg or MSCI or a third rating provider, that the results would differ. Therefore, the results

14 Danica Pension is a wholly owned subsidiary of Danske Bank Group. They specialize in pension schemes, life insurance and health insurance and has one million customers in Denmark and Norway
15 ATP Group is Denmark's largest pension and processing company with approximately 5 million members
16 Pensam is a labour market pension fund with approximately 500,000 members

that we present throughout this assignment should merely be perceived as an indication of the relationship between ESG, long-term alpha and short-term resiliency during a partly exogenous shock.

5.6 FACTOR DATA

Data for the factor models has been collected from Kenneth R. French Data Library (French, 2021). From this data library, we have collected the risk-free rate (R_F), excess market return (MKT), size factor (SMB), value factor (HML), momentum factor (WML), profitability factor (RMW) and investment factor (CMA). We have collected this data on a monthly basis and for the same sample period as our ESG data from Refinitiv. Since our dataset consist of more than 4.415 companies, from three different regions, we have downloaded regional factor data for each market. The Data Library provide different factor data for six different geographical regions. Figure 7 illustrates the countries that are in each of the six regions.

It is important to mention that the factor data do not exactly match each region. However, we argue that the collected data is representative for each regional market. For the European region, we have collected factor data from Kenneth R. French's European market, which consist of data for 17 European countries[17]. For the Asian region we have collected factor data from the Japanese market, since Kenneth R. French does not directly provide factors for the Asian region. The reason for choosing Japan, as a representation for the Asian region, is due to the fact that companies from Japan makes up the majority of the Asian sample.

For Oceania we have collected data from Asia Pacific, excluding Japan, because data from Australia and New Zealand contributes to the factors in this market. Even though, data from Hong Kong and Singapore, which is placed in our Asian sample, also contributes to the factors in this market, we believe this market is more representative than for example the "Developed Market" option or the "Developed Market without US" option. The fact that the collected factor data varies from the samples is something that needs to be considered when interpreting the empirical results. However, we strongly believe that the factor data is representative for each regional market.

[17] Our European data sample consist of data from 27 countries in Europe.

Figure 7: Countries located in each factor market (FF3, C4 and FF5 factor data)
We use the Europe factor market for the European region (dark blue), Japan factor market for the Asian region (light blue) and Asia Pacific (excluding Japan) factor market for the Oceanian region (grey).

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

5.7 PORTFOLIO METHODOLOGY

In the following section a thorough description of the portfolio methodology and its importance will be explained. The objective of portfolio analysis is to examine the cross-sectional relation between two variables and is one of the most commonly used statistical methodologies in asset pricing (Bali, Engle, & Murray, 2016). In this assignment, portfolio analysis will be employed to understand the cross-sectional relationship between ESG scores and stock returns.

5.7.1 *Univariate portfolio analysis*

Portfolio sorting has been an important part of modern empirical financial research and is widely used to test for, and establish, cross-sectional relationships between expected asset returns and asset class characteristics (Cattaneo, Crump, Farrell, & Schaumburg, 2016). Motivated by Blume (1970) the majority of empirical financial research in modern asset pricing today uses portfolios instead of individual stocks when analyzing the relationship between expected return and asset class characteristics.

Additionally, several studies have examined if the usage of portfolios compared to individual stocks enhances the analysis (Fama & Macbeth (1973), Fama & French (1992), Black, Jensen, & Scholes (1972)). The studies found that by using portfolios, the standard errors of factor loadings are reduced significantly due to decreasing idiosyncratic risk. Intuitively, this makes sense and is in accordance with Markowitz's (1959) Modern Portfolio Theory that explains that by investing in more than one stock an investor can achieve benefits from diversification and reduce the riskiness of the portfolio (McClure, 2020). There exist multiple ways of conducting portfolio sorting. In this thesis, we have chosen to use the univariate sorting methodology introduced by Banz (1981). The objective of a univariate portfolio analysis is to assess the cross-sectional relation between X (Stock returns), the sort variable, and Y (ESG scores), the outcome variable. In this thesis, we will follow the four-step procedure put forth by Bali, Engle, & Murray (2016).

5.7.2 *Number of portfolios*

The first step is to group the stocks in the sample into portfolios based on values of the ESG score. We have pulled data from a combined 4,415 listed companies in Oceania, Asia, and Europe from 2007 to 2020. When we segment these stocks according to their ESG score, it results in 3,043 observations for Oceania, 12,841 observations for Asia and 7,233 observations for Europe with an ESG score for every year. In each year, the stocks have been divided into decile portfolios based on their ESG score for the respective year. The ten portfolios range from PF1 (lowest ESG score) to PF10 (highest ESG score), where PF1 consist of the 10% lowest ESG scores while PF10 consist of the 10% highest ESG scores. This sorting methodology is applied for all regions.

Choosing an appropriate number of portfolios is a trade-off, as fewer portfolios lead to less cross-sectional dispersion within the factor loadings. A decreased dispersion of the sort variable X across the portfolios can make it relatively more difficult to detect the cross-sectional relationship between ESG scores and stock returns, as the difference in ESG score across the portfolios are reduced (Bali, Engle, & Murray, 2016). On the other hand, it is assumed that a higher number of portfolios would result in more dispersed information in the cross-section. As the number of portfolios increases, the number of companies in each portfolio decreases which will result in increased noise when using the sample mean to calculate the true mean value for each portfolio.

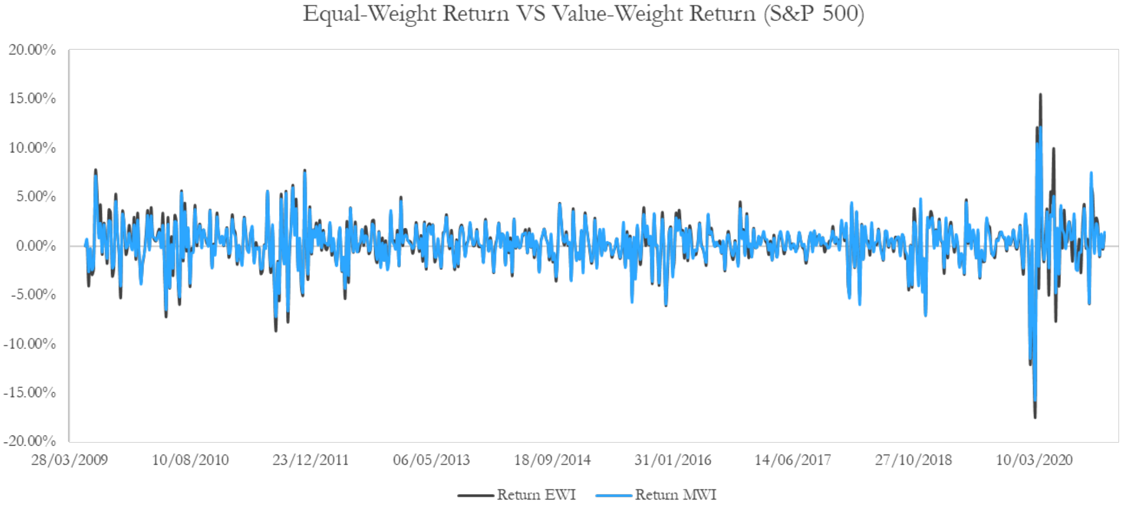
Historically, well known empirical studies like Fama & Macbeth (1973) used 20 portfolios, Fama & French (1992) used 25 portfolios and Black, Jensen, & Scholes (1972) used 10 portfolios. In our study within the field of ESG scores, it is assumed that ten portfolios sorted on a univariate variable (ESG score), is suitable and will provide results that are easy to interpret.

5.7.3 *Portfolio Analysis*

In this section we will describe different ways to weight each stock in a portfolio and which method we have applied on our ten decile ESG portfolios. The most common methods to weigh stocks in a portfolio or index is by equally weighting (EW) each stock or value weight (VW) each stock based on their market capitalization. Even though two portfolios/indices consist of the same companies, they can behave very differently and can affect investments substantially (Hayes, 2020).

In an EW portfolio/index, the investor places an equal bet on every company's success, which is a passive decision. On the contrary, a VW portfolio/index based on market capitalization has a higher concentration of larger companies and assumes that yesterday's winners will continue to win. Figure 9 below illustrates how the S&P 500 Equally Weighted Index (S&P 500 EWI) and S&P 500 Market Weight Index (S&P 500 MWI) has performed since May 2009. The table illustrates that the indices perform almost identically over an 11-year period from 2009-2020. However, it is worth mentioning that the S&P 500 EWI is a bit more volatile than the S&P 500 MWI, which might be caused by the greater volatility among small-cap stocks and their larger weights compared to S&P 500 MWI.

Figure 9: Weekly return for S&P 500 equally weighted index and S&P 500 market-weighted-index
Figure 9 illustrates the weekly return for S&P 500 EWI and S&P 500 MWI. The illustration shows that S&P 500 EWI is indeed more volatile, but experienced are higher average return than S&P 500 MWI.



	S&P 500 EWI	S&P 500 MWI
Average Return	0.262%	0.255%
Standard Deviation	0.0256	0.0227
Min.	-16.96%	-14.98%
Max.	15.50%	12.10%

The fact that small-cap stocks are more volatile is not necessarily negative, because over a long-time horizon small-cap stocks has performed a better risk-adjusted return than large-cap stocks, a view that is supported by Fama & French (1992).

Based on the descriptions above, we have chosen to VW the companies based on their market capitalization for the previous year. This means that the stocks in portfolio one for 2007 is weighted based on their respective market capitalization in 2006. If a company does not have a market capitalization in the previous year the weight will be based on the company's market capitalization for the same year. An analysis of whether this method results in the best risk adjusted ESG portfolio return or not, is outside the scope of this master thesis and will not be examined.

5.8 DATA VALIDATION

We have now presented the data which will be used in this thesis. In the following section we investigate the econometric robustness of this data. We use cross-sectional and time series data. These types of data are combined in the first analysis, where our data samples are sorted on ESG and combined with stock return each month between January 2007 and December 2020. Additionally, we use cross-sectional data in the second analysis, where a multiple regression analysis is applied. All the models applied in part IV rely on the Ordinary Least Square (OLS) estimation. We test for robustness in the data to verify that our regression models satisfy the main assumptions in OLS regression described in section 4.6. A fulfillment of the OLS assumptions will indicate that our data and thus models are robust. The following three test will check if three of the OLS assumptions are fulfilled. Specifically, the Breusch-Pagan (BP) test will check for Homoskedasticity, the Breusch-Godfrey (BG) will check for Autocorrelation and the Jarque-Bera (JB) test will check for Normality. In addition to these tests, we use a Variation Inflation Factor (VIF) (Investopedia, 2021) to test for multicollinearity and "Residual vs Fitted" plots to test for linearity. Table 5 presents the results from the BP, BG and JB test for the European region. We have conducted the same tests for the Oceanian and Asian region which show similar results as Table 5 (Appendix 4 and 5).

Table 5: Econometric tests and robustness

Table 5 show three econometric test for the data collected from the European region for all decile portfolios (PF1-PF10), our long-short portfolio (LS PF) and our multiple regression analyses (MRA). Panel A presents the results from the Breusch-Pagan test (1979) for Homoskedasticity. Panel B presents the results from the Breusch-Godfrey test (1978) for Autocorrelation. Panel C presents the results from the Jarque-Bera test (1980) for Normality. Significance levels: p-value < 0.05 (*). p-value < 0.01 (**). p-value < 0.001 (***).

EUROPE												
	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	LS PF	MRA
Panel A: Breusch-Pagan test results												
BP test statistics	4.72	14.17	3.58	4.93	17.85	9.41	6.74	12.12	13.69	20.01	8.02	60.77
p-value	0.45	0.01*	0.61	0.43	0.00**	0.09	0.24	0.03*	0.02*	0.00**	0.16	0.00**
Panel B: Breusch-Godfrey test results												
BG test statistics	0.40	0.06	0.34	2.52	0.87	0.06	0.15	2.30	0.37	1.34	0.61	0.00
p-value	0.53	0.81	0.56	0.11	0.35	0.80	0.70	0.13	0.54	0.25	0.44	0.98
Panel C: Jarque-Bera test results												
JB test statistics	0.59	0.67	0.07	0.51	0.22	0.14	0.07	1.12	0.39	0.07	0.28	0.48
p-value	0.74	0.71	0.96	0.78	0.90	0.50	0.97	0.57	0.82	0.97	0.87	0.79

In Panel A, which presents the Breusch-Pagan (1979) test, we observe that we cannot reject the hypothesis arguing for Homoskedasticity for in PF1, PF3, PF4, PF6, PF7 and LS PF. This indicates that the OLS assumption about constant variance in the residuals are fulfilled. Contrary to this, we can reject the hypothesis arguing for Homoskedasticity in PF2, PF5, PF8, PF9, PF10 and MRA, suggesting Heteroskedasticity and a non-constant variance in the residuals, indicating that the OLS assumption is violated.

As mentioned in section 4.6, a violation of the homoskedasticity assumption must be quite severe to present a major problem due to the robust nature of OLS regression (Statistics Solutions, 2021). Based on our results, no corrections will be made to the data, but we are aware of the results. In Panel B, which present the results from the Breusch-Godfrey (1978) test, we observe that we fail to reject the hypothesis that autocorrelation is present in our data, which is in line with the OLS assumption about no autocorrelation. In Panel C, which present the Jarque-Bera (1980) test, we observe that we cannot reject the hypothesis that our data is normally distributed. This means that our residuals are normally distributed.

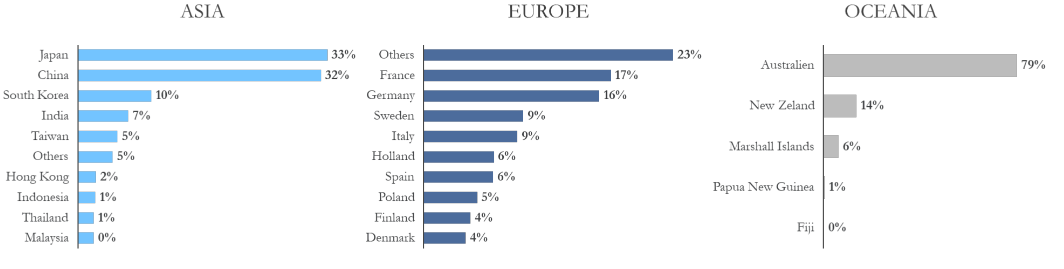
The VIF test measuring the amount of multicollinearity in a set of multiple regression variables have solely been calculated for the Multiple Regression Analysis in section 6.3. The result from this test for the data collected from the three regions are presented in Appendix (6), (7) and (8). The test has been made using the package "mctest" in R. A VIF of 1 indicates that two variables are not correlated, a VIF between 1 and 5 suggest moderate correlation, and a VIF above 5 indicates high correlation (Investopedia, 2021). Common for all regions is that the variables ESG, E, S, and G all have a VIF above 5, which indicate a high correlation between these variables. This is in line with the correlation matrix in section 5.5. Additionally, Earnings show a VIF above 5 in Europe and Oceania and a VIF of 4.7 in Asia, suggesting a high correlation with other variables in the regression. As a result of these VIF values, we decide to remove E, S, G and Earnings from our regression analysis for all regions. When we test for multicollinearity again no variables show a VIF above 5. Lastly, residual plots of the "Residuals vs Fitted" for all regions are presented in Appendix (9), (10) and (11). These plots indicate that the assumptions about linearity are fulfilled for all portfolio regressions using the FF5 model and the multiple regression model. The residual plots should ideally show a fitted pattern and the red line should be approximately horizontal at zero. This is the case for every residual plot.

5.9 SAMPLE SELECTION BIAS

To mitigate sample selection bias, it is crucial that the notion of independence is satisfied. This is a common challenge when researchers create their own dataset. Our sample is not completely random in that it is selected based on geographical relevance and a clear criterion that they must have an ESG score, thus not perfectly random. However, since all observations in our sample have the same probability of being chosen, independence is said to be satisfied. Our dataset includes a large span of countries (48), which minimizes any geographic-specific tilt. Figure 8 presents the geographic distribution of the companies within our dataset.

Figure 8: Geographical dispersion of the companies within our dataset

Figure 8 plots the geographical dispersion of the companies within the data set. All countries included in each region are listed in full below the plot. The sample period is January 2007 to December 2020.



Source: Self-developed

Europe: Lithuania, Malta, Bulgaria, Estonia, Slovakia, Czech Republic, Hungary, Slovenia, Croatia, Cyprus, Romania, Portugal, Greece, Austria, Luxembourg, Ireland, Denmark, Belgium, Finland, Poland, Spain, Holland, Italy, Sweden, Germany & France. **Asia:** Kyrgyzstan, Sri Lanka, Uzbekistan, Bangladesh, Kazakhstan, Pakistan, Vietnam, Singapore, Philippines, Malaysia, Thailand, Indonesia, Hong Kong, Taiwan, India, South Korea, China & Japan. **Oceania:** Fiji, Papua New Guinea, Marshall Islands, New Zealand & Australia

EMPIRICAL FINDINGS 6

With the theory, data, regression models, and methodological approach in place, we will now move on to the implementation stage of the models. We will perform the analysis with two objectives in mind. The first objective is to examine the cross-sectional relation between the overall ESG score and the expected returns for the different decile portfolios using three well-known factor models. The second objective is to uncover if ESG, E, S and/or G provide a resilient-like protection to an exogenous shock like COVID-19. To examine the second objective, we will run a multiple regression analysis on the overall ESG score, the individual pillars, and numerous other variables to estimate the proportion of the explanatory power for returns that each set of variable contributes.

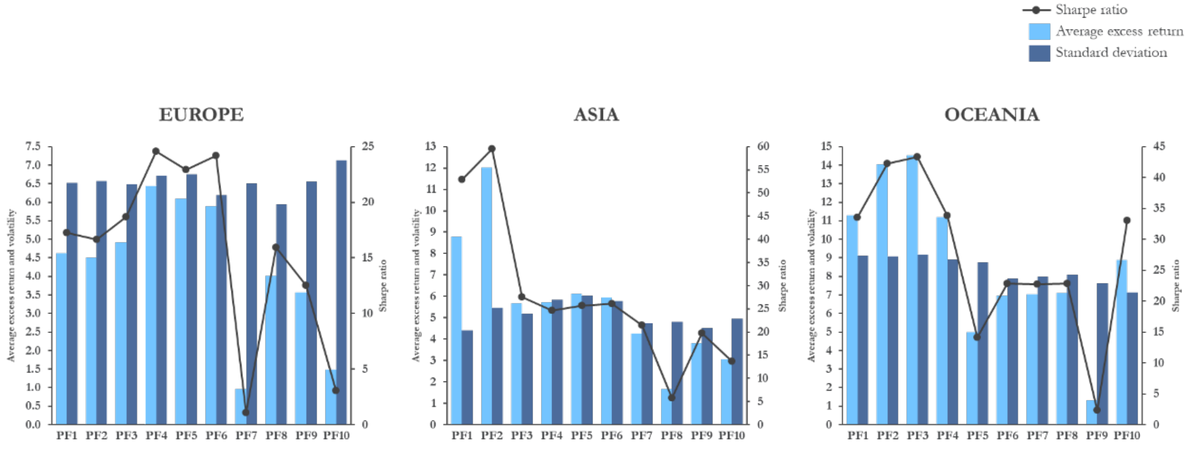
We will begin our analysis with a short elaboration of the empirical results for objective one. Specifically, we will evaluate the performance and excess return of the decile portfolios and a long-short portfolio before moving on to an analysis of the alphas.

6.1 PERFORMANCE EVALUATION

In order to answer the first sub-question, whether an investor has to sacrifice returns or receive a premium for investing into "green" stocks, we find it useful to assess how returns evolved over our sample period. In section 5.5.2, we mentioned that larger companies dominated the high-rated decile portfolios and argued that this would produce an expected lower excess return relatively to the low-rated decile portfolios. From Figure 10, we can observe that this relation seems to hold. However, we do observe that all portfolios had a positive annualized average excess return during the full period specification.

We cannot identify a clear linear pattern from PF1 to PF10, but we can conclude that the lowest ESG rated portfolios produces higher average excess returns than the highest ESG rated portfolios. The positive average excess returns also translate into positive Sharp Ratios. Furthermore, with slightly lower standard deviations we find that the highest ESG rated portfolios appear less volatile than the lowest ESG rated portfolios. In sum, the highest ESG rated portfolios records the worst risk-return-trade-off. These results are in line with Banz (1981) and that of Hong & Kacperczyk (2009) who argue that sin stocks have higher expected returns than otherwise comparable stocks.

Figure 10: Excess return, Sharpe Ratio and Standard deviation for all decile portfolios in all regions
Figure 10 plots the arithmetic average annualized excess return, the annualized volatility, and the Sharpe ratio for the decile portfolios. The portfolios are rebalanced yearly using the individual ESG score. PF1 contains the stocks with the lowest rating and PF10 the highest rated. The figure presents the Europe (left plot), Asia (middle plot) and Oceania (right plot) respectively. The sample period is January 2007 to December 2020.



Source: Self-developed table

When investigating the distributions of returns across the three regions, we find a negative skewness with values between -0.08 and -0.82, indicating that the distribution is moderately skewed, and that the distribution has a fatter tail in the area with low returns (Table 6). Furthermore, the kurtosis values are positives, indicating the distribution of the returns are peaked and has moderate tails.

Table 6: Summary statistics for all decile portfolios in Europe, Asia and Oceania

Table 6 reports the performance statistics for the decile portfolios for our three regions. Panel A presents the results for Europe, Panel B Asia, and Panel C Oceania. Each month the deciles are created with stocks ranked by their ESG score with decile PF1 (PF10) consisting of the lowest (highest) rated stocks. Value weighted long positions are taken within each decile. Further the table presents the arithmetic average excess return (annualized), volatility (annualized), skewness, kurtosis, and Sharpe ratio. Sample period is January 2007 to December 2020.

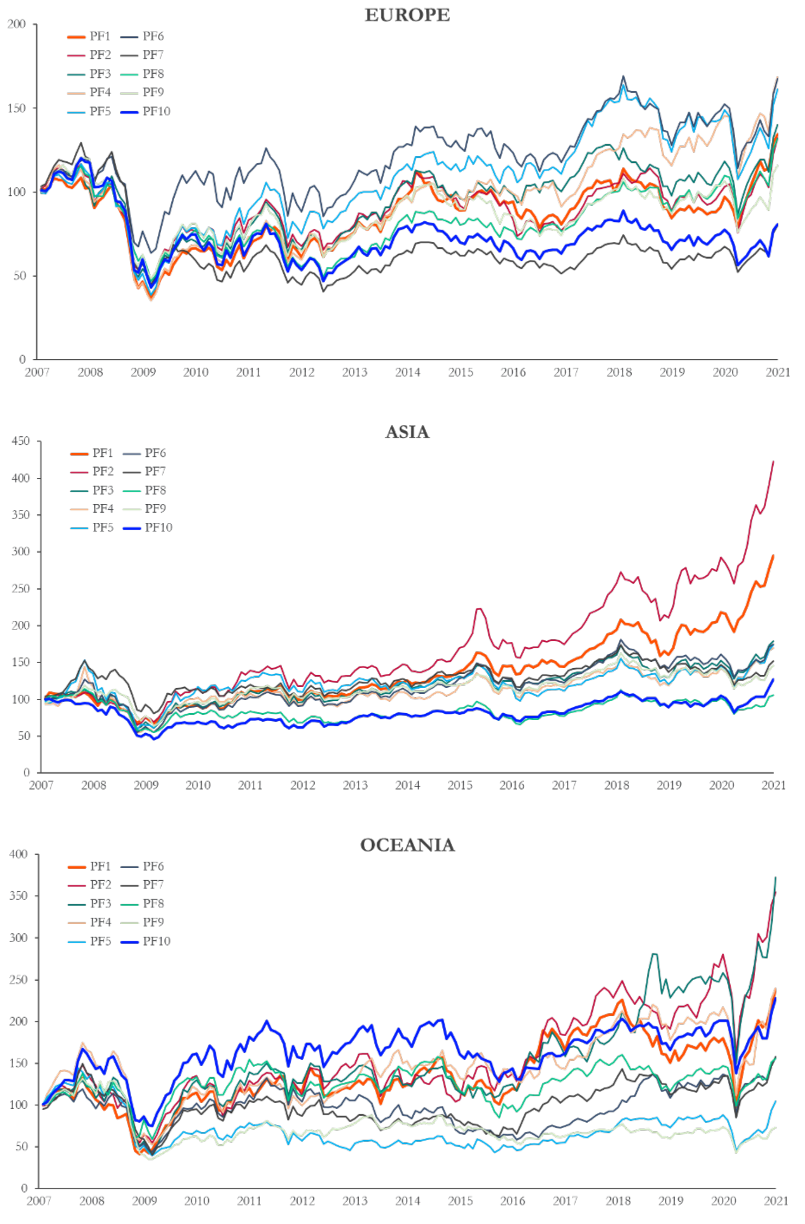
Portfolios	PF1	PF2	F3	PF4	PF5	PF6	PF7	PF8	PF9	PF10
Panel A: Europe										
Avg. excess return	4.62%	4.51%	4.92%	6.44%	6.09%	5.90%	0.96%	4.01%	3.56%	1.48%
Standard deviation	6.52%	6.57%	6.49%	6.71%	6.75%	6.19%	6.51%	5.95%	6.56%	7.13%
Skewness	-0.56	-0.33	-0.71	-0.76	-0.29	-0.18	-0.68	-0.22	-0.33	-0.37
Kurtosis	1.63	1.70	2.72	3.89	2.20	1.17	2.63	0.70	2.08	1.91
Sharpe ratio	0.17	0.17	0.19	0.25	0.23	0.24	0.01	0.16	0.12	0.03
Panel B: Asia										
Avg. excess return	8.79%	12.02%	5.67%	5.72%	6.12%	5.95%	4.25%	1.67%	3.82%	3.07%
Standard deviation	4.41%	5.48%	5.17%	5.85%	6.05%	5.78%	4.76%	4.80%	4.53%	4.96%
Skewness	-0.28	-0.08	-0.50	-0.11	-0.67	-0.82	-0.40	-0.41	-0.28	-0.21
Kurtosis	-0.08	0.80	1.34	1.43	2.13	3.51	1.58	1.12	0.99	1.35
Sharpe ratio	0.53	0.60	0.28	0.25	0.26	0.26	0.21	0.06	0.20	0.14
Panel C: Oceania										
Avg. excess return	11.30%	14.03%	14.51%	11.18%	4.99%	6.97%	7.03%	7.11%	1.33%	8.87%
Standard deviation	9.11%	9.10%	9.19%	8.91%	8.74%	7.90%	8.00%	8.08%	7.63%	7.12%
Skewness	-0.49	-0.25	-0.27	-0.63	-0.40	-0.28	-0.08	-0.33	-0.79	-0.31
Kurtosis	2.45	1.52	2.10	4.23	2.86	1.38	1.43	3.51	2.84	1.20
Sharpe ratio	0.34	0.42	0.43	0.34	0.14	0.23	0.23	0.23	0.02	0.33

Finally, Figure 11 below plots the time series of cumulative returns from January 2007 to December 2020. Starting from 2011, PF1 and PF2 in Asia displays significantly better stock performance than the rest of the portfolios in that region. For Europe, the decile portfolios display a rather similar pattern. However, PF6, PF5 and PF4 are displaying relatively better stock performance while PF10 and PF7 are the worst performers. In Oceania, PF3 and PF2 are displaying significantly better stock performance than the rest of the deciles in that region, while PF5 and PF9 are the worst performers.

The key takeaway from the time series performance is that the mid-to-low rated ESG portfolios indicate a relatively better performance than the higher-rated ESG portfolios. Secondly, the time series performance also indicates that the best performing portfolios are persistent over time. Thirdly, the difference in returns for most of the portfolios is not that excessive. This implies that many of the portfolios are unlikely to earn excess risk-adjusted returns, unless there is a large deviation in the risk of the portfolios.

Figure 11: Time series return performance for all decile portfolios in Europe, Asia and Oceania

Figure 11 plots the cumulative return for each of the ten constructed decile portfolios over time for the Europe (first plot), Asia (second plot), and Oceania (Third plot) respectively. The sample period is January 2007 to December 2020.



6.2 RISK-ADJUSTED PERFORMANCE (LOOKING FOR ALPHA)

Simple returns, or volatility-adjusted returns such as the Sharpe Ratio, do not answer the focal point of our research question. Secondly, they are not relevant for investors because they ignore the interaction with other important components. This section presents the empirical results we get from accounting for the well-known measures of risk through three different factor models – FF3, C4 and FF5. We have divided the section into three subsections: Sub-section 6.2.1 European region, Sub-section 6.2.2 Asian region and Sub-section 6.2.3 Oceanian region. Each sub-section will consist of two panels. Panel A presents the intercept (alpha) for FF3, C4 and FF5, respectively. Panel B presents the different regression coefficients estimated by FF5 and the Adjusted R-Squared (Adj. R^2). We present the coefficients from the FF3 and C4 models in Appendix (12), (13) and (14). A correlation matrix between the portfolio excess return and the factors are presented in appendix (15), (16) and (17). The significant coefficients are marked with the following significant codes:

0.001 (***), 0.01 (**), 0.05 (*)

Furthermore, we consider a coefficient insignificant if 0 is contained within the 95 % confidence interval of the coefficient estimate. We have made this decision since we want the coefficient to be statistically different from 0. The particular reason for this is that it cannot be rejected that an insignificant coefficient is statistically different from zero. Thus, a coefficient of zero indicate that it has no effect in the regression model (Agresti, Franklin, & Klingerberg, 2017).

Before explaining the reason for choosing Adjusted R-Squared, it is essential to explain the R-square as the two are interconnected. The R-square is defined as the coefficient of determination and is a statistical measure that assess fit or explanatory power of regression models. In this thesis, it measures how much of the variability in the dependent variable (risk-adjusted excess return of the respective decile portfolios) that is explained by the models. The Adjusted R-square was introduced by academics to address the key drawback of R-square i.e., the R-square does not take into consideration the effects of factors which arbitrarily increases the explanatory power of the model, based on the numbers of explanatory variables. The Adjusted R-square value will therefore always be lower than the R-square and is therefore preferred in this type of analysis (Gujarati & Porter, 2009). Across all multifactor regressions, the adjusted R-square values are relatively high for the decile portfolios, with values ranging between 40% (Asia) and 95% (Europe). However, we note that high R-square values seems to be a general characteristic for multifactor models (Carhart, 1997; Fama & French, 1992 and 1996).

6.2.1 *Results from Europe*

We present the European results from our analysis of the decile portfolios in Table 7. When looking at the alpha, or the decile portfolios intercept, we find that the decile portfolios performed quite differently compared to each other. However, only one of the ESG portfolios (PF7) produce a statistically significant alpha on the 5% level in the FF3 model[18].

We observe that the annualized alphas for the FF5 model follow a somewhat downward sloping tendency, with values decreasing from 1.18% in PF1 to -1.44% in PF2 and then increasing to 1.26% in PF5. Furthermore, we observe that PF7, which consist of the seventh decile of stocks with the highest ESG score, is producing the lowest alpha of -2.48%. The results show that ESG-rated portfolios have neither systematically higher nor systematically lower excess returns or risk. Additionally, we observe that a long-short strategy in PF10-PF1 would generate an alpha of -2.78%, which is of economic relevance but not statistically significant.

In FF3, the alpha is decreasing from -1.13% in PF1 to -1.42% in PF2 before increasing to 1.18% in PF6. When we introduce the momentum factor (Winner minus loser or WML) in the C4 model we see slightly higher positive and negative alphas but the same overall tendency. The C4 model show a negative alpha for PF1 of -1.28%. The alpha is increasing to 2.19% in PF5 before decreasing to -4.02% in PF7 and then increasing to -1.61% in PF10. The general indication that is formed, is that there are return and risk differences between the portfolios, but that the differences are mainly driven by portfolio specific criteria rather than a homogenous ESG factor. Additionally, we see that some alpha value changes significantly across different factor models. For instance, for PF1, alpha is negative in C4 and FF3, but positive in FF5.

[18] Additionally, we have conducted the same cross-sectional analysis on the underlying E, S, and G scores for the European region. Similar to the aggregated ESG score, the results from the FF5 model do not yield any significant alphas, for any of the isolated pillars, across the decile portfolios or in the long-short portfolio (PF10-PF1). The results from the FF5 mode, for all pillars, can be found in Appendix (28)

Table 7: Empirical results for the European region using aggregated ESG scores (Alpha)

Table 7 presents the results from the FF3, C4 and FF5 for all decile portfolios, including a long-short portfolio (PF10-PF1) in the European region and their ability to earn alpha, when controlling for risk factors. In this strategy the stocks have been sorted into decile portfolios based on their ESG scores. The 10% stocks with the lowest (highest) ESG scores are found in PF1 (PF10). All alphas are annualized, and the square brackets present the t-statistics. Significant codes: 0.001 (***), 0.01 (**), 0.05 (*). The sample period is between January 2007 and December 2020.

Panel A: EUROPE											
Portfolios	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-PF1
FF3 - alpha	-1.13%	-1.42%	-1.06%	0.07%	0.74%	1.18%	-4.06%*	0.35%	0.08%	-2.05%	-1.30%
	[-0.48]	[-0.78]	[-0.65]	[0.04]	[0.41]	[0.78]	[-2.03]	[0.24]	[0.05]	[-1.41]	[0.00]
C4 - alpha	-1.28%	-0.82%	-1.04%	1.30%	2.19%	1.55%	-4.02%	0.53%	0.20%	-1.61%	-0.63%
	[-0.53]	[-0.44]	[-0.62]	[0.69]	[1.24]	[1.01]	[-1.96]	[0.36]	[0.13]	[-1.09]	[0.00]
FF5 – alpha	1.18%	-1.44%	-0.67%	-0.26%	1.26%	1.35%	-2.48%	-0.07%	-0.34%	-1.18%	-2.78%
	[0.49]	[-0.75]	[-0.39]	[-0.13]	[0.67]	[0.85]	[-1.21]	[-0.05]	[-0.22]	[-0.79]	[0.00]

Table 8 presents the coefficients for all decile portfolios in the European region from the FF5. We observe that the regression yields statistically significant market coefficients, otherwise specified as the traditional beta of the portfolio, with coefficients that are significant at the 0.1% level. This indicates that the returns of our portfolios are heavily correlated with the market excess return and that market excess return explains a lot of the variation in the portfolio excess return. Furthermore, the majority of these coefficients are close to one, which indicates that our portfolios are almost as sensitive, or volatile, as the market. The market coefficient is increasing from 0.99 in PF1 to 1.16 in PF10, indicating that the highest rated ESG-portfolios are relatively more volatile. For the long-short strategy in PF10-PF1 we find very little systematic risk with a market coefficient of 0.16, indicating that the portfolio has close to no market exposure.

For the SMB coefficient we observe that PF1 to PF4 have positive SMB coefficients ranging from 0.18 to 0.41, where PF2, PF3 and PF4 are statistically significant at a 5% level, indicating that the average excess returns of the portfolios are positively exposed to the SMB factor. This positive exposure suggest that companies included in the four portfolios are tilted towards stocks with smaller market caps. For PF5 to PF10, the SMB coefficients are negative and statistically significant for PF8, PF9 and PF10 at a 1% (PF8 and PF10 at the 0.01% level) level. The coefficients range from -0.01 to -0.39, indicating that the companies in these portfolios are tilted towards stocks with larger market caps.

Table 8: Empirical results for the European region using aggregated ESG scores (Factors)

Table 8 presents the results from the coefficients for the FF5 for all decile portfolios in the European region. In this strategy the stocks have been sorted into decile portfolios based on their ESG scores. The 10% stocks with the lowest (highest) ESG scores are found in PF1 (PF10). The square brackets present the t-statistics. Significant codes: 0.001 (***), 0.01 (**), 0.05 (*). The sample period is between January 2007 and December 2020.

Panel B: EUROPE											
Portfolios	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-PF1
FF5 - coefficients											
MKT	0.99***	1.09***	1.07***	1.10***	1.09***	1.07***	1.03***	0.98***	1.07***	1.16***	0.16**
	[21.78]	[29.85]	[32.93]	[29.92]	[30.67]	[36.01]	[26.51]	[34.33]	[37.03]	[41.15]	[0.05]
SMB	0.20	0.36***	0.41***	0.18*	-0.09	-0.01	-0.02	-0.27***	-0.19**	-0.39***	-0.60***
	[1.95]	[4.33]	[5.48]	[2.19]	[-1.15]	[-0.10]	[-0.27]	[-4.06]	[-2.92]	[-6.00]	[0.11]
HML	-0.03	0.02	0.03	0.13	0.16	-0.11	0.04	0.16	0.27**	0.12	0.18
	[-0.18]	[0.14]	[0.26]	[1.13]	[1.42]	[-1.18]	[0.32]	[1.84]	[3.02]	[1.42]	[0.16]
RMW	-0.45*	0.03	-0.03	0.27	0.01	-0.14	-0.29	0.09	0.05	-0.32**	0.16
	[-2.33]	[0.19]	[-0.21]	[1.74]	[0.10]	[-1.14]	[-1.75]	[0.75]	[0.42]	[-2.63]	[0.22]
CMA	-0.49**	-0.05	-0.19	-0.38**	-0.36**	0.21	-0.37*	0.07	0.15	0.14	0.57**
	[-2.78]	[-0.34]	[-1.48]	[-2.66]	[-2.62]	[1.78]	[-2.46]	[0.62]	[1.35]	[1.24]	[0.20]
Adj. R^2	0.86	0.91	0.93	0.91	0.92	0.93	0.90	0.93	0.95	0.96	0.31

Table 8 show that 9 out of 10 HLM coefficients are statistically insignificant, indicating that the hypothesis stating that HML is different from zero cannot be rejected. HML are generally negative for PF1 to PF4, ranging from -0.27 to 0.02, indicating that companies in these portfolios are tilted towards growth-stocks. Conversely, for PF8 to PF10 we find positive HLM coefficients, where the HML coefficients of PF9 is statistically significant at the 1%, suggesting that there is a tilt towards value-stocks in this portfolio.

Additionally, the RMW coefficients show no clear tendency. We observe that 8 out of 10 RMW coefficients are statistically insignificant. Only PF1 and PF10 is statistically significant at respectively the 5% and 1% level, both showing negative coefficients of respectively -0.45 and -0.32. From Table 8 we also observe that 4 out of 10 CMA coefficients are negative and statistically significant at the 5% level (PF1, PF4 and PF5 is on the 1% level), suggesting a negative exposure to this factor. The overall influence of the risk factors in the European region is not very consistent. Some ESG portfolios had statistically significant and positive exposure to a given factor, while others had a significant but negative exposure to the same factor – and some had insignificant or no noteworthy exposure to that same factor.

6.2.2 *Results from Asia*

After having analyzed the relation between ESG and risk-adjusted excess returns for our decile portfolios in the European region, we now move on to the results from Asia. In table 9, we rapport the results from our analysis of the excess return for the ten VW portfolios[19]. We observe that the monthly excess returns for the FF5 model follow a downward sloping tendency, with values decreasing from 5.97% in PF1 to 0.14% in PF10. Furthermore, we observe that PF2 is producing the highest alpha of 10.15%, significant at the 5% level. A long-short strategy, as shown in PF10-PF1, would generate an alpha of -5.76%, which is of economic relevance and statistically significant at the 5% level. The significant effect of ESG on excess returns in the long-short portfolio indicates that a strong ESG proposition have a negative effect on risk-adjusted excess returns.

In the FF3, the alpha is increasing from 4.99% in PF1 to 9.22% in PF2 before decreasing to 2.97% in PF10. The alphas of these two portfolios are statistically significant at a 5%-level across all three factor models. This indicate that, based upon the risk exposure to the various systematic factors, the portfolios performed excessively well.

When we introduce the momentum factor in the C4, we see slightly lower coefficients and a larger decline from PF1 (5.59%) to PF10 (-0.07%). The indication that is formed, is that there exists stronger return and risk difference between the portfolios, compared to the portfolios in the European region. However, we solely base this statement on the long-short portfolio which is statistically significant at the 5% level. We present the coefficients for all decile portfolios in the Asian Region from the FF5 regression in Table 10.

[19] Additionally, we have conducted the same cross-sectional analysis on the underlying E, S, and G scores for the Asian region. For E, S and G, we only observe few significant alphas in the FF5 model. E provides a significant alpha at a 5% level at PF1 with an annualized 9.6% return ((0.008*12)*100), PF10 with 9.6% return and P10-PF1 with -7.2% return. S provides a significant return at 1% level at PF5 with 8.4%, PF3 with 7.2% return and PF10 with 8.4%. G do not provide any significant alphas at any acceptable significance level. The results for the FF5 model can be found in Appendix (29).

Table 9: Empirical results for the Asian region using aggregated ESG scores (Alpha)

Table 9 presents the results from the FF3, C4 and FF5 for all decile portfolios, including a long-short portfolio (PF10-PF1) in the Asian region and their ability to earn alpha, when controlling for risk factors. In this strategy the stocks have been sorted into decile portfolios based on their ESG scores. The 10% stocks with the lowest (highest) ESG scores are found in PF1 (PF10). All alphas are annualized, and the square brackets present the t-statistics. Significant codes: 0.001 (***), 0.01 (**), 0.05 (*). The sample period is between January 2007 and December 2020.

Panel A: ASIA											
Portfolios	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-PF1
FF3 - alpha	4.99%*	9.22%*	2.86%	2.10%	3.29%	3.00%	0.91%	-1.30%	1.06%	2.97%	-5.65%*
	[2.01]	[2.37]	[0.83]	[0.51]	[0.75]	[0.80]	[0.34]	[-0.47]	[0.42]	[0.00]	[0.00]
C4 - alpha	5.59%*	9.21%*	2.83%	2.04%	3.37%	2.93%	0.90%	-1.34%	1.03%	-0.07%	-5.77%*
	[2.03]	[2.36]	[0.82]	[0.50]	[0.74]	[0.78]	[0.33]	[-0.48]	[0.41]	[-0.03]	[0.00]
FF5 – alpha	5.97%*	10.15%*	3.54%	3.24%	4.59%	3.65%	1.81%	-1.07%	1.16%	0.14%	-5.76%*
	[2.14]	[2.60]	[1.02]	[0.81]	[1.07]	[0.99]	[0.67]	[-0.39]	[0.45]	[0.14]	[0.00]

Similar to Europe, we observe that the market factor increased relatively monotonous from 0.72 in PF1 to 0.93 in PF10 and proved highly significant at the 1% level across the entire portfolio universe. Again, this indicates that the portfolios with the lowest ESG score are less volatile compared to the portfolios with the highest ESG score, which suggests a volatility that mirrors that of the benchmark.

The SMB coefficients are negative across all portfolios and is decreasing from -0.11 in PF1 to -0.42 in PF6 and is then increasing slightly to -0.37 in PF10. This indicates that the average excess return of the portfolios is positively exposed to the SMB factor. This was also the case for the top decile portfolios in the European region. We notice that the SMB coefficients for PF1, PF4 and PF7 are not statistically significant, while the coefficients for PF2, PF3, PF5, PF6, PF8, PF9 and PF10 are statistically significant at the 5%, 1% and 0.1% level.

Table 10: Empirical results for the Asian region using aggregated ESG scores (Factors)
Table 10 presents the results from the coefficients for the FF5 for all decile portfolios in the Asian region. In this strategy the stocks have been sorted into decile portfolios based on their ESG scores. The 10% stocks with the lowest (highest) ESG scores are found in PF1 (PF10). The square brackets present the t-statistics. Significant codes: 0.001 (***), 0.01 (**), 0.05 (*). The sample period is between January 2007 and December 2020.

Panel B: ASIA											
Portfolios	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-PF1
FF5 - coefficients											
MKT	0.72***	0.75***	0.76***	0.78***	0.76***	0.85***	0.82***	0.83***	0.81***	0.93***	0.20***
	[12.50]	[9.24]	[10.72]	[9.54]	[8.62]	[11.18]	[14.74]	[14.69]	[15.31]	]19.07]	[0.05]
SMB	-0.11	-0.32*	-0.32*	-0.17	-0.33*	-0.42**	-0.19	-0.27*	-0.31**	-0.37***	-0.25*
	[-1.07]	[-2.18]	[-2.43]	[-1.13]	[-2.02]	[-3.01]	[-1.81]	[-2.64]	[-3.21]	[-4.13]	[0.09]
HML	-0.16	-0.16	-0.08	-0.05	0.07	-0.03	-0.01	0.08	-0.02	0.10	0.26*
	[-1.40]	[-0.98]	[-0.54]	[-0.33]	[0.38]	[-0.20]	[-0.11]	[0.70]	[-0.21]	[1.05]	[0.10]
RMW	-0.10	-0.24	-0.10	-0.11	-0.18	0.01	-0.22	0.09	0.04	0.06	0.16
	[-0.52]	[-0.92]	[-0.43]	[-0.43]	[-0.61]	[0.04]	[-1.19]	[0.47]	[0.23]	[0.40]	[0.17]
CMA	-0.23	-0.44*	-0.44*	-0.83***	-0.87***	-0.60**	-0.45**	-0.36*	-0.16	-0.40**	-0.16
	[-1.54]	[-2.11]	[-2.40]	[-3.92]	[-3.82]	[-3.06]	[-3.11]	[-2.46]	[-1.15]	[-3.19]	[0.13]
Adj. R^2	0.56	0.44	0.51	0.49	0.44	0.55	0.64	0.64	0.64	0.75	0.15

All HML and RMW coefficients are insignificant at any acceptable level. The HLM coefficient increases from -0.16 in PF1 to 0.07 in PF5 and then decreases to -0.03 in PF6 before increasing again to 0.10 in PF10. The CMA coefficient is decreasing from -0.23 in PF1 to -0.87 in PF5 before increasing to -0.40 in PF10. The CMA coefficient is only insignificant for PF1 and PF9, while the rest of the portfolios show significant coefficients at the 5%, 1% and 0.1% significance level. For the long-short portfolio, we observe that only the MKT, SMB and HML factors are significant at the 5% level. This indicates a quadradic relationship where the portfolios in the middle decile, to a larger extend, consist of companies with aggressive investments, compared to the low and high deciles that consist of companies with more conservative investments.

As a final note, we can conclude that we do not find statistical evidence for a negative or positive relationship between ESG and risk-adjusted excess returns for the individual decile portfolios. However, we observe that a long-short strategy for the Asian region would yield a negative and statistically significant excess return at the 5% level. We now turn our focus towards the last of the three regions, namely Oceania.

6.2.3 *Results from Oceania*

After having analyzed the relation between ESG and risk-adjusted excess returns for our decile portfolios in the European and Asian region, we now move on to the results from Oceania. In Table 11, we rapport the results from our analysis of the excess returns for the ten VW portfolios[20]. We observe that the monthly excess returns for the FF5 follows an overall downward trend with values decreasing from 1.73% in PF1 to -0.06% in PF10. However, we observe that PF3 is producing the highest, although insignificant, alpha of 7.18%. The alpha for PF3 in the FF3 model is statistically significant at the 5% level. A long-short strategy, as shown in PF10-PF1, would generate an alpha of -1.90%, which similarly to the European region is of economic relevance but statistically insignificant. We do not observe statistical evidence for either a positive or a negative relation between ESG and risk-adjusted excess returns for the Oceanian region.

Table 11: Empirical results for the Oceanian region using aggregated ESG scores (Alpha)
Table 11 presents the results from the FF3, C4 and FF5 for all decile portfolios, including a long-short portfolio (PF10-PF1) in the Oceanian region and their ability to earn alpha, when controlling for risk factors. In this strategy the stocks have been sorted into decile portfolios based on their ESG scores. The 10% stocks with the lowest (highest) ESG scores are found in PF1 (PF10). All alphas are annualized, and the square brackets present the t-statistics. Significant codes: 0.001 (***), 0.01 (**), 0.05 (*). The sample period is between January 2007 and December 2020.

Panel A: OCEANIA											
Portfolios	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-PF1
FF3 - alpha	5.47%	7.65%	8.73%*	4.99%	-1.80%	1.39%	0.74%	-0.33%	-5.17%	1.83%	-3.76%
	[1.31]	[1.46]	[2.00]	[1.16]	[-0.43]	[0.38]	[0.18]	[-0.09]	[-1.59]	[0.84]	[0.00]
C4 - alpha	4.98%	7.73%	8.46%	4.80%	-3.21%	1.26%	-0.36%	-0.69%	-5.97%	1.16%	-3.94%
	[1.18]	[1.46]	[1.92]	[1.11]	[-0.78]	[0.34]	[-0.09]	[-0.19]	[-1.83]	[0.53]	[0.00]
FF5 – alpha	1.73%	5.58%	7.18%	-0.12%	-7.14%	-0.63%	-3.79%	0.54%	-10.7%**	-0.06%	-1.90%
	[0.41]	[1.01]	[1.60]	[-0.03]	[-1.70]	[-0.17]	[-0.94]	[0.15]	[-3.26]	[-0.03]	[0.00]

[20] Additionally, we have conducted the same cross-sectional analysis on the underlying E, S, and G scores for the Oceanian region. For E, S and G similar, overall negative, results are found in FF5 model. E provides a significant alpha at a 5% level at PF3 with an annualized -8.4% return ((-0.007*12)*100) and PF8 with -6% return. S provides a significant return at 5% level at PF7 with -6%, PF9 with -1.2% return. G provides a significant return at a 5% level at PF1 with 7.2%, at a 0.1% level at PF9 with -1.2% and at a 1% level at PF10-PF1 with -12%. The results for the FF5 model can be found in Appendix (30).

In the FF3, the alpha is following the same trend as in the Asian region. The alpha is increasing from 5.47% in PF1 to 7.65% in PF2 and then to 8.73% in PF3 before decreasing to 1.83% in PF10. When we introduce the momentum factor in the C4 model, we see slightly lower coefficients and a larger decline from PF1 (4.98%) to PF10 (-1.16%). The lowest alpha values are observed in PF5 and PF9 with values of -3.21% and -5.97%, indicating that an investment in ESG portfolios with low ESG scores would be optimal in terms of achieving the highest possible alpha. However, like the Asian region, the indication that is formed is that there exists stronger return and risk difference between the portfolios, compared to the portfolios in the European region. However, the regression does not yield statistical evidence to support the general indication of a negative relation between ESG and excess risk-adjusted returns. We present the coefficients for all decile portfolios in the Oceanian Region from the FF5 regression in Table 12.

We observe a similar trend to that of Asia for the SMB, RMW, and CMA factor. However, the market factor is decreasing relatively monotonous and are statistically significant for all decile portfolios at the 0.1% level. MKT is close to one and is decreasing from 1.20 in PF1 to 1.08 in PF10. This indicates that the lowest rated ESG portfolio is approximately 20% more volatile than PF10. The SMB coefficients are only negative in PF9 and PF10 with values of -0.05 and -0.18, respectively.

Table 12: Empirical results for the Oceanian region using aggregated ESG scores (Factors)

Table 12 presents the results from the coefficients for the FF5 for all decile portfolios in the Oceanian region. In this strategy the stocks have been sorted into decile portfolios based on their ESG scores. The 10% stocks with the lowest (highest) ESG scores are found in PF1 (PF10). The square brackets present the t-statistics. Significant codes: 0.001 (***), 0.01 (**), 0.05 (*). The sample period is between January 2007 and December 2020.

Panel B: OCEANIA											
Portfolios	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-PF1
FF5 - coefficients											
MKT	1.20***	1.13***	1.17***	1.21***	1.22***	1.04***	1.07***	1.12***	1.11***	1.08***	-0.12*
	[21.56]	[15.35]	[19.59]	[20.36]	[21.77]	[21.06]	[19.83]	[22.57]	[25.44]	[36.05]	[0.06]
SMB	0.60***	0.37*	0.32*	0.40**	0.43**	0.20	0.16	0.08	-0.05	-0.18*	-0.77***
	[4.43]	[2.09]	[2.23]	[2.79]	[3.21]	[1.66]	[1.23]	[0.63]	[-0.44]	[-2.44]	[0.14]
HML	-0.37*	-0.19	-0.69***	-0.30	0.00	-0.45**	-0.04	-0.12	-0.21	-0.24*	0.13
	[-2.16]	[-0.83]	[-3.78]	[-1.68]	[0.01]	[-2.99]	[-0.25]	[-0.81]	[-1.57]	[-2.59]	[0.18]
RMW	-0.09	-0.09	-0.19	0.19*	0.08	-0.14	-0.11	-0.29***	0.21**	-0.01	0.07
	[-0.97]	[-0.76]	[-1.91]	[1.98]	[0.87]	[-1.71]	[-1.28]	[-3.63]	[2.96]	[-0.29]	[0.09]
CMA	0.89***	0.58*	0.67**	0.60**	0.87***	0.66***	1.09***	0.41*	0.64***	0.39***	-0.50*
	[4.60]	[2.26]	[3.20]	[2.93]	[4.46]	[3.83]	[5.82]	[2.40]	[4.22]	[3.74]	[0.20]
Adj. R^2	0.79	0.63	0.76	0.75	0.77	0.78	0.74	0.79	0.82	0.90	0.20

The SMB coefficients are decreasing from 0.60 in PF1 to -0.18 in PF10. This indicates that the lowest rated ESG portfolios are tilted toward small cap stocks, while the higher rated ESG portfolios are tilted towards large cap. We notice that the SMB coefficients for PF6, PF7, PF8, and PF9 are not statistically significant, while the coefficients for PF1, PF2, PF3, PF4, PF5 and PF10 are statistically significant at the 0.1%, 1% and 5% level.

The HLM coefficient increases from -0.37 in PF1 to 0.00 in PF5 and then decreases to -0.24 in PF10. The HML coefficient in PF1, PF3, PF6 and PF10 are all statistically significant at the 0.1%, 1% and 5% level. The FF5 model show significant CMA coefficients for all portfolios at the 0.01%, 1% and 5% level. In contrast to the results from Europe and Asia the CMA is positively related to portfolio returns of low investment stocks with coefficient values decreasing from 0.89 in PF1 to 0.60 in PF4 before increasing to 1.09 in PF7 and then decreasing again to 0.39 in PF10. For the long-short portfolio, we observe that only the MKT, SMB and CMA factors are significant at the 0.1%, 1% and 5% level.

As a final note, we can conclude that we do not find statistical evidence for a negative or positive relationship between ESG and risk-adjusted excess returns. We acknowledge that a long-short strategy for the Oceanian region would yield a negative but statistically insignificant abnormal return of -1.90%.

6.2.4 *Summary of findings (Europe)*

Our analysis was designed to tests if there exist a Green-to-Brown premium between January 2007 to December 2020. We mobilized this empirical interest by creating a long-short portfolio (PF10-PF1) with a long position in the highest ESG rated portfolios and a short position in the lowest ESG rated portfolios. We focused on Jensen's alpha measure for which we created a set of null- and alternative hypotheses. In all our regressions, we tested the following hypotheses:

$$H_0\colon \alpha_{\text{long minus short}} = 0$$

$$H_1\colon \alpha_{\text{long minus short}} \neq 0$$

For the European region, we analyzed ten decile portfolios and a long-short portfolio. The portfolios consist of the largest stocks in Europe, defined by an operating revenue of USD 500 million. First, we calculated financial measures (Average excess return, Sharpe Ratio, and the cumulative return for the whole period) to get an overview of any apparent visible differences between Green and brown portfolios. We observed that large numerical differences existed with brown portfolios turning out to be the winners over a 14-year period, producing more attractive returns, showed by a greater Sharpe Ratio value. However, it did not uncover whether what we observed was statistically significant or if the results were merely coincidental. To better understand how well our data predicts the variability of excess returns across the decile portfolios and whether any significant excess returns are present, we control for well-known measures of risk by running three different factor model regressions – FF3, C4 and FF5. In conclusion, we find non-significant alpha coefficients for the decile portfolios and the long-short portfolio. As such, we fail to reject our null hypothesis of no difference in financial performance for all individual portfolios (PF1 to PF10). Specifically, we fail to find statistically significant evidence of overperformance or underperformance for our ten-value weighted decile portfolios. Our findings are in line with a large part of the existing body of literature suggesting no statistically significant green alpha. Constituents of this body of literature include but is not limited to Blankenberg & Gottschalk (2018). We observe that the MKT loading is significant throughout all decile portfolios and in our long-short portfolio, thereby indicating that the associated returns are heavily explained by the market volatility. This relation is supported by the correlation between the MKT and the long-short portfolios show in (Appendix 15). Furthermore, for the decile portfolio, the majority of the MKT coefficients are all close to one, which suggests that the volatility of our decile portfolios mirror that of the market. We do observe a significantly low MKT loading for the long-short portfolio, indicating that the portfolio has close to zero systematic risk.

6.2.5 *Summary of findings (Asia)*

In a fashion identical to that of subsection 6.2.4, this subsection highlights the key takeaways from our analysis, but for the Asian region. Following the performance evaluation in section 6.1, which showed the largest numerical differences in the cumulative returns and volatility (and hence large differences in the Sharpe Ratios), we improved our robustness by controlling for well-known measures of risk from three different factor models – FF3, C4 and FF5.

We find statistically significant alpha values for the long-short strategy at the 5% level across all factor models, and we thus reject the null hypothesis and conclude that a long-short portfolio underperformed based on the risk exposure to various factors with an abnormal return of -5.65%.

This underperformance is in contrasts with our findings from Europe and the large body of literature suggesting equal performance or no-significant performance differences. However, our findings are in line with that of Lee & Faff (2009). Their global study of how stock markets view corporate sustainability found that lagging (Brown) sustainability companies outperform the leading (Green) portfolio. However, their study considered data from 1998 to 2002, which makes it difficult to compare their results with ours. It is worth noting that our findings, which show statistically significant alphas for the long-short strategy, do not hold when we examine the individual decile portfolios (PF1 to PF10). Here, we observe that the ESG-rated portfolios do not show systematically statistically significant abnormal returns. In fact, only PF1 and PF2 in the FF5 model show statistically significant alphas at the 5% significance level. As we expected, the MKT loadings are statistically significant at the 0.1% level throughout our FF5 model, thereby indicating that the variation of the stock return in our decile portfolios are heavily explained by the market volatility. Again, our MKT coefficients are close to one, meaning that our decile portfolios closely mirror the market volatility. We hypothesize that this is likely a product of the well-diversified nature of the decile portfolios.

6.2.6 *Summary of findings (Oceania)*

In a fashion identical to that of subsection 6.2.4 and 6.2.5, this subsection highlights the key takeaways from our analysis, but for the Oceanian region. Our results from Oceania are very similar to those of Europe. We find non-significant alpha coefficients for the long-short portfolio across all factor models. As such, we fail to reject our null hypothesis of no difference in financial performance for all portfolios. Specifically, we fail to find statistically significant evidence of overperformance or underperformance of our value weighted ESG portfolios. Our findings are in line with that from Europe and with the existing body of literature suggesting no statistically significant green alpha. We acknowledge that a few "outliers", limited to PF3 and PF7, are showing statistically significant alphas but do not consider these results as a general indication for the region. Again, the MKT loadings are statistically significant at the 0.1% level throughout our FF5 model, thereby indicating that the variation of the stock return in our decile portfolios are heavily explained by the market volatility. Again, our MKT coefficients are somewhat close to one, meaning that our decile portfolios closely mirror the market volatility. Different from Europe and Asia, we now observe that the brown portfolios are more volatile than the green portfolios, with the latter having an MKT factor that is closer to zero.

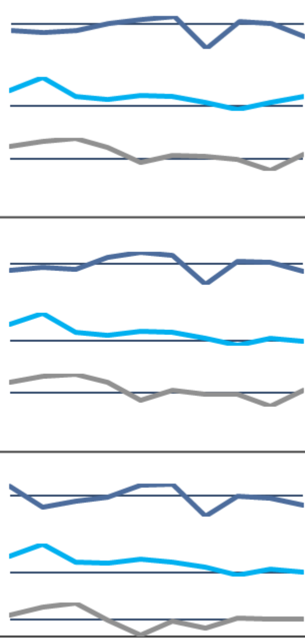
6.2.7 *Summary of findings (Cross-regional)*

In section 6.2.4, 6.2.5, and 6.2.6 we presented the results for our region-specific regressions. While these conclusions are interesting on their own, we now compare the results from all three regions. In line with previous sections, we will present two panels. Panel A presents the trend of the intercept (alpha) for the decile portfolios and the alpha for the long-short portfolio. Panel B presents the different regression coefficients estimated by the FF5 model for all regions. We present the trend of the alphas for all regions in Figure 12.

In Figure 12, we do not observe significant inter-regional differences for the alpha across the factor models. However, we observe that Asia and Oceania are both showing a slightly U formed, but downward sloping, trend with positive or close to zero alphas in each end of the trend lines. In comparison, Europe is showing an inverse relation with positive alphas for the middle portfolios and negative alphas in each end of the trend line. However, of these, no factor model regressions provide any statistically significant evidence that our individual ESG portfolios either outperform or underperform, i.e., they are showing no significant performance impact.

Figure 12: Alpha results for the all regions using the aggregated ESG score

Figure 12 presents the alpha coefficient trend from the FF3, C4 and FF5 for all decile portfolios, including a long-short portfolio (PF10-PF1) and their ability to earn alpha, when controlling for risk factors.



		Alpha trend for PF1 to PF10	PF10-PF1
	Europe		-1.30%
FF3	Asia		-5.65%*
	Oceania		-3.76%
	Europe		-0.63%
C4	Asia		-5.77%*
	Oceania		-3.94%
	Europe		-2.78%
FF5	Asia		-5.76%*
	Oceania		-1.90%

As we have presented in Table 7, 9 and 11, almost all our alpha coefficients for the long-short portfolios are negative, but their statistical insignificance disallows rejection of our null hypotheses, except for the Asian region. Here, we reject the null hypothesis on a 5% significance level and conclude that a long-short strategy underperformed under the previously described circumstances.

From Table 13, we observe that all MKT coefficients lie in the range between 0.72 and 1.22, indicating that all individual portfolios (PF1 to PF10), across all regions, follow the market volatility closely. Secondly, we observe that the R-squared values are increasing from PF1 to PF10. We hypothesize that this finding is likely a product of the well-diversified nature of the top 5 decile portfolios, which implies that a majority of the idiosyncratic risk has been diversified away, leaving only the systematic risk behind.

Table 13: Factor coefficients for the FF5 regression for all decile portfolios across all regions

Table 13 presents the results from the coefficients for the FF5 for all decile portfolios across all the regions. In this strategy the stocks have been sorted into decile portfolios based on their ESG scores. The 10% stocks with the lowest (highest) ESG scores are found in PF1 (PF10). The square brackets present the t-statistics. Significant codes: 0.001 (***), 0.01 (**), 0.05 (*). The sample period is between January 2007 and December 2020.

Portfolios		PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-PF1
	Europe	0.99***	1.09***	1.07***	1.10***	1.09***	1.07***	1.03***	0.98***	1.07***	1.16***	0.16**
MKT	Asia	0.72***	0.75***	0.76***	0.78***	0.76***	0.85***	0.82***	0.83***	0.81***	0.93***	0.20***
	Oceania	1.20***	1.13***	1.17***	1.21***	1.22***	1.04***	1.07***	1.12***	1.11***	1.08***	-0.12*
	Europe	0.20	0.36***	0.41***	0.18*	-0.09	-0.01	-0.02	-0.27***	-0.19**	-0.39***	-0.60***
SMB	Asia	-0.11	-0.32*	-0.32*	-0.17	-0.33*	-0.42**	-0.19	-0.27*	-0.31**	-0.37***	-0.25*
	Oceania	0.60***	0.37*	0.32*	0.40**	0.43**	0.20	0.16	0.08	-0.05	-0.18*	-0.77***
	Europe	-0.03	0.02	0.03	0.13	0.16	-0.11	0.04	0.16	0.27**	0.12	0.18
HML	Asia	-0.16	-0.16	-0.08	-0.05	0.07	-0.03	-0.01	0.08	-0.02	0.10	0.26*
	Oceania	-0.37*	-0.19	-0.69***	-0.30	0.00	-0.45**	-0.04	-0.12	-0.21	-0.24*	0.13
	Europe	-0.45*	0.03	-0.03	0.27	0.01	-0.14	-0.29	0.09	0.05	-0.32**	0.16
RMW	Asia	-0.10	-0.24	-0.10	-0.11	-0.18	0.01	-0.22	0.09	0.04	0.06	0.16
	Oceania	-0.09	-0.09	-0.19	0.19*	0.08	-0.14	-0.11	-0.29***	0.21**	-0.01	0.07
	Europe	-0.49**	-0.05	-0.19	-0.38**	-0.36**	0.21	-0.37*	0.07	0.15	0.14	0.57**
CMA	Asia	-0.23	-0.44*	-0.44*	-0.83***	-0.87***	-0.60**	-0.45**	-0.36*	-0.16	-0.40**	-0.16
	Oceania	0.89***	0.58*	0.67**	0.60**	0.87***	0.66***	1.09***	0.41*	0.64***	0.39***	-0.50*
	Europe	0.86	0.91	0.93	0.91	0.92	0.93	0.90	0.93	0.95	0.96	0.31
Adj. R^2	Asia	0.56	0.44	0.51	0.49	0.44	0.55	0.64	0.64	0.64	0.75	0.15
	Oceania	0.79	0.63	0.76	0.75	0.77	0.78	0.74	0.79	0.82	0.90	0.20

For the long-short portfolio we see a different pattern with MKT coefficients in the range between -0.12 to 0.20. This indicates that the value of the long-short portfolio in Europe and Asia remains unchanged when the market moves. For Oceania, the MKT coefficient is negative, indicating an inverse relation to the market, i.e., when the market moves up the portfolio moves down. This relationship is highly unlikely and the coefficient with the smallest statistical significance level at 0.05. For all regions, the SMB coefficient indicates that the decile portfolios are primarily large cap. Intuitively, this makes sense due to our centralized focus on the largest companies in Europe, Asia, and Oceania. For the CMA coefficient we find different trends for each region. For Europe we observe that the lowest rated ESG portfolios show negative CMA coefficients, indicating that a majority of the stocks within these portfolios are aggressive stocks. Conversely the highest rated ESG portfolios show positive CMA coefficients, indicating that a majority of the stocks within these portfolios are conservative stocks. For Asia, we observe that the CMA coefficient is negative for all portfolios, again indicating that these are comprised of aggressive stocks. Finally, Oceania show only positive CMA coefficients, indicating that these are comprised of conservative stocks.

Table 14 below show the Adj. R^2 for the ten decile portfolios and the long-short portfolio across the three regions. From the table, we observe that the FF5 model, in the European region, explain between 86% and 96% of the variation of the ten portfolio's excess returns. For the long-short portfolio, the explained variation of the portfolios excess return is 20%, showing a significantly lower degree of explanatory power compared to the decile portfolio in the European region. In Asia, the FF5 model explain between 44% and 75% of the variation in the excess portfolio return, while this range lies between 63% and 90% in Oceania. From these observations, we can conclude that the average excess return for the decile portfolios is best explained by the market factors for the European region. This relation holds for the long-short portfolio where we observe that the Adj. R^2 for the European region (31%) is higher than for the Asian (15%) and the Oceanian region (20%). We hypothesize that the difference in explanatory power is partly due to the fact that we have collected regional factor data that varies across Europe, Asia and Oceania. Secondly, we hypothesize that the significantly lower Adj. R^2 for the Asian region is caused by the regional factor data that only covers Japanese companies. In comparison, our data for the Asian region covers companies from 18 different countries.

Table 14: Adj. R^2 from the FF5 regression for all regions

FF5 Adj. R^2	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-PF1
Europe	0.86	0.91	0.93	0.91	0.92	0.93	0.90	0.93	0.95	0.96	0.31
Asia	0.56	0.44	0.51	0.49	0.44	0.55	0.64	0.64	0.64	0.75	0.15
Oceania	0.79	0.63	0.76	0.75	0.77	0.78	0.74	0.79	0.82	0.90	0.20

6.3 ESG AS AN INDICATOR OF SHARE PRICE RESILIENCE

ESG performance has been widely hyped as a positive explanatory power and indicator of share price resilience during the first quarter of 2020 – a period where the financial markets were struck by a partly exogenous shock due to the COVID-19 pandemic[21]. To investigate this claim, we run a series of regressions, designed to uncover the relationship between ESG and excess returns. The primary objective is to analyse sub-question two and the following hypotheses for each region:

Hypothesis I: ESG score

$$H_1: X_{ESG} = 0$$

$$H_a: X_{ESG} \neq 0$$

Where X_{ESG} is the coefficient for the independent variable, ESG, for the January-March 2020 COVID-19 crisis period buy-and-hold excess returns. Additionally, and to fully answer sub-question two, this thesis also aims to uncover the individual influence of the three pillars that constitute the overall ESG score. Performing such an analyzes, will allow us to uncover whether any of the isolated elements of ESG are more material to investors and thus stock market returns during Q1 of 2020. We mobilize this analyzes through the following hypotheses:

Hypothesis II: Environmental score

$$H_1: X_E = 0$$

$$H_a: X_E \neq 0$$

Hypothesis III: Social score

$$H_1: X_S = 0$$

$$H_a: X_S \neq 0$$

Hypothesis IV: Governance score

$$H_1: X_G = 0$$

[21] https://www.wbcsd.org/Overview/News-Insights/WBCSD-insights/Increasing-risk-management-resilience-through-ESG-investing

$$H_a: X_G \neq 0$$

Where $X_{E,S,G}$ is the coefficients for the independent variables, E, S and G, for the January-March 2020 COVID-19 crisis period buy-and-hold excess returns. We will comment on the isolated elements of ESG in the analysis for each region. However, all the results from the fully specified model for the E, S and G pillar will be shown in Appendix (24), (25) and (26).

We start out by introducing the dependent variable and all the independent variables. Secondly, we examine the summary statistics for each region - Oceania, Europe, and Asia - with an objective to analyse the region-specific characteristics for the observations in our dataset. Finally, we set out to examine our results with the objective of uncovering whether the overall ESG and/or decomposed individual pillars, E, S and G, are important determinants of outbreak period buy-and-hold excess returns either instead of, or incrementally to, sector affiliation, market-based measures of risk and company financials.

6.3.1 *Description of dependent and independent variables*

We decompose the R-squared value to assess the relative importance of the independent determinants by running a number of variants on the following regression[22]:

$$\begin{aligned} BHARQ1 = {} & y_0 + y_1 ESG + y_2 E + y_3 S + y_4 G + y_5 MKT + y_6 SMB + y_7 HML + \\ & y_8 MOM + y_9 Momentum + y_{10} IdioRisk + y_{11} Size + y_{12} ROA + \\ & y_{13} DE + y_{14} DPR + y_{15} Debt + y_{16} FCF + \sum_{i=1}^{11} \delta_i \, sector + \varepsilon \end{aligned} \tag{13}$$

An overview of each independent variable applied, can be found in Appendix (18). The first group or variables, ESG/E/S/G, consist of either the overall ESG score, isolated E score, isolated S score or isolated G score.

[22] According to Antweiler (2014), the computation of more than twenty parameters of interest will stress the model and create questionable results. Therefore, we restrict ourselves to the chosen regressors

In addition to the ESG scores we also control for market factors. These include the MKT, SMB, HML and MOM. The market factors are estimated by regressing each individual stock return on Carhart's (1997) four factors. We mobilize this calculation by using a 60-month window from January 2015 to December 2019. The calculation requires at least 12 months of stock return data. The regression will provide four coefficients, per stock, which are applied as independent variables in the multiple regression analysis. We also control for every company's idiosyncratic risk and their stock return 12 month prior to January 2020, which we label Momentum. The idiosyncratic risk is calculated using stock and market return from 60-months prior to January 2020. The calculation also requires at least 12 months of available return. A more detailed description of the calculation of the idiosyncratic risk is found in Appendix (22). Moreover, we control for sector affiliation through the independent variable called Sector. We categorize the companies in our dataset in one of the eleven sectors described in Appendix (23).

Finally, the multiple regression analysis includes company-specific financial measures. These include the free cash flow (FCF), total debt (Debt), debt-to-equity ratio (DE), return on assets (ROA) and the dividend-pay-out ratio (DPR). All these independent variables are collected from TRR and is the reported values for the fiscal year of 2019. Furthermore, to account for size, we have taken the logarithmic function of each company's market capitalization. We decided to take the logarithmic function of the company's market capitalization because the variable is highly skewed with extremely high values that might cause problems in our regression analysis. The logarithmic function will make the variable behave more in line with the normality assumption mentioned in section 5.6.

In addition to this, we observe that FCF and Debt values are significantly higher than the rest of the variables. This can be solved using scaling, which is a method used to normalize the range of independent variables. In this paper FCF and Debt have been standardized using the following equation:

$$y = \frac{x \text{ - } mean}{Standard\ deviation}$$

The first specification of the model only includes the aggregated ESG score and sector fixed effects. The second specification adds market-based measures of risk, including the C4 factors, momentum, and idiosyncratic risk. The third specification adds size, while the fourth and full specification regress' excess buy-and-hold returns on all regressors. In addition to the aggregated

ESG score, the individual three pillars E, S and G will also be considered through a similar analysis. The motivation for running a separate analysis for the isolated components of the ESG score is mainly because the individual pillars are highly correlated with the aggregated ESG score. We show the correlation between all variables in Appendix (19), (20) and (21). Furthermore. Frost (2021) argue that a high correlation among independent variables can cause problems when fitting the model and when interpreting the results. To calculate the decomposition of the R-square values, we use the R package "relaimpo" developed by Grömping (2016)[23].

We split the independent variables into 4 groups:

I. ESG/E/S/G
II. Stock risk, return and factor loadings
III. Sector
IV. Company financial

We have now described all the variables in our multiple regression analysis. The next section will show the summary statistics for all the variables before we deep-dive into the results for each region.

6.3.2 *Summary statistics (Oceania)*

The following section will examine the summary statistics for each region. We begin the section with the Oceanian region, followed by the European and Asian region. There are 331 observations in this region. Table 15 shows that the average (median) buy-and-hold excess return (hereafter BHARQ1) for the first quarter of 2020 is equal to -40.42% (-41.22%), with only five observations showing a positive excess return. The BHARQ1 show the tremendous toll of the COVID-19 crisis on returns during this period which created a sharp downturn.

The BHARQ1 range between -85.88% and 20.96% with a standard deviation of 17.93%. The average (median) Refinitiv Eikon ESG score is 42.93 (40.71) ranging from 6.41 to 91.20 with a standard deviation of 19.64 suggesting a great deal of cross-sectional variation in the explanatory variable of particular interest.

[23] The package is located at: https://prof.beuth-hochschule.de/groemping/software/relaimpo/

Table 15: Summary statistics COVID-19 January through March outbreak period for the Oceanian region

Variables	N	Mean	Std. Dev.	Min	Max	p25	p75	Median
BHARQ1	331	-40.42%	17.93%	-85.88%	20.96%	-50.61%	-28.79%	-41.22%
ESG	331	42.93	19.64	6.41	91.20	27.65	56.68	40.71
E	331	27.71	26.05	0.00	96.28	3.28	46.13	21.91
S	331	43.68	21.44	1.10	96.89	27.83	58.85	41.14
G	331	53.32	21.20	2.68	96.48	37.36	71.32	53.96
MKT	331	1.12	0.57	-0.19	3.65	0.75	1.35	1.05
SMB	331	0.42	0.85	-3.05	3.31	-0.10	0.91	0.29
HML	331	-0.01	1.57	-6.92	5.43	-0.77	0.75	-0.08
MOM	331	-0.06	0.71	-3.11	2.75	-0.39	0.26	-0.07
IdioRisk	331	0.10	0.06	0.02	0.46	0.06	0.13	0.09
Momentum	331	0.16	0.45	-0.79	2.09	-0.07	0.31	0.10
Size	331	9.03	0.72	7.18	11.11	8.60	9.50	8.98
FCF	331	36.674.370	513.425.654	-3.169.000.000	7.154.000.000	-29.522.436	31.243.763	3.922.780
Debt	331	2.782.840.985	15.744.220.420	0	163.003.307.012	34.436.108	805.974.607	176.906.283
DE	331	109.70%	704.27%	0.00%	12642.34%	14.73%	72.78%	39.26%
ROA	331	5.45%	11.09%	-60.75%	58.22%	1.42%	9.41%	5.46%
DPR	331	66.68%	112.09%	0.00%	1460.71%	0.00%	86.27%	55.24%
Beta	331	1.027	0.575	-0.148	4.883	0.698	1.206	0.926

Additionally, Table 15 shows the individual pillar score for Environment (E), Social (S) and Governance (G). The governance pillar shows the highest average score with 53.32 while E and S shows respectively 27.71 and 43.68. The full range of the individual pillar scores is between 0 and 96.48 with the Environmental pillar score showing the highest standard deviation. We hypothesize that the low environmental score is due to inter-regional differences and sector weights.

If we look at the company-specific accounting measures, we observe that the average size (median) of the 331 companies is 9.03 (8.98), corresponding to a market capitalization of around USD 4.5 billion with a maximum value of around USD 130 billion and a minimum of USD 15 billion. Additionally, 43.4% of the companies in the Oceanian region had a negative free cash flow in 2019. Furthermore, the companies average (median) ROA for 2019 was 5.45% with a minimum of -60.75% and a maximum of 58.22%, indicating a large portion of cross-sectional variation in the reported ROA.

We observe that the average market factor, also known as beta, (median) is 1.12 (1.05), indicating that an average stock in the data sample will be more volatile than the market. The minimum beta is -0.19 while the maximum beta is 3.65. A negative beta indicates that a stock moves the opposite direction of the market. Four companies in the data sample have a negative beta, while 23 has a beta exceeding two. The three other factors SMB, HML and MOM shows average values (median) of respectively 0.42, -0.01 and -0.06 (0.29, -0.08, -0.07). The idiosyncratic variable shows an average value (median) of 0.10 ranging from 0.02 to 0.46 with a standard deviation of 0.06. The idiosyncratic risk indicates the portion of risk that is left unexplained by beta.

Finally, Momentum shows that the average (median) stock return for the 331 stocks in the Oceanian region is around 16% ranging from -79% to 209% with a standard deviation of 45%. 30% of the stocks full year return in 2019 was negative while 70% of the stocks return was positive.

6.3.3 *Summary statistics (Europe)*

The following section examine the summary statistics for the European region. There are 691 observations is this region. Table 16 show that the average (median) *BHARQ1* is -30.43% (-32.21) with 96% of the observations showing a negative excess return in the first quarter of 2020. Out of the 30 observations with a positive excess return in Q1 2020, 53% of these companies were in the Health Care sector. Five companies in the Consumer Staples sector and three companies in respectively Utilities and Communication Services reported a positive excess return in the first quarter of 2020.

Table 16: Summary statistics COVID-19 January through March outbreak period for the European region

Variables	N	Mean	Std. Dev.	Min	Max	p25	p75	Median
BHARQ1	691	-30.43%	17.07%	-74.95%	56.86%	-41.99%	-19.79%	-32.21%
ESG	691	60.63	18.23	2.99	94.45	49.39	74.48	63.16
E	691	58.64	24.44	0.00	98.87	41.63	78.71	61.54
S	691	67.04	19.74	0.45	97.67	53.63	82.18	70.48
G	691	53.48	23.01	3.55	96.93	35.56	72.54	54.33
MKT	691	1.14	0.45	-0.27	3.64	0.85	1.37	1.11
SMB	691	0.35	0.84	-2.62	3.95	-0.24	0.88	0.34
HML	691	0.11	0.84	-2.08	5.88	-0.46	0.53	0.10
MOM	691	0.03	0.43	-1.86	2.03	-0.23	0.28	0.02
IdioRisk	691	0.07	0.03	0.02	0.36	0.05	0.08	0.07
Momentum	691	18.07%	34.25%	-77.91%	247.92%	-3.42%	34.44%	16.73%
Size	691	9.66	0.63	7.85	11.37	9.20	10.10	9.65
FCF	691	268.270.305	1.304.936.308	-8.129.186.164	20.122.258.923	-4.872.007	348.553.766	74.646.351
Debt	691	8.930.064.102	27.914.154.642	0	282.845.903.294	386.976.443	4.841.484.189	1.391.182.677
DE	691	107.48%	167.54%	0.00%	2025.24%	32.13%	121.33%	63.51%
ROA	691	4.72%	5.55%	-28.16%	36.25%	1.68%	6.91%	3.93%
DPR	691	50.93%	68.79%	0.00%	1157.31%	18.72%	64.73%	40.38%
Beta	691	1.15	0.46	-0.34	3.82	0.84	1.40	1.11

BHARQ1 show values between -74.95% and 56.86%, with a standard deviation of 17.07%. The average (median) ESG score is 60.63 (63.16) ranging from 2.99 to 94.45 indicating a great deal of cross-sectional variation in the variable of particular interest. Furthermore, we observe that the Social pillar score has the highest average (median) of 67.04 (70.48), while the Governance pillar has the lowest average score (median) of 53.48 (54.33). The ESG pillar scores ranges from around 0 to 98.

If we look at the company-specific accounting measures, the average size (median) is 9.66 (9.65) corresponding to a market capitalization of around USD 12.9 billion, with a maximum value of USD 234.7 billion and a minimum value of USD 70 million. In 2019, 27% reported negative free cash flow. Additionally, the companies average (median) ROA reported in 2019 is 4.72% with a minimum and maximum value of respectively -28.16% and 36.25%.

The average beta value (median) for the 691 companies is 1.14 (1.11), with a minimum and maximum value of respectively -0.27 and 3.64. Only two companies have a negative beta value. The three other factors estimated through Carhart's (1997) four factor model SMB, HML and MOM shows average values of respectively 0.35, 0.11 and 0.03 (0.34, 0.10 and 0.02). The average (median) idiosyncratic risk is 0.07 (0.07), ranging from 0.02 to 0.36 and with a standard deviation of 0.03. This indicates low cross-sectional variation relative to the other variables. Finally, the momentum variable shows an average (median) of 18.07% (16.73) ranging from -77.91% to 247.92% and a standard deviation of 35.25%. For the European region, 71% of the companies reported a positive stock return in 2019, while 29% reported a negative stock return.

6.3.4 *Summary statistics (Asia)*

The following section examine the summary statistics for the Asian region. There are 1.350 observations in this region. Table 17 show that the average (median) BHARQ1 for the Asian companies is -21.44% (-21.71%) with a standard deviation of 18.04% and values ranging from -77.97% to 70.78%. Only 131, or 10%, of the companies achieved a positive return. The sector with the most companies achieving a positive return in Q1 of 2020 was Consumer Staples, Information Technology and Health Care with respectively 26%, 23% and 16% of the companies with a positive return in the period. Additionally, it is worth mentioning that none of the companies in the sample data, for the Asian region and classified in the Financial sector, achieved a positive return in Q1 of 2020.

The average (median) ESG score is 47.26 ranging from 1.82 to 91.42 and with a standard deviation of 20.85. This also indicate cross-sectional variation in the variable of particular interest. Moreover, the individual ESG pillar scores show that the Governance pillar score has the highest average (median) of 50.76 (51.40), while the Environmental pillar has the lowest average score of 44.9. The aggregated ESG score scores range from close to 0 to 97.5.

Table 17: Summary statistics COVID-19 January through March outbreak period for the Asian region

Variables	N	Mean	Std. Dev.	Min	Max	p25	p75	Median
BHARQ1	1.350	-21.44%	18.04%	-77.97%	70.78%	-32.75%	-11.92%	-21.71%
ESG	1.350	47.26	20.85	1.82	91.42	31.05	63.61	48.84
E	1.350	44.90	27.16	0.00	97.51	21.24	67.12	47.74
S	1.350	45.19	25.36	0.47	97.12	23.35	66.26	46.00
G	1.350	50.76	22.30	0.48	97.32	32.66	69.33	51.40
MKT	1.350	1.05	0.52	-2.52	3.55	0.70	1.37	1.02
SMB	1.350	0.23	0.83	-3.69	5.16	-0.26	0.68	0.20
HML	1.350	0.13	0.63	-2.48	3.91	-0.26	0.51	0.12
MOM	1.350	0.04	0.58	-2.40	5.07	-0.30	0.37	0.04
IdioRisk	1.350	0.09	0.04	0.03	0.61	0.06	0.10	0.08
Momentum	1.350	0.17	0.39	-0.94	3.82	-0.06	0.30	0.09
Size	1.350	9.78	0.48	7.72	11.51	9.47	10.06	9.74
FCF	1.350	291.742.398	1.785.710.303	-8.803.094.551	26.997.463.397	-36.841.124	347.994.290	102.974.284
Debt	1.350	9.638.925.956	33.159.305.816	0	654.925.947.311	475.529.317	6.513.729.498	1.893.301.159
DE	1.350	100.55%	148.66%	0.00%	2634.64%	19.41%	124.44%	55.61%
ROA	1.350	5.38%	5.72%	-31.85%	45.20%	1.81%	7.58%	4.17%
DPR	1.350	42.57%	84.93%	0.00%	2322.17%	20.22%	49.05%	31.39%
Beta	1.350	0.87	0.45	-1.85	2.91	0.56	1.16	0.86

If we look at the company-specific accounting measures, the average size (median) of the 1.350 companies is 9.78 (9.74), corresponding to a market capitalization of USD 14 billion. The minimum and maximum market capitalization in the Asian region is respectively USD 41 million and USD 500 billion. In 2019, 31% reported negative free cash flow. Additionally, the average (median) reported ROA in 2019 is 5.38% (4.17%), with values ranging between -31.85% and 45.20%.

The average beta value (median) is 1.05 (1.02), indicating that the average Asian company is a little more volatile than the market. The minimum and maximum beta value is respectively -2.52 and 3.55, with 13 companies having a negative beta value. The three other factors SMB, HML and MOM shows average values of respectively 0.23, 0.13, 0.04 (0.20, 0.12, 0.04). The average (median) idiosyncratic risk is 0.09 (0.08) with a standard deviation of 0.04 and values ranging between 0.03 and 0.61. Finally, the momentum variable shows an average stock return (median) for 2019 of 17% (9%), with minimum and maximum values of respectively -94% and 382%.

6.3.5 *Summary statistics (Cross-regional)*

Following the regional summary statistics examined above, we now move on to a cross-regional comparison. Table 18 gives an overview of the central variables' mean values. First, we observe that the companies in the Asian region on average performed better during the first quarter of 2020 with an average negative buy-and-hold excess return of -21.44%. Oceania was the region that was hit the hardest by the COVID-19 crisis, showing BHARQ1 of -40.42%. Europe was also hit hard with an average stock return of -30.43%.

Table 18: Summary statistic for key variables (mean value)

Table 18 is showing the mean values for BHARQ1, ESG, E, S, G, MKT, Momentum and size across Asia, Europe, and Oceania

	ASIA	EUROPE	OCEANIA
BHARQ1	-21.44%	-30.43%	-40.42%
ESG	47.26	60.63	42.93
E	44.90	58.64	27.71
S	45.19	67.04	43.68
G	50.76	53.48	53.32
MKT	1.05	1.14	1.12
Momentum	16.59%	18.07%	15.81%
Size	9.78	9.66	9.03

Secondly, we observe that the average beta for each region is close to the market beta of 1. The European companies have the highest average beta values (1.14), followed by Oceania (1.12) and Asia (1.05). Fourth, we observe that the average SMB coefficients for each market lies between 0.23 and 0.42 and is overall similar across all regions. The average HML coefficient is very similar between the European and Asian region with values of respectively 0.11 and 0.13, while the HML coefficient in Oceania is -0.01. The same relationship is true for the MOM coefficients. Here we observe that the value of the coefficients is similar between Europe and Asia with average values of 0.03 and 0.04 whereas the average value of the MOM coefficient is -0.06 in Oceania. These observations are in line with what we observe for the momentum variable. Out of 2.362 companies across all regions, only 166 companies realised a positive BHAR in Q1 of 2020. Compared to the BHARQ1, Europe realized the highest average return in 2019 (18.07%), while Oceania realized the lowest average stock return (15.81%). Asia realized an average stock return of 16.59% in 2019.

By comparing company-specific financial measures, such as Size, FCF, Debt, DE and DPR, we can conclude that the European and Asian region consist of significantly larger companies, characterized by their relatively higher free cash flow and outstanding debt. These key financial measures and the fact that the European and Asian region consist of larger companies might explain why Oceania was more affected by COVID-19.

6.3.6 *Results from Oceania*

The coefficient and t-statistics from estimating the four different regression models for Oceania are presented in Table 19. In all four regression models the independent variable, Sector, is included. We have decided not to show the Sector variables dummy coefficients, although an interpretation of their effect will be discussed.

Column (1) presents the results from the first specification. Consistent with that of Ding, Levine, Lin, & Xie (2020) and Demers, Hendrikse, Joos, & Lev , (2020), we observe that ESG is positively related, albeit marginally so, to returns in the absence of other control variables with a coefficient of 0.0005. However, we observe that this is of economic relevance but not statistically significant at any conventionally acceptable level. When we include market factors, risk, and momentum, shown in Column (2), we notice that the R-Squared increases significantly from 19.94% to 27.80%. This indicates that the proportion of explanatory power for returns are higher for the market factors, risk, and momentum variables. Both MKT and Momentum are statistically significant on a 1% level, while none of the other independent variables are statistically significant at any acceptable level.

In Column (3), Size is added to the regression model. We observe that the coefficient is positive (0.0757) and statistically significant at a 0.01% level, indicating that Size is significantly positively associated with BHARQ1. Furthermore, we observe that the R-Squared increases from 27.80% to 31.06% by adding size to the model, indicating that this more specified model is better at explaining BHARQ1.

In column (4), we present the complete model that controls for company-specific financial measures such as ROA, DE, DPR, Debt and FCF. We observe that the R-Squared increases from 31.06% to 32.36%, indicating that these variables do not have a large effect on the explanatory power of the models. We only observe two statistically significant variables in the full specification. These are Size and MKT. However, it is worth mentioning that sectors like Consumer Staples, Health Care, Real Estate, Utilities, and Information Technology presents statistically significant coefficients on acceptable levels. Additionally, these sector dummies all present positive coefficients, indicating that they have a positive relation with BHARQ1, relative to the reference variable which is Communications Services.

These results suggest that a company's market capitalization, low beta (MKT) and sector affiliation are all economically and statistically significant indicators of a company's share price resilience during the partly exogenous COVID-19 pandemic downturn in the first quarter of 2020.

Table 19: COVID-19 January to March outbreak period within sample regressions for Oceania

Table 19 show the results from regressing the buy-and-hold excess return (BHARQ1) on our independent variables. In Column (1) we regress BHARQ1 on Refinitiv Eikons ESG Score and Sector. In Column (2) we add market factors, risk, and return related variables. In Column (3) we add Size and in Column (4) we add company-specific accounting variables. All variables except BHARQ1 and ESG are winsorized at the 2% and 98% levels. All variables are defined in Appendix (18).

OCEANIA				
	(1)	(2)	(3)	(4)
Variables	BHARQ1	BHARQ1	BHARQ1	BHARQ1
Intercept	-0.4304***	-0.3795***	-1.0567***	-1.1769***
	-10.667	-8.237	-5.983	-5.644
ESG	0.0005	0.0002	-0.0011	-0.0009
	1.079	0.358	-1.745	-1.414
MKT		-0.0594**	-0.0725***	-0.0709***
		-3.021	-3.711	-3.589
SMB		-0.0029	0.0076	0.0087
		-0.020	0.535	0.607
HML		-0.0047	-0.0049	-0.0020
		-0.649	-0.698	-0.281
MOM		0.0204	0.0156	0.0155
		1.320	1.028	1.013
Momentum		0.0706**	0.0459*	0.0417
		3.287	2.091	1.864
IdioRisk		-0.1977	0.2165	0.2506
		-0.864	0.872	0.973
Size			0.0757***	0.0863***
			3.844	3.781
ROA				0.1573
				1.486
DE				0.0065
				0.480
DPR				-0.0065
				-0.315
Debt				-0.1145
				-0.845
FCF				-0.0141
				-1.405
Multiple R-Squared	0.1994	0.2780	0.3106	0.3236
Observations	331	331	331	331
Industry Dummies	YES	YES	YES	YES

We emphasize that our results demonstrate that, contrary to that of Ding, Levine, Lin, & Xie (2020), the overall ESG score is not statistically significant in explaining crisis period returns. Accordingly, we fail to reject our null hypothesis. Specifically, we fail to find statistically significant evidence indicating that ESG is a resilience factor during Q1 of the COVID-19 pandemic. In Appendix (26), we show the results from the isolated ESG pillars. For the Environmental pillar, we find a negative but insignificant coefficient, meaning that we also fail to reject the null hypothesis. Additionally, and similar to the overall ESG score analysis, we also find that MKT and size is significant at a 0.1% and 1% level. Notably, we also observe that FCF is negatively associated with BHARQ1 and statistically significant. We observe the same result for the Social and Governance specific analyses. Thus, we also fail to reject the null hypothesis for these pillars and conclude that a company's market capitalization, sector affiliation and low beta (MKT) are all economically and statistically significant indicators of a company's share price resilience during the outbreak period. However, in order to gain a better understanding of the relative importance of ESG, E, S, G and the other independent variables in explaining crisis period returns, we have conducted an Owen-Shapley decomposition. The results are presented in Figure 13.

Figure 13: Owen-Shapley R^2 Decomposition analysis outbreak period for Oceania

Figure 13 represents the Owen-Shapley R^2 decomposition analysis during the outbreak period for the Oceanian region. ESG consist of: Aggregated ESG score. Stocks risk, return and factor loadings consist of: MKT, HML, SMB, MOM, Momentum and IdioRisk. Sector consist of: All 11 sectors. Company financial consist of: Size, ROA, DE, DPR, Debt and FCF.

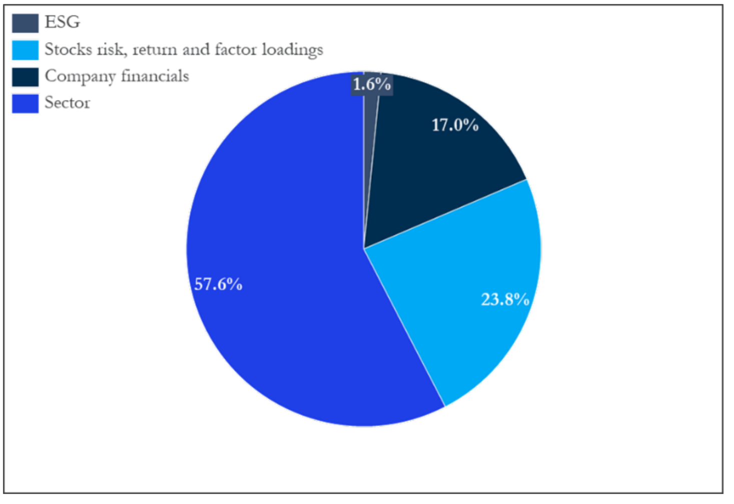


Table 19 reports that our most complete regression model (4) explains approximately 32.36% of the cross-sectional variation in the COVID-19 pandemic period returns for the observations in our sample. Figure 13 presents a pie chart illustrating the proportion of the 32.36% that is explained by each group of variables. We observe that sector contributes, by far, the most to the overall R-square, with 57.6% of the explained variation being credited to this variable. Stock's risk, return and factor loadings are second, accounting for 23.8% of the explained variation. Company financials account for 17.0% of the explained variation in stock returns, while notably, the aggregated ESG score is the least important category, contributing just 1.6% of the overall explained variation in returns during the COVID-19 downturn period in Q1 of 2020. For the isolated pillar specific analyses, we observe an almost identical distribution across all four groups of variables (Figure 16). Specifically, we find that E contributes 1.5%, S contributes 1.6% and G contributes 0.5%.

Taken together, our results from the multiple regression analyses and Owen-Shapley decomposition suggest that sector fixed effects and classic market-based determinants of returns are the biggest contributors in explaining excess returns during the specified period. By contrast, ESG, E, S and G does not significantly contribute to the explanation of returns, meaning that we fail to reject the null hypothesis for the aggregated ESG score and all the isolated pillars. Secondly, and as shown by the Owen Shapely decomposition, we can conclude that ESG, E, S and G performance in Oceania does not meaningfully contribute to the explanation of returns during the pandemic crisis.

6.3.7 *Results from Europe*

The coefficient and t-statistics from estimating the four different regression models for Europe are presented in Table 20. We follow the same structure as in section 6.3.1.

Column (1) presents the results from the first specification. Consistent with the results from Oceania, we observe that ESG is positively related, albeit marginally so, to returns in the absence of other control variables with a coefficient of 0.004. Again, we observe that this is of economic relevance but not statistically significant at any conventionally acceptable level.

When we include market factors, risk, and momentum, shown in Column (2), we notice that the R^2 increases significantly from 24.90% to 36.31%. Like Oceania, this indicates that the proportion of explanatory power for returns are higher for the market factors, risk, and momentum variables. We observe that MKT, HML and IdioRisk are negative and statistically significant. Furthermore, we observe that Momentum is positively associated with BHARQ1 and significant at a 1% level.

In Column (3), Size is added to the regression model. We observe that the coefficient is positive but statistically insignificant. Furthermore, we observe that R^2 increases slightly from 36.31% to 36.62% by adding size to the model, indicating that the more specified model is only marginally better at explaining BHARQ1. In column (4), we present the complete model that controls for company-specific financial measures such as ROA, DE, DPR, Debt and FCF.

We observe that companies that are highly leveraged performed less well during the market downturn (i.e., *DE* is negative and significant). Notably, the company's profitability (ROA) is positive and a significant determinant of returns during the crisis period. These results suggest that most of traditional accounting-based measures of the company's financial performance are significant determinants of a company's share price resilience during the partly exogenous shock.

It is worth mentioning that sectors like Consumer Discretionary, Energy, Health Care, Industrials, Real Estate, and Utilities present statistically significant coefficients on acceptable levels. We observe that Consumer Discretionary, Energy, Industrials and Real Estate is negatively associated with returns while, not surprisingly, Healthcare and Utilities present positive coefficients, indicating that companies in these sectors performed relatively better during the crisis period. Similar to that of Oceania, the aggregated ESG score in column (4) is not statistically significant in explaining market crisis returns in the first quarter of 2020. As such, we again fail to reject our null hypothesis.

In Appendix (24), we analyze the isolated ESG pillars for the European region. For the Environmental pillar, we find a positive but insignificant coefficient, meaning that we also fail to reject the null hypothesis. Additionally, and similar to the aggregated ESG score analysis, we also find that MKT and DE is significant at a 0.1% level. Notably, the company's profitability (ROA) and its market capitalization (size) are positive and significant determinants of returns during the crisis period.

We observe significantly different result for the Social and Governance specific analyses. Specifically, we observe that the Social pillar is positive and statistically significant at the 5% level. As such, we reject our null hypothesis and conclude that the Social factor is an important and positive indicator of a company's share price resilience during the outbreak period. In line with Forbes (2020), we hypothesize that the significant result for the social pillar is caused by COVID-19 related social issues which became more material. These issues include but is not limited to employee health and safety, labor practices, product quality and safety and access and affordability.

Table 20: COVID-19 January to March outbreak period within sample regressions for Europe
Table 20 show the results from regressing the buy-and-hold excess return (BHARQ1) on our independent variables. In Column (1) we regress BHARQ1 on Refinitiv Eikons ESG Score and Sector. In Column (2) we add market factors, risk, and return related variables. In Column (3) we add Size and in Column (4) we add company-specific accounting variables. All variables except BHARQ1 and ESG are winsorized at the 2% and 98% levels. All variables are defined in Appendix (18).

EUROPE				
	(1)	(2)	(3)	(4)
Variables	BHARQ1	BHARQ1	BHARQ1	BHARQ1
Intercept	0.3583***	-0.2632***	0.3764**	-0.3182*
	-7.671	-5.541	-2.993	-2.170
ESG	0.0004	0.0001	-0.0002	0.0002
	1.383	0.346	-0.576	0.447
MKT		-0.0851***	-0.0829***	-0.0783***
		-5.274	-5.125	-4.815
SMB		-0.0124	-0.0090	-0.0129
		-1.626	-1.156	-1.656
HML		-0.0432***	-0.0416***	-0.0372***
		-4.716	-4.527	-4.005
MOM		-0.0134	-0.0139	-0.0100
		-0.95	-0.982	-0.714
Momentum		0.0568**	0.0481*	0.0432*
		2.763	2.279	2.046
IdioRisk		-0.4815*	-0.3183	-0.3742
		-2.17	-1.332	-1.535
Size			0.0233	0.0165
			1.816	1.106
ROA				0.3877**
				2.801
DE				-0.0162**
				-2.995
DPR				-0.0200
				-1.396
Debt				-0.0072
				0.185
FCF				0.0014
				-1.123
Multiple R-Squared	0.2490	0.3631	0.3662	0.3874
Observations	691	691	691	691
Industry Dummies	YES	YES	YES	YES

We find opposite results for the Governance specific analysis. In Appendix (24), we find that the G pillar is negatively related to BHARQ1 and statistically significant at the 5% level. As such, we reject the null hypothesis and conclude that the Governance pillar is a significant but negative indicator of a company's share price resilience during the outbreak period. We present the results from the Owen-Shapley decomposition of R-square for the European region in Figure 14.

Figure 14: Owen-Shapley R^2 Decomposition analysis outbreak period for Europe

Figure 14 represents the Owen-Shapley R^2 decomposition analysis during the outbreak period for the European region. ESG consist of: Aggregated ESG score. Stocks risk, return and factor loadings consist of: MKT, HML, SMB, MOM, Momentum and IdioRisk. Sector consists of: All 11 sectors. Company financial consist of: Size, ROA, DE, DPR, Debt, Earnings and FCF.

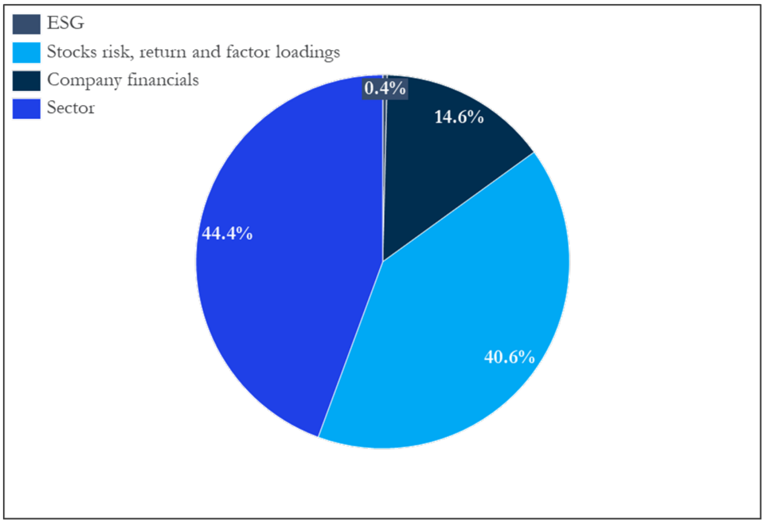


Table 20 reports that our most complete regression model (4) explains 38.74% of the cross-sectional variation in the COVID-19 pandemic period returns for the observations in our sample. Figure 14 presents a pie chart illustrating the proportion of the 38.74% that is explained by each group of variables. Similar to Oceania, we observe that Sector contributes the most to the overall R^2, with about 44.4% of the explained variation being credited to this variable. Stock's risk, return and factor loadings are now a close second, accounting for 40.6% of the explained variation. Company financials account for 14.6% of the explained variation in stock returns, while notably, the ESG group is the least important category, contributing just 0.39% of the overall explained variation in returns during the COVID-19 downturn period in Q1 of 2020.

For the isolated pillar specific analyses, we find similar results despite of S and G being statistically significant at a 5% level (Figure 16). Specifically, we find that E contributes 0.29%, S contributes 1.62% and G contributes 1.32%. Taken together, our multiple regression analyses and Owen-Shapley decomposition again suggest that sector fixed effects and classic market-based determinants of returns are the biggest contributors in explaining excess returns during the specified period. Firstly, due to the insignificant ESG and E coefficients, we fail to reject the claim that ESG or E is a significant share price resilience factor during the first quarter of COVID-19 pandemic. Secondly, we observe that S is positively associated with returns during the outbreak period while G is negatively associated. We conclude that both findings are of economical and statistically significant relevance and thus reject the null hypothesis for both pillars. Finally, and in line with that of Oceania, the Owen Shapely decomposition provides robust evidence that ESG, E, S and G performance in Europe does not meaningfully contribute to the explanation of returns during the pandemic crisis.

6.3.8 *Results from Asia*

The coefficient and t-statistics from estimating the four different regression models for Asia are presented in Table 21. We follow the same structure as in section 6.4.1 and section 6.4.2.

Column (1) presents the results from the first specification with only the aggregated ESG score and sector dummies. We observe that ESG is negatively related, albeit marginally so, to returns in the absence of other control variables with a coefficient of -0.0017. Conversely to that of Oceania and Europe, we observe that this is of economic relevance and statistically significant at the 0.1% level. This relationship holds across all four specifications.

When we include market factors, risk, and momentum, shown in Column (2), we notice that the R^2 increases significantly from 19.30% to 25.77%. Like Oceania and Europe, this indicates that the proportion of explanatory power for returns are higher for the market factors, risk, and momentum variables.

Contrary to the findings from Oceania and Europe, the MKT is statistically insignificant at all levels. Instead, SMB and Momentum present statistically significant coefficients at the 1% and 0.1% level. The Momentum coefficient is positive (0.1384), indicating that companies that had high returns during 2019 was more resilient to the market selloff in Q1 of 2020.

In Column (3), Size is added to the regression model. We observe that larger companies, expressed as the log transformed market capitalization, performed better during the market downturn, and thus concludes that Size is a positive resilient factor (i.e., size is positive and significant at the 0.1% level). In column (4), we present the complete model that controls for company-specific financial measures such as ROA, DE, DPR, Debt and FCF. Notably, we observe that higher leverage, expressed by the debt-to-equity ratio, and level of free cash flow is negative and significant determinants of returns during the Q1 of the COVID-19 pandemic. Conversely, investors seem to reward companies with a high dividend-pay-out ratio during the period (i.e., DPR is positive and significant at the 5% level).

Again, it is worth mentioning that almost all of the 11 sectors present statistically significant coefficient at acceptable levels. We observe that only Information Technology, Utilities and Real Estate show insignificant coefficients. Similar to that of Europe, we find positive coefficients for the Health Care sector, indicating that companies in this sector performed relatively better during the crisis period. Different to that of Oceania and Europe, the aggregated ESG score is statistically significant in explaining crisis period returns. The aggregated ESG score is negatively related to BHARQ1 and statistically significant at the 0.1% level. As such, we reject the null hypothesis and conclude that the aggregated ESG score is a significant but negative indicator of a company's share price resilience during the outbreak period.

In Appendix (25), we analyze the isolated ESG pillars for the Asian region. For the Environmental pillar, we find a negative but significant coefficient (at the 0.1% level), meaning that we also reject the null hypothesis and conclude that the Environmental factor is a negative indicator of a company's share price resilience during the outbreak period (Appendix 25). Additionally, and similar to the aggregated ESG score analysis, we also find that Momentum and Size is significant at a 0.1% level. We observe similar results for the Social pillar specific analysis. Specifically, we observe that the Social pillar is negative (-0.0020) and statistically significant at the 0.1% level. As such, we reject our null hypothesis and conclude that the Social factor, contrary to that of Europe, is a negative indicator of a company's share price resilience during the outbreak period. We find different results for the Governance specific analysis.

In Appendix (25), we find that the G pillar is negatively related to BHARQ1 but statistically insignificant at any acceptable level. As such, we fail to reject the null hypothesis. Specifically, we fail to find statistically significant evidence that indicates if G is a resilience factor or not during Q1 of the COVID-19 pandemic.

Table 21: COVID-19 January to March outbreak period within sample regressions for Asia

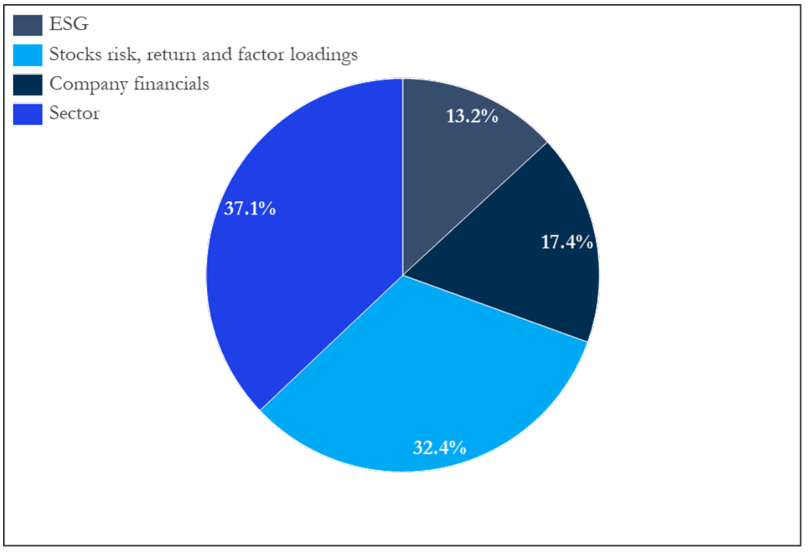
Table 21 show the results from regressing the buy-and-hold excess return (BHARQ1) on our independent variables. In Column (1) we regress BHARQ1 on Refinitiv Eikons ESG Score and Sector. In Column (2) we add market factors, risk, and return related variables. In Column (3) we add Size and in Column (4) we add company-specific accounting variables. All variables except BHARQ1 and ESG are winsorized at the 2% and 98% levels. All variables are defined in Appendix (18).

ASIA				
	(1)	(2)	(3)	(4)
Variables	BHARQ1	BHARQ1	BHARQ1	BHARQ1
Intercept	-0.1442***	-0.1790***	-0.8364***	-0.7676***
	-6.026	-6.232	-7.508	-5.853
ESG	-0.0017***	-0.0014***	-0.0018***	-0.0018***
	-7.976	-6.384	-8.072	-7.991
MKT		0.0081	0.0062	0.0077
		0.757	0.596	0.733
SMB		-0.0205**	-0.0188**	-0.0189**
		-3.046	-2.838	-2.820
HML		-0.0113	-0.0104	-0.0100
		-1.146	-1.070	-1.021
MOM		0.087	0.0058	0.0058
		0.889	0.610	0.593
Momentum		0.1384***	0.1069***	0.1060***
		8.891	6.672	6.503
IdioRisk		-0.1295	0.0760	0.18256
		-0.811	0.475	1.094
Size			0.0721***	0.0659***
			6.699	4.989
ROA				0.0406
				0.371
DE				-0.0153**
				-2.924
DPR				0.0345*
				2.282
Debt				0.0149*
				2.282
FCF				-0.0097
				-1.909
Multiple R-Squared	0.1930	0.2577	0.2819	0.2919
Observations	1.350	1.350	1.350	1.350
Industry Dummies	YES	YES	YES	YES

We present the results from the Owen-Shapley decomposition of R-square for the Asian region in Figure 15. Figure 15 reports that our most complete regression model (4) explains approximately 29.19% of the cross-sectional variation in the COVID-19 pandemic period returns for the observations in our sample. Figure 15 presents a pie chart illustrating the proportion of the 29.19% that is explained by each group of variables. Conversely to Oceania and Europe, we now observe a slightly more equally divided contribution to the variance in return.

Figure 15: Owen-Shapley R^2 Decomposition analysis outbreak period for Asia

Figure 15 represents the Owen-Shapley R^2 decomposition analysis during the outbreak period for the Asia region. ESG consist of: Aggregated ESG score. Stocks risk, return and factor loadings consist of: MKT, HML, SMB, MOM, Momentum and IdioRisk. Sector consist of: All 11 sectors. Company financial consist of: Size, ROA, DE, DPR, Debt and FCF.



Specifically, we observe that Sector contributes the most to the overall R^2, with about 37.1% of the explained variation being credited to this variable. Stock's risk, return and factor loadings are a close second, accounting for 32.4% of the explained variation. Company financial accounts for 17.4% of the explained variation in stock returns. Finally, the aggregated ESG score now accounts for 13.2% of the explained variation. For the isolated pillar specific analyses, we find a correspondingly, relatively, high explanatory power for the Environmental and Social pillar (Figure 16). Specifically, we find that E contributes 10.10 %, S contributes 20.94% and G contributes 0.17%. Taken together, our results from Asia show quite different indications to those we observed for the Oceanian and European region. Common for all regions is that our multiple regression analyses and Owen-Shapley decomposition suggest that sector fixed effects and classic market-based determinants of returns are the biggest contributors in explaining excess returns during the specified period. However, we now observe that the Environmental and Social pillar explains a lot more of the variation in returns.

6.3.9 *Summary of findings – Cross-regional*

Throughout sections 6.4.1, 6.4.2, and 6.4.3 we presented the results for our region-specific multiple regression analysis and Owen-Shapley decomposition of R^2. While these conclusions are interesting on their own, we now compare the results from all three regions.

Proponents of socially responsible investing claim that ESG investing is particularly valuable as a downside risk protection strategy during periods of crisis. In our outbreak period analysis, we have scrutinized if both ESG and the isolated Environmental, Social and Governance scores offer such share price resilience during the COVID-19 pandemic.

Through a multiple regression analysis of the combined ESG score, we find that only Asia yield statistically significant results. Specifically, we conclude that the overall ESG score is not an indicator of share price resilience for this region.

In Table (19) and (20), we present the results from Oceania and Europe. For these two regions, we provide evidence that companies with higher ESG scores do not experience either superior returns (i.e., smaller losses) or inferior returns during the outbreak period once sector affiliation, marked-based determinants of returns and company financials have been properly controlled for. Specifically, we find that the coefficients for most of the model specifications are negative, but their statistical insignificance disallows rejection of our null hypothesis. Instead, we observe that sector and traditional accounting-based measures of the company's financial performance are significant determinants of a company's share price resilience during the partly exogenous shock. Thus, summarizing the findings of the multiple regression analysis for the overall ESG score, we find significant variations between the three regions and conclude that there exist inter-regional differences.

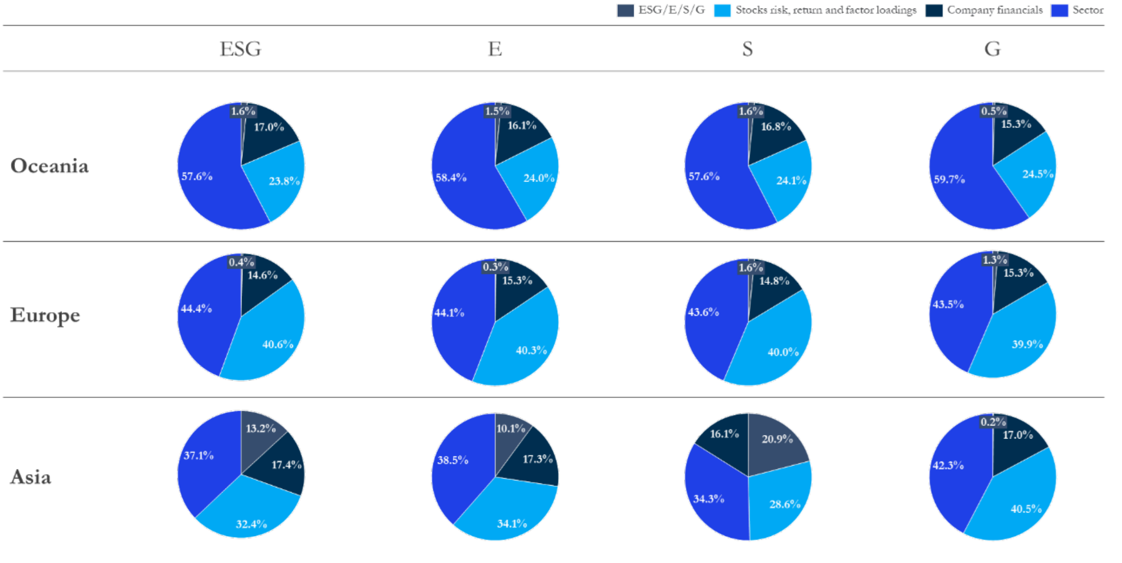
To identify the particular determinants of our results, we deemed it vital to consider the individual pillars. Thus, to contribute to existing literature and in line with that of Dorfleitner & Halbritter (2015), we considered both the overall ESG score and the isolated pillar effects. As a result, we have comparable coefficients for the total ESG score (ESG), as well as for the individual score of the pillars Environment (E), Social (S) and Governance (G).

For the multiple regression analyses of the particular pillars, we do not find a consistent pattern across the three regions. Again, this emphasizes that there exist inter-regional differences and that the rating methodology of TTR[24] has a significant impact on the results. In Oceania, we find that the Environmental, Social and Governance pillars do not show significant explanatory power of returns during the outbreak period. However, in Europe we find that both the Social and the Corporate Governance pillars exhibit significant coefficients. However, they feature in opposite directions with the Social pillar having a positive effect on returns and the Governance pillar having a negative impact on a company's return.

In general, we observe that corporate governance practices appear to have a negative impact on BHARQ1. We hypothesize that this is driven by the companies' size, which we account for in the logarithmic transformed market capitalization variable (Size). Specifically, we find that large corporations typically tend to achieve higher governance ratings and lower returns than smaller firms. For the Asian region, we observe that the significant impact on a company's BHARQ1 is mainly driven by the Environmental and Social pillars.

Figure 16: Owen-Shapley R^2 Decomposition analysis outbreak period for all regions

Figure 16 represents the Owen-Shapley R^2 decomposition analysis during the outbreak period for all regions. ESG consist of: Aggregated ESG score and the individual E, S and G score. Stock's risk, return and factor loadings consist of: MKT, HML, SMB, MOM, Momentum and IdioRisk. Sector consist of: All 11 sectors. Company financial consist of: Size, ROA, DE, DPR, Debt and FCF.



[24] The weights for the Environmental and Social pillar varies across industries and the governance pillar varies across regions

Solely, companies with high Environmental and Social ratings do not achieve downside risk protection or share price resiliency during the COVID-19 pandemic selloff. This indicates that companies that are perceived to be doing "socially" and "environmentally" better than their relative social/environmental-performing peers, are not rewarded by shareholders during the outbreak period. In order to understand the importance of each set of variables in explaining BHARQ1 during the outbreak period, we undertook an Owen-Shapley R^2 decomposition.

As shown in Figure 16, the general magnitudes of the explanatory contribution of each group of variables are very similar in Oceania and Europe. For these regions, we observe that both the overall ESG and individual pillar scores are showing only a marginal contribution to the explanation of returns during the outbreak period.

Taken together, our results from the regression analyses and Owen-Shapley decomposition in Oceania and Europe suggest that stocks risk, return and factor loadings, company financials and sector dominate the explanatory power of outbreak crisis period stock returns. In Asia, we observe that the overall ESG score and isolated Environmental and Social pillar explains a lot more of returns.

Part V
CONCLUSION AND DISCUSSION

The final chapter of our thesis concludes and discusses our work. Section 7, the conclusion, presents the objective of our thesis, the empirical findings and the conclusions to the main research question and associated two sub-questions. Section 8, the discussion, briefly discusses our findings' implications for investors. Finally, in section 9, we outline the central limitations of our approach and suggestions for future research.

CONCLUSION 7

Our thesis is a result of academic and empirical curiosity. For years, socially responsible investing has been growing. Investors have become more conscientious about the companies they invest in and have begun prioritizing sustainability-focused companies (Fink, 2021). Investors who choose to tilt their investments towards companies that are environmentally conscious, socially responsible and implement stakeholder-friendly practices usually constrain their investment universe. In accordance with classic portfolio theory, such rationale should not provide investors with long-term or crisis-period superior financial returns. However, does this hold in practice? To answer this question, we defined a main research question:

Can a sustainable investment strategy produce alpha and did ESG performance carry important resilient properties during the first quarter of 2020?

Secondly, to answer the two focal points of our research question, we outlined two sub-questions. We will comment on both sub-questions in the coming sections, starting with sub-question one.

7.1 Sub-question one: *is there a green-to-brown premium?*

For sub-question one, we distinguish between investors with stronger than average ESG preference who hold portfolios that have a green tilt away from the average, whereas investors with a weaker than average ESG preference take a position with a brown tilt. We decided to focus on three particular measures of financial performance, all of which are extensively used in previous literature: 1) Sharpe ratio, 2) cumulative returns and 3) Jensen's alpha. In doing so, we managed to consider both the returns of the portfolios and their associated risk. In our analysis, we used the cumulative returns and the Sharpe ratio to gain an overview of inter-regional and inter-portfolio differences in return-to-volatility trade-offs. Specifically, we presented Sharpe ratios for the full-period specification and compared the values across portfolios and regions. While useful, the focal point of our thesis is to analyze the statistical significance of the risk-adjusted returns, something that neither the Sharpe ratio nor the cumulative portfolio returns account for. In pursuit of risk-adjusted excess returns, we deployed a cross-sectional analysis and used well-known factor models such as the FF3, C4 and the FF5 to look for significant differences in the returns across our long-short portfolios and regions. In sum, this analysis was designed to determine whether we can reject the two alternate null hypotheses stated in section 1.2.1:

$$H_0\text{: } \alpha_{\text{long minus short}} = 0$$

$$H_1\text{: } \alpha_{\text{long minus short}} \neq 0$$

With our results from section 6.2.4, 6.2.5 and 6.2.6, we fail to reject our null hypothesis for Europe and Oceania. However, for Asia, we reject the null hypothesis on a 5% significance level and conclude that a long-short strategy underperformed under the previously described circumstances. Thus, we conclude that there exist inter-regional differences and that there appears to be no significant performance differences between green-and-brown tilted portfolios in Europe and Oceania. These insignificant findings are in line with those of Pastor, Stambaugh, & Taylor (2019), who's model prediction of alphas showed that "green assets" have positive but insignificant alphas. Secondly, they also follow that of Corten, Van de Velde, & Vermeir (2005), who documented insignificant, although positive, alphas for most portfolios in their study. Corten, Van de Velde, & Vermeir (2005) theorized that a study covering a longer period would be able to compute significant alphas, since the performance of high-rated ESG portfolios are more long-term oriented. This is in line with that of the European Commission (2016), who argue that the lack of significance may be explained by the short-term orientation of investors who ignore ESG information. This implies that the ESG-related efforts of companies with a high ESG score are not rewarded accordingly, and "sin" stocks may be overvalued. However, this study cannot prove or disprove this speculation. The findings of our regression for the European and Oceanian region are thereby in line with a vast majority of SRI-related studies who show evidence indicating that the relationship between ESG and CFP is insignificant. Conversely, we find that there exist significant performance differences in Asia. The results indicate that an investor who shorts brown-tilted portfolios to fund an investment in green-tilted portfolios would produce a negative alpha. When we decompose the ESG score into its individual Environmental (Appendix 28), Social (Appendix 29), and Governance (Appendix 30) pillars, we observe no considerably different results. The significant alphas for the Environmental long-short portfolio in the Asian region and the Governance long-short portfolio in the Oceanian region show negative alphas. Similar to the results from Asia, this indicates that an investor who shorts brown-tilted portfolios to fund an investment in green-tilted portfolios, for the Environmental pillar in Asia and Governance pillar in Oceania, would produce negative alphas. We arrive at this conclusion after conducting what, to the best of our knowledge, is the first tri regional ESG and pillar specific analysis, using comparable rating methodologies.

7.2 Sub-question two: *Are high performing ESG, Environmental, Social and Governance companies more resilient to a partly exogenous shock like COVID-19?*

For sub-question two, we set out to test the claim that ESG activities will contribute to stock price resilience. To mobilize this test, we undertake a series of analyses designed to uncover whether the overall ESG score and/or isolated Environmental, Social and Governance scores are significant share price resilience factors either instead of, or more than, market-based measures of risk, company financials and sector fixed effects. We first perform a multiple regression analysis of buy-and-hold excess returns during the “outbreak” period (i.e., January through March 2020). We regress BHARQ1 on four groups of variables, all of which include sector dummies. In sum, this analysis was designed to determine whether we can reject the null hypotheses stated in section 1.2.2:

Hypothesis I: ESG score

$$H_0: X_{ESG} = 0$$

$$H_1: X_{ESG} \neq 0$$

Hypothesis II: Environmental score

$$H_0: X_E = 0$$

$$H_1: X_E \neq 0$$

Hypothesis III: Social score

$$H_0: X_S = 0$$

$$H_1: X_S \neq 0$$

Hypothesis IV: Governance score

$$H_0: X_G = 0$$

$$H_1: X_G \neq 0$$

With our results from part six, we fail to reject our null hypothesis for the overall ESG score in Oceania and Europe but reject the null hypothesis for Asia. Contrary to the findings of most contemporaneous studies who examine the GFC and COVID-19 period (Ding, Levine, Lin, & Xie (2020); Lins, Servaes, & Tamayo, (2016); Albuquerque, Koskinen, Yang, & Zhang (2020), as well as claims from Larry Fink, ESG data purveyors and asset managers, our results from the Asian region show that the ESG resilience narrative is, at best, flawed.

For the individual pillars, we do not find a consistent pattern across the three regions. In Oceania, we observe that all individual pillars are insignificant while the magnitude and direction show a generally negative relation. Thus, we fail to reject the null hypotheses for this region. In Europe, we find that both the Social and the Corporate Governance pillars exhibit significant coefficients. However, they feature in opposite directions with the Social pillar having a positive effect on returns and the Governance pillar having a negative impact on a company's return. As such we reject the null hypothesis for the Social and Governance pillar in Europe. For the Asian region, we observe that the significant impact on a company's BHARQ1 is mainly driven by the Environmental and Social pillars. Thus, we reject our null hypothesis for the Asian region. Solely, companies with high Environmental and Social ratings do not achieve downside risk protection or share price resiliency during the COVID-19 pandemic selloff.

To substantiate the irrelevancy of the aggregated ESG score as a resilient factor in Oceania and Europe, we undertake an Owen-Shapley decomposition of the explained variation in returns

(Grömping, 2012). For Oceania and Europe, the results of these analyses indicate that two groups of explanatory variables, Sector and the Stock's risk, return and factor loadings, offer approximately 80% (Oceania) and 85% (Europe) of the model's explanatory power of returns (Figure 16). Notably, ESG is only responsible for 1.6% and 0.4% of the total explained variation in the fully specified model (4). However, for the Asian region our results paint a slightly different picture. For this region, the overall ESG score is responsible for 13.2% of the explained variation. We hypothesize that the higher degree of explanatory power is driven by the Environmental and Social pillar coefficient which yielded negative economical and significant relevance at a 0.1% level. In Figure 16, we observe that the social pillar accounts for 20.9% of the explained variation in returns. This finding is somewhat contradicting to the that of Bassen, Busch, & Friede (2015), who argues that the Social factor is the least correlated with corporate financial performance. Thus, we can conclude that companies in the Asian region, who invest in the Environmental and Social pillar, do not build an "insurance-like" factor that pays off when the overall level of trust in the company and the market suffers a negative shock.

7.3 *Combined conclusion for sub-question one and sub-question two*

Despite the increase in investor preference for sustainable assets during recent years, the questions as to whether environmental, social and governance-based investments pay off for shareholders – either through long-term outperformance or as a resilience factor during the pandemic-driven sell off in Q1 of 2020 - remains a topic of considerable debate. Proponents of ESG and numerous academic papers claimed to show that ESG investing can generate long-term alpha and be a significant "equity vaccine" that provides downside protection to shocks in financial markets. Consistent with this view, Larry Fink, the CEO of Blackrock, have been purporting that ESG can offer investors positive alpha and that this was specifically noticeable during the first quarter downturn.

The extensive analyses presented in this study speak to both the longer-term shareholder value creation and the resiliency of such, before and during a partly exogenous shock. Our findings indicate that an investment strategy that goes long in "green" stocks and short in "brown stocks" in the European and Oceanian region suffer neither outperformance nor underperformance. In line with portfolio theory, we find that a similar investment strategy, over a similar period, would generate a negative alpha for the Asian region.

Inconsistent with the resilience narrative, we document that high ESG, Environmental-and Social-rated companies in Asia display higher losses during the outbreak period. This finding stands in sharp contrast to that Albuquerque, Koskinen, Yang, & Zhang (2020), who finds the opposite relation for Environmental and Social firms in North America. In line with that of Albuquerque, Koskinen, Yang, & Zhang (2020), we find that the Social pillar is significantly benefiting companies' stock performance and resiliency in Europe during the first quarter of 2020. Taken together, our multiple regression analysis and Owen-Shapley decomposition provide robust evidence that sector affiliation, classic market-based determinants of returns and company financials together dominate the explanatory power of the outbreak period returns models.

We argue that our approach has several fundamental advantages to it. First, our exhaustive measurement period and the fact that we use monthly data points, covering 14 years, for all dependent and independent variables across three different regions, reduces uncertainty. Secondly, a majority of previous studies on ESG-investing have used Jensen's alpha in multifactor models as their main performance measure. In this study, we use both cumulative returns, return-to-volatility measures (Sharpe Ratio), the proven Jensen's alpha measure, multiple regression analyses and the Owen-Shapley decomposition of R-square. Third, our study brings depth by analyzing if an investor can generate both alpha and resilience by favoring more socially responsible companies, something that to our knowledge have not been examined collectively before. Fourth and finally, our study offers both an overall ESG-and pillar specific analyses, something that most studies do not consider.

In section 4.1, we presented a short description of the Efficient Market Hypothesis and the Random Walk Theory. We will now employ these theories to discuss and hypothesize possible explanations for our results in Oceania, Europe and Asia.

In his paper, Manescu (2010) outlines three scenarios that could potentially explain the relation between ESG performance and returns. The first scenario, called "no effect", discusses a scenario in which no difference is found between the bottom and top performing ESG companies. This scenario is consistent with our results from the first analyses in 6.2.4 and 6.2.6, for Europe and Oceania, and with the Efficient Market Hypothesis. Accordingly, this relationship states that ESG information is either currently irrelevant for stock market performance, or all ESG related information is already correctly priced into the value of the asset.

The second and third scenario that Manescu (2010) mentions, relates to a scenario where significant differences between the stock returns of the bottom and top performing ESG portfolios are found. We call this scenario "risk-related". In this scenario, low-performing ESG companies will achieve higher risk-adjusted returns. The relationship is explained by the underlying level of risk in the asset[25], which is expected to be relatively lower for companies with higher ESG performance. Accordingly, these companies should achieve lower risk-adjusted returns. As we discovered for the Asian region, this scenario seems to hold and could therefore be a hypothetical explanation for our results for this region. We note that our results from Europe, Oceania and Asia stands in contrast to most of the previous academic papers and financial articles we have encountered throughout the process of writing this thesis, most of which report that ESG screening leads to significantly observable financial outperformance. However, we hypothesize that the general indication of our findings supports a third and fourth scenario.

As we mention in section 2.2, the term "ESG integration" has gained popularity amongst asset managers in Europe and Oceania. As ESG grows, it becomes more prevalent, and the distinguishing features may not be as diversifying as previously assumed. We hypothesize that when everyone can offer you a bit of ESG, or the *new alpha* as argued by Larry Fink, it becomes

[25] Manescu, (2010) characterizes risk as environmental risk, lower investor trust and litigation risk.

more difficult to generate alpha through ESG investment strategies. This may explain why we do not observe any significant outperformance or underperformance for the European and Oceanian region. Our insignificant findings may indicate that ESG, as an investment strategy, is becoming more of a risk mitigation tool than an alpha generator.

Alternatively, one could also argue that our findings support the "mispricing scenario". According to Manescu (2010), ESG performance do affect a company's cash flow, but financial markets are imperfect at pricing in information about sustainability effects. Moreover, and in line with Bfinance (2021) and Blackrock (2020), we hypothesize that this is caused by the lack of standardization within the field of ESG reporting and because financial markets are still in the early stages of a long transition towards sustainability.

Bauer, Derwall, Guenster, & Koedijk (2005) argue that the material long-term impact of ESG is mispriced due to short-term thinking within financial markets. Blackrock (2020) further argue that the lack of historical precedence linked to sustainability makes it hard to quantify the effects. Finally, a survey conducted by McKinsey show that most C-suite executives and investment professional largely agree E, S and G programs make more of a positive long-term contribution than short-term, where long-term value is defined as five years from today[26] (Appendix 27). These arguments form a strong case, arguing that the tectonic shift towards a more widespread adoption of sustainable investing is not yet embedded in current market prices. When market-pricing and financial markets starts to reflect the shift towards sustainability, ESG may turn out to be a favorable sign of profitability and economic fundamentals, making it a source of alpha (Blackrock, 2020).

As of today, our mostly nonnegative results in Europe and Oceania supports the case for socially responsible investing in these regions. We do not find significant evidence that a return sacrifice is necessary when adopting sustainable investing. Moreover, for the European region we find a positive and significant Social coefficient, suggesting that investors considered these companies more resilient to the negative effects of the COVID-19 pandemic.

[26] The survey was conducted in 2019 – today reflects the opinions of C-suite executives in 2019

We argue that our findings can inspire future research, in the area of sustainability and corporate financial performance, to investigate whether the signs of equal performance, found in Europe and Oceania, and negative performance, found in Asia, have merit. Secondly, we argue that our findings from a partly exogenous shock, present strong evidence that ESG, in itself, did not significantly immunize stocks from the COVID-19 pandemic selloff, during the first quarter of 2020. The shift towards sustainability would potentially provide new and more sufficient data to test our results. Thus, waiting a few years would potentially increase the robustness and yield different results. Furthermore, as presented in section 5.5.4, it is crucial to keep in mind that ESG scores vary across agencies, which, again, could alter the results if a similar study were conducted with ESG scores from another rating provider. Secondly, a more in-depth investigation of how ESG implementation strategies can be incorporated in a real-life context would be relevant. Specifically, this thesis does not account for taxes or transaction costs. Third and finally, there have only been a few event studies that investigates the ESG-CFP relationship. We argue that a comparison study, investigating multiple rating agencies down or upgrades of a company's ESG score would potentially yield valuable information about whether the market actively prices ESG information.

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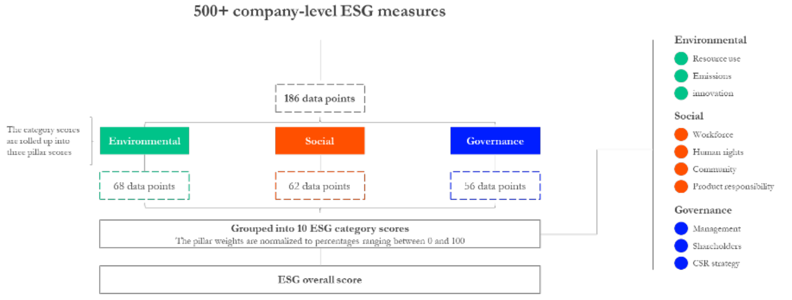
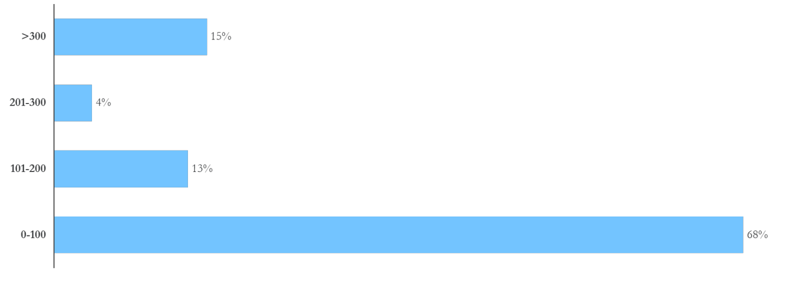
APPENDIX 1: Thomson Reuters Refinitiv Rating Methodology



Source: Self-developed graph based on Refinitiv (2021)

APPENDIX 2: Average sample size from academic papers investigation the ESG-CFP relation



Source: Self-developed graph based on von Wallis and Klein (2015)

APPENDIX 3: Dropping of companies per region and in total

EUROPE

Droppings	
Total observations	**1.115**
No stock return (2015-2019)	204
No available ESG-score	220
Total observations dropped	424
Total observations in data sample	**691**

ASIA

Droppings	
Total observations	**2.740**
No stock return (2015-2019)	47
No available ESG-score	1.343
Total observations dropped	1.390
Total observations in data sample	**1.350**

OCEANIA

Droppings	
Total observations	**560**
No stock return (2015-2019)	40
No available ESG-score	189
Total observations dropped	229
Total observations in data sample	**331**

TOTAL DROPPINGS

Droppings	
Total observations	**4.415**
No stock return (2015-2019)	291
No available ESG-score	1.752
Total observations dropped	2.043
Total observations in data sample	**2.372**

APPENDIX 4: Econometric tests and robustness – Oceania

Appendix 4 show four econometric test for the data collected from the Oceanian region. Panel A presents the results from the Breusch-Pagan test (1979) for Homoskedasticity. Panel B presents the results from the Breusch-Godfrey test (1978) for Autocorrelation. Panel C presents the results from the Jarque-Bera test (1980) for Normality. Significance levels: p-value < 0.05 (*). p-value < 0.01 (**). p-value < 0.0001 (***).

Oceania												
Portfolios	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	LS PF	MRA
Panel A: Breusch-Pagan test results												
BP test statistics	4.32	5.50	5.43	4.59	31.06	3.33	3.98	13.11	7.63	6.52	3.11	35.56
p-value	0.50	0.36	0.37	0.47	0.00***	0.65	0.55	0.02*	0.18	0.26	0.68	0.13
Panel B: Breusch-Godfrey test results												
BG test statistics	0.17	0.56	0.32	0.64	0.88	0.00	0.69	0.34	1.15	0.08	0.08	0.64
p-value	0.68	0.46	0.57	0.42	0.35	0.99	0.40	0.56	0.28	0.45	0.78	0.43
Panel C: Jarque-Bera test results												
JB test statistics	0.60	0.59	0.88	0.45	0.14	0.87	0.91	0.10	0.51	0.01	0.51	0.05
p-value	0.74	0.74	0.64	0.80	0.93	0.65	0.64	0.95	0.77	0.99	0.77	0.97

APPENDIX 5: Econometric tests and robustness – Asia

Appendix 5 show four econometric test for the data collected from the Asian region. Panel A presents the results from the Breusch-Pagan test (1979) for Homoskedasticity. Panel B presents the results from the Breusch-Godfrey test (1978) for Autocorrelation. Panel C presents the results from the Jarque-Bera test (1980) for Normality. Significance levels: p-value < 0.05 (*). p-value < 0.01 (**). p-value < 0.0001 (***).

Asia												
Portfolios	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	LS PF	MRA
Panel A: Breusch-Pagan test results												
BP test statistics	1.87	2.72	0.80	2.26	8.22	7.45	5.91	4.75	8.20	3.78	2.66	163.65
p-value	0.87	0.74	0.98	0.81	0.14	0.19	0.32	0.45	0.15	0.58	0.75	0.00***
Panel B: Breusch-Godfrey test results												
BG test statistics	0.18	0.03	3.70	0.01	4.02	8.23	0.00	0.14	3.90	3.48	1.39	44.68
p-value	0.67	0.87	0.05	0.93	0.05*	0.01**	0.99	0.71	0.05*	0.06	0.24	0.00***
Panel C: Jarque-Bera test results												
JB test statistics	0.49	1.39	0.51	0.03	3.30	0.31	0.19	1.15	0.75	0.82	0.01	0.33
p-value	0.78	0.50	0.77	0.98	0.19	0.86	0.91	0.56	0.69	0.66	1.00	0.85

APPENDIX 6: VIF test for multicollinearity – Europe

```
Call:
imcdiag(mod = LM4)


All Individual Multicollinearity Diagnostics Result

                               VIF    TOL       Wi        Fi Leamer     CVIF Klein   IND1   IND2
ESG                        39.3044 0.0254 978.2346 1018.8961 0.1595 124.7751     1 0.0010 1.7913
E                           7.9302 0.1261 176.9878  184.3446 0.3551  25.1753     1 0.0049 1.6063
S                          10.0953 0.0991 232.2802  241.9352 0.3147  32.0484     1 0.0039 1.6560
G                           7.0450 0.1419 154.3805  160.7975 0.3768  22.3650     1 0.0056 1.5772
MKTRF                       1.6030 0.6238  15.3997   16.0399 0.7898   5.0889     0 0.0244 0.6914
SMB                         1.3991 0.7148  10.1913   10.6149 0.8454   4.4414     0 0.0280 0.5243
HML                         1.9670 0.5084  24.6961   25.7226 0.7130   6.2445     1 0.0199 0.9036
MOM                         1.1520 0.8681   3.8806    4.0419 0.9317   3.6570     0 0.0340 0.2425
Momentum                    1.3650 0.7326   9.3219    9.7094 0.8559   4.3334     0 0.0287 0.4915
IdioRisk                    1.7802 0.5617  19.9247   20.7528 0.7495   5.6513     1 0.0220 0.8056
Size                        3.6842 0.2714  68.5513   71.4007 0.5210  11.6959     1 0.0106 1.3392
ROA                         1.5606 0.6408  14.3168   14.9119 0.8005   4.9542     0 0.0251 0.6603
DE                          1.5188 0.6584  13.2483   13.7990 0.8114   4.8214     0 0.0258 0.6278
DPR                         1.2834 0.7792   7.2384    7.5393 0.8827   4.0744     0 0.0305 0.4059
Earnings                    5.5675 0.1796 116.6474  121.4960 0.4238  17.6746     1 0.0070 1.5079
Debt                        3.3741 0.2964  60.6304   63.1506 0.5444  10.7113     1 0.0116 1.2933
FCF                         2.6040 0.3840  40.9629   42.6656 0.6197   8.2665     1 0.0150 1.1322
SectorConsumerDiscretionary 2.6161 0.3822  41.2738   42.9894 0.6183   8.3052     1 0.0150 1.1355
SectorConsumerStaples       1.9350 0.5168  23.8775   24.8700 0.7189   6.1427     1 0.0202 0.8882
SectorEnergy                1.5765 0.6343  14.7230   15.3350 0.7964   5.0048     0 0.0248 0.6722
SectorFinancials            2.9958 0.3338  50.9689   53.0874 0.5778   9.5103     1 0.0131 1.2245
SectorHealthCare            2.4308 0.4114  36.5403   38.0591 0.6414   7.7168     1 0.0161 1.0819
SectorIndustrials           4.0085 0.2495  76.8332   80.0269 0.4995  12.7254     1 0.0098 1.3795
SectorInformationTechnology 2.1045 0.4752  28.2073   29.3798 0.6893   6.6809     1 0.0186 0.9647
SectorMaterials             2.4887 0.4018  38.0194   39.5997 0.6339   7.9006     1 0.0157 1.0995
SectorRealEstate            1.3307 0.7515   8.4467    8.7978 0.8669   4.2246     0 0.0294 0.4568
SectorUtilities             1.8429 0.5426  21.5266   22.4214 0.7366   5.8505     1 0.0212 0.8407

1 --> COLLINEARITY is detected by the test
0 --> COLLINEARITY is not detected by the test

ESG , E , S , SMB , MOM , Momentum , IdioRisk , Size , DPR , Debt , FCF , SectorConsumerStaples , SectorFinancials , SectorInformation
Technology , SectorMaterials , coefficient(s) are non-significant may be due to multicollinearity

R-square of y on all x: 0.4094

* use method argument to check which regressors may be the reason of collinearity
===================================
```

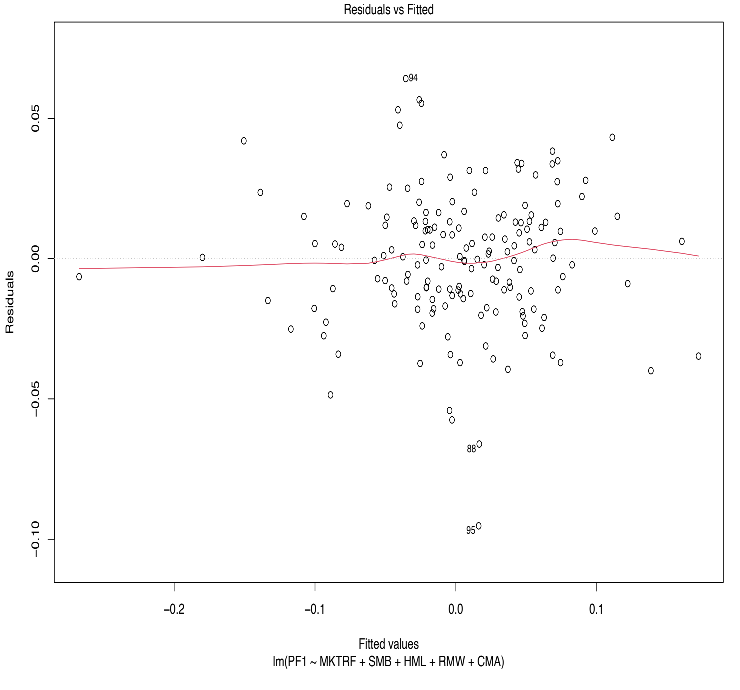
APPENDIX 7: VIF test for multicollinearity – Asia

```
Call:
imcdiag(mod = LM4)


All Individual Multicollinearity Diagnostics Result

                               VIF    TOL        Wi        Fi Leamer    CVIF Klein   IND1   IND2
ESG                        49.1171 0.0204 2448.4223 2548.2838 0.1427 82.8461     1 0.0004 1.6733
E                           9.6508 0.1036  440.1923  458.1460 0.3219 16.2780     1 0.0020 1.5311
S                          15.2457 0.0656  724.8874  754.4527 0.2561 25.7150     1 0.0013 1.5961
G                           5.7599 0.1736  242.2037  252.0822 0.4167  9.7152     1 0.0034 1.4116
MKTRF                       1.4387 0.6951   22.3206   23.2310 0.8337  2.4266     0 0.0137 0.5208
SMB                         1.4720 0.6794   24.0154   24.9949 0.8242  2.4828     0 0.0134 0.5477
HML                         1.8318 0.5459   42.3281   44.0545 0.7388  3.0898     1 0.0107 0.7757
MOM                         1.5165 0.6594   26.2798   27.3516 0.8121  2.5578     1 0.0130 0.5817
Momentum                    1.5704 0.6368   29.0271   30.2110 0.7980  2.6489     1 0.0125 0.6205
IdioRisk                    1.6891 0.5920   35.0632   36.4933 0.7694  2.8490     1 0.0116 0.6968
Size                        2.5412 0.3935   78.4222   81.6208 0.6273  4.2862     1 0.0077 1.0359
ROA                         1.6428 0.6087   32.7080   34.0420 0.7802  2.7709     1 0.0120 0.6684
DE                          2.0376 0.4908   52.7973   54.9507 0.7006  3.4368     1 0.0096 0.8698
DPR                         1.1884 0.8415    9.5866    9.9776 0.9173  2.0045     0 0.0165 0.2708
Earnings                    4.7133 0.2122  188.9473  196.6537 0.4606  7.9499     1 0.0042 1.3457
Debt                        3.2713 0.3057  115.5740  120.2879 0.5529  5.5177     1 0.0060 1.1860
FCF                         2.4421 0.4095   73.3794   76.3722 0.6399  4.1191     1 0.0080 1.0087
SectorConsumerDiscretionary 3.3140 0.3017  117.7484  122.5509 0.5493  5.5898     1 0.0059 1.1927
SectorConsumerStaples       2.6982 0.3706   86.4102   89.9346 0.6088  4.5510     1 0.0073 1.0751
SectorEnergy                1.9157 0.5220   46.5962   48.4967 0.7225  3.2313     1 0.0103 0.8165
SectorFinancials            3.8086 0.2626  142.9142  148.7431 0.5124  6.4240     1 0.0052 1.2596
SectorHealthCare            2.0648 0.4843   54.1823   56.3922 0.6959  3.4827     1 0.0095 0.8809
SectorIndustrials           4.7028 0.2126  188.4169  196.1017 0.4611  7.9323     1 0.0042 1.3449
SectorInformationTechnology 3.4043 0.2937  122.3423  127.3322 0.5420  5.7421     1 0.0058 1.2064
SectorMaterials             3.3790 0.2959  121.0534  125.9907 0.5440  5.6993     1 0.0058 1.2026
SectorRealEstate            1.9868 0.5033   50.2136   52.2616 0.7094  3.3512     1 0.0099 0.8484
SectorUtilities             1.9506 0.5127   48.3692   50.3420 0.7160  3.2900     1 0.0101 0.8324

1 --> COLLINEARITY is detected by the test
0 --> COLLINEARITY is not detected by the test

ESG , E , G , MKTRF , HML , MOM , IdioRisk , ROA , Earnings , Debt , SectorInformationTechnology , SectorRealEstate , SectorUtilities
 , coefficient(s) are non-significant may be due to multicollinearity

R-square of y on all x: 0.3275

* use method argument to check which regressors may be the reason of collinearity
```

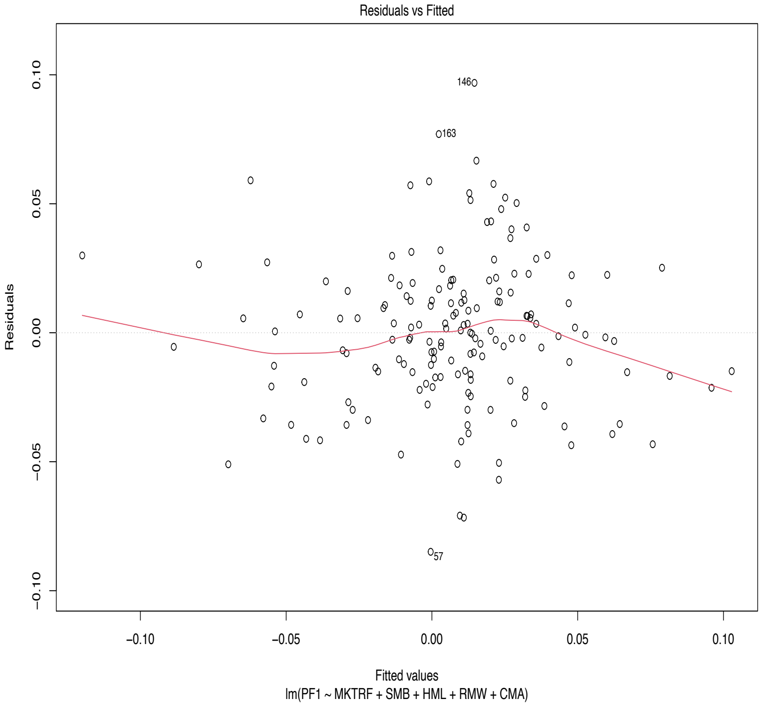
APPENDIX 8: VIF test for multicollinearity – Oceania

```
Call:
imcdiag(mod = LM4)


All Individual Multicollinearity Diagnostics Result

                                VIF    TOL       Wi       Fi Leamer    CVIF Klein   IND1   IND2
ESG                         40.1864 0.0249 458.1794 478.0740 0.1577 48.9857     1 0.0021 1.6571
E                            8.6103 0.1161  88.9814  92.8451 0.3408 10.4956     1 0.0099 1.5020
S                           11.7422 0.0852 125.6007 131.0544 0.2918 14.3133     1 0.0073 1.5547
G                            5.9549 0.1679  57.9347  60.4503 0.4098  7.2589     1 0.0144 1.4140
MKTRF                        1.6489 0.6065   7.5874   7.9168 0.7788  2.0100     1 0.0519 0.6688
SMB                          1.8115 0.5520   9.4883   9.9003 0.7430  2.2081     1 0.0472 0.7613
HML                          1.6128 0.6200   7.1651   7.4762 0.7874  1.9659     1 0.0530 0.6457
MOM                          1.4580 0.6859   5.3556   5.5881 0.8282  1.7773     0 0.0587 0.5339
Momentum                     1.3256 0.7544   3.8066   3.9719 0.8686  1.6158     0 0.0645 0.4174
IdioRisk                     2.5415 0.3935  18.0235  18.8061 0.6273  3.0980     1 0.0337 1.0307
Size                         3.9293 0.2545  34.2499  35.7371 0.5045  4.7896     1 0.0218 1.2669
ROA                          1.2845 0.7785   3.3268   3.4713 0.8823  1.5658     0 0.0666 0.3764
DE                           1.7130 0.5838   8.3364   8.6984 0.7641  2.0881     1 0.0499 0.7073
DPR                          1.6802 0.5952   7.9532   8.2986 0.7715  2.0481     1 0.0509 0.6880
Earnings                     5.3834 0.1858  51.2518  53.4773 0.4310  6.5621     1 0.0159 1.3837
Debt                         4.6020 0.2173  42.1154  43.9441 0.4662  5.6096     1 0.0186 1.3301
FCF                          2.1261 0.4703  13.1668  13.7385 0.6858  2.5916     1 0.0402 0.9001
SectorConsumerDiscretionary  3.0306 0.3300  23.7425  24.7734 0.5744  3.6942     1 0.0282 1.1386
SectorConsumerStaples        2.2625 0.4420  14.7615  15.4025 0.6648  2.7579     1 0.0378 0.9483
SectorEnergy                 2.3843 0.4194  16.1862  16.8890 0.6476  2.9064     1 0.0359 0.9867
SectorFinancials             2.6679 0.3748  19.5020  20.3488 0.6122  3.2521     1 0.0321 1.0624
SectorHealthCare             2.0653 0.4842  12.4555  12.9964 0.6958  2.5175     1 0.0414 0.8766
SectorIndustrials            3.2475 0.3079  26.2787  27.4197 0.5549  3.9586     1 0.0263 1.1761
SectorInformationTechnology  2.2565 0.4432  14.6919  15.3299 0.6657  2.7506     1 0.0379 0.9463
SectorMaterials              4.1827 0.2391  37.2130  38.8288 0.4890  5.0985     1 0.0204 1.2931
SectorRealEstate             2.4111 0.4148  16.4984  17.2148 0.6440  2.9390     1 0.0355 0.9946
SectorUtilities              1.7700 0.5650   9.0029   9.3938 0.7516  2.1575     1 0.0483 0.7393

1 --> COLLINEARITY is detected by the test
0 --> COLLINEARITY is not detected by the test

ESG , E , S , G , SMB , HML , MOM , Momentum , IdioRisk , ROA , DE , DPR , Earnings , Debt , SectorConsumerDiscretionary , SectorEnerg
y , SectorFinancials , SectorIndustrials , SectorMaterials , SectorRealEstate , coefficient(s) are non-significant may be due to multi
collinearity

R-square of y on all x: 0.3375

* use method argument to check which regressors may be the reason of collinearity
```

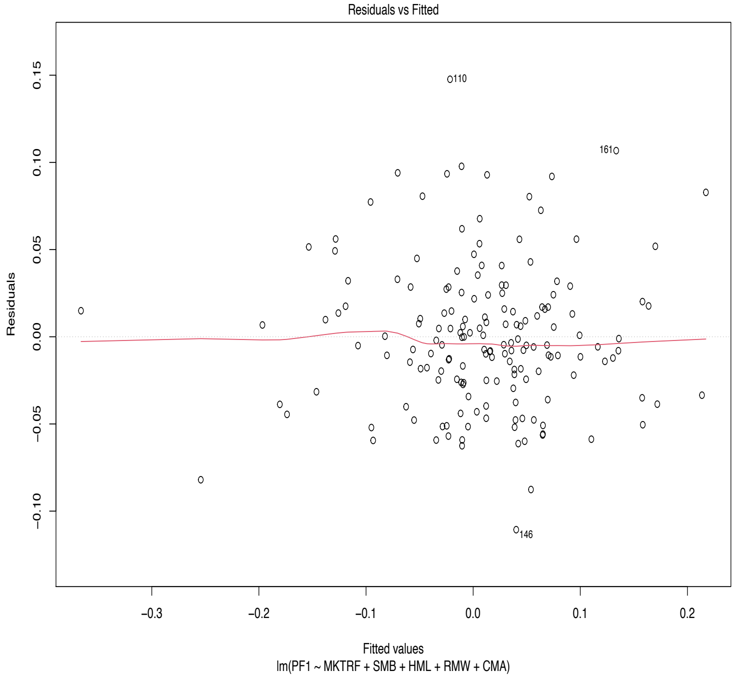
APPENDIX 9: Test for linearity – Europe



APPENDIX 10: Test for linearity – Asia



APPENDIX 11: Test for linearity - Oceania



APPENDIX 12: Coefficients from the FF4 and C4 models – Europe

EUROPE											
Portfolios	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-PF1
Panel A: Fama French 3-Factor Model											
Alpha	-1.13%	-1.42%	-1.06%	0.07%	0.74%	1.18%	-4.06%*	0.35%	0.08%	-2.05%	-1.30%
	[-0.48]	[-0.78]	[-0.65]	[0.04]	[0.41]	[0.78]	[-2.03]	[0.24]	[0.05]	[-1.41]	[0.00]
MKT	1.05***	1.10***	1.10***	1.16***	1.14***	1.04***	1.08***	0.98***	1.05***	1.14***	0.08
	[26.46]	[35.61]	[39.70]	[36.07]	[37.23]	[40.95]	[32.04]	[40.25]	[42.82]	[46.65]	[0.04]
SMB	0.31**	0.37***	0.44***	0.23**	-0.04	0.03	0.05	-0.28***	-0.22***	-0.39***	-0.71***
	[3.03]	[4.64]	[6.20]	[2.79]	[-0.46]	[-0.47]	[0.62]	[-4.54]	[-3.50]	[-6.22]	[0.11]
HML	0.00	-0.02	-0.03	-0.15*	0.01	0.04	0.04	0.15**	0.30***	0.33***	0.32**
	[0.04]	[-0.25]	[-0.53]	[-2.13]	[0.15]	[0.71]	[0.48]	[2.75]	[5.66]	[6.16]	[0.09]
Adj. R^2	0.85	0.91	0.93	0.91	0.92	0.93	0.89	0.93	0.95	0.95	0.28
Panel B: Carhart 4-Factor Model											
Alpha	-1.28%	-0.82%	-1.04%	1.30%	2.19%	1.55%	-4.02%	0.53%	0.20%	-1.61%	-0.63%
	[-0.53]	[-0.44]	[-0.62]	[0.69]	[1.24]	[1.01]	[-1.96]	[0.36]	[0.13]	[-1.09]	[0.00]
MKT	1.05***	1.08***	1.10***	1.13***	1.10***	1.04***	1.08***	0.97***	1.04***	1.13***	0.06
	[25.45]	[33.95]	[38.03]	[34.82]	[36.42]	[39.08]	[30.68]	[38.44]	[40.93]	[44.60]	[0.04]
SMB	0.31**	0.36***	0.44***	0.22**	-0.05	-0.03	0.05	-0.28***	-0.22***	-0.39***	-0.71***
	[3.03]	[4.58]	[6.17]	[2.72]	[-0.68]	[-0.53]	[0.61]	[-4.56]	[-3.51]	[-6.31]	[0.11]
HML	0.02	-0.07	-0.03	-0.27***	-0.13	0.00	0.03	0.13*	0.29***	0.29***	0.26*
	[0.19]	[-0.99]	[-0.49]	[-3.50]	[-1.81]	[0.06]	[0.38]	[2.16]	[4.83]	[4.80]	[0.11]
WML	0.02	-0.08	0.00	-0.16***	-0.19***	-0.05	-0.01	-0.02	-0.02	-0.06	-0.08
	[0.33]	[-1.67]	[-0.05]	[-3.38]	[-4.24]	[-1.25]	[-0.10]	[-0.62]	[-0.41]	[-1.52]	[0.07]
Adj. R^2	0.85	0.91	0.93	0.92	0.93	0.93	0.89	0.93	0.94	0.95	0.28

APPENDIX 13: Coefficients from the FF4 and C4 models – Asia

ASIA											
Portfolios	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-PF1
Panel A: Fama French 3-Factor Model											
Alpha	4.99%*	9.22%*	2.86%	2.10%	3.29%	3.00%	0.91%	-1.30%	1.06%	2.97%	-5.65%*
	[2.01]	[2.37]	[0.83]	[0.51]	[0.75]	[0.80]	[0.34]	[-0.47]	[0.42]	[0.00]	[0.00]
MKT	0.74***	0.80***	0.81***	0.87***	0.85***	0.91***	0.87***	0.69***	0.83***	0.96***	0.22***
	[13.49]	[10.21]	[11.73]	[10.60]	[9.69]	[12.18]	[15.94]	[15.69]	[16.28]	[20.12]	[0.05]
SMB	-0.13	-0.35*	-0.35**	-0.24	-0.40*	-0.48***	-0.21*	-0.31**	-0.33***	-0.41***	-0.28**
	[-1.23]	[-2.36]	[-2.69]	[-1.55]	[-2.39]	[-3.36]	[-2.06]	[-2.99]	[-3.42]	[-4.50]	[0.09]
HML	-0.21*	-0.24	-0.21*	-0.32*	-0.19	-0.26*	-0.10	-0.09	-0.10	-0.07	0.14
	[-2.36]	[-1.86]	[-1.81]	[-2.40]	[-1.34]	[-2.11]	[-1.12]	[-0.94]	[-1.15]	[-0.86]	[0.08]
Adj. R^2	0.56	0.43	0.49	0.44	0.40	0.52	0.63	0.62	0.64	0.74	0.15
Panel B: Carhart 4-Factor Model											
Alpha	5.59%*	9.21%*	2.83%	2.04%	3.37%	2.93%	0.90%	-1.34%	1.03%	-0.07%	-5.77%*
	[2.03]	[2.36]	[0.82]	[0.50]	[0.74]	[0.78]	[0.33]	[-0.48]	[0.41]	[-0.03]	[0.00]
MKT	0.76***	0.79***	0.80***	0.84***	0.84***	0.89***	0.86***	0.85***	0.81***	0.94***	0.17***
	[13.52]	[9.89]	[11.25]	[10.06]	[9.24]	[11.57]	[15.37]	[15.05]	[15.64]	[19.36]	[0.05]
SMB	-0.16	-0.35*	-0.33*	-0.20	-0.37*	-0.43**	-0.20	-0.29**	-0.31**	-0.35***	-0.19*
	[-1.52]	[-2.27]	[-2.47]	[-1.25]	[-2.14]	[-2.96]	[-1.89]	[-2.68]	[-3.12]	[-3.88]	[0.09]
HML	-0.19*	-0.24	-0.22	-0.36*	-0.22	-0.30*	-0.11	-0.10	-0.11	-0.11	0.07
	[-2.04]	[-1.83]	[-1.91]	[-2.60]	[-1.48]	[-2.38]	[-1.21]	[-1.13]	[-1.32]	[-1.39]	[0.08]
WML	0.10	-0.01	-0.06	-0.12	-0.09	-0.15	-0.04	-0.07	-0.06	-0.16**	-0.25***
	[1.37]	[-0.10]	[-0.70]	[-1.22]	[-0.86]	[-1.57]	[-0.55]	[-1.06]	[-1.02]	[-2.71]	[0.06]
Adj. R^2	0.56	0.42	0.49	0.45	0.39	0.53	0.63	0.62	0.64	0.75	0.23

APPENDIX 14: Coefficients from the FF4 and C4 models - Oceania

OCEANIA											
Portfolios	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-PF1
Panel A: Fama French 3-Factor Model											
Alpha	5.47%	7.65%	8.73%*	4.99%	-1.80%	1.39%	0.74%	-0.33%	-5.17%	1.83%	-3.76%
	[1.31]	[1.46]	[2.00]	[1.16]	[-0.43]	[0.38]	[0.18]	[-0.09]	[-1.59]	[0.84]	[0.00]
MKT	1.17***	1.11***	1.16***	1.15***	1.17***	1.03***	1.03***	1.13***	1.05***	1.06***	-0.10
	[20.46]	[15.48]	[19.35]	[19.66]	[20.53]	[20.45]	[17.95]	[22.43]	[23.53]	[35.47]	[0.05]
SMB	0.33*	1.20	0.12	1.69	0.18	0.00	-0.16	-0.05	-0.23*	-0.29***	-0.62***
	[2.57]	[1.23]	[0.91]	[0.22]	[1.40]	[0.02]	[-1.25]	[-0.43]	[-2.27]	[-4.28]	[0.13]
HML	-0.9***	-0.45*	-0.97***	-0.67***	-0.46***	-0.75***	-0.56***	-0.24	-0.59***	-0.43***	0.36*
	[-5.55]	[-2.52]	[-6.48]	[-4.54]	[-3.25]	[-5.94]	[-3.91]	[-1.94]	[-5.31]	[-5.75]	[0.14]
Adj. R^2	0.76	0.62	0.74	0.74	0.74	0.75	0.69	0.76	0.79	0.89	0.17
Panel B: Carhart 4-Factor Model											
Alpha	4.98%	7.73%	8.46%	4.80%	-3.21%	1.26%	-0.36%	-0.69%	-5.97%	1.16%	-3.94%
	[1.18]	[1.46]	[1.92]	[1.11]	[-0.78]	[0.34]	[-0.09]	[-0.19]	[-1.83]	[0.53]	[0.00]
MKT	1.21***	1.11***	1.18***	1.17***	1.28***	1.04***	1.12***	1.16***	1.11***	1.11***	-0.09
	[17.35]	[12.61]	[16.15]	[16.31]	[18.85]	[16.92]	[16.16]	[18.88]	[20.66]	[31.09]	[0.07]
SMB	0.36**	0.20	0.14	0.24	0.27*	0.01	-0.09	-0.03	-0.18	-0.25***	-0.61***
	[2.73]	[1.16]	[1.01]	[1.72]	[2.09]	[0.10]	[-0.68]	[-0.22]	[-1.72]	[-3.58]	[0.13]
HML	-0.9***	-0.44*	-1.00***	-0.69***	-0.63***	-0.76***	-0.69***	-0.29*	-0.69***	-0.51***	0.34*
	[-5.50]	[-2.23]	[-6.16]	[-4.31]	[-4.17]	[-5.57]	[-4.50]	[-2.10]	[-5.73]	[-6.38]	[0.15]
WML	0.21	-0.03	0.12	0.08	0.60**	0.06	0.46*	0.16	0.34*	0.28*	0.07
	[0.98]	[-0.11]	[0.52]	[0.37]	[2.85]	[0.30]	[2.19]	[0.83]	[2.03]	[2.57]	[0.22]
Adj. R^2	0.76	0.62	0.74	0.74	0.75	0.75	0.70	0.76	0.80	0.90	0.17

APPENDIX 15: Sub-question one – Correlation between variables – Europe

	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-1	MKT	SMB	HML	RMW	CMA	WML
PF1	1																
PF2	0.9032	1															
PF3	0.9050	0.9431	1														
PF4	0.8990	0.9282	0.9287	1													
PF5	0.9079	0.9283	0.9242	0.9310	1												
PF6	0.9017	0.9262	0.9255	0.9129	0.9385	1											
PF7	0.8944	0.9082	0.9339	0.9281	0.9059	0.9110	1										
PF8	0.8849	0.9204	0.9123	0.9013	0.9202	0.9342	0.9044	1									
PF9	0.8925	0.9217	0.9086	0.9101	0.9335	0.9486	0.9254	0.9417	1								
PF10	0.8839	0.9121	0.9168	0.9073	0.9343	0.9459	0.9318	0.9461	0.9736	1							
PF10-1	-0.0640	0.1848	0.1914	0.1827	0.2231	0.2600	0.2441	0.2931	0.3369	0.4101	1						
MKT	0.9219	0.9497	0.9559	0.9508	0.9594	0.9664	0.9466	0.9609	0.9647	0.9648	0.2610	1					
SMB	0.1240	0.1402	0.1602	0.1008	0.0213	0.0209	0.0456	-0.0653	-0.0420	-0.0826	-0.4180	0.0327	1				
HML	0.4642	0.4719	0.4690	0.4374	0.4945	0.5076	0.4935	0.5463	0.5877	0.5909	0.3558	0.5116	-0.0681	1			
RMW	-0.3939	-0.3543	-0.3583	-0.3013	-0.3643	-0.3923	-0.3935	-0.3935	-0.4326	-0.4639	-0.2217	-0.3802	-0.0173	-0.7809	1		
CMA	-0.2487	-0.2180	-0.2426	-0.2734	-0.2174	-0.1434	-0.2176	-0.1132	-0.0827	-0.0733	0.3287	-0.1879	-0.2775	0.4331	-0.3543	1	
WML	-0.4473	-0.4990	-0.4722	-0.5117	-0.5474	-0.5058	-0.4768	-0.5105	-0.5276	-0.5405	-0.2810	-0.4976	-0.0136	-0.5949	0.4384	0.0525	1

APPENDIX 16: Sub-question one – Correlation between variables – Asia

	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-1	MKT	SMB	HML	RMW	CMA	WML
PF1	1																
PF2	0.9067	1															
PF3	0.8644	0.8989	1														
PF4	0.7925	0.8283	0.8785	1													
PF5	0.7644	0.8231	0.8581	0.8706	1												
PF6	0.8010	0.8328	0.8988	0.8890	0.8936	1											
PF7	0.8037	0.7934	0.8652	0.8651	0.8370	0.8688	1										
PF8	0.8330	0.8195	0.8766	0.8513	0.8502	0.9016	0.8626	1									
PF9	0.7969	0.8103	0.8656	0.8303	0.7853	0.8383	0.8970	0.8677	1								
PF10	0.8016	0.7924	0.8441	0.7949	0.7866	0.8455	0.8611	0.8720	0.8788	1							
PF10-1	-0.1440	-0.0219	0.1260	0.1501	0.1778	0.2214	0.2433	0.2182	0.2824	0.4763	1						
MKT	0.7399	0.6427	0.6910	0.6577	0.6218	0.7025	0.7893	0.7815	0.7913	0.8412	0.3043	1					
SMB	-0.0919	-0.1649	-0.1813	-0.1077	-0.1760	-0.2117	-0.1495	-0.1967	-0.2119	-0.2428	-0.2667	-0.0799	1				
HML	-0.2354	-0.1853	-0.1821	-0.2313	-0.1515	-0.1888	-0.1648	-0.1430	-0.1490	-0.1330	0.1260	-0.1727	-0.2400	1			
RMW	-0.0665	-0.1462	-0.1910	-0.1878	-0.1926	-0.2403	-0.1976	-0.2327	-0.2337	-0.3090	-0.4136	-0.2032	0.2786	-0.2069	1		
CMA	0.1030	0.0728	0.0964	0.1440	0.0947	0.1315	0.0537	0.1029	0.0821	0.0935	0.0032	0.0501	0.0677	-0.5797	0.1472	1	
WML	-0.3482	-0.3403	-0.3652	-0.4495	-0.4091	-0.4060	-0.3774	-0.3646	-0.3154	-0.3827	-0.1213	-0.3098	0.0027	0.5156	0.2656	-0.4935	1

APPENDIX 17: Sub-question one – Correlation between variables - Oceania

	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-1	MKT	SMB	HML	RMW	CMA	WML
PF1	1																
PF2	0.8186	1															
PF3	0.8096	0.7617	1														
PF4	0.7958	0.7922	0.8338	1													
PF5	0.7923	0.7593	0.8186	0.8025	1												
PF6	0.8163	0.7642	0.8504	0.7991	0.8039	1											
PF7	0.7848	0.7419	0.8152	0.7773	0.7900	0.8307	1										
PF8	0.8041	0.7438	0.8028	0.8052	0.7959	0.8122	0.7848	1									
PF9	0.7897	0.7183	0.8053	0.8120	0.8123	0.8276	0.7991	0.7459	1								
PF10	0.8354	0.7607	0.8180	0.8248	0.8354	0.8638	0.8375	0.8445	0.8756	1							
PF10-1	-0.6283	-0.4056	-0.3083	-0.2736	-0.2523	-0.2555	-0.2357	-0.2607	-0.1905	-0.0973	1						
MKT	0.8408	0.7808	0.8243	0.8378	0.8525	0.8406	0.8145	0.8730	0.8698	0.9295	-0.2068	1					
SMB	0.2247	0.1705	0.1651	0.1916	0.1769	0.1303	0.0674	0.1041	0.0501	0.0259	-0.3701	0.1307	1				
HML	-0.3589	-0.2557	-0.3944	-0.3260	-0.2753	-0.3678	-0.3007	-0.2187	-0.3261	-0.2924	0.2360	-0.1695	-0.1062	1			
RMW	-0.5557	-0.5136	-0.5592	-0.5540	-0.4747	-0.5592	-0.4543	-0.5107	-0.5035	-0.5240	0.2645	-0.5877	-0.2858	0.4154	1		
CMA	-0.1382	-0.1428	-0.1607	-0.0310	-0.0928	-0.1620	-0.1684	-0.2576	-0.0206	-0.1361	0.0576	-0.1563	0.0067	-0.1662	0.1701	1	
WML	0.1370	0.0619	0.1507	0.0822	0.1013	0.1598	0.2149	0.0438	0.1475	0.1005	-0.1058	-0.0876	-0.3173	-0.5055	0.0946	0.0332	1

APPENDIX 18: Multiple regression analysis – Variable definitions

BHRRQ1	BHRRQ1 is the buy-and-hold raw return for each stock in the period from 31/12/2019 until 31/03/2020 (Quarter 1 of 2020)
ESG	Refinitiv EIKON ESGScore for FY2019
E	Refinitiv EIKON EScore for FY2019
S	Refinitiv EIKON SScore for FY2019
G	Refinitiv EIKON GScore for FY2019
MKT	Coefficient on Carhart 4-factor model
SMB	Coefficient on Carhart 4-factor model
HML	Coefficient on Carhart 4-factor model
MOM	Coefficient on Carhart 4-factor model
IdioRisk	The risk specific to an investment in particular stock, also referred to as idiosyncratic or firm-specific risk. Requiring at least 12 months of available stock return.
Momentum	The 12-month raw buy-and-hold return before the start of the period. Return for the full year of 2019.
Size	The natural logarithm of Market Capitalization collected from Refinitiv Eikon database
FCF	A company's free cash flow collected from Refinitiv Eikon Database
Earnings	A company's earnings before tax collected from Refinitiv Eikon Database
Debt	A company's total debt collected from Refinitiv Eikon Database
DE	A company's total debt collected from Refinitiv Eikon Database
ROA	A company's ROA collected from Refinitiv Eikon Database
DPR	A company's Dividend Payout Ratio collected from Refinitiv Eikon Database

APPENDIX 19: Sub-question two – Correlation between variables – Europe

	BHARQ1	ESG	E	S	G	MKT	SMB	HML	MOM	IdioRisk	MOM2	Size	FCF	ROA	Debt	DPR	DE
BHARQ1	1																
ESG	0.0526	1															
E	0.0265	0.8355	1														
S	0.1120	0.8685	0.7006	1													
G	-0.0334	0.7187	0.3947	0.4239	1												
MKT	-0.3492	0.0209	-0.0107	0.0378	0.0089	1											
SMB	-0.1485	-0.3144	-0.2607	-0.2966	-0.1967	0.0129	1										
HML	-0.3844	0.0327	0.0665	-0.0043	0.0148	0.2119	0.0489	1									
MOM	-0.1019	-0.0851	-0.0403	-0.0795	-0.0655	-0.0274	-0.0577	0.1410	1								
IdioRisk	-0.2062	-0.2246	-0.2512	-0.1927	-0.1492	0.3962	0.1679	0.2285	0.0381	1							
MOM2	0.0976	0.0656	0.0373	0.0807	0.0621	0.2343	-0.1517	-0.2276	-0.0267	0.0723	1						
Size	0.2238	0.5534	0.4826	0.4918	0.4008	-0.1782	-0.3728	-0.1190	-0.0567	-0.4591	0.2179	1					
FCF	-0.0019	0.1995	0.1900	0.1726	0.1338	0.0259	-0.0775	0.0969	0.0306	-0.1481	0.0460	0.3169	1				
ROA	-0.0041	0.3742	0.3550	0.3086	0.2702	-0.0329	-0.2147	0.1518	0.0118	-0.2711	0.0050	0.6215	0.6719	1			
Debt	-0.0910	0.2357	0.2692	0.1887	0.1684	0.0611	-0.0993	0.2517	0.0127	-0.0991	-0.0469	0.3606	0.3492	0.6419	1		
DPR	-0.1509	0.0591	0.0615	0.0509	0.0365	0.0908	-0.0912	0.1853	0.0401	0.0433	-0.0543	0.0039	0.0170	0.0588	0.3437	1	
DE	0.2212	-0.0510	-0.0704	-0.0438	-0.0201	-0.1484	0.0871	-0.2534	-0.0954	-0.1922	0.0786	0.1965	0.1397	0.1301	-0.1600	-0.1998	1

APPENDIX 20: Sub-question two – Correlation between variables – Asia

	BHARQ1	ESG	E	S	G	MKT	SMB	HML	MOM	IdioRisk	MOM2	Size	FCF	ROA	Debt	DPR	DE
BHARQ1	1																
ESG	-0.2042	1															
E	-0.1863	0.8531	1														
S	-0.2575	0.9100	0.7374	1													
G	-0.0153	0.6468	0.3578	0.4083	1												
MKT	-0.0016	-0.0841	-0.0357	-0.1401	0.0155	1											
SMB	-0.1809	0.0769	0.0671	0.0622	0.0450	0.1111	1										
HML	-0.2580	0.0694	0.0938	0.0301	0.0409	0.1552	0.3731	1									
MOM	0.0507	-0.0890	-0.1056	-0.0680	-0.0537	0.0194	-0.2018	0.3216	1								
IdioRisk	0.0693	-0.2474	-0.2694	-0.2527	-0.0636	0.3402	0.1510	0.0628	0.0959	1							
MOM2	0.3067	-0.1257	-0.1147	-0.1344	-0.0288	0.1646	-0.0456	-0.3162	-0.1793	0.2172	1						
Size	0.1910	0.2903	0.2391	0.2760	0.1952	-0.0629	-0.0773	-0.1293	-0.0532	-0.2095	0.2232	1					
FCF	0.0197	0.1069	0.0961	0.0948	0.0736	-0.0317	0.0495	-0.0040	-0.0548	-0.1208	0.0008	0.3567	1				
ROA	0.0353	0.1585	0.1422	0.1354	0.1231	-0.0116	0.0528	0.0239	-0.0738	-0.1440	-0.0149	0.5166	0.8270	1			
Debt	-0.0169	0.1106	0.0913	0.0778	0.1099	0.0023	0.0543	0.0796	-0.1265	-0.1097	-0.0491	0.3399	0.3995	0.5521	1		
DPR	0.1645	-0.0562	-0.0692	-0.0128	-0.0358	-0.0387	-0.0086	-0.1953	0.0651	0.0606	0.1273	0.2147	0.0705	0.0358	-0.1704	1	
DE	-0.0162	0.0147	0.0138	0.0213	0.0056	-0.0673	-0.0311	-0.0224	-0.0059	-0.0975	-0.0172	-0.0517	-0.0305	-0.0291	-0.0172	0.0028	1

APPENDIX 21: Sub-question two – Correlation between variables - Oceania

	BHARQ1	ESG	E	S	G	MKT	SMB	HML	MOM	IdioRisk	MOM2	Size	FCF	ROA	Debt	DPR	DE
BHARQ1	1																
ESG	0.0610	1															
E	0.0876	0.8394	1														
S	0.0503	0.8961	0.6916	1													
G	0.0566	0.7755	0.5579	0.5429	1												
MKT	-0.2046	-0.1029	-0.0768	-0.0887	-0.0877	1											
SMB	-0.1433	-0.2281	-0.1983	-0.2011	-0.1699	0.4719	1										
HML	-0.0423	-0.0612	0.0400	-0.0668	0.0006	0.0362	0.3048	1									
MOM	0.1917	-0.0038	-0.0028	0.0167	-0.0800	-0.2924	-0.3079	-0.0718	1								
IdioRisk	-0.1297	-0.4472	-0.3830	-0.3933	-0.3386	0.3800	0.3098	0.2320	-0.0286	1							
MOM2	0.1632	-0.0744	-0.0869	-0.0515	-0.0792	0.0517	0.1151	0.0710	0.1747	0.0670	1						
Size	0.2263	0.6569	0.6482	0.6161	0.4621	-0.1045	-0.2922	-0.0809	0.0657	-0.5490	0.1393	1					
FCF	0.0075	0.1498	0.1498	0.1758	0.0456	0.0382	0.0149	0.0567	-0.0040	-0.0711	0.0120	0.2074	1				
ROA	0.1003	0.0799	0.0540	0.0919	-0.0082	-0.0685	-0.1058	-0.1680	0.1128	-0.0888	0.0486	0.1860	0.0664	1			
Debt	0.0156	0.3021	0.2992	0.2811	0.2195	-0.0174	-0.0498	-0.0098	-0.0004	-0.1569	-0.0439	0.3546	0.3340	-0.0512	1		
DPR	0.0629	0.2159	0.2489	0.1763	0.1478	-0.0841	-0.1410	-0.1032	0.0600	-0.2211	-0.0401	0.2392	-0.1198	0.0704	0.0810	1	
DE	-0.0153	0.1261	0.1168	0.0974	0.0872	-0.0598	-0.0565	-0.0185	0.0106	-0.0603	0.0105	0.0863	-0.0287	-0.0380	0.0652	0.0932	1

APPENDIX 22: Calculation of the idiosyncratic risk

In financial terms risk is defined as the chance that an outcome or investment's actual gains will differ from an expected outcome or return (Chen, 2020). Additionally, two types of risk are often applied in finance, systematic risk and unsystematic risk (idiosyncratic risk). Systematic risk is the risk inherent to the entire market and is known as "undiversifiable risk" because it affects the overall market as a whole and not just a particular stock or sector (Fontinelle, 2021). On the other hand, idiosyncratic risk is the risk unique to a specific company or sector and can in the context of an investment portfolio be reduced through diversification. In finance systematic risk can be estimated using the capital asset pricing model (CAPM) and is often referred to as beta. Furthermore, idiosyncratic risk is the portion of risk that is unexplained in beta.

In the multiple regression model beta (MKT) is estimated through the Carhart 4-model and is applied as an explanatory variable like a company's ESG score. Additionally, we will estimate the idiosyncratic risk of each stock and analyze if a company's idiosyncratic risk can explain a stock's buy-and-hold raw return in the first quarter of 2020. The idiosyncratic risk is calculated as the standard deviation of the residuals from a regression that uses beta to estimate the relationship between the market and a given asset. The calculation is based on 60 months of stock return requiring at least 12 months of available data. Additionally, the market return used to estimate the betas is collected form Kenneth R. French website (French, 2021).

The applied formula's is listed below:

CAPM:

$$E\left[R_{i,t}\text{-}R_{f,t}\right] = \beta_{i,t}\left(R_{m,t} - R_{f,t}\right) + \varepsilon_{i,t}$$

Where $E\left[R_{i,t} - R_{f,t}\right]$ is expected return for stock *i* in period *t*, $\left(R_{m,t} - R_{f,t}\right)$ is the market excess return at time *t*, $\beta_{i,t}$ is the systematic risk of stock *i* at time *t* and $\varepsilon_{i,t}$ is the idiosyncratic return of stock *i* at time *t*.

Residuals

$$\varepsilon_{i,t} = \left[R_{i,t} - R_{f,t}\right] - E\left[R_{i,t} - R_{f,t}\right]$$

Where $\varepsilon_{i,t}$ is the idiosyncratic return for stock *i* at time *t*, $\left[R_{i,t} - R_{f,t}\right]$ is the observed stock *i* return at time *t* and $E\left[R_{i,t}\text{-}R_{f,t}\right]$ is the expected excess return of stock *i* for time *t* based on CAPM above.

Idiosyncratic risk

$$\text{IdioRisk}_{i,t} = \sqrt{\text{var}(\varepsilon_{i,t})}$$

Where $\text{IdioRisk}_{i,t}$ is the estimated idiosyncratic risk of stock *i* for time *t* and $\sqrt{\text{var}(\varepsilon_{i,t})}$ is the standard deviation of stock *i* at time *t*.

APPENDIX 23: Sectors covered in our dataset

Economic sector	Industry groups	Short description
Communication services	› Telecommunication Services	Voice and data services. The most common form of telecommunications service is phone service. Other services may include Internet, television, and networking for businesses and homes
Consumer discretionary	› Cyclical Consumer Services	Goods and services that are classified as non-essential by consumers. Examples include durable goods, high-end apparel, entertainment and leisure
Consumer staples	› Non-Cyclical Consumer Services	Goods that are considered essential products such as Food & Beverages, Household goods, hygiene products, tobacco, medical equipment etc.
Energy	› Coal › Oil and gas › Renewable	Companies that are producing or supplying sources of energy
Financials	› Banking and investment services › Real estate › Insurance	Includes but are not limited to companies that provide investment banking and brokerage services, work as financial & commodity market operators, insurance brokers and real estate developments and operations
Healthcare	› Healthcare services › Pharmaceuticals & Medical research	Includes but are not limited to companies that provide advanced medical equipment, supplies and distribution, biotechnology & medical research and generic and specialty pharmaceuticals
Industrials	› Industrial goods › Industrial services › Transportation	Includes but are not limited to companies that provide construction and engineering, environmental services, heavy machinery and vehicles, airline services and marine services
Information technology	› Software and services › Technology hardware › Semiconductor equipment	Consist of companies that produce software, hardware, internet or related services
Materials	› Chemicals › Mineral resources › Applied resources	Consist of companies that produce or supply commodity, agricultural or diversified chemicals, produce metals and minerals, produce construction materials or produce paper products
Real estate	› Real estate operations › Residential & Commercial REITs	Consist of companies that develop and operate within the real estate industry, provide serv ices and companies that manage diversified, commercial or residential REITs
Utility	› Electric utilities › Natural gas utilities › Water & Other utilities	Consist of companies that provide basic services. Most companies are public service and are therefore heavily regulated

APPENDIX 24: Regressing buy-and-hold excess return (BHARQ1) on E, S and G - Europe

Appendix 24 show the results from regressing the buy-and-hold excess return (BHARQ1) on our independent variables in the full specification model (4). All variables except BHARQ1 and ESG are winsorized at the 2% and 98% levels.

Environmental pillar

```
Call:
lm(formula = BHARQ1 ~ E + MKTRF + SMB + HML + MOM + Momentum +
    IdioRisk + Size + ROA + DE + DPR + Earnings + Debt + FCF +
    Sector, data = Data)

Residuals:
     Min       1Q   Median       3Q      Max
-0.32927 -0.08805 -0.00989  0.08389  0.75964

Coefficients:
                             Estimate Std. Error t value Pr(>|t|)
(Intercept)                 -0.4746419  0.1543025  -3.076 0.002184 **
E                            0.0000642  0.0002636   0.244 0.807683
MKTRF                       -0.0766507  0.0161173  -4.756 2.42e-06 ***
SMB                         -0.0139070  0.0077342  -1.798 0.072609 .
HML                         -0.0354557  0.0092714  -3.824 0.000144 ***
MOM                         -0.0090070  0.0138908  -0.648 0.516941
Momentum                     0.0365122  0.0211250   1.728 0.084382 .
IdioRisk                    -0.3700794  0.2429610  -1.523 0.128182
Size                         0.0330182  0.0153566   2.150 0.031907 *
ROA                          0.4248872  0.1382853   3.073 0.002209 **
DE                          -0.0193421  0.0055303  -3.497 0.000501 ***
DPR                         -0.0204004  0.0141452  -1.442 0.149711
Earnings                    -0.0313500  0.0121489  -2.580 0.010080 *
Debt                         0.0156800  0.0093854   1.671 0.095256 .
FCF                          0.0065763  0.0083047   0.792 0.428714
SectorConsumerDiscretionary -0.1043618  0.0259975  -4.014 6.64e-05 ***
SectorConsumerStaples        0.0490879  0.0286950   1.711 0.087607 .
SectorEnergy                -0.0980534  0.0333399  -2.941 0.003385 **
SectorFinancials            -0.0389411  0.0268672  -1.449 0.147700
SectorHealthCare             0.1027533  0.0282818   3.633 0.000301 ***
SectorIndustrials           -0.0638338  0.0231936  -2.752 0.006080 **
SectorInformationTechnology -0.0279036  0.0321596  -0.868 0.385894
SectorMaterials             -0.0269354  0.0269845  -0.998 0.318556
SectorRealEstate            -0.0958138  0.0436476  -2.195 0.028496 *
SectorUtilities              0.0549519  0.0304677   1.804 0.071744 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1354 on 666 degrees of freedom
Multiple R-squared:  0.3934,	Adjusted R-squared:  0.3716
F-statistic:    18 on 24 and 666 DF,  p-value: < 2.2e-16
```

Social pillar

```
Call:
lm(formula = BHARQ1 ~ S + MKTRF + SMB + HML + MOM + Momentum +
    IdioRisk + Size + ROA + DE + DPR + Earnings + Debt + FCF +
    Sector, data = Data)

Residuals:
     Min       1Q   Median       3Q      Max
-0.34643 -0.08687 -0.01134  0.08430  0.73807

Coefficients:
                             Estimate Std. Error t value Pr(>|t|)
(Intercept)                 -0.3895157  0.1543854  -2.523 0.011867 *
S                            0.0007908  0.0003234   2.445 0.014748 *
MKTRF                       -0.0818636  0.0161456  -5.070 5.15e-07 ***
SMB                         -0.0119958  0.0077360  -1.551 0.121460
HML                         -0.0377786  0.0092316  -4.092 4.80e-05 ***
MOM                         -0.0052250  0.0139003  -0.376 0.707114
Momentum                     0.0400194  0.0210627   1.900 0.057863 .
IdioRisk                    -0.3843403  0.2416390  -1.591 0.112184
Size                         0.0198265  0.0155903   1.272 0.203916
ROA                          0.4850444  0.1374736   3.528 0.000447 ***
DE                          -0.0197541  0.0055085  -3.586 0.000360 ***
DPR                         -0.0253105  0.0141778  -1.785 0.074680 .
Earnings                    -0.0308417  0.0120878  -2.551 0.010949 *
Debt                         0.0163698  0.0093192   1.757 0.079452 .
FCF                          0.0057924  0.0082498   0.702 0.482848
SectorConsumerDiscretionary -0.1074166  0.0257239  -4.176 3.36e-05 ***
SectorConsumerStaples        0.0483888  0.0284442   1.701 0.089375 .
SectorEnergy                -0.0987264  0.0331265  -2.980 0.002985 **
SectorFinancials            -0.0310184  0.0268738  -1.154 0.248822
SectorHealthCare             0.0956811  0.0282726   3.384 0.000756 ***
SectorIndustrials           -0.0662513  0.0230426  -2.875 0.004167 **
SectorInformationTechnology -0.0346734  0.0320232  -1.083 0.279309
SectorMaterials             -0.0282297  0.0266471  -1.059 0.289807
SectorRealEstate            -0.1005897  0.0430692  -2.336 0.019811 *
SectorUtilities              0.0575350  0.0301163   1.910 0.056507 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1348 on 666 degrees of freedom
Multiple R-squared:  0.3988,	Adjusted R-squared:  0.3771
F-statistic: 18.41 on 24 and 666 DF,  p-value: < 2.2e-16
```

Governance pillar

```
Call:
lm(formula = BHARQ1 ~ G + MKTRF + SMB + HML + MOM + Momentum +
    IdioRisk + Size + ROA + DE + DPR + Earnings + Debt + FCF +
    Sector, data = Data)

Residuals:
     Min       1Q   Median       3Q      Max
-0.32548 -0.08360 -0.00654  0.07808  0.76377

Coefficients:
                             Estimate Std. Error t value Pr(>|t|)
(Intercept)                 -0.5449399  0.1519315  -3.587 0.000359 ***
G                           -0.0005832  0.0002500  -2.333 0.019970 *
MKTRF                       -0.0745224  0.0160096  -4.655 3.91e-06 ***
SMB                         -0.0145342  0.0076996  -1.888 0.059505 .
HML                         -0.0347240  0.0091771  -3.784 0.000168 ***
MOM                         -0.0110525  0.0138324  -0.799 0.424559
Momentum                     0.0344353  0.0210294   1.637 0.102002
IdioRisk                    -0.3527841  0.2418463  -1.459 0.145116
Size                         0.0435053  0.0149711   2.906 0.003783 **
ROA                          0.3789709  0.1357901   2.791 0.005407 **
DE                          -0.0191539  0.0055087  -3.477 0.000540 ***
DPR                         -0.0165136  0.0141021  -1.171 0.242016
Earnings                    -0.0311062  0.0120909  -2.573 0.010306 *
Debt                         0.0154737  0.0093220   1.660 0.097404 .
FCF                          0.0069406  0.0082444   0.842 0.400170
SectorConsumerDiscretionary -0.1024152  0.0256905  -3.987 7.45e-05 ***
SectorConsumerStaples        0.0503961  0.0284514   1.771 0.076968 .
SectorEnergy                -0.0954330  0.0331482  -2.879 0.004118 **
SectorFinancials            -0.0411961  0.0266690  -1.545 0.122890
SectorHealthCare             0.1013533  0.0281283   3.603 0.000338 ***
SectorIndustrials           -0.0634093  0.0230216  -2.754 0.006042 **
SectorInformationTechnology -0.0228484  0.0319422  -0.715 0.474671
SectorMaterials             -0.0237089  0.0266624  -0.889 0.374203
SectorRealEstate            -0.0907043  0.0430357  -2.108 0.035434 *
SectorUtilities              0.0567454  0.0301229   1.884 0.060028 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1348 on 666 degrees of freedom
Multiple R-squared:  0.3983,	Adjusted R-squared:  0.3766
F-statistic: 18.37 on 24 and 666 DF,  p-value: < 2.2e-16
```

APPENDIX 25: Regressing buy-and-hold excess return (BHARQ1) on E, S and G - Asia

Appendix 25 show the results from regressing the buy-and-hold excess return (BHARQ1) on our independent variables in the full specification model (4). All variables except BHARQ1 and ESG are winsorized at the 2% and 98% levels.

Environmental pillar

```
Call:
lm(formula = BHARQ1 ~ E + MKTRF + SMB + HML + MOM + Momentum +
    IdioRisk + Size + ROA + DE + DPR + Earnings + Debt + FCF +
    Sector, data = Data)

Residuals:
     Min       1Q   Median       3Q      Max
-0.61265 -0.09611 -0.00110  0.08560  0.66687

Coefficients:
                             Estimate Std. Error t value Pr(>|t|)
(Intercept)                 -0.6309960  0.1468795  -4.296 1.87e-05 ***
E                           -0.0011683  0.0001768  -6.608 5.62e-11 ***
MKTRF                        0.0092965  0.0105795   0.879 0.379708
SMB                         -0.0206541  0.0067101  -3.078 0.002126 **
HML                         -0.0089445  0.0098260  -0.910 0.362839
MOM                          0.0049602  0.0098122   0.506 0.613282
Momentum                     0.1175343  0.0164751   7.134 1.60e-12 ***
IdioRisk                     0.1708308  0.1697329   1.006 0.314374
Size                         0.0474071  0.0147591   3.212 0.001350 **
ROA                          0.0382966  0.1105838   0.346 0.729162
DE                          -0.0157020  0.0053178  -2.953 0.003205 **
DPR                          0.0306890  0.0162594   1.887 0.059317 .
Earnings                     0.0127938  0.0091171   1.403 0.160771
Debt                         0.0124645  0.0075449   1.652 0.098764 .
FCF                         -0.0150679  0.0065599  -2.297 0.021776 *
SectorConsumerDiscretionary -0.0808072  0.0230574  -3.505 0.000473 ***
SectorConsumerStaples        0.0813838  0.0243050   3.348 0.000835 ***
SectorEnergy                -0.1376711  0.0296677  -4.640 3.82e-06 ***
SectorFinancials            -0.0749888  0.0242793  -3.089 0.002053 **
SectorHealthCare             0.0948390  0.0270494   3.506 0.000470 ***
SectorIndustrials           -0.0511742  0.0219994  -2.326 0.020160 *
SectorInformationTechnology -0.0038023  0.0237519  -0.160 0.872838
SectorMaterials             -0.0378837  0.0240298  -1.577 0.115142
SectorRealEstate            -0.0392793  0.0288388  -1.362 0.173420
SectorUtilities              0.0028525  0.0288155   0.099 0.921161
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1543 on 1325 degrees of freedom
Multiple R-squared:  0.2816,	Adjusted R-squared:  0.2686
F-statistic: 21.64 on 24 and 1325 DF,  p-value: < 2.2e-16
```

Social pillar

```
Call:
lm(formula = BHARQ1 ~ S + MKTRF + SMB + HML + MOM + Momentum +
    IdioRisk + Size + ROA + DE + DPR + Earnings + Debt + FCF +
    Sector, data = Data)

Residuals:
     Min       1Q   Median       3Q      Max
-0.57875 -0.09229 -0.00205  0.08501  0.67579

Coefficients:
                             Estimate Std. Error t value Pr(>|t|)
(Intercept)                 -0.7405624  0.1430646  -5.176 2.61e-07 ***
S                           -0.0020124  0.0001832 -10.987  < 2e-16 ***
MKTRF                        0.0015845  0.0102862   0.154 0.877601
SMB                         -0.0170839  0.0065419  -2.611 0.009118 **
HML                         -0.0120505  0.0095280  -1.265 0.206185
MOM                          0.0073588  0.0095040   0.774 0.438899
Momentum                     0.1000288  0.0161531   6.193 7.88e-10 ***
IdioRisk                     0.1008343  0.1636041   0.616 0.537782
Size                         0.0642307  0.0144234   4.453 9.17e-06 ***
ROA                          0.0633799  0.1066592   0.594 0.552461
DE                          -0.0126579  0.0051820  -2.443 0.014710 *
DPR                          0.0385744  0.0158406   2.435 0.015016 *
Earnings                     0.0123362  0.0088703   1.391 0.164543
Debt                         0.0067749  0.0073655   0.920 0.357837
FCF                         -0.0150118  0.0063800  -2.353 0.018771 *
SectorConsumerDiscretionary -0.0955120  0.0223655  -4.271 2.09e-05 ***
SectorConsumerStaples        0.0659210  0.0235324   2.801 0.005164 **
SectorEnergy                -0.1372003  0.0287448  -4.773 2.02e-06 ***
SectorFinancials            -0.0646216  0.0236279  -2.735 0.006322 **
SectorHealthCare             0.0897028  0.0262467   3.418 0.000651 ***
SectorIndustrials           -0.0644747  0.0212824  -3.029 0.002497 **
SectorInformationTechnology  0.0014673  0.0229611   0.064 0.949058
SectorMaterials             -0.0569668  0.0232163  -2.454 0.014266 *
SectorRealEstate            -0.0450286  0.0279318  -1.612 0.107180
SectorUtilities             -0.0202452  0.0279894  -0.723 0.469613
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1501 on 1325 degrees of freedom
Multiple R-squared:  0.3199,	Adjusted R-squared:  0.3076
F-statistic: 25.97 on 24 and 1325 DF,  p-value: < 2.2e-16
```

Governance pillar

```
Call:
lm(formula = BHARQ1 ~ G + MKTRF + SMB + HML + MOM + Momentum +
    IdioRisk + Size + ROA + DE + DPR + Earnings + Debt + FCF +
    Sector, data = Data)

Residuals:
     Min       1Q   Median       3Q      Max
-0.61666 -0.09978 -0.00121  0.09278  0.69136

Coefficients:
                             Estimate Std. Error t value Pr(>|t|)
(Intercept)                 -0.4803555  0.1478048  -3.250 0.001183 **
G                           -0.0001559  0.0001985  -0.786 0.432273
MKTRF                        0.0059800  0.0107443   0.557 0.577914
SMB                         -0.0228842  0.0068116  -3.360 0.000803 ***
HML                         -0.0142435  0.0099536  -1.431 0.152669
MOM                          0.0113816  0.0099236   1.147 0.251621
Momentum                     0.1305605  0.0166642   7.835 9.57e-15 ***
IdioRisk                     0.4210731  0.1681211   2.505 0.012379 *
Size                         0.0267430  0.0147921   1.808 0.070845 .
ROA                          0.1405771  0.1114776   1.261 0.207519
DE                          -0.0157678  0.0054035  -2.918 0.003582 **
DPR                          0.0230547  0.0165177   1.396 0.163020
Earnings                     0.0140190  0.0092620   1.514 0.130367
Debt                         0.0135017  0.0076655   1.761 0.078409 .
FCF                         -0.0166941  0.0066608  -2.506 0.012319 *
SectorConsumerDiscretionary -0.0936039  0.0233737  -4.005 6.56e-05 ***
SectorConsumerStaples        0.0652030  0.0245779   2.653 0.008075 **
SectorEnergy                -0.1612565  0.0299390  -5.386 8.51e-08 ***
SectorFinancials            -0.0721775  0.0246707  -2.926 0.003496 **
SectorHealthCare             0.0806832  0.0273976   2.945 0.003287 **
SectorIndustrials           -0.0672078  0.0222306  -3.023 0.002549 **
SectorInformationTechnology -0.0300532  0.0237899  -1.263 0.206713
SectorMaterials             -0.0570685  0.0242499  -2.353 0.018751 *
SectorRealEstate            -0.0602351  0.0291489  -2.066 0.038979 *
SectorUtilities             -0.0107557  0.0292311  -0.368 0.712965
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1568 on 1325 degrees of freedom
Multiple R-squared:  0.2583,	Adjusted R-squared:  0.2449
F-statistic: 19.23 on 24 and 1325 DF,  p-value: < 2.2e-16
```

APPENDIX 26: Regressing buy-and-hold excess return (BHARQ1) on E, S and G – Oceania

Appendix 26 show the results from regressing the buy-and-hold excess return (BHARQ1) on our independent variables in the full specification model (4). All variables except BHARQ1 and ESG are winsorized at the 2% and 98% levels.

Environmental pillar

```
Call:
lm(formula = BHARQ1 ~ E + MKTRF + SMB + HML + MOM + Momentum +
    IdioRisk + Size + ROA + DE + DPR + Earnings + Debt + FCF +
    Sector, data = Data)

Residuals:
     Min       1Q   Median       3Q      Max
-0.34701 -0.08814 -0.00255  0.08498  0.53130

Coefficients:
                             Estimate Std. Error t value Pr(>|t|)
(Intercept)                -1.1255435  0.2187678  -5.145 4.79e-07 ***
E                          -0.0006109  0.0004770  -1.281 0.201280
MKTRF                      -0.0692552  0.0197412  -3.508 0.000519 ***
SMB                         0.0072038  0.0144197   0.500 0.617730
HML                        -0.0020075  0.0071538  -0.281 0.779195
MOM                         0.0169114  0.0152709   1.107 0.268978
Momentum                    0.0434637  0.0224017   1.940 0.053274 .
IdioRisk                    0.2768573  0.2570180   1.077 0.282244
Size                        0.0766735  0.0235433   3.257 0.001254 **
ROA                         0.1519119  0.1058126   1.436 0.152118
DE                          0.0105860  0.0137033   0.773 0.440405
DPR                        -0.0021147  0.0201369  -0.105 0.916431
Earnings                    0.0281594  0.0190806   1.476 0.141023
Debt                       -0.0281227  0.0178770  -1.573 0.116723
FCF                        -0.0241780  0.0121860  -1.984 0.048141 *
SectorConsumerDiscretionary -0.0275993  0.0421254  -0.655 0.512850
SectorConsumerStaples       0.2562592  0.0478710   5.353 1.70e-07 ***
SectorEnergy                0.0500954  0.0502621   0.997 0.319706
SectorFinancials            0.0747849  0.0466470   1.603 0.109920
SectorHealthCare            0.1297055  0.0474228   2.735 0.006600 **
SectorIndustrials           0.0080762  0.0428315   0.189 0.850565
SectorInformationTechnology 0.1041171  0.0485423   2.145 0.032750 *
SectorMaterials             0.1050449  0.0445883   2.356 0.019109 *
SectorRealEstate            0.0416355  0.0484709   0.859 0.391024
SectorUtilities             0.1931915  0.0575899   3.355 0.000895 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.153 on 306 degrees of freedom
Multiple R-squared:  0.3273,    Adjusted R-squared:  0.2745
F-statistic: 6.203 on 24 and 306 DF,  p-value: 1.009e-15
```

Social pillar

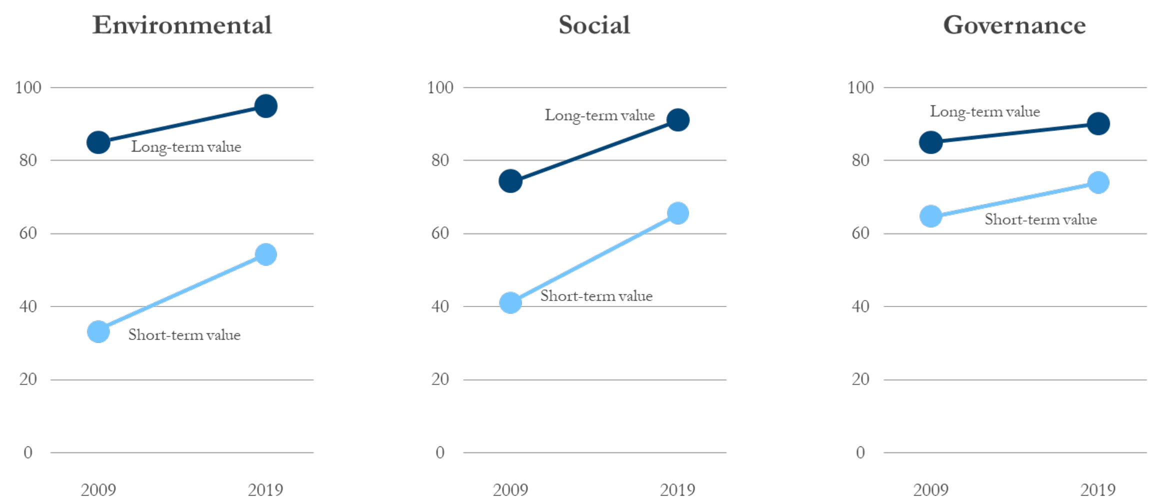
```
Call:
lm(formula = BHARQ1 ~ S + MKTRF + SMB + HML + MOM + Momentum +
    IdioRisk + Size + ROA + DE + DPR + Earnings + Debt + FCF +
    Sector, data = Data)

Residuals:
     Min       1Q   Median       3Q      Max
-0.34324 -0.09008 -0.00568  0.08508  0.53802

Coefficients:
                             Estimate Std. Error t value Pr(>|t|)
(Intercept)                -1.1153050  0.2111014  -5.283 2.41e-07 ***
S                          -0.0009771  0.0005473  -1.785 0.075204 .
MKTRF                      -0.0695051  0.0196917  -3.530 0.000480 ***
SMB                         0.0079124  0.0143697   0.551 0.582290
HML                        -0.0027576  0.0071331  -0.387 0.699326
MOM                         0.0170100  0.0152250   1.117 0.264768
Momentum                    0.0429586  0.0222179   1.934 0.054095 .
IdioRisk                    0.2899280  0.2559425   1.133 0.258191
Size                        0.0787630  0.0229792   3.428 0.000692 ***
ROA                         0.1491764  0.1055314   1.414 0.158504
DE                          0.0106342  0.0136655   0.778 0.437063
DPR                        -0.0011439  0.0200757  -0.057 0.954600
Earnings                    0.0339155  0.0193867   1.749 0.081221 .
Debt                       -0.0322345  0.0177985  -1.811 0.071109 .
FCF                        -0.0262243  0.0121967  -2.150 0.032329 *
SectorConsumerDiscretionary -0.0315514  0.0418770  -0.753 0.451770
SectorConsumerStaples       0.2421513  0.0469149   5.161 4.42e-07 ***
SectorEnergy                0.0394084  0.0499493   0.789 0.430741
SectorFinancials            0.0814604  0.0466559   1.746 0.081818 .
SectorHealthCare            0.1323982  0.0473537   2.796 0.005502 **
SectorIndustrials          -0.0039540  0.0424559  -0.093 0.925859
SectorInformationTechnology 0.1030707  0.0484146   2.129 0.034059 *
SectorMaterials             0.0970080  0.0436561   2.222 0.027008 *
SectorRealEstate            0.0426602  0.0482623   0.884 0.377431
SectorUtilities             0.1787431  0.0580918   3.077 0.002281 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1526 on 306 degrees of freedom
Multiple R-squared:  0.3306,    Adjusted R-squared:  0.2781
F-statistic: 6.298 on 24 and 306 DF,  p-value: 5.227e-16
```

Governance pillar

```
Call:
lm(formula = BHARQ1 ~ G + MKTRF + SMB + HML + MOM + Momentum +
    IdioRisk + Size + ROA + DE + DPR + Earnings + Debt + FCF +
    Sector, data = Data)

Residuals:
     Min       1Q   Median       3Q      Max
-0.34061 -0.09369 -0.00355  0.08515  0.52424

Coefficients:
                             Estimate Std. Error t value Pr(>|t|)
(Intercept)                -1.032e+00  2.074e-01  -4.974 1.10e-06 ***
G                           6.217e-05  4.741e-04   0.131 0.895762
MKTRF                      -6.931e-02  1.980e-02  -3.501 0.000532 ***
SMB                         8.151e-03  1.448e-02   0.563 0.573918
HML                        -2.407e-03  7.170e-03  -0.336 0.737294
MOM                         1.793e-02  1.539e-02   1.165 0.245062
Momentum                    4.869e-02  2.217e-02   2.196 0.028866 *
IdioRisk                    2.993e-01  2.581e-01   1.160 0.247119
Size                        6.438e-02  2.219e-02   2.901 0.003986 **
ROA                         1.612e-01  1.062e-01   1.518 0.130079
DE                          1.108e-02  1.374e-02   0.806 0.420641
DPR                        -5.113e-03  2.007e-02  -0.255 0.799048
Earnings                    2.698e-02  1.919e-02   1.406 0.160696
Debt                       -3.018e-02  1.785e-02  -1.691 0.091933 .
FCF                        -2.434e-02  1.223e-02  -1.990 0.047461 *
SectorConsumerDiscretionary -3.218e-02  4.210e-02  -0.764 0.445245
SectorConsumerStaples       2.448e-01  4.714e-02   5.193 3.79e-07 ***
SectorEnergy                4.370e-02  5.015e-02   0.871 0.384190
SectorFinancials            7.516e-02  4.678e-02   1.606 0.109198
SectorHealthCare            1.266e-01  4.757e-02   2.662 0.008183 **
SectorIndustrials           9.142e-04  4.259e-02   0.021 0.982888
SectorInformationTechnology 1.034e-01  4.871e-02   2.123 0.034576 *
SectorMaterials             9.370e-02  4.387e-02   2.136 0.033489 *
SectorRealEstate            3.522e-02  4.836e-02   0.728 0.466972
SectorUtilities             1.948e-01  5.787e-02   3.365 0.000862 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1534 on 306 degrees of freedom
Multiple R-squared:  0.3237,    Adjusted R-squared:  0.2707
F-statistic: 6.103 on 24 and 306 DF,  p-value: 2.014e-15
```

APPENDIX 27:

Figure 27 is based on answers from 558 participants representing the full range of regions, industries, and company sizes. Out of the 558 participants, 439 are C-level executives and 119 are investment professionals. Figure is based Mckinsey (2020) and the survey was conducted in 2019.



Source: Self-developed based on Mckinsey global survey 2020: "The ESG premium: New perspectives on value and performance

APPENDIX 28: Testing (E), (S) and (G) pillar scores for alpha – European region

Appendix 28 presents the results of the FF5 factor test on the European region sorted on the (E), (S) and (G) pillar scores and the decile portfolio's ability to earn alpha when controlling for risk factors. In this strategy we have sorted the stocks into decile portfolios, where the stocks with the lowest (highest) rating is found in P1 (P10). Panel A: presents the results from the (E) pillar. Panel B presents the results from the (S) pillar. Panel C presents the results from (G) pillar. The square brackets present the t-statistics. Significant codes: 0.001 (***), 0.01 (**), 0.05 (*). The sample period is between January 2007 and December 2020.

Panel A: The (E) pillar score

	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-PF1
Alpha	-0.000	-0.001	-0.000	-0.000	-0.000	0.000	-0.000	0.000	-0.001	-0.000	0.000
	[-0.227]	[-0.943]	[-0.208]	[-0.003]	[-0.100]	[0.371]	[-0.324]	[0.335]	[-1.318]	[-0.227]	[0.270]
MKT	0.965***	1.013***	1.126***	1.107***	1.041***	1.079***	0.979***	1.113***	0.868***	0.965***	0.153***
	[21.054]	[27.137]	[28.145]	[35.570]	[35.318]	[37.828]	[33.873]	[40.627]	[29.817]	[21.054]	[3.037]
SMB	0.150	0.280***	0.212*	0.231***	-0.053	0.032	-0.187**	-0.285***	-0.235***	0.150	-0.469***
	[1.436]	[3.289]	[2.331]	[3.257]	[-0.795]	[0.501]	[-2.846]	[-4.578]	[-3.583]	[1.436]	[-4.073]
HML	0.036	0.023	0.045	0.040	-0.039	0.017	0.156	-0.105	0.020	0.036	0.381*
	[0.255]	[0.202]	[0.370]	[0.424]	[-0.429]	[0.197]	[1.752]	[-1.247]	[0.849]	[0.255]	[2.441]
RMW	-0.501*	-0.138	-0.022	0.066	0.165	0.062	-0.042	-0.024	0.142	-0.501*	0.430*
	[-2.575]	[-0.872]	[-0.133]	[0.506]	[1.326]	[0.516]	[-0.348]	[-0.213]	[-3.59]	[-2.575]	[2.006]
CMA	-0.358*	-0.405**	-0.313*	0.086	-0.081	-0.048	0.050	0.119	-0.061	-0.358*	0.444*
	[-2.017]	[-2.802]	[-2.022]	[0.721]	[-0.713]	[-0.435]	[0.452]	[1.130]	[-0.61]	[-2.017]	[2.267]

Panel B: The (S) pillar score

	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-PF1
Alpha	0.002	-0.000	-0.001	-0.001	-0.001	-0.001	0.000	-0.000	-0.001	0.002	-0.002
	[1.407]	[-0.305]	[-0.778]	[-1.045]	[-1.009]	[-1.005]	[0.655]	[-0.238]	[-1.741]	[1.407]	[-1.286]
MKT	1.003***	1.044***	1.104***	1.042***	1.089***	1.041***	1.043***	1.057***	0.868***	1.003***	0.166***
	[24.953]	[32.453]	[32.130]	[33.915]	[34.948]	[28.061]	[32.098]	[34.128]	[37.573]	[24.953]	[3.456]
SMB	0.266**	0.201**	0.029	-0.062	-0.076	-0.169*	-0.228***	-0.193**	-0.235***	0.266**	-0.553***
	[2.904]	[2.752]	[0.381]	[-0.885]	[-1.074]	[-2.004]	[-3.085]	[-2.733]	[-3.074]	[2.904]	[-5.059]
HML	-0.149	-0.041	0.120	0.254**	-0.051	-0.047	0.027	0.136	0.020	-0.149	0.446***
	[-1.204]	[-0.416]	[1.139]	[2.685]	[-0.536]	[-0.413]	[0.274]	[1.423]	[1.304]	[-1.204]	[3.009]
RMW	-0.313	-0.129	-0.105	0.177	-0.019	-0.219	0.033	0.082	0.142	-0.313	0.008
	[-1.836]	[-0.946]	[-0.722]	[1.362]	[-0.144]	[-1.392]	[0.244]	[0.627]	[-1.44]	[-1.836]	[0.043]
CMA	-0.406**	-0.097	-0.132	-0.028	0.205	-0.173	0.135	0.223	-0.061	-0.406**	0.314
	[-2.609]	[-0.782]	[-0.994]	[-0.239]	[1.704]	[-1.207]	[1.076]	[1.866]	[0.041]	[-2.609]	[1.691]

Panel C: The (G) pillar score

	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-PF1
Alpha	0.004	0.002	0.000	0.003	0.001	0.003	0.003	2.714	-0.001	0.004	-0.002
	[1.795]	[1.001]	[0.259]	[1.192]	[0.670]	[1.380]	[1.315]	[0.001]	[-0.290]	[1.795]	[-1.572]
MKT	0.759***	0.782***	0.837***	0.815***	0.928***	0.808***	0.775***	0.847***	0.868***	0.759***	0.118**
	[12.307]	[12.323]	[10.515]	[11.191]	[13.054]	[13.279]	[11.541]	[14.915]	[14.406]	[12.307]	[2.606]
SMB	-0.228*	-0.207	-0.243	-0.364**	-0.314*	-0.250*	-0.219	-0.290**	-0.235***	-0.228*	-0.114
	[-2.019]	[-1.777]	[-1.667]	[-2.726]	[-2.414]	[-2.237]	[-1.779]	[-2.788]	[-4.043]	[-2.019]	[-1.376]
HML	-0.052	-0.003	0.104	-0.043	0.033	0.033	-0.124	-0.039	0.020	-0.052	0.092
	[-0.418]	[-0.026]	[0.6443]	[-0.291]	[0.234]	[0.270]	[-0.911]	[-0.346]	[0.511]	[-0.418]	[1.009]
RMW	-0.026	-0.025	0.314	-0.200	0.008	0.078	-0.152	-0.178	0.142	-0.026	0.021
	[-0.133]	[-0.124]	[1.212]	[-0.843]	[0.034]	[0.394]	[-0.697]	[-0.962]	[0.016]	[-0.133]	[0.146]
CMA	-0.380*	-0.374*	-0.487*	-0.563***	-0.566***	-0.362*	-0.589***	-0.358*	-0.061**	-0.380*	-0.114
	[-2.397]	[-2.292]	[-2.378]	[-3.005]	[-3.094]	[-2.313]	[-3.404]	[-2.450]	[-2.872]	[-2.397]	[-0.983]

APPENDIX 29: Testing (E), (S) and (G) pillar scores for alpha – Asian region

Appendix 29 presents the results of the FF5 factor test on the Asian region sorted on the (E), (S) and (G) pillar scores and the decile portfolio's ability to earn alpha when controlling for risk factors. In this strategy we have sorted the stocks into decile portfolios, where the stocks with the lowest (highest) rating is found in P1 (P10). Panel A: presents the results from the (E) pillar. Panel B presents the results from the (S) pillar. Panel C presents the results from (G) pillar. The square brackets present the t-statistics. Significant codes: 0.001 (***), 0.01 (**), 0.05 (*). The sample period is between January 2007 and December 2020.

					Panel A: The (E) pillar score						
	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-PF1
Alpha	0.008*	0.001	0.004	0.003	-0.00	-0.000	0.002	-0.002	-0.001	0.008*	-0.006*
	[2.292]	[0.564]	[1.719]	[0.925]	[-0.548]	[-0.076]	[1.121]	[-0.979]	[-0.632]	[2.292]	[-2.186]
MKT	0.755***	0.772***	0.713***	0.858***	0.883***	0.722***	0.789***	0.842***	0.868***	0.755***	0.217**
	[8.727]	[10.328]	[10.247]	[9.942]	[11.765]	[10.576]	[13.866]	[15.705]	[18.925]	[8.727]	[2.877]
SMB	-0.342*	-0.212	-0.374**	-0.261	-0.245	-0.258*	-0.208	-0.398***	-0.235**	-0.342*	-0.011
	[-2.154]	[-1.547]	[-2.928]	[-1.648]	[-1.784]	[-2.063]	[-1.993]	[-4.047]	[-2.799]	[-2.154]	[-0.083]
HML	-0.153	-0.093	-0.142	-0.102	-0.031	0.202	0.049	-0.047	0.020	-0.153	0.387*
	[-0.876]	[-0.614]	[-1.012]	[-0.584]	[-0.209]	[1.460]	[0.432]	[-0.436]	[0.224]	[-0.876]	[2.521]
RMW	-0.129	0.063	-0.295	-0.214	0.014	0.311	-0.149	0.190	0.142	-0.129	0.169
	[-0.457]	[0.259]	[-1.30]	[-0.761]	[0.059]	[1.398]	[-0.803]	[1.087]	[0.954]	[-0.457]	[0.686]
CMA	-0.592**	-0.390*	-0.640***	-0.699***	-0.429*	-0.469**	-0.510***	-0.228	-0.061	-0.592**	0.145
	[-2.659]	[-2.029]	[-3.569]	[-3.147]	[-2.222]	[-2.670]	[-3.482]	[-1.656]	[-0.519]	[-2.659]	[0.748]
					Panel B: The (S) pillar score						
	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-PF1
Alpha	0.007**	0.004	0.006*	-0.00	0.001	0.000	0.001	-0.000	-0.001	0.0074**	-0.003
	[2.661]	[1.554]	[2.095]	[-0.15]	[0.400]	[0.339]	[0.685]	[-0.21]	[-0.93]	[2.661]	[-1.27]
MKT	0.737***	0.847***	0.679***	0.832***	0.815***	0.837***	0.747***	0.874***	0.868***	0.737***	0.138*
	[10.707]	[11.619]	[9.1734]	[11.970]	[11.378]	[11.892]	[11.387]	[14.666]	[19.674]	[10.707]	[2.239]
SMB	-0.262*	-0.169	-0.282*	-0.376**	-0.171	-0.253	-0.179	-0.441***	-0.235***	-0.262*	-0.102
	[-2.078]	[-1.267]	[-2.075]	[-2.952]	[-1.306]	[-1.962]	[-1.491]	[-4.035]	[-3.721]	[-2.078]	[-0.905]
HML	-0.168	-0.015	-0.108	-0.156	0.136	0.119	0.068	0.003	0.020	-0.168	0.272*
	[-1.204]	[-0.102]	[-0.721]	[-1.111]	[0.938]	[0.835]	[0.516]	[0.032]	[-1.016]	[-1.204]	[2.180]
RMW	-0.194	0.006	-0.482	-0.080	0.337	0.020	-0.245	0.109	0.142	-0.194	0.274
	[-0.868]	[0.027]	[-1.999]	[-0.355]	[1.445]	[0.088]	[-1.149]	[0.562]	[0.027]	[-0.868]	[1.365]
CMA	-0.441*	-0.298	-0.765***	-0.394*	-0.527**	-0.560***	-0.542***	-0.483***	-0.061	-0.441*	-0.035
	[-2.489]	[-1.589]	[-4.011]	[-2.199]	[-2.861]	[-3.091]	[-3.205]	[-3.150]	[-1.166]	[-2.489]	[-0.226]
					Panel C: The (G) pillar score						
	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-PF1
Alpha	0.004	0.003	0.001	0.004	0.002	0.003	0.004	0.000	-0.001	0.004	-0.003
	[1.796]	[1.002]	[0.259]	[1.193]	[0.671]	[1.380]	[1.316]	[0.001]	[-0.291]	[1.796]	[-1.572]
MKT	0.759***	0.782***	0.838***	0.815***	0.928***	0.809***	0.776***	0.848***	0.869***	0.759***	0.118*
	[12.308]	[12.323]	[10.515]	[11.191]	[13.055]	[13.280]	[11.541]	[14.915]	[14.406]	[12.308]	[2.607]
SMB	-0.229*	-0.207	-0.244	-0.364**	-0.315*	-0.250*	-0.219	-0.291**	-0.236***	-0.229*	-0.114
	[-2.019]	[-1.778]	[-1.668]	[-2.727]	[-2.414]	[-2.238]	[-1.779]	[-2.789]	[-4.043]	[-2.019]	[-1.377]
HML	-0.052	-0.003	0.104	-0.043	0.034	0.033	-0.124	-0.040	0.021	-0.052	0.093
	[-0.418]	[-0.026]	[0.644]	[-0.292]	[0.234]	[0.271]	[-0.911]	[-0.346]	[0.511]	[-0.418]	[1.010]
RMW	-0.027	-0.026	0.315	-0.200	0.008	0.078	-0.153	-0.178	0.143	-0.027	0.022
	[-0.134]	[-0.125]	[1.213]	[-0.844]	[0.035]	[0.394]	[-0.697]	[-0.963]	[0.016]	[-0.134]	[0.147]
CMA	-0.381*	-0.375*	-0.488*	-0.564***	-0.567***	-0.363*	-0.589***	-0.359*	-0.061**	-0.381*	-0.115
	[-2.398]	[-2.292]	[-2.379]	[-3.0059]	[-3.095]	[-2.314]	[-3.405]	[-2.450]	[-2.873]	[-2.398]	[-0.984]

APPENDIX 30: Testing (E), (S) and (G) pillar scores for alpha – Oceanian region

Appendix 30 presents the results of the FF5 factor test on the Oceanian region sorted on the (E), (S) and (G) pillar scores and the decile portfolio's ability to earn alpha when controlling for risk factors. In this strategy we have sorted the stocks into decile portfolios, where the stocks with the lowest (highest) rating is found in P1 (P10). Panel A: presents the results from the (E) pillar. Panel B presents the results from the (S) pillar. Panel C presents the results from (G) pillar. The square brackets present the t-statistics. Significant codes: 0.001 (***), 0.01 (**), 0.05 (*). The sample period is between January 2007 and December 2020.

Panel A: The (E) pillar score											
	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-PF1
Alpha	-0.001	-0.004	-0.007*	-0.002	0.000	-0.003	0.001	-0.005*	-0.001	-0.001	0.001
	[-0.445]	[-1.002]	[-2.155]	[-0.809]	[0.132]	[-1.199]	[0.382]	[-2.251]	[-2.612]	[-0.44]	[0.332]
MKT	1.146***	1.173***	1.121***	1.173***	1.111***	1.014***	0.980***	1.048***	0.868***	1.146***	0.001
	[19.526]	[17.554]	[20.190]	[20.502]	[15.570]	[19.246]	[22.672]	[25.404]	[27.223]	[19.526]	[0.021]
SMB	0.285*	0.413*	0.341*	0.045	0.084	0.096	0.018	-0.079	-0.235	0.285*	-0.520**
	[2.017]	[2.568]	[2.556]	[0.329]	[0.493]	[0.761]	[0.180]	[-0.801]	[0.879]	[2.017]	[-2.921]
HML	-0.229	-0.167	0.157	-0.166	-0.941***	-0.256	-0.106	-0.146	0.020	-0.229	-0.233
	[-1.276]	[-0.821]	[0.925]	[-0.950]	[-4.314]	[-1.589]	[-0.803]	[-1.157]	[0.646]	[-1.276]	[-1.029]
RMW	-0.059	-0.214	-0.020	0.171	0.047	0.0039	-0.038	-0.19**	0.142	-0.059	0.137
	[-0.615]	[-1.955]	[-0.226]	[1.822]	[0.408]	[0.045]	[-0.547]	[-2.826]	[-0.927]	[-0.615]	[1.132]
CMA	0.868***	1.012***	1.305***	0.843***	0.172	0.341	0.653***	0.559***	-0.061***	0.868***	-0.735**
	[4.247]	[4.350]	[6.755]	[4.234]	[0.693]	[1.859]	[4.343]	[3.892]	[7.124]	[4.247]	[-2.853]
Panel B: The (S) pillar score											
	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-PF1
Alpha	0.005	0.000	-0.000	-0.003	-0.000	-0.005	-0.005*	-0.001	-0.001*	0.005	-0.007
	[1.334]	[0.146]	[-0.056]	[-0.806]	[-0.274]	[-1.586]	[-2.071]	[-0.699]	[-2.048]	[1.334]	[-1.505]
MKT	0.995***	1.189***	1.256***	1.255***	1.192***	1.114***	1.072***	1.114***	0.868***	0.995***	0.106
	[14.409]	[18.498]	[20.941]	[20.310]	[21.859]	[21.299]	[25.033]	[25.212]	[27.669]	[14.409]	[1.391]
SMB	0.416*	0.570***	0.209	0.271	0.254	0.297*	0.106	0.120	-0.235	0.416*	-0.599***
	[2.503]	[3.684]	[1.453]	[1.823]	[1.938]	[2.357]	[1.034]	[1.130]	[-0.584]	[2.503]	[-3.256]
HML	-0.381	-0.013	-0.275	-0.709***	-0.484**	-0.007	-0.019	-0.020	0.020	-0.381	0.011
	[-1.803]	[-0.070]	[-1.498]	[-3.755]	[-2.904]	[-0.047]	[-0.147]	[-0.149]	[-0.518]	[-1.803]	[0.050]
RMW	-0.123	-0.169	-0.239*	0.218*	-0.25**	-0.059	0.068	0.007	0.142	-0.123	0.172
	[-1.087]	[-1.604]	[-2.433]	[2.151]	[-2.894]	[-0.688]	[0.977]	[0.103]	[-0.989]	[-1.087]	[1.372]
CMA	0.823***	0.798***	0.882***	0.265	0.410*	0.846***	1.133***	0.557***	-0.061***	0.823***	-0.491
	[3.424]	[3.569]	[4.225]	[1.233]	[2.161]	[4.649]	[7.603]	[3.622]	[6.245]	[3.424]	[-1.846]
Panel C: The (G) pillar score											
	PF1	PF2	PF3	PF4	PF5	PF6	PF7	PF8	PF9	PF10	PF10-PF1
Alpha	0.006*	0.001	-0.003	0.006	-0.001	-0.002	-0.003	0.000	-0.001***	0.006*	-0.010**
	[2.038]	[0.360]	[-1.053]	[1.386]	[-0.534]	[-0.788]	[-1.461]	[0.323]	[-3.334]	[2.038]	[-2.879]
MKT	1.097***	1.220***	1.278***	1.061***	1.053***	1.206***	1.119***	1.062***	0.868***	1.097***	-0.064
	[20.225]	[19.747]	[21.843]	[15.329]	[24.542]	[22.501]	[27.424]	[22.765]	[32.033]	[20.225]	[-1.085]
SMB	0.316*	0.642***	0.123	0.455**	0.079	-0.176	0.104	0.144	-0.235	0.316*	-0.359*
	[2.425]	[4.315]	[0.873]	[2.734]	[0.771]	[-1.367]	[1.063]	[1.289]	[-0.118]	[2.425]	[-2.503]
HML	-0.205	-0.543**	-0.777***	-0.193	-0.233	-0.463**	-0.085	-0.310*	0.020	-0.205	0.249
	[-1.237]	[-2.874]	[-4.340]	[-0.911]	[-1.780]	[-2.829]	[-0.686]	[-2.178]	[0.217]	[-1.237]	[1.368]
RMW	-0.072	-0.003	0.114	-0.057	0.085	-0.143	-0.010	-0.083	0.142	-0.072	-0.020
	[-0.812]	[-0.039]	[1.187]	[-0.509]	[1.217]	[-1.626]	[-0.159]	[-1.087]	[0.160]	[-0.812]	[-0.214]
CMA	0.756***	0.819***	0.384	0.514*	0.547***	0.385*	0.942***	0.527***	-0.061***	0.756***	0.157
	[4.003]	[3.808]	[1.886]	[2.134]	[3.662]	[2.066]	[6.634]	[3.247]	[5.897]	[4.003]	[0.757]

APPENDIX 31: R-code

R Code for dividing stocks into decile portfolios

```
"==============================================================
        Divide observations into ESG decile portfolios
=============================================================="

cat("\014") # Clear console
rm(list=ls()) # Clear variables

#Set working directory
setwd("~/OneDrive - CBS - Copenhagen Business School/Speciale 2021/Data/final data/All")

# R packages applied
library(openxlsx)
library(data.table)


# Define Area ("O", "E", "A"):
Area = "O"

# Read in new excel file:
ifelse(Area=="O", Data <- loadWorkbook("Oceania.xlsx"),
       ifelse(Area=="E", Data <- loadWorkbook("Europe.xlsx"),
              ifelse(Area=="A", Data <- loadWorkbook("Asia.xlsx"))))


#Specify different sheets into datasets
sheetNames <- paste0(sheets(Data))
for(i in 1:length(sheetNames)){
  assign(sheetNames[i], readWorkbook(Data, sheet=i))
}

Data <- `Sheet 1`
rm(`Sheet 1`)

# Rename datasets:
ReturnsFactors <- `ParametersFactors and Stock return`
rm(`ParametersFactors and Stock return`)

```

```
# Add Column with year for all parameters
Parameters2007$Year <- 2007
Parameters2008$Year <- 2008
Parameters2009$Year <- 2009
Parameters2010$Year <- 2010
Parameters2011$Year <- 2011
Parameters2012$Year <- 2012
Parameters2013$Year <- 2013
Parameters2014$Year <- 2014
Parameters2015$Year <- 2015
Parameters2016$Year <- 2016
Parameters2017$Year <- 2017
Parameters2018$Year <- 2018
Parameters2019$Year <- 2019
Parameters2020$Year <- 2020

#Collect all parameters in one dataset
Parameters <- rbind(Parameters2007, Parameters2008, Parameters2009, Parameters2010, Parameters2011, Parameters2012, Parameters2013,
                    Parameters2014, Parameters2015, Parameters2016, Parameters2017, Parameters2018, Parameters2019, Parameters2020)

# Remove old datasets:
rm(Parameters2007, Parameters2008, Parameters2009, Parameters2010, Parameters2011, Parameters2012, Parameters2013,
   Parameters2014, Parameters2015, Parameters2016, Parameters2017, Parameters2018, Parameters2019, Parameters2020)

# Rename columns
cols <- c("ISIN", "E", "S", "G", "ESG", "FreeCashFlow", "Cash", "ROA", "TotalDebt", "DividendPayoutRatio", "DebtToEquity",
          "Beta", "Earnings", "MarketCap","Sector", "Year")
colnames(Parameters) <- cols

# Define function to divide stocks 10 decile portfolios:
gruppe <- function(x){
  reps = rep((length(x)-(length(x) %% 10))/10, 10)
  rest = (length(x) %% 10)
  reps[0:rest] = reps[0:rest]+1
  rep(1:10, reps)
}

# Remove stocks without an ESG score or Market cap:
Data <- Data[complete.cases(Data[ , 5]),]
Data <- Data %>% filter(ESG!= 0)
Data <- Data %>% filter(MarketCap != 0)

# Divide stocks into 10 deceile portfolios based on their ESG score
Data <- Data[order(Data$Year, Data$ESG),]
Data <- data.table(Data)
Data[, ESGGrp:=gruppe(ESG), by=Year]

```

R Code for calculating the weighted monthly stock return for all stocks

```
"==============================================================
          Calculate weigted stock return for each stock
==============================================================="

cat("\014") # Clear console
rm(list=ls()) # Clear variables

#Set working directory
setwd("~/OneDrive - CBS - Copenhagen Business School/Speciale 2021/Data/final data/All")

#R Packages
library(openxlsx)
library(data.table)

# Define Area ("O", "E", "A"):
Area = "O"

# Read in new excel file:
ifelse(Area=="O", Data <- loadWorkbook("Oceania-ESG-weight.xlsx"),
       ifelse(Area=="E", Data <- loadWorkbook("Europe-ESG-weight.xlsx"),
              ifelse(Area=="A", Data <- loadWorkbook("Asia-ESG-weight.xlsx"))))


#Specify different sheets into datasets
sheetNames <- paste0(sheets(Data))
for(i in 1:length(sheetNames)){
  assign(sheetNames[i], readWorkbook(Data, sheet=i))
}

# Rename datasets
WeightedReturns <- `Sheet 1`
rm(`Sheet 1`) # Clear variables

# Calculate weighted stock return:
WeightedReturns$WeightedJanuary <- WeightedReturns$January*WeightedReturns$Weight
WeightedReturns$WeightedFebruary <- WeightedReturns$February*WeightedReturns$Weight
WeightedReturns$WeightedMarch <- WeightedReturns$March*WeightedReturns$Weight
WeightedReturns$WeightedApril <- WeightedReturns$April*WeightedReturns$Weight
WeightedReturns$WeightedMay <- WeightedReturns$May*WeightedReturns$Weight
WeightedReturns$WeightedJune <- WeightedReturns$June*WeightedReturns$Weight
WeightedReturns$WeightedJuly <- WeightedReturns$July*WeightedReturns$Weight
WeightedReturns$WeightedAugust <- WeightedReturns$August*WeightedReturns$Weight
WeightedReturns$WeightedSeptember <- WeightedReturns$September*WeightedReturns$Weight
WeightedReturns$WeightedOctober <- WeightedReturns$October*WeightedReturns$Weight
WeightedReturns$WeightedNovember <- WeightedReturns$November*WeightedReturns$Weight
WeightedReturns$WeightedDecember <- WeightedReturns$December*WeightedReturns$Weight
```

```r
# Prepare dataframes for results:
WeightedResults <- data.frame(Year=as.numeric(),
                              Portfolio=as.numeric(),
                              January=as.numeric(),
                              February=as.numeric(),
                              March=as.numeric(),
                              April=as.numeric(),
                              May=as.numeric(),
                              June=as.numeric(),
                              July=as.numeric(),
                              August=as.numeric(),
                              September=as.numeric(),
                              October=as.numeric(),
                              November=as.numeric(),
                              December=as.numeric(),
                              stringsAsFactors = FALSE)

# Determine monthly weighted return for every ESG portfolio
k=1 # Define count variable
for(year in min(WeightedReturns$Year, na.rm=T):max(WeightedReturns$Year, na.rm=T)){
  DF1 <- subset(WeightedReturns, WeightedReturns$Year==year)
  for(group in min(WeightedReturns$GGrp, na.rm=T):max(WeightedReturns$GGrp, na.rm=T)){
    DF <- subset(DF1, DF1$GGrp==group)
    j=0 # Define count variable
    l=0 # Define count variable
    WeightedResults[k, j <- j+1] <- year
    WeightedResults[k, j <- j+1] <- group
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedJanuary, na.rm=T)
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedFebruary, na.rm=T)
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedMarch, na.rm=T)
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedApril, na.rm=T)
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedMay, na.rm=T)
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedJune, na.rm=T)
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedJuly, na.rm=T)
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedAugust, na.rm=T)
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedSeptember, na.rm=T)
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedOctober, na.rm=T)
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedNovember, na.rm=T)
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedDecember, na.rm=T)

```

```r
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedJanuary, na.rm=T)/sd(DF$WeightedJanuary, na.rm=T)
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedFebruary, na.rm=T)/sd(DF$WeightedJanuary, na.rm=T)
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedMarch, na.rm=T)/sd(DF$WeightedJanuary, na.rm=T)
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedApril, na.rm=T)/sd(DF$WeightedJanuary, na.rm=T)
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedMay, na.rm=T)/sd(DF$WeightedJanuary, na.rm=T)
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedJune, na.rm=T)/sd(DF$WeightedJanuary, na.rm=T)
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedJuly, na.rm=T)/sd(DF$WeightedJanuary, na.rm=T)
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedAugust, na.rm=T)/sd(DF$WeightedJanuary, na.rm=T)
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedSeptember, na.rm=T)/sd(DF$WeightedJanuary, na.rm=T)
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedOctober, na.rm=T)/sd(DF$WeightedJanuary, na.rm=T)
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedNovember, na.rm=T)/sd(DF$WeightedJanuary, na.rm=T)
    WeightedResults[k, j <- j+1] <- sum(DF$WeightedDecember, na.rm=T)/sd(DF$WeightedJanuary, na.rm=T)
    k=k+1
  }
}

WeightedResults[WeightedResults==0] <- NA

k=1 # Definer count variable
for(year in min(WeightedResults$Year, na.rm=T):max(WeightedResults$Year, na.rm=T)){
  DF1 <- subset(WeightedResults, WeightedResults$Year==year)
  for(Pf in min(WeightedResults$Portfolio, na.rm=T):max(WeightedResults$Portfolio, na.rm=T)){
    DF <- subset(DF1[,c(3:14)], WeightedResults$Portfolio==Pf)
    YearlyPortfolioTotals[k, 1] <- year
    YearlyPortfolioTotals[k, 2] <- Pf
    YearlyPortfolioTotals[k, 3] <- rowMeans(DF[1,], na.rm=T)
    YearlyPortfolioTotals[k, 4] <- rowMeans(DF[1,], na.rm=T)/sd(DF[1,], na.rm=T)
    k=k+1
  }
}

k=1 # Define count variable
for(pf in min(YearlyPortfolioTotals$Portfolio, na.rm=T):max(YearlyPortfolioTotals$Portfolio, na.rm=T)){
  DF <- subset(YearlyPortfolioTotals, YearlyPortfolioTotals$Portfolio==pf)
  j=0 # Define count variable
  PortfolioTotals[k, 1] <- pf
  PortfolioTotals[k, 2] <- mean(DF$Return, na.rm=T)
  PortfolioTotals[k, 3] <- mean(DF$Return, na.rm=T)/sd(DF$Return, na.rm=T)
  k=k+1
}

# Calculate monthly return for all portfolios
AccReturns <- as.data.frame(rep(NA, 168))
for(pf in min(WeightedResults$Portfolio, na.rm=T):max(WeightedResults$Portfolio, na.rm=T)){
  DF <- subset(WeightedResults, WeightedResults$Portfolio==pf)
  DF <- DF[-c(1:2,15:27)]
  DF <- unmatrix(DF, byrow=T)
  DF <- as.data.frame(DF)
  AccReturns <- cbind(AccReturns, DF)
}
```

R Code for the 3 factor models and OLS assumptions tests

```r
"============================================================
              FAMA FRENCH MODELS (FF3, C4, FF5)
============================================================"

cat("\014") # Clear console
rm(list=ls()) # Clear variables

#Set working directory
setwd("~/OneDrive - CBS - Copenhagen Business School/Speciale 2021/Data/15. FF Resultater/")

#Data packages applied
library(lmtest)
library(tseries)
library(DescTools)
library(readxl)
library(openxlsx)

#Read data from excel files
Data <- loadWorkbook("Final Results Portfolios.xlsx")

#Specify different sheets into datasets
sheetNames <- paste0(sheets(Data)) # Definer fane-navne
for(i in 1:length(sheetNames)){ # Specificer hver fane ud i separate datas?t
  assign(sheetNames[i], readWorkbook(Data, sheet=i))
}

# Remove sheets
rm(`ASIA ESG`,`ASIA E`,`ASIA S`, `ASIA G`,`EUROPE ESG`,`Europe Correlation`,`EUROPE E`,`EUROPE S`,`EUROPE G`,`OCEANIA ESG`,
   `Oceania correlation`,`OCEANIA E`,`OCEANIA S`,`OCEANIA G`,`Template`,`Overall factors`, `Asia Correlation`)

# EUROPE
rm(`Asia Factor`,`Oceania Factor`,`Graph`)

# OCEANIA
rm(`Asia Factor`,`Europe Factor`,`Graph`)

# ASIA
rm(`Europe Factor`,`Oceania Factor`,`Graph`)


#EUROPE EUROPE EUROPE

#FAMA FRENCH 3-FACTOR MODEL
PF1FF3 <- lm(PF1 ~ MKTRF + SMB + HML, data=`Europe factor`)
PF2FF3 <- lm(PF2 ~ MKTRF + SMB + HML, data=`Europe Factor`)
PF3FF3 <- lm(PF3 ~ MKTRF + SMB + HML, data=`Europe Factor`)
PF4FF3 <- lm(PF4 ~ MKTRF + SMB + HML, data=`Europe Factor`)
PF5FF3 <- lm(PF5 ~ MKTRF + SMB + HML, data=`Europe Factor`)
PF6FF3 <- lm(PF6 ~ MKTRF + SMB + HML, data=`Europe Factor`)
PF7FF3 <- lm(PF7 ~ MKTRF + SMB + HML, data=`Europe Factor`)
PF8FF3 <- lm(PF8 ~ MKTRF + SMB + HML, data=`Europe Factor`)
PF9FF3 <- lm(PF9 ~ MKTRF + SMB + HML, data=`Europe Factor`)
PF10FF3 <- lm(PF10 ~ MKTRF + SMB + HML, data=`Europe Factor`)
Model1 <- lm(PF101 ~ MKTRF + SMB + HML, data=`Europe Factor`)

#CARHART 4-FACTOR MODEL
PF1C4 <- lm(PF1 ~ MKTRF + SMB + HML + WML, data=`Europe Factor`)
PF2C4 <- lm(PF2 ~ MKTRF + SMB + HML + WML, data=`Europe Factor`)
PF3C4 <- lm(PF3 ~ MKTRF + SMB + HML + WML, data=`Europe Factor`)
PF4C4 <- lm(PF4 ~ MKTRF + SMB + HML + WML, data=`Europe Factor`)
PF5C4 <- lm(PF5 ~ MKTRF + SMB + HML + WML, data=`Europe Factor`)
PF6C4 <- lm(PF6 ~ MKTRF + SMB + HML + WML, data=`Europe Factor`)
PF7C4 <- lm(PF7 ~ MKTRF + SMB + HML + WML, data=`Europe Factor`)
PF8C4 <- lm(PF8 ~ MKTRF + SMB + HML + WML, data=`Europe Factor`)
PF9C4 <- lm(PF9 ~ MKTRF + SMB + HML + WML, data=`Europe Factor`)
PF10C4 <- lm(PF10 ~ MKTRF + SMB + HML + WML, data=`Europe Factor`)
Model2 <- lm(PF101 ~ MKTRF + SMB + HML + WML, data=`Europe Factor`)
summary(Model2)

#FAMA FRENCH 5-FACTOR MODEL
PF1FF5 <- lm(PF1 ~ MKTRF + SMB + HML + RMW + CMA, data=`Europe Factor`)
PF2FF5 <- lm(PF2 ~ MKTRF + SMB + HML + RMW + CMA, data=`Europe Factor`)
PF3FF5 <- lm(PF3 ~ MKTRF + SMB + HML + RMW + CMA, data=`Europe Factor`)
PF4FF5 <- lm(PF4 ~ MKTRF + SMB + HML + RMW + CMA, data=`Europe Factor`)
PF5FF5 <- lm(PF5 ~ MKTRF + SMB + HML + RMW + CMA, data=`Europe Factor`)
PF6FF5 <- lm(PF6 ~ MKTRF + SMB + HML + RMW + CMA, data=`Europe Factor`)
PF7FF5 <- lm(PF7 ~ MKTRF + SMB + HML + RMW + CMA, data=`Europe Factor`)
PF8FF5 <- lm(PF8 ~ MKTRF + SMB + HML + RMW + CMA, data=`Europe Factor`)
PF9FF5 <- lm(PF9 ~ MKTRF + SMB + HML + RMW + CMA, data=`Europe Factor`)
PF10FF5 <- lm(PF10 ~ MKTRF + SMB + HML + RMW + CMA, data=`Europe Factor`)
Model3 <- lm(PF101 ~ MKTRF + SMB + HML + RMW + CMA, data=`Europe Factor`)

```

```
#Breusch-Pagan test
bptest(PF1FF5)
bptest(PF2FF5)
bptest(PF3FF5)
bptest(PF4FF5)
bptest(PF5FF5)
bptest(PF6FF5)
bptest(PF7FF5)
bptest(PF8FF5)
bptest(PF9FF5)
bptest(PF10FF5)
bptest(Model3)

#Breusch-Godfrey test
bgtest(PF1FF5)
bgtest(PF2FF5)
bgtest(PF3FF5)
bgtest(PF4FF5)
bgtest(PF5FF5)
bgtest(PF6FF5)
bgtest(PF7FF5)
bgtest(PF8FF5)
bgtest(PF9FF5)
bgtest(PF10FF5)
bgtest(Model3)

#Jarque Bera test for normality
PF1FF1 <- rnorm(PF1FF5)
PF1FF2 <- rnorm(PF2FF5)
PF1FF3 <- rnorm(PF3FF5)
PF1FF4 <- rnorm(PF4FF5)
PF1FF5 <- rnorm(PF5FF5)
PF1FF6 <- rnorm(PF6FF5)
PF1FF7 <- rnorm(PF7FF5)
PF1FF8 <- rnorm(PF8FF5)
PF1FF9 <- rnorm(PF9FF5)
PF1FF10 <- rnorm(PF10FF5)
Model1JB <- rnorm(Model3)
```

```


jarque.bera.test(PF1FF1)
jarque.bera.test(PF1FF2)
jarque.bera.test(PF1FF3)
jarque.bera.test(PF1FF4)
jarque.bera.test(PF1FF5)
jarque.bera.test(PF1FF6)
jarque.bera.test(PF1FF7)
jarque.bera.test(PF1FF8)
jarque.bera.test(PF1FF9)
jarque.bera.test(PF1FF10)
jarque.bera.test(Model1JB)
```

R Code for the estimation of factor loadings for each stock

```r
"===============================================================
              ESTIMATION OF FACTOR LOADINGS
==============================================================="

cat("\014") # Clear console
rm(list=ls()) # Clear variables

#Set working directory
setwd("~/OneDrive - CBS - Copenhagen Business School/Speciale 2021/Data/16. Resilient Analysis/Europe")

# R packages
library(openxlsx)
library(readxl)

# Read data from Excel:
Data <- loadWorkbook("Oceania Factors.xlsx")
Data <- loadWorkbook("Europe Factors.xlsx")
Data <- loadWorkbook("ASIA Factors.xlsx")

#Specify different sheets into datasets
sheetNames <- paste0(sheets(Data)) # Definer fane-navne
for(i in 1:length(sheetNames)){ # Specificer hver fane ud i separate datas?t
  assign(sheetNames[i], readWorkbook(Data, sheet=i))
}

# Rename dataset
rm(Sheet1)
Factors <- `Momentum factors`
rm(`Momentum factors`)
Factors <- `Excess return`
rm(`Excess return`)

# Split (OCEANIA)
Afkast <- Factors[, c(2:513)]
Faktorer <- Factors[, c(514:517)]
Faktorer <- as.matrix(Faktorer)

# Split (EUROPE)
Afkast <- Factors[, c(2:1116)]
Faktorer <- Factors[, c(1117:1121)]
Faktorer <- as.matrix(Faktorer)

# Split (ASIA)
Afkast <- Factors[, c(2:1351)]
Faktorer <- Factors[, c(1352:1355)]
Faktorer <- as.matrix(Faktorer)


Afkast <- Afkast[,colSums(is.na(Afkast))<nrow(Afkast)]
Loadings <- matrix(ncol=7, nrow=ncol(Afkast))
colnames(Loadings) <- c("Stock", "Intercept", "MKTRF", "SMB", "HML",)
Loadings[,1] <- colnames(Afkast)


for(i in 1:1121){
  LinReg <- lm(Afkast[,i]~Faktorer, na.rm=T)
  j=1
  Loadings[i,j <- j+1] <- coef(LinReg)["(Intercept)"]
  Loadings[i,j <- j+1] <- coef(LinReg)["FaktorerMKTRF"]
  Loadings[i,j <- j+1] <- coef(LinReg)["FaktorerSMB"]
  Loadings[i,j <- j+1] <- coef(LinReg)["FaktorerHML"]
  Loadings[i,j <- j+1] <- coef(LinReg)["FaktorerWML"]
}

Loadings <- t(Loadings)

Loadings <- as.data.frame(Loadings)

# Udskriv resultater til Excel:
write.xlsx(Loadings, 'EUROPE Factor coefficients.xlsx', col.names=F, row.names=T)
write.xlsx(Loadings, 'ASIA Factor coefficients.xlsx', col.names=F, row.names=T)
write.xlsx(Loadings, 'OCEANIA Factor coefficients.xlsx', col.names=F, row.names=T)
```

R Code for the multiple regression analysis

```r
"=============================================================
              Multiple Regresssion Analysis
============================================================="

cat("\014") # Clear console
rm(list=ls()) # Clear variables

#Set working directory
setwd("~/OneDrive - CBS - Copenhagen Business School/Speciale 2021/Data/16. Resilient Analysis/Final version")

#Data packages applied
library(openxlsx)
library(data.table)
library(gdata)
library(tidyverse)
library(fastDummies)
library(relaimpo)
library(ggfortify)
library(DescTools)
library(robustHD)
library(dplyr)
library(corrplot)
library(lmtest)
library(mctest)

#Read data from regions

#ASIA
Data <- loadWorkbook("ASIA FINAL.xlsx")

#EUROPE
Data <- loadWorkbook("EUROPE FINAL.xlsx")

#OCEANIA
Data <- loadWorkbook("OCEANIA FINAL.xlsx")

#Specify different sheets into datasets
sheetNames <- paste0(sheets(Data))
for(i in 1:length(sheetNames)){
  assign(sheetNames[i], readWorkbook(Data, sheet=i))
}

#Remove sheets
rm(Data)
Data <- `Winsorized data`
rm(`Winsorized data`)
```

```
#Create dummy variables for Sector
Data <- dummy_cols(Data, select_columns = "Sector")

#BHAR Regression 1
LM1 <- lm(BHARQ1 ~ ESG + Sector, data=Data)
summary(LM1)


#BHAR Regression 2
LM2 <- lm(BHARQ1 ~ ESG + MKTRF + SMB + HML + MOM + Momentum + IdioRisk + Sector, data=Data)
summary(LM2)

#BHAR Regression 3
LM3 <- lm(BHARQ1 ~ ESG + MKTRF + SMB + HML + MOM + Momentum + IdioRisk + Sector + Size, data=Data)
summary(LM3)

#BHAR Regression 4
LM4 <- lm(BHARQ1 ~ ESG + MKTRF + SMB + HML + MOM + Momentum + IdioRisk + Sector + Size + ROA + DE + DPR + Debt + FCF, data=Data)
summary(LM4)

#Regression used to estimate the Decomposition of R-Squared
LM5 <- lm(BHARQ1 ~ G + MKTRF + SMB + HML + MOM + Momentum + IdioRisk + Size + ROA + DE + DPR + FCF + Sector_Energy + Sector_Financials +
            Sector_Materials + Sector_Industrials + Sector_Utilities + Sector_InformationTechnology + Sector_HealthCare +
            Sector_CommunicationServices + Sector_ConsumerDiscretionary + Sector_ConsumerStaples, data=Data)

metrics <- calc.relimp(LM5, type = c("lmg"))
metrics

# OLS ASSUMPTIONS TESTS

#Breusch-Pagan Test
bptest(LM4)

#Breusch-Godfrey Test
bgtest(LM4)

#Jarqur-Bera Test
LM1 <- rnorm(LM4)
jarque.bera.test(LM1)

#Multicollinearity test
LM6 <- lm(BHARQ1 ~ ESG + E + S + G + MKTRF + SMB + HML + MOM + Momentum + IdioRisk + Size + ROA +
            DE + DPR + Earnings + Debt + FCF + Sector, data=Data)

omcdiag(LM4)
imcdiag(LM4)
```