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DO LEADING ESG EQUITY PORTFOLIOS OUTPERFORM PEERS AND BENCHMARK? AN EMPIRICAL ANALYSIS ON PORTFOLIOS CONSTRUCTED BY CONSTITUENTS OF THE S&P 500 INDEX.

by

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ABSTRACT

The purpose of this master thesis is to examine whether ESG-ratings based investing could lead to superior financial performance and further investigate whether the ESG portfolios could generate abnormal returns. It extends the existing literature on ESG by analyzing the relationship between ESG ratings and equity portfolios in a recent time span that included a financial crisis which emerged from the exogenous COVID-19 pandemic. Also, conclusions are derived regarding one portfolio comprised of firms without exhibiting any ESG rating. In this study, by utilizing MSCI ESG ratings, seven ESG portfolios and one Non-ESG portfolio were constructed with equal weights from the constituents of the S&P 500 for the period from 30/06/2017 until 30/06/2021. Comparisons were made in terms of absolute returns, volatility and risk-adjusted returns between the constructed portfolios and to the benchmark S&P 500 Equal Weight Index (S&P 500 EWI). Whether the constructed portfolios generated abnormal yields were examined in the context of the Capital Asset Pricing Model (CAPM) and the Fama-French Three Factor Model (FF3FM). The findings revealed that the portfolios with the best ESG ratings exhibited higher returns both in absolute and risk-adjusted terms relevant to the rest of the portfolios and the benchmark. From the regression models, only one of the constructed portfolios exhibited statistically significant positive monthly alpha of 0,247%. Hence, high-ESG oriented investors favoring portfolios with the best ESG ratings for the aforementioned period would fare better, but when accounting for the exposure to common factors, any benefit vanishes. Whether or not ESG-ratings based investing enhances investment returns, remains still an open question.

Keywords: ESG, S&P 500, MSCI, Portfolio Management, Equity portfolios, SRI, CAPM, Fama-French Three Factor Model, Sustainability, Investments, Stocks, COVID-19

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LIST OF ABBREVIATIONS

AUM = Assets Under Management

B/M = book to market

cap = capitalization

CAPM = Capital Asset Pricing Model

CFP = Corporate Financial Performance

CMA = Conservative minus Aggressive

COVID-19 = coronavirus disease 2019

CSR = Corporate Social Responsibility

E = Environmental

EMH = Efficient Market Hypothesis

ESG = Environmental, Social, Governance

FF3FM = Fama-French Three Factor Model

G = Governance

GI = Governance Index

HML = High minus Low

IPO = Initial Public Offering

MKTRF = excess return of the market portfolio over the risk-free rate

MOM = Momentum

MPT = Modern Portfolio Theory

OLS = Ordinary Least Squares

PRI = Principles for Responsible Investment

Rf = risk-free rate

RMW = Robust minus Weak

S = Social

SDG = Sustainable Development Goal

SMB = Small minus Big

SRI = Socially Responsible Investing

SRMF = Socially Responsible Mutual Fund

S&P 500 EWI = S&P 500 Equal Weight Index

UN = United Nations

US = United States

VIF = Variance Inflation Factor

1. INTRODUCTION

Environmental, social and governance (ESG) factors involve a set of criteria that socially conscious asset owners utilize in order to screen potential investments. The environmental pillar emphasizes how a company operates as a steward for our planet (i.e. climate change, waste pollution, etc.). The social pillar focuses on the connection between the company and its workforce, customers, suppliers and the community where it operates (i.e. human rights, working conditions, etc.). The last pillar, governance refers to a system of rules, practices and procedures by which a company is managed and controlled (i.e. internal controls, executive compensation, etc.).

In the last two decades, a growing number of institutional investors incorporate ESG factors in traditional investment decisions. Indicatively, when the United Nations Principles for Responsible Investment (UN PRI) was set up in 2006 only 63 professional institutions committed to incorporate ESG criteria into their investment decisions. At that time those firms had $6.5 trillion in assets under management (AUM). Today, UN PRI number of signatories has exponentially grown to nearly 4,000 while their AUM have reached $121 trillion. Figure 1 demonstrates the number of signatories and their AUM from the inception of UN PRI until today.[1] Additionally, in the US the Sustainable Investment Forum reported that "*the total US-domiciled assets under management using sustainable investing strategies grew from $12.0 trillion at the start of 2018 to $17.1 trillion at the start of 2020*". As a result, one in three dollars of the total US AUM was invested according to sustainable investing strategies.[2]

[1] About the PRI
[2] The US SIF Foundation's Biennial "Trends Report" Finds That Sustainable Investing Assets Reach $17.1 Trillion, 16 November 2020

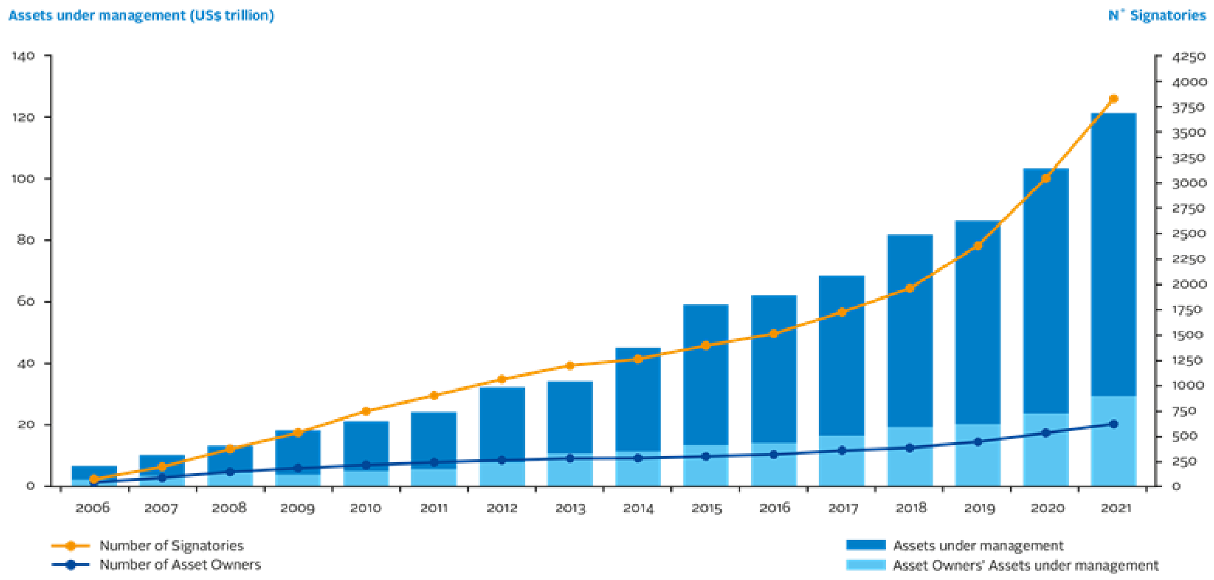

Figure 1: UN PRI number of signatories and assets under management (Source: About the PRI)

Sustainable investing does not have a consistent definition since it has multiple dimensions. Numerous terms are used interchangeably such as socially responsible investing (SRI), impact investing and ESG investing to describe the phenomenon. Creating long-term value for the society and the environment in combination with sustainable returns is the main aim of these terms. The primary focus of this thesis is on ESG investing which integrates non-financial information into profit-seeking investment decisions. Asset managers invest in companies with higher ESG ratings as these have a tendency to greater awareness of probable financial material risks and opportunities that can manage them more efficiently.

Due to the mounting interest from investors for additional, non-financial information, rating agencies such as MSCI, Sustainalytics (Morningstar), Vigeo Eiris (Moody's), RobecoSAM (S&P Global) and Asset4 (Refinitiv) nowadays evaluate firms and provide ESG ratings (Berg et al., 2020). These ratings have been used also by scholars who try to unveil the implication on risk-adjusted returns from the integration of ESG to investment decisions. So far they have provided vague conclusions with positive (Kempf and Osthoff, 2007, Friede, Busch and Bassen, 2015, Nagy et al., 2016), negative (Renneboog et al., 2008, Hong and Kacperczyk, 2009, Das et al., 2018) and neutral results (Auer and Schuhmacher, 2016, Hsu et al., 2018, Breedt et al., 2019).

The purpose of this master thesis is to examine whether ESG based investing could lead to superior financial performance, thus, rewarding socially conscious investors, and further investigate whether the ESG portfolios could generate abnormal returns. It extends the empirical research on ESG in two ways. Firstly, by analyzing the relationship between ESG ratings and equity portfolios on a more recent time period that involved a financial crisis that emerged from the exogenous COVID-19 pandemic. Secondly, conclusions are derived regarding a portfolio comprised of firms without exhibiting an ESG rating.

Multiple questions are raised. The first question to answer is if "*ESG leading equity portfolios*" (portfolios comprising stocks of companies with high ESG ratings) generate higher returns compared to the rest of the portfolios and the benchmark. The second question is whether "*ESG leading equity portfolios*" tend to exhibit lower volatility compared to the rest of the portfolios and the benchmark. Rather obviously the next question that arises is whether "*ESG leading equity portfolios*" exhibit higher risk-adjusted returns than the rest of the portfolios and the benchmark. During the sample period, a financial crisis arose from the coronavirus disease, thus, the performance prior, during and post this crisis was further examined. Lastly, instead of focusing only on how the backtested ESG portfolios performed through the sample period, we investigated whether the "*ESG leading equity portfolios*" or any of their counterparts managed to generate abnormal returns, or if their returns could be explained by well-known common factors.

In this study, the ESG rating data from one of the biggest providers, MSCI, were used in order to construct seven ESG portfolios and one Non-ESG portfolio from the constituents of the S&P 500 index at the start of August 2021. The firms that comprised the index were ranked each July by their ESG rating and distributed to the relevant portfolio, starting in July 2017 and ending in June 2021. The ones with missing ESG data were added to a portfolio named "*Non-ESG*". All the portfolios were equal-weighted and were rebalanced annually. The "*buy and hold*" strategy was implemented from July to June of the next year. The S&P 500 Equal Weight Index (S&P 500 EWI) was used as a benchmark for better comparisons with the equal-weighted portfolios instead of the S&P 500.

Responding to the aforementioned questions multiple financial tools were applied. The reply to the first question was derived by examining the geometric mean returns of the portfolios. Historical volatility was used as a proxy to measure portfolios risk and answer the second question. To respond to the third question a well-known risk-adjusted measure the Sharpe ratio was applied. Moreover, for the three sub-periods, the portfolios were examined by their cumulative returns. Finally, Capital Asset Pricing Model (CAPM) and Fama-French Three Factor Model (FF3FM) were employed to answer the last question.

The remainder of this paper is organized as follows. Sustainable investing and the ESG pillars are presented in the second section. Section three provides a review of the most relevant literature and the criticism on ESG investing. The foundations of portfolio management, CAPM, FF3FM and the Efficient Market Hypothesis (EMH) are presented in the fourth section. In section five, we present the data and the methodological approach. The empirical results are presented in the sixth section. In Section seven, we discuss the empirical findings. In the eighth and last section the conclusions and the limitations are presented. Furthermore, suggestions for future research are pointed out.

2. SUSTAINABLE INVESTING AND ESG FACTORS

In this section, the main approaches of sustainable investing, SRI, impact investing and ESG investing, are presented. In addition, a brief analysis of the E, S and G factors is exhibited along with their criteria. Lastly, how MSCI defines ESG investing and their methodology behind the computation of the ESG ratings is presented.

2.1 What is Sustainable Investing?

For the first time, United Nations World Commission on Environment and Development (the Brundtland Commission) in its report "*Our Common Future*" in 1987 defined the term sustainable development (Brundtland and Khalid, 1987). According to their definition, sustainable development aims "*to meet the needs of the present without compromising the ability of future generations to meet their own needs*".

Derived from the definition of sustainable development, it would be easy to define sustainable investing. Unfortunately, there is not a consistent definition of sustainable investing since it has multiple dimensions. By examining in depth sustainable investing, we come across terms such as SRI, impact investing and ESG investing. What these terms have in common is their long-term horizon and their aim to have a positive effect on the environment and society alongside financial returns. Emphasis should be given on the fact that there are differences in objectives concerning sustainable investing. Hence, it would be vital to shed some light on the terms SRI, impact investing and ESG investing, the three most common approaches for sustainable investing (Pai et al., 2019).

Socially responsible investing (SRI) positions ethical guidelines alongside financial goals. The motives vary to personal values, political beliefs or religion. This sort of investment initially focused on exclusionary screening or more frequently, negative screening by avoiding investments in firms, sectors or even countries that do not reflect investor's personal values. Common practices of SRI are to exclude companies associated with alcohol, adult entertainment, tobacco, gambling and weapons. These are referred to as "*sin stocks*" since their main driver of making money is from exploiting human weaknesses. Institutional investors such as pension funds, universities, religious organizations, insurance companies and banks shun the above industries as they do not want any association with sin stocks (Hong and Kacperczyk, 2009). Opposite of the negative screening is the positive screening, an investment strategy that focuses on buying businesses that are consistent with investor's personal social values, for example, companies that donate to charitable causes. In the end, the balance between making a profit and investor principles are the key to success for the SRI approach.

Impact investing refers to investments made into firms and funds with the purpose to yield positive, quantifiable, environmental and social impact alongside a financial return.[3] Investors deliberately supply capital to environmental and social businesses or community groups with a focus to solve critical issues and benefit the societies such as sustainable agriculture, healthcare and education. Therefore, this approach carries substantial investment risk. According to Global Impact Investing Network, asset owners are committed to measuring and reporting the social and environmental performance of their investments through formal frameworks such as the United Nations Sustainable Development Goals (SDGs).[3] On the financial performance of impact investing, this varies from below market return to risk-adjusted market return. As a result, social and environmental influence is primary and financial returns are secondary, for this approach of investment.

ESG Investing incorporates environmental, social and governance factors which are non-financial information into the fundamental investment approach and regards that these factors have an essential impact on a firm's success, valuation and market returns. Generally, for the non-financial information of companies, investors rely on ratings and scores provided by data vendors such as MSCI, Sustainalytics (Morningstar), Vigeo Eiris (Moody's), RobecoSAM (S&P Global), Asset4 (Refinitiv) (Berg et al., 2020). They favor corporations with higher ESG ratings compared to their peers in each industry. Instead of focusing on the overall ESG score of a company, asset owners also tilt to a specific factor for example the environmental and construct a portfolio with high scoring companies on this factor. The philosophy behind ESG investing summarizes the idea that corporations with high ESG ratings tend to have a greater awareness of possible risks that could one day become financial material and therefore can manage them more effectively. According to Amel-Zadeh and Serafeim (2017) the main reason why institutional investors utilize ESG information is that these issues are or will become financial material to investment results. Hence, ESG investing is an

[3] Global Impact Investing Network, "Core Characteristics of Impact Investing"

investment approach that aims to maximize risk-adjusted financial returns by utilizing ESG ratings and consequently, benefit the common good for the long-term.

After exploring the most common sustainable investing approaches it is notable to mention that these strategies are difficult to distinguish and can overlap. For instance, consider a company that is classified in the fossil fuels industry, typically, it has a low ESG score on the environmental factor. Asset owners with SRI principles would exclude this type of company from their investment universe. The same could be applied by investors who value rather high the environmental pillar from ESG and invest only in high E scoring corporations. As a result, the first type of investors because of their personal values negatively screen the company while the other investors view the low E score as a high risk in terms of polluting the environment. Therefore, avoiding investing in this company makes sense for both reasons.

2.2 Exploring the Pillars of ESG

ESG investing is the combination of traditional investment approaches with ESG insights incorporated by investors in order to pursue their long-term investment goals. Professional investors can use the three pillars separately or overall in order to evaluate firms compared with their peers. This is because not every sector has the same risks and issues and therefore, not all of these issues are financial material. As a result, ESG rating comparisons should be done among peers. In order, to integrate ESG into investment decisions it is vital for portfolio managers and investors to comprehend the three major pillars.

1. Environmental pillar is a broad category and emphasizes on the actions taken by a firm to protect our planet. Its criteria focus on climate change, waste pollution, deforestation, clean technology, etc. Figure 2 demonstrates ESG key criteria that are used by sustainable investors. In the last decades, more and more people are aware of climate change and therefore a lot of attention has been shifted on the environmental pillar from investors. Climate change affects all corporations no matter in which sector they operate, hence, it is considered a systematic risk (Oguntuase, 2020). While it is a systematic risk, not every company affects and is affected with the same magnitude from the environment. So, investors focus also on the other criteria regarding the environment and seek to answer questions in order to understand the risks and how the corporations mitigate those risks. For example, questions would be such as: How

does the company manage its impact on the environment? Is it affected by water pollution? Does it affect its profitability? What does it do to mitigate environmental risk? These are fair questions by environmental concerned investors since they would not want to be involved in an environmental catastrophe and for them also financial. A well-known example is BP's oil spill scandal in the Gulf of Mexico in 2010, which is considered the worst environmental disaster in US history since it released an estimated 3.19 million barrels of oil. BP had to pay $65 billion for fines, clean-up costs and local reparations. As of the share price, prior to the incident, it was roughly $59 dollars and it lost 54% between April 20, 2010, and June 25, 2010.[4] On the contrary, favorable outcomes for investors such as green building and clean technology improve profitability and lower costs of firms due to better energy efficiency.

2. Social pillar concentrates on people, no matter if they are in or out of the corporation. Thus, attention is shifted to the relationship between the company and its employees, customers, suppliers and the community where it functions. Key criteria are diversity and inclusion, human rights, working conditions, child labor, etc. (more on Figure 2). Investors who highly appreciate the social factor often monitor how companies foster their people as information regarding safety and human rights spread instantly across social media and news. In order to be more cautious on the social risks that threaten the reputation of a business that they are invested in, investors ask questions like: Does the company treat their labor force in an ethical manner? Does the corporation have a negative impact on the community it is located in? Is the firm involved in child labor? No institutional investor would like to have investments in a business that is involved in child labor or loose safety measures as it would mean severe reputational damage and hurt returns. On the other hand, good social practices enhance a corporation's reputation with customers and contribute to employee satisfaction. Having a more satisfied workforce has a positive correlation with shareholder returns (Edmans, 2011).

3. Governance pillar refers to a system of guidelines, practices and processes by which a company is managed and controlled. It ensures transparency, identifies who makes decisions, who has power and accountability and how the interests of all of its stakeholders are aligned. It is a set of tools that enables the board and management to navigate their business and achieve long-term strategic growth. The governance pillar exclusively focuses internally and not on how the company interacts with the outside world, like the other two pillars. The primary factors are internal controls, executive compensation, bribery and corruption, etc. (more on Figure 2).

[4] "BP leak the world's worst accidental oil spill". The Daily Telegraph, 2 August 2010

Investors are also interested in shareholder rights and accurate and transparent accounting and audit procedures. Poor corporate governance could lead to unpleasant situations and financial disaster for investors. The Enron collapse at the end of 2001 after the reveal of systematic accounting fraud practices was due to a lack of corporate governance from fraudulent management. Asset owners in Enron saw their stocks tumble from the highs of $90.75 to $0.26 in a couple of months.[5] The board of directors must ensure that the firm's corporate governance policies integrate the corporate strategy, accountability, transparency, risk management and ethical behavior. In order to achieve this, the management should constantly monitor and report on the company's performance as it will build trust with all the relevant stakeholders. Good governance is important as it enables the company to effectively create long-term value.

Figure 2: Example of ESG criteria (Source: Sustainable Investing Basics)

5 "Enron: Why Corporate Governance Matters". Candriam, 21 October 2019

In order to help asset managers, comprehend the above factors, corporations publish annual sustainability reports where they position themselves on how they tackle and mitigate their risks concerning ESG material issues. Governance and Accountability Institute announced that 90% of the companies included in the S&P 500 published annual sustainability reports in 2019, an all-time high. That's 4% higher than the previous year's 86%. Recalling, also, 2011 when only 20% of the firms published a sustainability report and one year later already did more than half, reaching 53%.[6] These sustainability reports and every public information that is available along with surveys are used from ESG data providers to assess the ESG ratings and scores for corporations.

2.3 MSCI Definition of ESG Investing and Their Approach to ESG Ratings

In the last decade due to an increased appetite for ESG scores from professional investors, academics and individual investors multiple data vendors started providing this kind of information. One of the main issues that emerged is the lack of access to reliable and consistent ESG data (Christensen et al., 2021). The foremost reason why ESG ratings diverge is because of different measurements applied in the same category from the data providers. Scope divergence is slightly less significant, while the least vital are weights applied in the categories (Berg et al., 2020). In this master's thesis, the ESG ratings from data vendor, MSCI, are used to construct the portfolios from the constituents of the S&P 500 index. Thus, it is notable to understand their definition of ESG investing, and how they compute the industry-adjusted final ESG ratings.

According to MSCI "*ESG investing is the consideration of environmental, social and governance factors alongside financial factors in the investment decision-making process*".[7] When it comes to evaluating each company to the specific E, S and G pillars, MSCI focuses exclusively on a set of "*key issues*" that are grouped into ten themes. Figure 3 depicts the ESG pillars with their related themes and key issues. Across the different industries, companies in

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[6] 90% of S&P 500 Index Companies Publish Sustainability Reports in 2019, G&A Announces in its Latest Annual 2020 Flash Report, Governance & Accountability Institute, 16 July 2020

[7] ESG 101: What is Environmental, Social and Governance?

the same industry face more or less the same risks and opportunities, not all of them are significant and not every company has the same exposure to them. Thus, they are evaluated only on material risks and opportunities, even though company specific exceptions are permitted. Material risk refers to a risk that will incur considerable losses to firms in a specific industry that are associated with it while an opportunity is considered material to companies in an industry when it is likely that they could benefit from it for profit.[8]

3 Pillars	10 Themes	35 ESG Key Issues	
Environment	**Climate Change**	Carbon Emissions Product Carbon Footprint	Financing Environmental Impact Climate Change Vulnerability
	Natural Capital	Water Stress Biodiversity & Land Use	Raw Material Sourcing
	Pollution & Waste	Toxic Emissions & Waste Packaging Material & Waste	Electronic Waste
	Environmental Opportunities	Opportunities in Clean Tech Opportunities in Green Building	Opportunities in Renewable Energy
Social	**Human Capital**	Labor Management Health & Safety	Human Capital Development Supply Chain Labor Standards
	Product Liability	Product Safety & Quality Chemical Safety Financial Product Safety	Privacy & Data Security Responsible Investment Health & Demographic Risk
	Stakeholder Opposition	Controversial Sourcing Community Relations	
	Social Opportunities	Access to Communications Access to Finance	Access to Health Care Opportunities in Nutrition & Health
Governance*	**Corporate Governance**	Ownership & Control Board	Pay Accounting
	Corporate Behavior	Business Ethics Tax Transparency	

** The Governance Pillar carries weight in the ESG Rating model for all companies.*

Figure 3: MSCI ESG themes and key issues (Source: MSCI ESG Ratings Methodology)

The E pillar includes under its umbrella four themes, climate change, natural capital, pollution and waste, and environmental opportunities. Among these themes, there are multiple risks like carbon emissions, water stress, electronic waste and opportunities in renewable energy, green building and clean tech. The S pillar pays attention to human capital, product

[8] MSCI ESG Ratings Methodology

liability, stakeholder opposition and social opportunities. Labor management, health and safety, privacy and data security and community relations are some of the numerous key issues. The opportunities include access to healthcare, communications, finance, and nutrition and health. The G pillar has only two themes, corporate governance and corporate behavior. Key issues can be summarized as ownership and control, board pay, accounting, business ethics and tax transparency. Governance concerns all firms and thereby it carries weight in all of them.

In order to derive a score for each key issue MSCI measures a score between 0-10 scale for exposure and management, zero means no exposure and no management efforts while ten refers to high exposure and very strong management. Each key issue then has a score between 0-10, where zero is very poor and ten is very good. Then a weighted score is calculated for every pillar. In order to assign a final ESG rating for each company, MSCI takes "*the weighted average of individual Key Issue Scores*" and "*is normalized relative to ESG Rating Industry peers*".[8] Their rating scale ranges from CCC (worst) to AAA (best) and they categorize the firms as leaders (AAA, AA), average (A, BBB, BB) or laggards (B, CCC) according to their ESG rating. Their database has extensive coverage of 8.500 companies with available ESG ratings and more than 680.000 equities and fixed income securities from 14.000 issuers. Every firm receives at least annually a thorough review, even though MSCI monitors the situation on a daily basis for score changes especially for governance events and disputes.

3. LITERATURE REVIEW

In the last two decades, ESG investing gained momentum from investment professionals to scholars and many examined the relationship between ESG and financial returns. Early reports going back to 1970 scrutinized the connection between Corporate Social Responsibility (CSR) or specific issues related to E, S and G with financial performance as back then the term ESG did not exist. So, within the academic literature ESG investing is confused with SRI and CSR. Thus, discussions about SRI, CSR and ESG investing often refer to the same term. Hereby, in this thesis, we refer to ESG.

Back in 1970, the belief of a corporation’s social responsibility as cited by Milton Friedman was to maximize its profit, as this is for the best interests of its shareholders (Friedman, 1970). Any involvement of the business in socially responsible activities would signify a lower return for the business owners, thus, it would destroy shareholder wealth. Although this was the general belief at that time there were several studies that tried to find a connection between CSR and Corporate Financial Performance (CFP). Among the different views, Moskowitz (1972) found a positive connection, Vance (1975) a negative, and Alexander and Buchholz (1978) found no significant connection. As these readings are way back of our time, the attention of this thesis is shifted to more recent studies. In our days, many researchers support the notion “*do well by doing good*” as quoted by Eccles et al. (2014) in their study. Towards this belief, some of the recent academic papers examine the relationship between specific E, S and G issues with financial performance.

The first subchapter examines the connection of specific E, S and G pillars with financial returns while the second with the overall ESG score. In the third subchapter, we observe how ESG firms performed during the COVID-19 pandemic while in the next one the main criticism on ESG is presented. The last section provides a summary of the literature review.

3.1 Equity Returns and the E, S and G Dimension

Derwall et al. (2005) ranked US firms by their eco-efficiency rating, retrieved from Innovest database for the period of 1995-2003. They constructed two mutually exclusive equity portfolios, one comprised of companies with the lowest eco-efficiency scores and one with the highest. These portfolios were re-ranked and rebalanced on an annual basis. Following CAPM, FF3FM and Carhart multifactor model their results demonstrated that the high-ranked portfolio exhibited superior financial performance even when adjusted for volatility as measured by the Sharpe ratio. The best-in-class portfolio generated a 6% excess return over the worst-in-class portfolio with a 5% significance level. This performance difference persisted even after including transaction costs. According to the authors, a portfolio focusing on the E component constructed by the best eco-friendly firms could sizably outperform its counterpart.

Shifting the attention to the S dimension of ESG, these papers pay attention to employee related issues. Edmans (2011) examined the relationship between employee welfare and shareholder returns in an analysis starting from 1984 to 2009. He formed a value-weighted and an equal-weighted portfolio with the "*100 Best Companies to Work for in America*". In order to compute the risk-adjusted excess returns, he followed the Carhart multifactor model. Both portfolios produced significant alphas over the three benchmarks that were used, the risk-free rate, the industry-adjusted and the characteristics-adjusted benchmark. For example, the value-weighted portfolio yielded an abnormal annual return of 3,5% over the risk-free rate and 2,1% over the industry-adjusted benchmark while the equal-weighted portfolio exhibited slightly higher returns of 3,7% and 2,4%, respectively. His findings demonstrated a positive long-term correlation between employee satisfaction and equity returns. Although, the author stated that the implications of his study are unclear for future portfolio performance since intangibles are hard to embody into stock prices.

Another study that focuses on social screens like employee relations is from Derwall et al. (2011). The authors divided socially responsible investors into two categories, the "*values-driven*" and the "*profit-seeking*" investors. The first ones integrate negative screening while the later ones incorporate positive screening into their investment decisions. Values-driven asset owners could accept negative performance since they derive non-financial utility from the incorporation of social screens, while for profit-seeking investors main motive is financial excess returns. They used two hypotheses, the shunned-stock and the errors-in-expectations in order to demonstrate financial outperformance from the controversial sin stocks portfolio and the socially strong equity portfolio with a high-employee relations score. For the social responsibility scores, they used the KLD database (now MSCI ESG ratings) for public listed US firms from 1992-2008. As for the computation of abnormal equity returns the Carhart multifactor model was used. The study results denoted outperformance of controversial sin stocks like the Hong and Kacperczyk (2009) study also displayed. The strong employee relations portfolio also generated positive abnormal returns but the effect diminished over the long run. The authors cited that social strong portfolios could yield significant alphas over specific periods compared to their competitors.

Besides the environmental and social dimensions of sustainability, scholars have also investigated the effect of governance issues on stock market performance. The most prominent study on corporate governance and equity returns was published by Gompers, Ishii and Metrick (2003). The researchers constructed a Governance Index (GI) and calculated the score for about 1500 firms. A score equal to or above 14 would imply a poorly-governed firm, while a score equal to or below five described a well-governed firm. For the calculation of returns, they employed the Carhart multifactor model and they created ten portfolios. The first portfolio consisted of firms with GI score equal to or below five while the tenth portfolio of firms with equal or above 14 GI score. In between portfolios consisted of firms with GI score equal to six up to 13. The first portfolio exhibited a positive monthly excess return of 29 basis points while the tenth portfolio generated a negative monthly excess return of 42 basis points, both returns significant at 1% level. In addition, the authors used a long-short investment strategy to construct a portfolio that went long on the first portfolio and short on the last portfolio. Their results showed that a high corporate governance portfolio earned risk-adjusted annual abnormal return of 8,5% over the period of 1990-1999 compared to the portfolio comprised by poorly governed corporations. Hence, superior governance quality led to better financial performance.

The aforementioned studies are only a fraction of the existing academic literature that examined the correlation between E, S and G related issues with portfolio performance. The next subchapter scrutinizes the relationship between the overall ESG score and portfolio returns.

3.2 Equity Returns and the Overall ESG

While other studies focused solely on one particular ESG element, this subchapter investigates environmental, social and governance related aspects as a whole in association with financial returns. Prior empirical evidence results vary since many studies showed a neutral, a positive and a negative effect of ESG on financial performance.

3.2.1 Neutral Impact of ESG on Portfolio Returns

There is an ongoing dispute on the connection between ESG and portfolio returns. Here the emphasis is on studies that exhibited a neutral, mixed or no significant correlation, meaning that ESG investing strategies do not hurt returns but neither yield substantial positive returns.

Auer and Schuhmacher (2016) explored risk-adjusted performance as measured by the Sharpe ratio of high and low ESG portfolios in three regions, Asia-Pacific, US and Europe and compared them to their benchmarks. They divided the sample into four industry sectors and utilized ESG data from Sustainalytics for the period of 2004 to 2012. By ranking the companies with their specific E, S, G and the overall ESG score for every region and industry with a 5% cut-off rate (portfolios comprising stocks of the best/worst 5% companies) they constructed 60 portfolios of high ESG companies and 60 portfolios of low ESG firms. The results exhibited that 15 out of 60 best ESG portfolios had higher risk-adjusted performance compared to their benchmark. Surprisingly, in Europe, not a single high-rated ESG portfolio displayed a higher Sharpe ratio. On the contrary, 34 out of 60 low-rated ESG portfolios outperformed their benchmarks. Evaluating the performance between the high ESG and low ESG portfolios, 18 out of 60 times the best ESG portfolios exhibited superior performance compared to their lower counterpart. Among those 18 outperformances, 11 happened in the US region and not a single in Europe. The authors in order to have more robust results repeated the computations for different cut-off rates. The conclusion of their research is that high-ranked and low-ranked ESG portfolios do not provide superior or inferior performance compared to their benchmarks in the regions of Asia-Pacific and the US. In contrast, ESG investors in Europe should sacrifice financial performance in order to construct sustainable portfolios.

Breedt et al. (2019) scrutinized if ESG should be used as an equity factor or as an investment guide from asset owners. They employed MSCI ESG rating database for the ESG ratings of firms, for the period of 2007 – 2017. They constructed a universal equity market neutral portfolio in order to examine if ESG could be considered as an equity factor. The results showed that the portfolio did not yield any significant performance neither with a tilt at the specific E, S, G elements nor at the combined ESG. When they made adjustments by removing the market cap and volatility bias, ESG as an equity factor had returns compatible with noise. Hence, a portfolio incorporating ESG ratings did not provide an additional benefit neither it affects negatively returns. Their interpretation of results mentions that any advantage from integrating ESG into a market-neutral portfolio is already captured by other well-known equity factors. Their conclusion is that ESG should not be considered as a unique equity factor by asset owners.

Another study that explores the performance of ESG investments is from Hsu et al. (2018). The scholars constructed portfolios by deriving ESG data from two sources, Bloomberg and Thomson Reuters for the period of 2006-2017. Every year they chose the 500 largest firms in their universe and ranked them according to their specific E, S, G score and the overall ESG score. They constructed long-only portfolios with an E, S, G and overall ESG score above the median, below the median and stocks that did not have an ESG rating at that time (nonresponder). In addition, they created a top minus bottom and a responder minus nonresponder portfolios. For the construction of the portfolios, they used two weighting methods, equal and capitalization. In order to explain the return difference, they incorporated Carhart multifactor model. The top ESG portfolio generated insignificant lower returns compared to its counterpart especially with the cap-weighted method for both datasets. In the dataset from Bloomberg, the responders and nonresponders portfolios had no statistically significant return difference while on the Thomson Reuters dataset there was a weak significance outperformance of the responders with the equal weighting method. The authors cited that they "*cannot conclude whether responders outperform or underperform nonresponders or whether ESG firms outperform or underperform non-ESG firms*". Furthermore, they constructed an "*ESG in Need*" index that invested in the top ESG corporations with a high cost of capital. The index produced annualized excess return above 3% over the benchmark for both datasets. According to their conclusion asset managers who highly value ESG and target return optimization should invest in ESG in need firms as this is a way to yield higher returns and be more socially valuable than traditional ESG investing.

3.2.2 Positive Impact of ESG on Portfolio Returns

Within the academic literature, there are multiple papers that found superior performance from ESG investments. In this part, we focus on the most notable ones.

One of the most prominent studies in the academic literature regarding the relation between ESG and CFP is from Friede, Busch and Bassen (2015) who performed a literature review on more than 2000 empirical studies starting from 1970 until the end of 2014. They chose a two-step research method where the first step included vote-count studies while the second meta-analysis studies. The results exhibited roughly 90% a nonnegative correlation among ESG and CFP. Positive findings accounted for 48,2% while neutral and mixed findings accounted for 23% and 18%, respectively. The authors also examined the relationship between different asset classes. The positive results accounted for 52,2%, 63,9% and 71,4% for equities, bonds and real estate, respectively. Only equities displayed negative findings with 4,4%, although, the number of studies examined for bonds and real estate was considerably low. Among the E, S, G factors the results showed that the G factor had the biggest positive and negative correlation with 62,3% and 9,2%, respectively. Another major finding was that emerging markets exhibited higher (lower) positive (negative) findings compared to developed markets. Last but not least, on portfolio performance, the outcome of the study revealed neutral mixed results with 73,5%, while positive and negative findings were 15,5% and 11%, respectively. Hence, according to the authors, that is the cause of dispute among academics and practitioners on the association of ESG to CFP.

Nagy et al. (2016) analyzed two investment strategies for the period of 2007-2015 while using ESG data from MSCI. The first strategy "*ESG tilt*" invested in the best stocks in terms of ESG rating while minimizing the active risk (difference between the managed portfolio's return less the benchmark return) of the portfolio. The second strategy "*ESG momentum*" invested in equities that enhanced their ESG rating during the past twelve months. The two strategies differ on the time horizon since tilt strategy is more focused on the long run while momentum is focused on the short term. MSCI World Index was used as a benchmark and from its constituents the two portfolios were formed. The results of the study unveiled that both strategies outperformed the benchmark with annualized active returns of 1,1% (ESG-tilt) and 2,2% (ESG-momentum) and enhanced the ESG scores of the portfolios. The ESG tilt strategy tended to have lower unsystematic risk, favored mid-cap stocks and tended away from value stocks. Most of the active return was driven by style factors while the active risk was driven from stock-specific risks. On the momentum strategy, the active performance was derived mainly from exposure to stock-specific returns but the style and industry factors played a significant role. In terms of risk again the stock-specific factor had the major part. The ESG momentum strategy favored mid-cap stocks and equities with positive price momentum. According to the scholars, asset managers who are willing to take some active risk while simultaneously wanting to increase the ESG score of their portfolio could integrate the above strategies in their investment process.

Kempf and Osthoff (2007) examined the returns of SRI portfolios by employing negative, positive and best-in-class screens for the period of 1992-2004. They utilized KLD SRI ratings (now MSCI ESG ratings) to rank the firms and construct value-weighted portfolios. The portfolios were rebalanced annually. As previous scholars, for the portfolio performance, they applied Carhart multifactor model. The top portfolio consisted of the best 10% of all stocks while the bottom portfolio consisted of the worst 10% of all stocks. Also, they constructed a long-short portfolio, which went long on the top portfolio and short on the bottom portfolio. The evidence from the negative screening showed that the bottom portfolio exhibited higher alpha than the top portfolio while the long-short portfolio had a negative alpha but all of them were insignificant. In contrast, the long-short portfolio revealed a 4,46% alpha when employed positive screens. When they applied a combination of negative and positive screening in a long-short portfolio the excess return was even higher, 4,80%, both statistically significant on 10% level. Looking at the factor loadings the most interesting result was that the top portfolio consisted of more growth stocks than the bottom portfolio. Shifting the attention to the best-in-class approach the results were even more robust. Both significant at 5% level, the long-short portfolios with positive screening and the combination of positive and negative screening yielded 4,90% and 5,21%, respectively. As Derwall et al. (2005) the authors also examined if the excess return remains statistically significant after including transaction costs for the long-short strategy. Only, the best-in-class approach generated statistically significant positive abnormal returns. Additionally, they scrutinized if the profitability of the long-short portfolios changed when incorporating different cut-offs like Auer and Schuhmacher (2016). The outcome revealed that the best-in-class approach delivered an excess return of up to 8,7% when the 5% cut-off rate was implemented. Lastly, they observed if there was a material change on the alphas because of the weighting methodology, thus, they constructed equal-weighted portfolios to test this. The outcome was similar. As a result, asset owners could earn high excess returns by incorporating positive or best-in-class screening. Negative screening led to inferior performance while the best-in-class screening focusing on the very best companies (5% cut-off rate) generated supreme performance.

3.2.3 Negative Impact of ESG on Portfolio Returns

There are a few studies in the academic literature that find negative evidence on ESG investing. Hong and Kacperczyk (2009) study is arguably one of the most cited paper that explores the effect of negative screening on portfolio returns. They analyzed US "*sin stocks*" return for the period of 1926-2004. By "*sin stock*" they referred to corporations involved in the tobacco, alcohol and gambling sectors. The authors did not include adult entertainment companies because there were a few of them during the period of the study and also did not include firms involved in the weapon industry as many Americans did not consider it as a sin. They constructed a long-short portfolio that went long on an equal-weighted portfolio of sin stocks and short on an equal-weighted portfolio of comparable ethical stocks. For the performance measurement, they used notable regression models like CAPM, FF3FM and Carhart multifactor model. With the CAPM the portfolio yielded a 0,45% monthly excess return statistically significant on a 5% level. The FF3FM and Carhart model revealed statistically significant on 1% and 5% level positive monthly alphas of 0,57% and 0,39%, respectively. Therefore, the portfolio comprised of sin stocks outperformed a portfolio of comparable stocks from the industry groups 2 (food), 3 (soda), 7 (fun) and 43 (meals and hotels) that belong to Fama and French (1997) study. In addition, the authors investigated the ownership structure of sin stocks and found that few of them were held by professional investors because of social norms. The results of the paper denoted that stocks that promote vice had higher expected returns since most of the institutional investors shunned them and because the possibility of litigation was higher, thus, compensation should be paid for investors who hold them.

Das et al. (2018) investigated the risk-adjusted performance of socially responsible mutual funds (SRMF) during the period 2005-2016 and for three sub-periods. The three sub-periods were 2005-2008 (before and during the Great Recession), 2009-2012 (immediate recovery after the Great Recession) and 2013-2016 (economic expansion). They utilized Morningstar database for the ESG scores of the mutual funds and divided them into three equal categories. The high ESG category consisted of the 33% best SRMF while the low ESG contained the worst 33% of SRMF and in between there was the mid ESG. The Overall category was used as the benchmark and consisted of all the above SRMF. During the whole period of the study, the low ESG fund exhibited statistically significant higher monthly return and the biggest inflow while the mid ESG fund had the biggest Sharpe ratio and the lowest expense ratio. In contrast, the high ESG fund underperformed on monthly return and risk-adjusted return while it had also the biggest expense ratio. During the first sub-period, before and after the Great Recession, the high ESG fund had the lowest significant negative monthly return and the highest significant Sharpe ratio. During the next two sub-periods, the high ESG fund underperformed the other two SRMF and the benchmark both in terms of raw monthly returns and on a risk-adjusted basis. Also, it exhibited the highest cost as measured by the expense ratio. The conclusion of the study was that the high ESG fund performed better only during the sub-period of the financial crisis since on all the other sub-periods and the overall period of the study it underperformed. On the overall period of the study and on the other two sub-periods the low ESG fund had the biggest raw returns and the biggest inflow of funds while the mid ESG fund had the best risk-adjusted returns and the lowest expense ratio.

Renneboog et al. (2008) examined the performance of SRI equity funds around the world. The SRI funds were from Europe, North America and Asia-Pacific. They employed regression models such as CAPM and Carhart multifactor model in order to measure the abnormal returns on equally weighted portfolios. The sample period ranged from 1991 until 2003 and they utilized multiple data sources (S&P, Bloomberg, Datastream, CRSP) for the SRI funds and the conventional funds data. SRI funds used 21 screening criteria in total that could be classified into four major categories, environmental, corporate governance and social, ethical and sin. The results of the study demonstrated that the alphas of the SRI funds as computed by the CAPM were lower compared to the rest and the benchmarks and significant on 5 countries in Europe, US, Japan and Singapore. In contrast, the differences in alphas between SRI and conventional funds were significant for only a small number of differences. In line with the CAPM results, the evidence from the Carhart model was again the same, SRI funds underperformed the stock market indexes and in most cases their peers. Once more alphas were significant for five countries in Europe, the North-America region, Japan and Malaysia. Statistically significant abnormal returns ranged from -4% to -7% exhibiting strong underperformance of SRI funds. Furthermore, the authors examined the impact of management fees in the performance of SRI funds and provided similar results, thus, the underperformance could not be explained by the imposition of management fees. The above paper provided worldwide evidence of underperformance from SRI equity funds compared to conventional funds and the respective benchmarks.

3.3 ESG Equities During COVID-19

Throughout the study period of this thesis an unprecedented stock market crash arose due to the effect of the coronavirus pandemic. Major indices faced sharp declines, the Dow Jones and S&P 500 plummeted 11% and 12% on the last week of February 2020 before they bounced back to pre-pandemic levels in May 2020.[9] Thus, it is vital to browse some studies and their empirical results in order to have a better understanding of how the best ESG and the worst ESG companies performed during the COVID-19.

Borovkova and Wu (2020) examined the returns and volatility of high and low ESG firms in the US (S&P 500) and Europe (STOXX 600) for a period of four and a half months during the pandemic. The period stretched from the start of January until mid-May and ESG data from Refinitiv were used. In the US more sustainable companies exhibited lower losses when compared to the overall ESG score while when compared to the G pillar, well-governed firms displayed higher and positive average returns relative to their peers. In contrast, high E firms had inferior average returns than their counterparts. On the S pillar, both sustainable and less sustainable firms had roughly the same negative performance. Shifting the attention on risk, less sustainable corporations presented higher variability of their stock price. High and low firms on the E and S pillar were affected nearly the same as the benchmark. The best firms on the G factor had less volatility, further supporting the theory that well-governed firms are more resilient during hard times. Breaking the sample into sectors, the evidence revealed that high ESG companies in Materials and Health Care sectors outperformed their conventional peers both when compared on the overall ESG score and on the specific E, S, and G pillar. Firms on the Consumer Staples and Utilities industries also performed better than their less sustainable counterparts and the performance was driven by high G (for Consumer Staples) and E (for Utilities) companies. According to the authors, the analysis on the European companies revealed that sustainable and less sustainable firms had suffered similar losses and performed

[9] "The Biggest Stock Market Crashes in History". The Motley Fool, 3 September 2021

nearly the same during the COVID-19 period. The figures showed that on the unique E, S and G pillars high sustainable firms had lower average returns. When compared on volatility high, low ESG firms and the benchmark were roughly similar. High ESG businesses in industries like Energy, Materials and Utilities exhibited higher performance in comparison to their peers. The outcome of the white paper was that during the pandemic crisis sustainable firms suffered less in terms of returns and were less risky than their peers. The best-governed companies were more resilient while the best social firms underperformed.

Another recent study that examined the role of ESG performance during the pandemic crisis was from Broadstock et al. (2021). The authors utilized ESG data from Syntao for the constituents of the CSI 300 index which incorporates blue chip (stock of an established, financially sound, and stable company) companies from China. They formed industry-neutral portfolios with high ESG and low ESG firms. The high ESG portfolio consisted of companies that had an ESG score bigger than the ESG score of the median while the low ESG portfolio had the opposite. The study period spanned from mid-2015 to mid-2020 and portfolios were rebalanced bi-annually. During the whole period of the study, high ESG portfolio outperformed its counterpart with a differential cumulative return of 9,4%. Another major finding was that companies with high book to market ratio experienced smaller price declines while more leveraged firms experienced sharper declines. High ESG firms had lower volatility throughout the COVID-19 pandemic. High S companies were impacted negatively by the pandemic while high E and G firms were more resilient. Hence, the evidence of the paper revealed that ESG investments in China were more robust during the recent crisis.

3.4 Criticism on ESG Investing

As ESG integration has increased a lot in the last few years, sustainable investing has evolved from niche to mainstream. When something becomes mainstream and gets a lot of attention it is therefore inevitable that criticism will occur.

The first criticism on ESG investing stems its root from the Modern Portfolio Theory (MPT). According to MPT, a well-diversified portfolio will be more efficient, meaning that it will have a higher expected return and lower expected volatility. Instead, ESG investing with the incorporation of constraints such as negative screening limits the investment universe and leads to an inefficient and suboptimal portfolio, as would be assessed by Markowitz (1952). Thus, the ESG portfolio will suffer an indirect cost from low diversification and as a result, it will generate lower expected risk-adjusted returns.

One more argument against the benefits from ESG on financial performance is claimed by the supporters of the Efficient Market Theory. Fama (1970) who wrote the Efficient Market Theory asserted that all available information is fully reflected in stock prices when markets are efficient. In an efficient market where all investors have access to all newly available information like ESG ratings, such information is immediately priced into the stock market, thus, a portfolio constructed with ESG tilts is impossible to generate positive abnormal risk-adjusted returns.

Another criticism mentioned in the papers asks if a positive connection between high ESG engagement and financial outperformance exists then what causes this relationship? For example, one can argue that firms with high ESG scores better mitigate their risks, have a lower cost of capital and therefore higher valuations. Alternatively, corporations with higher valuations might be in healthier financial shape and have the ability to choose to spend their resources in a socially responsible way so that such investments can improve their ESG profile. As mentioned by Krueger (2015) the empirical studies do not differentiate between correlation and causality. Thus, the investigation goes on.

3.5 Summary from Prior Empirical Evidence

Taking into consideration the empirical literature on ESG investing it is evident that it constitutes an ambiguous concept with varying results. As we saw from the aforementioned studies ESG investing can benefit asset owners positively (Kempf and Osthoff, 2007, Friede, Busch and Bassen, 2015, Nagy et al., 2016), negatively (Renneboog et al., 2008, Hong and Kacperczyk, 2009, Das et al., 2018) and some studies exhibit neutral results (Auer and Schuhmacher, 2016, Hsu et al., 2018, Breedt et al., 2019). Contrary, there are some concepts that produce the same conclusions. First of all, the integration of negative screening, exclusion of sin stocks, results in the underperformance of portfolios held from socially responsible asset owners (Kempf and Osthoff, 2007, Hong and Kacperczyk, 2009, Derwall et al., 2011). In addition, when transaction costs are incorporated on empirical models the portfolios behave the same as before the incorporation, only returns are a bit lower which is obvious but the ranking remains the same (Derwall et al., 2005, Kempf and Osthoff, 2007, Renneboog et al., 2008). Moreover, throughout financial crises such as the Great Recession and the COVID-19 pandemic, ESG portfolios benefit investors with lower negative returns and lower risk (Das et al., 2018, Borovkova and Wu, 2020, Broadstock et al., 2021).

The bottom line from the criticism that ESG investing has received is that it reduces diversification and leads to suboptimal portfolios with inferior risk-adjusted returns, in efficient markets it does not yield abnormal returns, and the contingent for endogeneity through reverse causality.

4. THEORETICAL BACKGROUND

In this section, the foundations of portfolio management from the existing literature are presented. We start with the innovative for its time Modern Portfolio Theory (MPT) and continue with the equilibrium model Capital Asset Pricing Model (CAPM). Next, we discuss multifactor models. Lastly, Efficient Markets Hypothesis (EMH) is presented and we close the section with a measure of risk-adjusted returns, the Sharpe ratio. Understanding everything that is presented in this section is vital since these are used in the next section where we construct, measure and evaluate the ESG portfolios.

4.1 Modern Portfolio Theory (MPT)

One of the major advances in the investment field was the basic portfolio model developed by Markowitz (1952). In his article, he found a reasonable way to quantify risk and complemented it with the expected rate of return. The risk was measured from the variance of the returns. Most importantly, he created a formula to compute the risk of a portfolio and displayed that diversification among securities matters as it reduces the total risk. His theory was based on a set of assumptions like (Reilly and Brown, 2011):

1. Every investment alternative could be represented by a probability distribution of the anticipated returns over some time period.
2. Investors maximize one-period expected utility, and their utility curves exhibit diminishing marginal utility of wealth.
3. The portfolio risk is being measured by the variability of expected returns.
4. Investors decisions are solely based on expected returns and risk.
5. For a specified risk level, asset owners prefer higher returns compared to lower returns. Likewise, for a specified return level, asset owners desire less risk compared to more risk.

From the above assumptions, a security or a portfolio is considered to be efficient when no other security or portfolio with the same or lower risk generates a higher expected return or when no other security or portfolio with the same or higher expected return offers lower risk.

A collection of individually good securities does not necessarily produce a robust portfolio. The returns from all of these securities of the portfolio interact and this relationship of the assets is very important. The connection of these assets is measured by their covariance. Thus, assets in the same industry have high covariance while assets of different industries could have a low covariance. As a result, diversification among different industries and asset classes is very important in order to reduce the total risk of the portfolio.

To summarize, Markowitz was a pioneer and offered a formula to compute the risk of the portfolio. He showed that what matters the most in a portfolio's risk are the covariances between the different assets. Investors could benefit from diversification since in a well-diversified portfolio the risk of every individual security contributes a little to the portfolio's risk. Lastly, he displayed that in investment decisions it does not matter only to select good companies but it matters to select the best combination of companies so that the portfolio will generate the highest expected return given its level of risk, thus being efficient.

4.2 Capital Asset Pricing Model (CAPM)

Building on the earlier work from MPT, Sharpe (1964), Lintner (1965) and Mossin (1966) individually developed the Capital Asset Pricing Model (CAPM) which bases its calculation only on the market risk factor. The CAPM is a financial equilibrium model that gives investors the opportunity to evaluate the risk-return trade-off among individual securities or portfolios. The CAPM formula is displayed on equation (1):

$$R_{it} – Rf_t = \alpha_i + \beta_i (Rm_t – Rf_t) + \varepsilon_{it} \qquad (1)$$

Where:

R_{it} = is the return of stock/portfolio i at time t

Rf_t = is the risk-free rate at time t

Rm_t = is the return of the market portfolio at time t

ε_{it} = error term of stock/portfolio i at time t

In the above formula, we also have an intercept, α which is Jensen's alpha and is commonly known to represent the abnormal performance of the stock/portfolio. A positive and statistically significant alpha indicates that the stock/portfolio outperforms the market given its risk level. In contrast, a statistically significant negative alpha denotes underperformance. When alpha is not statistically different from zero then the stock/portfolio generated the expected return.

In addition to alpha, there is a coefficient named beta (β) which represents the sensitivity of the stock/portfolio compared to the market portfolio. The market portfolio beta is by rule one. Hence, a stocks/portfolios beta greater (lower) than one implies that the stock/portfolio is more (less) exposed to market risk than the market portfolio. In contrast, a beta lower than zero indicates a negative relation between the stock/portfolio and the market portfolio.

The total risk could be decomposed into systematic risk and idiosyncratic risk. The risk inherent to the entire market is often called systematic risk while the risk that is derived from a specific asset is called idiosyncratic risk. As shown by Markowitz (1952) a well-diversified portfolio could eliminate the idiosyncratic risk. Contrary, systematic risk could not be eliminated from a portfolio. Thus, the CAPM rewards asset owners only for bearing systematic risk and this reward is called risk premium. The risk premium ($Rm_t - Rf_t$) is calculated by subtracting the risk-free rate from the return of the market portfolio.

To sum up, the CAPM was the first model that allowed investors to calculate the required return for any given risky asset. In equilibrium, the required return for a stock/portfolio is equal to the risk-free rate plus the multiplication of the stock/portfolio beta with the risk premium.

4.3 Fama–French Three Factor Model (FF3FM)

Fama and French (1993) extended the traditional CAPM which captures only one risk factor. They added two more factors that explain the return of a risky asset. These two factors are Small minus Big (*SMB*) and High minus Low (*HML*). The *SMB* factor denotes the spread between the returns of well-diversified portfolios of small-cap and large-cap stocks. It captures the size effect meaning that a portfolio consisting of small-cap stocks outperforms a portfolio consisting of large-cap stocks. The other factor *HML* indicates the difference among the returns of well-diversified portfolios of value stocks and growth stocks. Value stocks tend to have a high book to market (B/M) ratio while growth stocks tend to have a low book to market ratio. This factor captures the value effect and indicates that a portfolio comprised of value stocks performs better than a growth portfolio. The FF3FM is defined as:

$$R_{it} - Rf_t = \alpha_i + \beta_{i1}(Rm_t - Rf_t) + \beta_{i2}SMB_t + \beta_{i3}HML_t + \varepsilon_{it} \qquad (2)$$

Where:

R_{it} = is the return of portfolio *i* at time *t*

Rf_t = is the risk-free rate at time *t*

Rm_t = is the return of the market portfolio at time *t*

SMB_t = is the excess return of small-cap stocks over large-cap stocks at time *t*

HML_t = is the excess return of value stocks over growth stocks at time *t*

ε_{it} = error term of portfolio *i* at time *t*

In addition, in the formula, we have alpha (α) which expresses the excess return of the portfolio over the market when it is positive and statistically significant. In contrast, when negative and statistically significant it denotes underperformance. Moreover, when it is not statistically significant it indicates that the portfolio generated returns that could be explained by the model.

The above equation has also three beta (β) coefficients. The first one is from the CAPM and explains the sensitivity of the portfolio to the market. The second one if positive indicates a tilt of the portfolio to small-cap stocks while negative denotes a tilt to large-cap stocks. The third beta coefficient when positive denotes a tilt of the portfolio to value stocks while negative a tilt to growth stocks.

Fama and French when evaluating portfolios found out that there are factors that are beyond the portfolio manager’s control. Hence, they extended the CAPM by adding size and value factors. After FF3FM other multifactor models were composed. Carhart (1997) expanded the FF3FM by adding Momentum (MOM) factor from the work of Jegadeesh and Titman (1993). Fama and French (2015) expanded their original model by adding Robust minus Weak (RMW) and Conservative minus Aggressive (CMA) factors.

This thesis focuses only on CAPM and FF3FM to explain the performance of the ESG portfolios, thus, exploring other multifactor models in this section is not necessary.

4.4 Efficient Market Hypothesis (EMH)

The main notion of the Efficient Market Hypothesis (EMH) as stated by Fama (1970) is that all available information of an underlying asset is "*fully reflected*" into its stock price. When new information is available in the market the security prices adjust rapidly to incorporate the new information. In efficient capital markets, the current security prices represent the fair values of the underlying assets, and as a result, investors could not systematically outperform the market. Although, in short time periods investors could yield abnormal returns.

Three forms of market efficiency have been presented depending on the information set: weak, semi-strong, and strong. In the weak form, the information set incorporates only the historical prices or returns of the assets to the current stock prices. As the past information is already reflected into the current stock price an investor should gain little by trading with rules on past performance, meaning that historical and future rates of returns are independent. The semi-strong form asserts that the information set integrates all publicly available information along with the historical prices. Earnings and dividend announcements, initial public offerings (IPOs) and stock splits are notable public available information. After the announcement of this information, an investor should not expect to derive meaningful higher returns. The semi-strong form is encompassed by the strong form as the information set includes all available public and non-public information. Due to the fact that a portion of asset owners has monopolistic access to relevant information non-public information is generally referred to as insider information. Investors who trade on inside information should not consistently generate risk-adjusted excess returns.

To sum up, when the EMH stands in the capital markets, investors who based their strategies on technical analysis, fundamental analysis and insider information should not consistently "*beat the market*".

4.5 Sharpe Ratio

The Sharpe ratio is commonly used by portfolio managers to evaluate the risk-adjusted returns of their portfolios (Sharpe 1966, 1994). It measures the excess return of the portfolio per unit of total risk. Excess return is computed by subtracting the average risk-free rate from the average portfolio return. Total risk or volatility is measured by the standard deviation of the portfolio's excess return. Formula (3) gives the Sharpe ratio:

$$Sharpe\ Ratio = \frac{Rp - Rf}{\sigma p} \qquad (3)$$

Where:

R_p = average return of the portfolio

R_f = average risk-free rate

σ_p = standard deviation of the portfolio's excess return

When ranking and comparing portfolios, the one that exhibits the highest Sharpe ratio outperforms all the others in terms of risk-adjusted returns. This higher Sharpe ratio could be explained either by a higher average return or by lower volatility of the portfolio or by both.

5. DATA AND METHODOLOGY

This part provides reasoning on the choice for the ESG data provider and a description of how the ESG and pricing data was gathered by using different databases. Furthermore, this section analyzes the construction of the ESG portfolios and explains how return, risk and the Sharpe ratio were calculated. Finally, it gives all the necessary information regarding the regressions with CAPM and FF3FM.

5.1 Data

The firms that were used in the study were the constituents of the S&P 500 index at the start of August 2021. The index is comprised of 505 common stocks issued by 500 large-cap corporations which represent about 80% of the US equity market by capitalization.[10] Within the index, five companies have two class of stocks and that's the reason why it has 505 constituents instead of 500. In the ESG portfolios, only one class of share was taken into account (class A). In addition, two companies have been excluded due to the lack of pricing data in the chosen time interval. These firms were introduced in the stock market after July 2020, thus, they could not be incorporated into the portfolios on the last rebalance as less than twelve monthly returns were available. For the same reason, seven more firms were excluded in the first and second years, but five of them were added back from the third year onwards and the remaining two were added back in the last year. As a result, in Table 1 we can see that data for 491 firms were used the first two years, for 496 in the third year and for 498 in the last year. The number of ESG rated stocks increased from 330 in the first year to 467 in the final year. The stocks of the companies that were omitted from the portfolios are presented in Table 9 in Appendix B.

[10] More information regarding S&P 500 index could be found on the official site.

Table 1: Number of constituents in every portfolio					
	1 Year	2 Year	3 Year	4 Year	Mean
Total Sample	491	491	496	498	494
Portfolio 7 AAA	9	13	16	18	14
Portfolio 6 AA	36	55	63	77	58
Portfolio 5 A	59	95	102	106	91
Portfolio 4 BBB	103	121	132	135	123
Portfolio 3 BB	68	100	100	95	91
Portfolio 2 B	45	51	39	28	41
Portfolio 1 CCC	10	14	13	8	11
Portfolio 0 Non-ESG	161	42	31	31	66
With ESG Rating	330	449	465	467	428

Note: The table presents a comprehensive overview of the stocks that were used each year and for every portfolio. The mean denotes the average number of constituents in each portfolio. The last row refers to the number of firms that exhibited an ESG rating. The first year spans from 30/06/2017 to 29/06/2018. The second year refers to 29/06/2018 until 28/06/2019 while the third year ranges from 28/06/2019 to 30/06/2020. Finally, the last year spans from 30/06/2020 until 30/06/2021.

Closing stock prices were taken from Google Sheets using the GOOGLEFINANCE function, for the period 30/06/2017 to 30/06/2021. By writing the ticker of a company someone can view its daily or weekly closing stock prices. Adjustments had to be made to obtain monthly data. Simply, the last daily closing stock price of the month was used. In total, 49 monthly closing stock prices were used to calculate 48 monthly returns. Dividends and transaction costs were not taken into account.

Multiple data vendors have emerged to assess firms in terms of ESG and provide valuable information for asset owners. In this study, the industry-adjusted final ESG ratings from MSCI were utilized. The main reason for the selection of this provider was that they are considered the largest ESG data provider and their ratings have been used in numerous studies, e.g., (Kempf and Osthoff, 2007, Nagy et al., 2016, Breedt et al., 2019, Bruno et al., 2021, Christensen et al., 2021) to name a few. Another driving factor was that their ESG data are publicly available which made it easier to retrieve them compared to other data providers.

For data acquisition, we have used the "*ESG Ratings Corporate Search Tool*".[11] By writing the ticker or the name of a company someone can view the company's last five ESG

[11] ESG Ratings Corporate Search Tool

ratings and when each was assigned. For efficiency reasons, a python code was developed to extract the ESG data instead of a manual process. The code is presented in Appendix A. Since MSCI only provides the month and the year of the evaluation, we assume that this happens on the first date of each month. In addition, we assume that the ESG rating for a given firm remains the same for the subsequent months until a rating change (upgrade or downgrade) occurs. The ESG rating of the companies each July is of our main interest as they are ranked this month so as to construct the portfolios.

Lastly, the risk-free rate (*Rf*) for the computation of the monthly portfolio excess return and Sharpe ratio and the values for *MKTRF*, *SMB* and *HML* for the regression models were derived from Kenneth R. French data library.[12]

5.2 Methodology

In order to construct the portfolios for each July, we ranked the firms according to their ESG rating starting in July 2017. The implemented strategy was "*buy and hold*" with an annual rebalancing of equal-weighted portfolios. Specifically, the rebalancing period for all portfolios was from July to June of the next year. This is a quite common choice in the relevant research literature.[13] Prior studies have reported evidence that equal-weighted portfolios tend to outperform value-weighted portfolios (DeMiguel et al., 2009). Summarizing, for each of the seven ESG rating classes an equal-weighted portfolio was formed. Stocks with missing ESG data were not excluded at each rebalancing date but instead, they were added to a portfolio named "*Non-ESG*", as in Hsu et al. (2018). Overall eight long-only, annually rebalanced, equal-weighted portfolios were constructed. In Table 1, we can see the number of constituents in each portfolio.

Even though it seems logical to compare the portfolios with the S&P 500 index, we have used as a benchmark the S&P 500 Equal Weight Index (S&P 500 EWI) instead. The S&P 500 is a value-weighted index, where larger capitalization securities have higher index weights than smaller capitalization securities while in the S&P 500 EWI all the constituents have the

[12] Calculations for returns, volatility and Sharpe ratio were executed with Excel while for the CAPM and FF3FM regressions with Gretl.

[13] See more: For equal weighted-portfolios see the works from Renneboog et al. (2008), Auer and Schuhmacher (2016), Hsu et al. (2018). Annual rebalance was used in the works of Kempf and Osthoff (2007), Hsu et al. (2018).

same weight. Since the ESG portfolios were equal-weighted it was, therefore, wiser to compare them with a similar benchmark.

Return and risk calculations were performed with monthly data. The monthly return for each company was calculated from the following formula (4):

$$Rit = \frac{Pit}{Pit-1} - 1 \qquad (4)$$

Where:

R_{it} = is the monthly return for stock *i* at the end of month *t*

P_{it} = is the closing price for stock *i* at the end of month *t*

P_{it-1} = is the closing price for stock *i* at the end of the previous month

Nominal capital of $100.000 was equally allocated to the constituted stocks of each of the eight portfolios. At the start of the sample period and on the three rebalance dates (29/06/2018, 28/06/2019 and 30/06/2020) each security on the portfolio received the same weight while on the subsequent eleven months the weights were changing as the stock prices changed. The monthly portfolio return was calculated from the following formula (5):

$$Rpt = \sum_{i=1}^{n} Wit * Rit \qquad (5)$$

Where:

Rp_t = is the monthly return of the portfolio at the end of month *t*

W_{it} = is the associated weight to the asset *i* in the portfolio at the end of month *t*

R_{it} = is the monthly return of asset *i* at the end of month *t*

n = is the total number of stocks in each portfolio

Historical volatility as measured by the standard deviation was used as a proxy to represent the risk of the portfolio. The formula is displayed on equation (6):

$$\sigma p = \sqrt{\sum_{i=1}^{t} \frac{(Rpt - \overline{Rp})^2}{t}} \qquad (6)$$

Where:

σ_p = is the monthly standard deviation of the portfolio calculated for the whole period

Rp_t = is the monthly return of the portfolio at the end of month *t*

$\overline{Rp}$ = is the mean monthly portfolio return

t = is the number of months

To evaluate the ESG portfolios on risk-adjusted terms the Sharpe Ratio was used (Sharpe 1966, 1994), which measures the excess return of the portfolio per unit of total risk. As a proxy for the risk-free rate, the one-month US treasury bill rate was used and was derived from the Kenneth R. French data library.[14] Earlier in formula (3) the Sharpe ratio was displayed as:

$$Sharpe\ Ratio = \frac{Rp-Rf}{\sigma p} \qquad (3)$$

Where:

R_p-R_f = is the average monthly excess return of the portfolio

σ_p = is the standard deviation of the portfolio's monthly excess returns

After evaluating the portfolios in terms of raw returns, volatility and the Sharpe ratio for the sample period, we also evaluated them for the COVID-19 period. The sample period was divided into three sub-periods. According to the National Bureau of Economic Research, the recession that emerged from COVID-19 pandemic lasted two months in the US, starting from February 2020 and ending in April 2020. [15] That period corresponds to the "*COVID-19*" sub-period. Consequently, the period spanned from the end of June 2017 until the end of January 2020 corresponds to the "*pro-COVID-19*" period and the "*post-COVID-19*" period ranged from the start of May 2020 until June 2021 - the end of the sample. The portfolios were ranked during the three different sub-periods by their cumulative returns.

Next, in order to investigate if the ESG portfolios generated abnormal returns and which factors explained their performance Ordinary Least Squares (OLS) regressions were run with

[14] Kenneth R. French data library
[15] "Business Cycle Dating Committee Announcement". National Bureau of Economic Research, 19 July 2021

CAPM and FF3FM. Previous scholars have extensively used these two asset pricing models.[16] Before running the regression models multiple tests were applied to the independent variables in order to check whether multicollinearity exists. Table 11 and Table 12 in Appendix B present the factors correlation matrix and the VIF test for multicollinearity, respectively.

In the first step, portfolio performance was measured with the CAPM which accounts only for the market risk factor. Its formula was displayed earlier on equation (1):

$$R_{it} - Rf_t = \alpha_i + \beta_i MKTRF_t + \varepsilon_{it} \qquad (1)$$

Where:

R_{it}-Rf_t = is the monthly excess return of portfolio *i* over the risk-free rate at time *t*

$MKTRF_t$ = is the monthly excess return of the market portfolio over the risk-free rate at time *t*

ε_{it} = error term of portfolio *i* at time *t*

The alpha coefficient is typically interpreted as a measure of out- or underperformance relative to the market proxy while the beta coefficient explains the sensitivity of portfolio *i* to the market factor.

In the second step, portfolios were analyzed with the FF3FM. Since the conventional CAPM captures the effect of only one factor, the market, Fama and French (1993) extended it in order to better explain the returns of risky assets. Two more factors were added to the model, the *SMB* and the *HML*. The *SMB* factor captures the size effect meaning that a portfolio consisting of small-cap stocks outperforms a portfolio consisting of large-cap stocks. The other factor *HML* captures the value effect and indicates that a portfolio comprised of value stocks performs better than a growth portfolio. The FF3FM was defined previously as:

$$R_{it} - Rf_t = \alpha_i + \beta_{i1} MKTRF_t + \beta_{i2} SMB_t + \beta_{i3} HML_t + \varepsilon_{it} \qquad (2)$$

Where:

R_{it}-Rf_t = is the monthly excess return of portfolio *i* over the risk-free rate at time *t*

$MKTRF_t$ = is the monthly excess return of the market portfolio over the risk-free rate at time *t*

[16] See more: CAPM was used in the works from Derwall et al. (2005) and Renneboog et al. (2008). Hong and Kacperczyk (2009) utilized both CAPM and FF3FM in their paper.

SMB_t = is the monthly excess return of small-cap portfolio over large-cap portfolio at time t

HML_t = is the monthly excess return of a value portfolio over a growth portfolio at time t

ε_{it} = error term of portfolio i at time t

Again alpha coefficient represents the monthly abnormal return of the portfolio while the sensitivity of the portfolio over the three factors is explained by the beta coefficients.

6. EMPIRICAL RESULTS

In this section, the empirical findings are presented. The results of the study are divided into three main categories. Firstly, as explained above volatility, absolute and risk-adjusted returns were calculated so as to rank the portfolios on these categories. Secondly, the portfolios were ranked during the three different sub-periods by their cumulative returns. Lastly, two regression models were applied to estimate whether the portfolios generate abnormal returns. More information regarding the regression outputs of the models is presented in Figures 5 to 20 in Appendix C.

6.1 Portfolio Returns, Risk and Sharpe Ratio Results

Figure 4 illustrates the development of the ESG portfolios values in comparison with each other's and the benchmark for the 4-year period with an initial start value of $100.000. All the portfolios faced a steep decline at the end of 2018. Similarly, they were challenged by the COVID-19 pandemic during February and March of 2020. As expected after the sharp decline in their values from the pandemic all of them demonstrated extremely high returns until the end of the sample period. Additionally, the value gap widened predominantly during the second half of the observation window. In the end, for the whole period, the ESG leading portfolio 7 (AAA) generated the highest value of $199.000,44 and in reality, it nearly doubled. Portfolio 1 (CCC) which is considered as ESG laggard produced the lowest portfolio value and was the only portfolio that underperformed the benchmark in absolute terms. Surprisingly, the other ESG laggard portfolio 2 (B) displayed a high portfolio value only below portfolios 7 (AAA) and 5 (A). The next table presents more analytically the returns of the ESG portfolios.

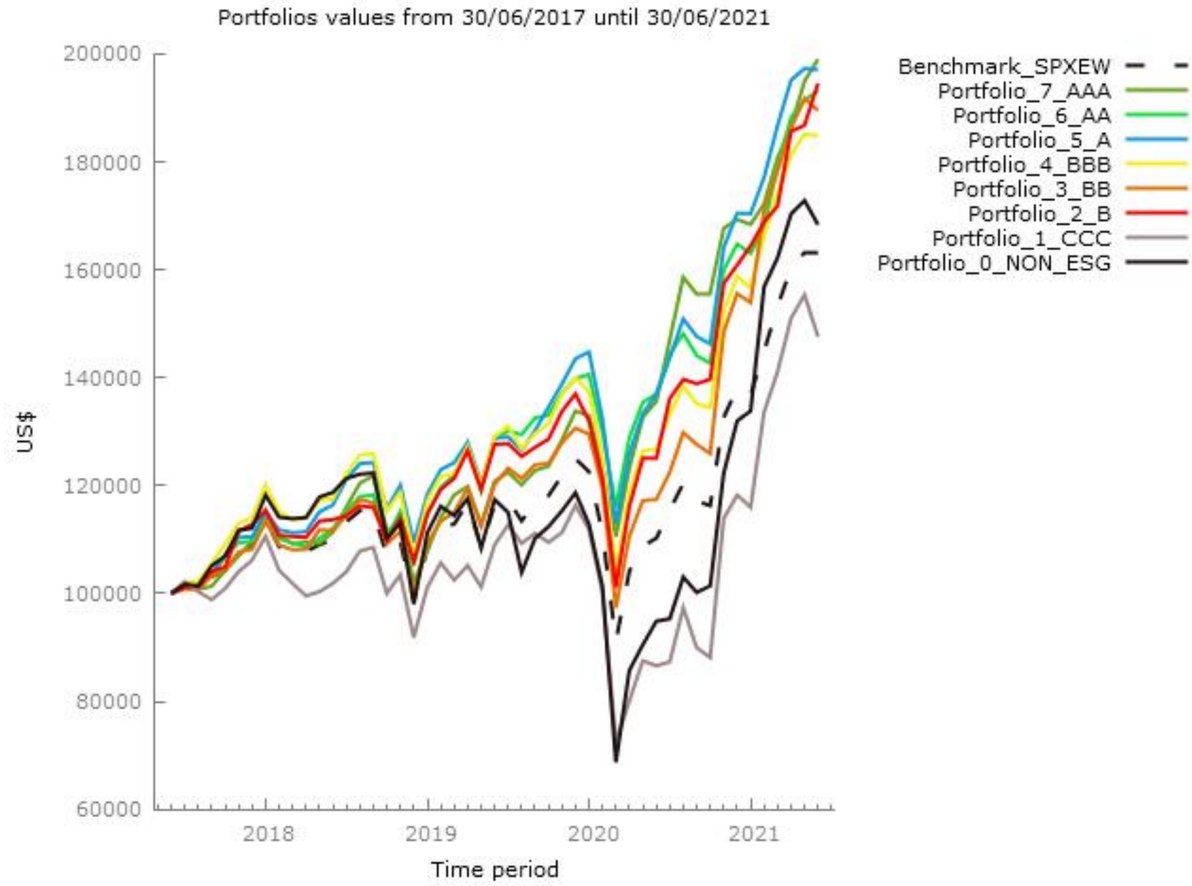

Figure 4: Evolution of $100.000 invested in each portfolio (Source: Own contribution)

Table 2 depicts the returns of every portfolio for every year and for the overall period. For the overall period, the calculation was based on the geometric mean return which takes into account the effect of compounding. First of all, portfolio 0 (Non-ESG) displayed for two years the highest annual return while for the other two years it had the lowest and the second lowest annual return. Portfolio 1 (CCC) for the first and the third year presented the lowest annual returns. In contrast, the two ESG leading portfolios 7 (AAA) and 6 (AA) generated the highest annual return in the third and the second year, respectively. The latter had the weakest annual return during the last year. Finally, portfolio 7 (AAA) outperformed the rest of the portfolios and the benchmark for the whole period since it produced a geometric mean return of 18,77% while portfolio 1 (CCC) an ESG laggard generated 10,21% and was the only portfolio to underperform the benchmark. Descriptive statistics regarding the portfolios and the benchmark are presented in Table 10 in Appendix B.

Table 2: Portfolio annual returns from 30/06/2017 until 30/06/2021					
	1 Year	2 Year	3 Year	4 Year	Overall Period
Benchmark	9,89%	5,99%	-5,34%	47,99%	13,02%
Portfolio 7 AAA	11,35%	8,46%	**12,28%**	46,76%	**18,77%**
Portfolio 6 AA	12,06%	**14,85%**	6,43%	**41,03%**	17,89%
Portfolio 5 A	16,41%	10,60%	6,30%	44,01%	18,49%
Portfolio 4 BBB	17,52%	9,83%	-1,80%	45,82%	16,60%
Portfolio 3 BB	11,61%	7,67%	-2,31%	61,44%	17,33%
Portfolio 2 B	13,67%	12,28%	-2,05%	55,61%	18,10%
Portfolio 1 CCC	**1,86%**	6,99%	**-20,55%**	70,42%	**10,21%**
Portfolio 0 Non-ESG	**18,72%**	**-1,12%**	-19,22%	**77,52%**	13,91%

Note: The table presents the annual returns of the portfolios without the inclusion of dividends and transaction costs. The return for the overall period is the geometric mean return which takes into account the effect of compounding during the period from 30/06/2017 until 30/06/2021, thus, 48 observations. The bolded returns represent the best and the worst return for each year. The first year spans from 30/06/2017 to 29/06/2018. The second year refers to 29/06/2018 until 28/06/2019 while the third year ranges from 28/06/2019 to 30/06/2020. Finally, the last year spans from 30/06/2020 until 30/06/2021.

Continuing with the risk of every portfolio, Table 3 reports the annualized volatility for every year and for the whole period. It is obvious that every year portfolios 1 (CCC) and 0 (Non-ESG) clashed over which one had the highest risk. In the first year and the last year portfolio 1 (CCC) exhibited the highest risk while the second and third year the portfolio that was composed by firms without an ESG rating had the highest annualized volatility. The two ESG leading portfolios 6 (AA) and 7 (AAA) demonstrated the lowest risk during the third and fourth year with an annualized volatility of 18,43% and 11,54%, respectively. The first year an ESG average, portfolio 5 (A) presented the lowest risk. Unexpectedly, for the second year portfolio 2 (B) which is considered as an ESG laggard had the lowest volatility. During the overall sample period, the ESG leading portfolios 7 (AAA) and 6 (AA) presented robustness against risk as they had the lowest annualized standard deviation with 15,72% and 15,48%, correspondingly. As a final point, three portfolios displayed higher risk than the benchmark for the overall period, portfolio 3 (BB) had an annualized volatility of 19,73% while portfolio 1 (CCC) and 0 (Non-ESG) had an extremely high annualized standard deviation of 27,47% and 29,60%, respectively.

Table 3: Portfolio annualized volatility from 30/06/2017 until 30/06/2021					
	1 Year	2 Year	3 Year	4 Year	Overall Period
Benchmark	7,83%	19,74%	26,14%	14,74%	18,96%
Portfolio 7 AAA	7,96%	18,84%	19,68%	**11,54%**	15,72%
Portfolio 6 AA	7,25%	18,71%	**18,43%**	13,35%	**15,48%**
Portfolio 5 A	**6,77%**	18,09%	22,55%	12,91%	16,52%
Portfolio 4 BBB	8,50%	20,10%	25,67%	14,03%	18,68%
Portfolio 3 BB	7,54%	19,05%	25,55%	19,02%	19,73%
Portfolio 2 B	8,09%	**16,36%**	25,72%	13,23%	17,76%
Portfolio 1 CCC	**9,53%**	20,61%	33,44%	**33,48%**	27,47%
Portfolio 0 Non-ESG	8,20%	**25,04%**	**44,44%**	24,29%	**29,60%**

Note: The table presents the annualized volatility of the portfolios for each year and for the overall period. The monthly standard deviation of the returns for the period from 30/06/2017 until 30/06/2021 was annualized and represents the annualized volatility for the overall period. The bolded annualized volatilities signify the best and the worst volatilities for each year. The lower the better. The first year spans from 30/06/2017 to 29/06/2018. The second year refers to 29/06/2018 until 28/06/2019 while the third year ranges from 28/06/2019 to 30/06/2020. Finally, the last year spans from 30/06/2020 until 30/06/2021.

Merging return and risk, Table 4 depicts a portfolio performance measurement on risk-adjusted terms, the Sharpe ratio. The benchmark was beaten on risk-adjusted returns from most of the portfolios except from portfolio 1 (CCC) and 0 (Non-ESG) which exhibited the lowest Sharpe ratios. In contrast, superior performance was demonstrated by the ESG leading portfolios 7 (AAA) and 6 (AA) which had the highest Sharpe ratios as computed for the sample period. Lastly, it is worth mentioning that two ESG average portfolios 4 (BBB) and 3 (BB) managed to be beaten by an ESG laggard portfolio 2 (B) on returns when adjusted for historical volatility. This happened as portfolio 2 (B) showed higher geometric mean return and lower annualized volatility.

Table 4: Portfolio Sharpe ratios	
	Overall Period
Benchmark	0,72
Portfolio 7 AAA	**1,19**
Portfolio 6 AA	1,15
Portfolio 5 A	1,13
Portfolio 4 BBB	0,92
Portfolio 3 BB	0,92
Portfolio 2 B	1,04
Portfolio 1 CCC	**0,48**
Portfolio 0 Non-ESG	0,60

Note: The table presents the Sharpe ratios of the portfolios for the period 30/06/2017 to 30/06/2021. The highest and lowest Sharpe ratios are marked in bold.

In Table 5 all the ESG portfolios are ranked from the best to the worst based on their earlier results. The outcome of the ranking revealed that the two portfolios with the best ESG rating portfolios 7 (AAA) and 6 (AA) displayed the lowest risk, the best Sharpe ratios and one of them generated the best performance. Portfolio 1 (CCC) ranked below the benchmark on all occasions while portfolio 0 (Non-ESG) surpassed the benchmark only on absolute return. All the other portfolios had a greater ranking than the benchmark on all categories except portfolio 3 (BB) which displayed higher annualized volatility.

Table 5: Portfolio ranking by the Sharpe ratio, geometric mean return and annualized volatility					
	Sharpe Ratio		Geometric Mean Return		Annualized Volatility
Portfolio 7 AAA	1,19	Portfolio 7 AAA	18,77%	Portfolio 6 AA	15,48%
Portfolio 6 AA	1,15	Portfolio 5 A	18,49%	Portfolio 7 AAA	15,72%
Portfolio 5 A	1,13	Portfolio 2 B	18,10%	Portfolio 5 A	16,52%
Portfolio 2 B	1,04	Portfolio 6 AA	17,89%	Portfolio 2 B	17,76%
Portfolio 4 BBB	0,92	Portfolio 3 BB	17,33%	Portfolio 4 BBB	18,68%
Portfolio 3 BB	0,92	Portfolio 4 BBB	16,60%	Benchmark	18,96%
Benchmark	0,72	Portfolio 0 Non-ESG	13,91%	Portfolio 3 BB	19,73%
Portfolio 0 Non-ESG	0,60	Benchmark	13,02%	Portfolio 1 CCC	27,47%
Portfolio 1 CCC	0,48	Portfolio 1 CCC	10,21%	Portfolio 0 Non-ESG	29,60%

Note: In this table, the portfolios are ranked from the best to the worst in terms of their Sharpe ratio, geometric mean return and annualized volatility that exhibited for the period from 30/06/2017 until 30/06/2021.

6.2 Portfolio Returns Prior, During and Post COVID-19

Table 6 presents the cumulative returns of the portfolios during three different periods. The first period named "*pro-COVID-19*" revealed that an ESG average portfolio 5 (A) generated the highest return. Throughout this period, portfolio 1 (CCC) and portfolio 0 (Non-ESG) were the only ones to underperform the benchmark. All the portfolios during the two-month pandemic period generated negative returns that ranged from 16,88% to 39,09%. The two ESG leading portfolios 7 (AAA) and 6 (AA) exhibited the lowest negative returns with 16,88% and 17,52%, respectively. In contrast, the only two portfolios that generated even lower returns than the benchmark (-25,69%) during the "*COVID-19*" period were again portfolio 1 (CCC) and 0 (Non-ESG) with negative returns of 35,25% and 39,09%, correspondingly. The "*post-COVID-19*" period reserved tremendous growth for all the portfolios. Throughout this period the situation changed and portfolios 1 (CCC) and 0 (Non-ESG) displayed the highest returns. Two ESG average portfolios 5 (A) and 4 (BBB) and one ESG leading portfolio 6 (AA) underperformed the benchmark from the start of April 2020 until the end of June 2021. Lastly, the other ESG leading portfolio 7 (AAA) surpassed the benchmark with almost 1% higher cumulative return but it was left considerably behind from the rest of the portfolios.

Table 6: Portfolio ranking during three sub-periods by cumulative returns

	pro-COVID-19		COVID-19		post-COVID-19
Portfolio 5 A	44,77%	Portfolio 7 AAA	-16,88%	Portfolio 0 Non-ESG	144,96%
Portfolio 6 AA	40,58%	Portfolio 6 AA	-17,52%	Portfolio 1 CCC	103,68%
Portfolio 4 BBB	37,46%	Portfolio 5 A	-22,10%	Portfolio 3 BB	94,66%
Portfolio 7 AAA	32,93%	Portfolio 2 B	-23,33%	Portfolio 2 B	92,31%
Portfolio 2 B	31,94%	Portfolio 4 BBB	-24,45%	Portfolio 7 AAA	80,09%
Portfolio 3 BB	29,55%	Portfolio 3 BB	-24,85%	Benchmark	79,15%
Benchmark	22,56%	Benchmark	-25,69%	Portfolio 4 BBB	77,98%
Portfolio 0 Non-ESG	12,83%	Portfolio 1 CCC	-35,25%	Portfolio 5 A	74,78%
Portfolio 1 CCC	11,87%	Portfolio 0 Non-ESG	-39,09%	Portfolio 6 AA	66,60%

Note: In this table, the portfolios were ranked from the best to the worst in terms of their cumulative return during the three sub-periods. The pro-COVID-19 period spans from 30/06/2017 until 31/01/2020, thus, 31 return observations. The crisis period starts from 31/01/2020 and ends on 31/03/2020 with 2 return observations. Finally, the post-COVID-19 period ranges from 31/03/2020 until the end of the observation sample, 30/06/2021, resulting in 15 return observations.

6.3 CAPM and FF3FM Regression Results

The next two tables examine the results from the regression models. Table 7 demonstrates the results from the first regression model, CAPM. From the alphas of the portfolios, half of them exhibit positive monthly excess return while the other half displays negative monthly alphas. The two ESG leading portfolios 7 (AAA) and 6 (AA) have the highest monthly alphas with 0,21% and 0,13%, correspondingly. Contrary, portfolio 1 (CCC) and portfolio 0 (Non-ESG) have the lowest monthly excess returns with -0,96% and -0,86%, respectively. Nevertheless, all of the monthly alphas are statistically insignificant on 1%, 5% and 10% levels. As a result, according to CAPM all of the above portfolios generated the required return in line with their associated systematic risk. The four portfolios that displayed positive monthly alphas also had lower exposure to systematic risk compared to the market as a whole. In Table 7 the betas for these portfolios are lower than one which characterizes the market's beta coefficient. On the other side, higher exposure to systematic risk compared to the market was presented by the portfolios which exhibited negative monthly alphas. All the beta coefficients of the portfolios are statistically significant at 1% level. Finally, the CAPM models showed adjusted R^2 between 0,74-0,95 and hence high goodness of fit for all portfolios during the examined period.

Table 7: Capital Asset Pricing Model regression results from 30/06/2017 until 30/06/2021

	Portfolio 7 AAA	**Portfolio 6 AA**	**Portfolio 5 A**	**Portfolio 4 BBB**	**Portfolio 3 BB**	**Portfolio 2 B**	**Portfolio 1 CCC**	**Portfolio 0 Non-ESG**
Alpha	0,002078	0,001304	0,000846	-0,001887	-0,001550	0,000385	-0,009578	-0,008564
	(0,002462)	(0,001927)	(0,001642)	(0,001995)	(0,002989)	(0,002906)	(0,006162)	(0,005791)
MKTRF	**0,856607*** **	**0,864031*** **	**0,936085*** **	**1,053493*** **	**1,077734*** **	**0,960471*** **	**1,375631*** **	**1,542651*** **
	(0,047403)	(0,037103)	(0,031614)	(0,038422)	(0,057559)	(0,055951)	(0,118656)	(0,111512)
Adjusted R- squared	0,873842	0,920108	0,949064	0,941088	0,881490	0,862039	0,739480	0,802002

Note: This table concludes the results of the CAPM for the whole sample period. The dependent variables are the monthly portfolio excess returns. The number of observations for each portfolio is 48. The monthly risk-free rate and the monthly excess return of the market (MKTRF) were derived from Kenneth R. French Data Library. The adjusted R-squared describes the goodness of fit of the model. The alpha denotes the monthly abnormal return of the portfolio while the beta coefficient describes the sensitivity of the portfolio to the market risk factor. Displayed in parenthesis is the standard error of the coefficient. Bold coefficients are significant. Significance levels are presented as follows: * Significant at a 10% level, ** Significant at a 5% level, *** Significant at a 1% level

The next regression model that was applied was FF3FM and its results are cited in Table 8. The first important thing is that all the portfolios with FF3FM exhibit higher adjusted R^2 than with the CAPM, thus, the goodness of fit is better and it spans from 0,80-0,96. In other words, *SMB* and *HML* factors added incrementally to the explanatory power of our models. Another important outcome is that more portfolios than with the CAPM generated positive abnormal returns. Again the alphas are not statistically different from 0 except for one portfolio. Portfolio 5 (A) outperformed the market with a monthly alpha of 0,2469% that is statistically significant on a 10% level. Consistent with the CAPM results the ESG portfolios that presented negative alphas also had higher exposure to systematic risk as showed from their betas. In contrast with the CAPM results two portfolios 4 (BBB) and 3 (BB) exhibited a beta of one, the same as the market's beta. Again all the beta coefficients are statistically significant on a 1% level. The *SMB* coefficient is negative only for the ESG leading portfolios, thus, these two portfolios had a tilt towards large-cap stocks during the examined period. All the other portfolios had a slight tilt to small-cap stocks. Nevertheless, the *SMB* coefficients were significant only for the extreme portfolios 7 (AAA) and 0 (Non-ESG) and as a result only for these two the interpretation of the factor stands. The factor loadings for the determinant *HML* are generally significantly positive, which implies a bias towards value stocks. Portfolios 7 (AAA) and 2 (B) exhibited not statistically different from zero *HML* coefficients and thus for these portfolios this factor does not explain much of their returns. Moreover, an interesting observation is that as the ESG rating decreases among the portfolios their *SMB* and *HML* coefficients increases. The only anomaly on this pattern stems from portfolio 2 (B). Finally, most of the portfolio's returns are explained by its exposure to the market and *HML* factors. For portfolio 2 (B) only the market factor plays a significant role while for portfolio 0 (Non-ESG) all the factors are statistically significant on a 1% level.

Table 8: Fama-French Three Factor Model regression results from 30/06/2017 until 30/06/2021								
	Portfolio 7 AAA	**Portfolio 6 AA**	**Portfolio 5 A**	**Portfolio 4 BBB**	**Portfolio 3 BB**	**Portfolio 2 B**	**Portfolio 1 CCC**	**Portfolio 0 Non-ESG**
Alpha	0,002247	0,002275	**0,002469***	0,000456	0,001698	0,001716	-0,003679	-0,001581
	(0,002515)	(0,001905)	(0,001454)	(0,001603)	(0,002494)	(0,002917)	(0,005521)	(0,004013)
MKTRF	**0,882110*****	**0,864939*****	**0,901862*****	**1,00312*****	**0,997176*****	**0,910096*****	**1,24595*****	**1,31547*****
	(0,051049)	(0,038664)	(0,029506)	(0,032526)	(0,050611)	(0,059213)	(0,112063)	(0,081454)
SMB	**-0,159226***	-0,104173	0,024786	0,04133	0,116888	0,144544	0,119652	**0,551848*****
	(0,090263)	(0,068365)	(0,052171)	(0,057513)	(0,089489)	(0,1047)	(0,198148)	(0,144027)
HML	0,032866	**0,105028****	**0,155048*****	**0,22313*****	**0,303245*****	0,114288	**0,560391*****	**0,620879*****
	(0,063384)	(0,048007)	(0,036635)	(0,040386)	(0,062840)	(0,073521)	(0,139142)	(0,101137)
Adjusted R- squared	0,877079	0,927113	0,962724	0,964529	0,923020	0,870185	0,804770	0,911243

Note: This table presents the estimates of the alpha and Fama-French three factors for the whole sample period. The dependent variables are the monthly portfolio excess returns. The number of observations for each portfolio is 48. MKTRF, SMB and HML represent the factor loadings. These data and the monthly risk-free rate were derived from Kenneth R. French Data Library. The adjusted R-squared describes the goodness of fit of the model. The alpha denotes the monthly abnormal return of the portfolio while the beta coefficients describe the sensitivity of the portfolio to the risk factors. Displayed in parenthesis is the standard error of the coefficient. Bold coefficients are significant. Significance levels are presented as follows: * Significant at a 10% level, ** Significant at a 5% level, *** Significant at a 1% level

7. DISCUSSION

This part offers a generalization of the results from Tables 2 to 8 in order to compare them with previous studies and answer the questions that were raised in the introductory part of the paper.

The evidence from Tables 2 and 4 demonstrated that the majority of the ESG portfolios outperformed the benchmark both on absolute returns and when adjusted for risk. This finding is in contrast with Auer and Schuhmacher (2016) who found that high-ranked and low-ranked ESG portfolios do not provide superior or inferior performance compared to their benchmarks in the US. Nevertheless, it is in line with Nagy et al. (2016) who found that the portfolios constructed with the "*ESG tilt*" strategy generated higher absolute returns than the benchmark.

Another useful finding stems from the comparison among portfolio 0 (Non-ESG) with the ESG portfolios. The Non-ESG portfolio displayed lower returns both absolute and risk-adjusted compared to the jointly ESG categories. Moreover, it had significantly higher volatility and sensitivity to the systematic risk than its counterparts. When analyzing the other two factor loadings it became clear that firms that do not showcase an ESG rating are considered small capitalization and value stocks.

Shifting the comparisons between the three main ESG categories (leading, average and laggards) the ESG leading portfolios collectively provided supreme performance against their less sustainable counterparts. Based on this finding, the answer to the first question if "*ESG leading equity portfolios*" generate higher returns compared to the rest of the portfolios and the benchmark is positive. When adjusting the returns with their associated risk the outcome remained consistent. Hence, the answer to question three is affirmative as the "*ESG leading equity portfolios*" jointly exhibited better risk-adjusted returns than the rest of the portfolios and the benchmark.

Next, the evaluation of the portfolios in relation to their risk as measured by their standard deviation revealed that only the ESG laggard portfolios together had a higher risk than the benchmark. In contrast, the ESG leading portfolios on average showcased significantly lower volatility. Hereby, the answer to the second question is again positive and in favor of the "*ESG leading equity portfolios*".

As seen from Table 6, prior to the COVID-19 incident, the ESG leading and average portfolios battled on which of the two categories collectively had the highest returns. The latter won this battle. During this sub-period, the ESG laggards together had slightly lower returns than the benchmark. Moving on to the crisis period the best ESG portfolios significantly performed better than their lower counterparts and the market as they exhibited the lowest negative returns. Contrary, throughout the third sub-period they underperformed both the benchmark and their lower sustainable peers. These findings confirm earlier findings by Borovkova and Wu (2020) who found that the best ESG firms performed better during the coronavirus pandemic but underperformed in the aftermath than the lower ESG companies. Moreover, they are consistent with Das et al. (2018) who found that the socially responsible mutual funds were hit less during the Great Recession but rebounded less on the period immediately after the Great Recession. From the above findings, there is evidence of a "*flight to quality*" effect during crisis periods meaning that sustainable firms are more resilient and outperform their less sustainable counterparts during hard times.

Continuing with the regression results from both models when grouping the portfolios into the three major categories one can identify a pattern. So, as we move from the laggard to the leading portfolios, thus the ESG rating category increases, the alphas for these categories also increase collectively. Although those alphas are insignificant this indicates that the ESG portfolios generated the theoretical expected return that was predicted by the model. Hence, this result could be denoted in favor of the EMH. Therefore, the response to the last question on whether the "*ESG leading equity portfolios*" or any of their counterparts managed to generate abnormal returns is negative as their returns could be explained by well-known common factors.

Moreover, as the ESG rating category increases the sensitivity of the portfolios to the market risk decreases. In other words, the ESG leading portfolios exhibit lower exposure to the systematic risk. As with the market factor, the relationship between the ESG rating category and the other two factors is the same. Indicatively, as the ESG rating category increases the exposure of the portfolios to the *SMB* and the *HML* factors collectively decreases. Consequently, the ESG laggard portfolios tilt to small-cap and value stocks while the ESG leading portfolios tend to large-cap and value stocks but this slope to value stocks is relatively low. This is particularly important as it confirms previous scholars. Bauer et al. (2005) found that environmentally and socially screened portfolios in the US favored large-cap and growth stocks while Nagy et al. (2016) found that the "*ESG tilt*" strategy tended away from value stocks.

To summarize, the portfolios that comprised highly ESG rated companies exhibited higher absolute and risk-adjusted returns, lower volatility and lower exposure to the systematic risk than the rest of the portfolios and the benchmark during the examined period. From the factor loadings, it was evident that the higher sustainable portfolios favored large-cap and value stocks. Throughout the "*COVID-19*" period the high ESG portfolios were more resilient to the crisis but in the aftermath, they grew at a smaller pace than the rest of the portfolios. As for the Non-ESG portfolio, it showcased a higher risk and underperformed the ESG rated portfolios. Lastly, most of the ESG rated portfolios yielded higher returns than the benchmark.

8. CONCLUSIONS

Past literature examined the relationship between ESG and financial performance. In this case, we extended the previous studies by providing evidence on a recent time span that also included a financial crisis that emerged from the exogenous COVID-19 pandemic. Most of the academic papers omit companies that do not display an ESG rating. Instead in this paper one portfolio comprised of such firms was evaluated alongside the ESG rated portfolios, as well.

In the introduction, we noted that our interest lines in the evaluation of the ESG portfolios in terms of absolute returns, volatility and risk-adjusted returns in comparison among themselves and to the S&P 500 EWI which was used as the benchmark. The outcome of the study revealed that ESG leading portfolios significantly performed better both on raw returns and when adjusted for risk. These portfolios also showcased lower risk. The findings would indicate an argument in favor of ESG based investing especially during the COVID-19 where the most sustainable portfolios led to lower negative yields, thus, protecting their asset owners.

As discussed previously, this study has a twofold purpose. Besides just examining the performance of portfolios exclusively with the MSCI ESG ratings, two regression models were employed to measure whether any abnormal returns were generated from the portfolios. Analyzing the results from the CAPM, not a single portfolio yielded significant out- or underperformance. While with the FF3FM there was one portfolio with a statistically significant monthly abnormal return, on average this outcome does not stand. Hence, during the examined period for the aforementioned ESG portfolios, their returns could be explained by their factor exposures. As a result, there is no convincing evidence that trading on ESG portfolios would yield abnormal returns and that is not a surprise. Therefore, it could be interpreted as an indication of efficient capital markets where the asset managers already priced the information that stemmed from the ESG ratings.

Analyzing the factor exposures revealed distinct investment styles between the portfolios. For example, the high ESG ranked portfolios were typically less exposed to market return variability, exhibited negative exposure to the size factor and were less oriented to the value factor. Contradictory, the less sustainable portfolios were heavily exposed to systematic risk and showcased a bias towards small-cap and value stocks.

The research revealed interesting conclusions regarding the companies that are not yet rated by data vendors. Firstly, it is better for firms to be appraised in terms of ESG and exhibit a rating as they are not omitted from the investment universe of socially conscious investors. Secondly, the Non-ESG portfolio ended up with lower returns and higher risk even when compared to the ESG laggard category.

Finally, the above inferences add to the line of ambiguous research results on ESG investing. An investor who has preferences for ESG should invest in portfolios with high ESG ratings since the Sharpe ratio is, on average, greater and because these portfolios are more resilient during market turmoil. However, the results from the CAPM and the FF3FM displayed that a high-ESG oriented investor should not expect abnormal returns. Nevertheless, probable outperformance from the best ESG portfolios in the future should not be ruled out.

As with every research paper, this one had also its limitations. One of these limitations is the utilized of ESG ratings from one data vendor, MSCI. Another is that the investment strategy was tested only with components from one specific index, the S&P 500, which represents only the US market. Furthermore, the portfolios were constructed with equal weights over a relatively short period that spanned from 30/06/2017 to 30/06/2021. Hence, this study can be complemented by future research to use an alternative ESG data provider or with a mix of data providers as it would enhance the insights. Let's not forget that one of the main issues regarding ESG is the lack of access to reliable and consistent data. (Christensen et al., 2021). Moreover, it would be interesting to see what would be the outcome if the portfolios were constructed with a different weighting methodology or for a longer period. One more proposal would be to test the ESG ratings on other indices and capital markets. Another suggestion would be to further include dividends and transaction costs on the calculations and investigate if the results remain robust. As a final note, measuring performance with other well-known multifactor models could also lead to fruitful comparisons.

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APPENDICES

Appendix A: Python Code for ESG Data Extraction

```
from msci_esg.ratefinder import ESGRateFinder

import pandas

import openpyxl

ratefinder = ESGRateFinder()

f = pandas.read_excel('C:\\Users\\George\\Desktop\\S&P 500-ESG Ratings.xlsx')

f = pandas.read_excel('C:\\Users\\George\\Desktop\\S&P500-ESGRatings.xlsx',sheet_name='RUNPY')

print (f.columns)

# symbols = f['Symbol'].values

symbols = f['Symbol'].tolist()

print (symbols)

for x in symbols:

    response = ratefinder.get_esg_rating(

    symbol=x,

    js_timeout=5

    )

    print (response)
```

Source: I developed part of the code while the other part was derived from https://pypi.org/project/py-msci-esg/

Appendix B: Out of Sample Stocks, Portfolio Descriptive Statistics, Factor Correlations, and VIF Test for Multicollinearity

Table 9: Stocks out of sample

Panel A: Excluded second class of stock for the below firms				
Firm	1 Year	2 Year	3 Year	4 Year
Alphabet Inc.	GOOG	GOOG	GOOG	GOOG
Discovery Inc.	DISCK	DISCK	DISCK	DISCK
Fox Corp.	FOX	FOX	FOX	FOX
News Corp.	NWS	NWS	NWS	NWS
Under Armour Inc.	UA	UA	UA	UA
Panel B: Excluded stocks for the below firms due to lack of pricing data				
Firm	1 Year	2 Year	3 Year	4 Year
Organon & Co.	OGN	OGN	OGN	OGN
Viatris Inc.	VTRS	VTRS	VTRS	VTRS
Carrier Global Corp.	CARR	CARR	CARR	
Otis Worldwide Corp.	OTIS	OTIS	OTIS	
Amcor PLC	AMCR	AMCR		
Corteva Inc.	CTVA	CTVA		
Dow Inc.	DOW	DOW		
Moderna Inc.	MRNA	MRNA		
Fox Corp.	FOXA	FOXA		

Note: The table presents the tickers of the companies that were omitted from the portfolios. Panel A reports firms that have more than one class of stock in the S&P 500 index. Thus, the second class was omitted and in the portfolios was only included their first class of stock with tickers GOOGL, DISCA, FOXA, NWSA and UAA. Panel B reports companies that were excluded from the portfolios due to non-available pricing data in the chosen interval. The first year spans from 30/06/2017 to 29/06/2018. The second year refers to 29/06/2018 until 28/06/2019 while the third year ranges from 28/06/2019 to 30/06/2020. Finally, the last year spans from 30/06/2020 until 30/06/2021.

Table 10: Portfolio descriptive statistics from 30/06/2017 until 30/06/2021						
	Min	Max	Median	Mean	Skewness	Kurtosis
Benchmark	-18,19%	14,33%	1,45%	1,18%	-0,7080	3,1353
Portfolio 7 AAA	-10,65%	11,49%	2,00%	1,55%	-0,6698	0,9570
Portfolio 6 AA	-10,80%	12,12%	1,74%	1,48%	-0,3898	1,2530
Portfolio 5 A	-14,79%	12,19%	2,50%	1,54%	-0,9030	2,6020
Portfolio 4 BBB	-16,99%	14,18%	2,15%	1,44%	-0,7404	2,5884
Portfolio 3 BB	-18,62%	17,89%	2,11%	1,50%	-0,4296	3,5752
Portfolio 2 B	-16,68%	14,75%	1,49%	1,53%	-0,5121	3,0482
Portfolio 1 CCC	-27,79%	29,29%	1,68%	1,13%	-0,0441	5,3598
Portfolio 0 Non-ESG	-32,19%	24,74%	1,70%	1,48%	-0,6934	5,1002

Note: The table presents an overview of descriptive statistics of the portfolios for the whole period. Min, max, median and mean returns are monthly.

Table 11: Factor correlations			
	MKTRF	SMB	HML
MKTRF	1		
SMB	0,3565	1	
HML	0,2463	0,1929	1

Note: The table presents the factor correlations between the independent variables which were used in the regression models. A low correlation is observed between MKTRF and SMB. The other factors have little if any correlation.

Table 12: VIF test for multicollinearity	
Dependent Variable	VIF
MKTRF	1,1903
SMB	1,1613
HML	1,0791

Note: The table presents the Variance Inflation Factor. It is a first test before running a multiple regression that checks for multicollinearity between the independent variables. Values of VIF that exceed 10 are often regarded as indicating multicollinearity.

Appendix C: Capital Asset Pricing Model and Fama-French Three Factor Model Regression Outputs for the Portfolios

```
Model 1: OLS, using observations 2017:07-2021:06 (T = 48)
Dependent variable: Portfolio_7_AAA

             coefficient   std. error   t-ratio    p-value
  --------------------------------------------------------
  const      0.00207768    0.00246178    0.8440   0.4031
  MKTRF      0.856607      0.0474032    18.07     1.59e-022 ***

Mean dependent var   0.014463   S.D. dependent var   0.046120
Sum squared resid    0.012344   S.E. of regression   0.016381
R-squared            0.876526   Adjusted R-squared   0.873842
F(1, 46)             326.5482   P-value(F)           1.59e-22
Log-likelihood       130.2697   Akaike criterion    -256.5394
Schwarz criterion   -252.7970   Hannan-Quinn        -255.1251
rho                 -0.010399   Durbin-Watson        2.016605
```

Figure 5: CAPM regression output for portfolio 7 (AAA) (Source: Own contribution)

```
Model 2: OLS, using observations 2017:07-2021:06 (T = 48)
Dependent variable: Portfolio_6_AA

             coefficient   std. error   t-ratio    p-value
  --------------------------------------------------------
  const      0.00130373    0.00192688    0.6766   0.5020
  MKTRF      0.864031      0.0371033    23.29     4.25e-027 ***

Mean dependent var   0.013796   S.D. dependent var   0.045363
Sum squared resid    0.007563   S.E. of regression   0.012822
R-squared            0.921807   Adjusted R-squared   0.920108
F(1, 46)             542.2906   P-value(F)           4.25e-27
Log-likelihood       142.0289   Akaike criterion    -280.0577
Schwarz criterion   -276.3153   Hannan-Quinn        -278.6435
rho                 -0.063553   Durbin-Watson        2.083694
```

Figure 6: CAPM regression output for portfolio 6 (AA) (Source: Own contribution)

```
Model 3: OLS, using observations 2017:07-2021:06 (T = 48)
Dependent variable: Portfolio_5_A

             coefficient   std. error   t-ratio    p-value
  --------------------------------------------------------
  const      0.000845635   0.00164182    0.5151   0.6090
  MKTRF      0.936085      0.0316143    29.61     1.34e-031 ***

Mean dependent var   0.014380   S.D. dependent var   0.048408
Sum squared resid    0.005490   S.E. of regression   0.010925
R-squared            0.950148   Adjusted R-squared   0.949064
F(1, 46)             876.7233   P-value(F)           1.34e-31
Log-likelihood       149.7135   Akaike criterion    -295.4271
Schwarz criterion   -291.6847   Hannan-Quinn        -294.0128
rho                  0.107557   Durbin-Watson        1.663525
```

Figure 7: CAPM regression output for portfolio 5 (A) (Source: Own contribution)

```
Model 4: OLS, using observations 2017:07-2021:06 (T = 48)
Dependent variable: Portfolio_4_BBB

             coefficient   std. error   t-ratio    p-value
  --------------------------------------------------------
  const     -0.00188659    0.00199535   -0.9455   0.3493
  MKTRF      1.05349       0.0384219    27.42     3.80e-030 ***

Mean dependent var   0.013345   S.D. dependent var   0.054704
Sum squared resid    0.008110   S.E. of regression   0.013278
R-squared            0.942342   Adjusted R-squared   0.941088
F(1, 46)             751.8054   P-value(F)           3.80e-30
Log-likelihood       140.3527   Akaike criterion    -276.7053
Schwarz criterion   -272.9629   Hannan-Quinn        -275.2911
rho                 -0.080139   Durbin-Watson        2.035912
```

Figure 8: CAPM regression output for portfolio 4 (BBB) (Source: Own contribution)

```
Model 5: OLS, using observations 2017:07-2021:06 (T = 48)
Dependent variable: Portfolio_3_BB

             coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const      -0.00154970   0.00298918   -0.5184   0.6066
  MKTRF       1.07773      0.0575587    18.72     3.76e-023 ***

Mean dependent var   0.014033   S.D. dependent var   0.057780
Sum squared resid    0.018200   S.E. of regression   0.019891
R-squared            0.884012   Adjusted R-squared   0.881490
F(1, 46)             350.5916   P-value(F)           3.76e-23
Log-likelihood       120.9522   Akaike criterion    -237.9043
Schwarz criterion   -234.1619   Hannan-Quinn        -236.4901
rho                  0.006885   Durbin-Watson        1.892295
```

Figure 9: CAPM regression output for portfolio 3 (BB) (Source: Own contribution)

```
Model 6: OLS, using observations 2017:07-2021:06 (T = 48)
Dependent variable: Portfolio_2_B

             coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const      0.000384582   0.00290571    0.1324   0.8953
  MKTRF      0.960471      0.0559514    17.17     1.25e-021 ***

Mean dependent var   0.014271   S.D. dependent var   0.052057
Sum squared resid    0.017197   S.E. of regression   0.019335
R-squared            0.864975   Adjusted R-squared   0.862039
F(1, 46)             294.6771   P-value(F)           1.25e-21
Log-likelihood       122.3116   Akaike criterion    -240.6232
Schwarz criterion   -236.8808   Hannan-Quinn        -239.2090
rho                 -0.205206   Durbin-Watson        2.389656
```

Figure 10: CAPM regression output for portfolio 2 (B) (Source: Own contribution)

```
Model 7: OLS, using observations 2017:07-2021:06 (T = 48)
Dependent variable: Portfolio_1_CCC

             coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const      -0.00957802   0.00616211   -1.554    0.1270
  MKTRF       1.37563      0.118656     11.59     3.01e-015 ***

Mean dependent var   0.010311   S.D. dependent var   0.080336
Sum squared resid    0.077343   S.E. of regression   0.041004
R-squared            0.745023   Adjusted R-squared   0.739480
F(1, 46)             134.4084   P-value(F)           3.01e-15
Log-likelihood       86.22794   Akaike criterion    -168.4559
Schwarz criterion   -164.7135   Hannan-Quinn        -167.0416
rho                  0.021514   Durbin-Watson        1.879273
```

Figure 11: CAPM regression output for portfolio 1 (CCC) (Source: Own contribution)

```
Model 8: OLS, using observations 2017:07-2021:06 (T = 48)
Dependent variable: Portfolio_0_NON_ESG

             coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const      -0.00856380   0.00579114   -1.479    0.1460
  MKTRF       1.54265      0.111512     13.83     5.26e-018 ***

Mean dependent var   0.013740   S.D. dependent var   0.086604
Sum squared resid    0.068311   S.E. of regression   0.038536
R-squared            0.806215   Adjusted R-squared   0.802002
F(1, 46)             191.3767   P-value(F)           5.26e-18
Log-likelihood       89.20828   Akaike criterion    -174.4166
Schwarz criterion   -170.6742   Hannan-Quinn        -173.0023
rho                 -0.078528   Durbin-Watson        2.094992
```

Figure 12: CAPM regression output for portfolio 0 (Non-ESG) (Source: Own contribution)

```
Model 1: OLS, using observations 2017:07-2021:06 (T = 48)
Dependent variable: Portfolio_7_AAA

             coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const      0.00224663    0.00251509    0.8933   0.3766
  MKTRF      0.882110      0.0510485    17.28     3.14e-021 ***
  SMB       -0.159226      0.0902633    -1.764    0.0847    *
  HML        0.0328660     0.0633839     0.5185   0.6067

Mean dependent var   0.014463   S.D. dependent var   0.046120
Sum squared resid    0.011504   S.E. of regression   0.016170
R-squared            0.884925   Adjusted R-squared   0.877079
F(3, 44)             112.7869   P-value(F)           1.11e-20
Log-likelihood       131.9605   Akaike criterion    -255.9210
Schwarz criterion   -248.4362   Hannan-Quinn        -253.0924
rho                 -0.044279   Durbin-Watson        2.083257

Excluding the constant, p-value was highest for variable 3 (HML)
```

Figure 13: FF3FM regression output for portfolio 7 (AAA) (Source: Own contribution)

```
Model 2: OLS, using observations 2017:07-2021:06 (T = 48)
Dependent variable: Portfolio_6_AA

             coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const      0.00227455    0.00190492    1.194    0.2389
  MKTRF      0.864939      0.0386640    22.37     1.15e-025 ***
  SMB       -0.104173      0.0683652    -1.524    0.1347
  HML        0.105028      0.0480068     2.188    0.0340    **

Mean dependent var   0.013796   S.D. dependent var   0.045363
Sum squared resid    0.006599   S.E. of regression   0.012247
R-squared            0.931765   Adjusted R-squared   0.927113
F(3, 44)             200.2768   P-value(F)           1.16e-25
Log-likelihood       145.2981   Akaike criterion    -282.5962
Schwarz criterion   -275.1114   Hannan-Quinn        -279.7677
rho                 -0.169951   Durbin-Watson        2.319766

Excluding the constant, p-value was highest for variable 2 (SMB)
```

Figure 14: FF3FM regression output for portfolio 6 (AA) (Source: Own contribution)

```
Model 3: OLS, using observations 2017:07-2021:06 (T = 48)
Dependent variable: Portfolio_5_A

             coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const      0.00246899    0.00145370    1.698     0.0965    *
  MKTRF      0.901862      0.0295056    30.57      2.84e-031 ***
  SMB        0.0247863     0.0521713     0.4751   0.6371
  HML        0.155048      0.0366353     4.232     0.0001    ***

Mean dependent var   0.014380   S.D. dependent var   0.048408
Sum squared resid    0.003843   S.E. of regression   0.009346
R-squared            0.965104   Adjusted R-squared   0.962724
F(3, 44)             405.6258   P-value(F)           4.62e-32
Log-likelihood       158.2740   Akaike criterion    -308.5480
Schwarz criterion   -301.0632   Hannan-Quinn        -305.7194
rho                 -0.179890   Durbin-Watson        2.242227

Excluding the constant, p-value was highest for variable 2 (SMB)
```

Figure 15: FF3FM regression output for portfolio 5 (A) (Source: Own contribution)

```
Model 4: OLS, using observations 2017:07-2021:06 (T = 48)
Dependent variable: Portfolio_4_BBB

             coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const      0.000455604   0.00160253    0.2843   0.7775
  MKTRF      1.00312       0.0325263    30.84      1.95e-031 ***
  SMB        0.0413302     0.0575126     0.7186   0.4762
  HML        0.223130      0.0403860     5.525     1.68e-06  ***

Mean dependent var   0.013345   S.D. dependent var   0.054704
Sum squared resid    0.004671   S.E. of regression   0.010303
R-squared            0.966793   Adjusted R-squared   0.964529
F(3, 44)             427.0116   P-value(F)           1.55e-32
Log-likelihood       153.5954   Akaike criterion    -299.1908
Schwarz criterion   -291.7060   Hannan-Quinn        -296.3623
rho                 -0.296010   Durbin-Watson        2.526359

Excluding the constant, p-value was highest for variable 2 (SMB)
```

Figure 16: FF3FM regression output for portfolio 4 (BBB) (Source: Own contribution)

```
Model 5: OLS, using observations 2017:07-2021:06 (T = 48)
Dependent variable: Portfolio_3_BB

             coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const      0.00169812    0.00249352    0.6810   0.4994
  MKTRF      0.997176      0.0506107    19.70     1.87e-023 ***
  SMB        0.116888      0.0894892     1.306    0.1983
  HML        0.303245      0.0628403     4.826    1.71e-05  ***

Mean dependent var   0.014033   S.D. dependent var   0.057780
Sum squared resid    0.011308   S.E. of regression   0.016031
R-squared            0.927934   Adjusted R-squared   0.923020
F(3, 44)             188.8505   P-value(F)           3.85e-25
Log-likelihood       132.3739   Akaike criterion    -256.7479
Schwarz criterion   -249.2631   Hannan-Quinn        -253.9193
rho                 -0.309610   Durbin-Watson        2.554073

Excluding the constant, p-value was highest for variable 2 (SMB)
```

Figure 17: FF3FM regression output for portfolio 3 (BB) (Source: Own contribution)

```
Model 6: OLS, using observations 2017:07-2021:06 (T = 48)
Dependent variable: Portfolio_2_B

             coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const      0.00171565    0.00291735    0.5881   0.5595
  MKTRF      0.910096      0.0592130    15.37     2.65e-019 ***
  SMB        0.144544      0.104700      1.381    0.1744
  HML        0.114288      0.0735213     1.554    0.1272

Mean dependent var   0.014271   S.D. dependent var   0.052057
Sum squared resid    0.015479   S.E. of regression   0.018756
R-squared            0.878471   Adjusted R-squared   0.870185
F(3, 44)             106.0175   P-value(F)           3.69e-20
Log-likelihood       124.8390   Akaike criterion    -241.6779
Schwarz criterion   -234.1931   Hannan-Quinn        -238.8494
rho                 -0.271146   Durbin-Watson        2.496912

Excluding the constant, p-value was highest for variable 2 (SMB)
```

Figure 18: FF3FM regression output for portfolio 2 (B) (Source: Own contribution)

```
Model 7: OLS, using observations 2017:07-2021:06 (T = 48)
Dependent variable: Portfolio_1_CCC

             coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const      -0.00367871   0.00552119   -0.6663   0.5087
  MKTRF       1.24595      0.112063     11.12     2.30e-014 ***
  SMB         0.119652     0.198148      0.6039   0.5490
  HML         0.560391     0.139142      4.027    0.0002    ***

Mean dependent var   0.010311   S.D. dependent var   0.080336
Sum squared resid    0.055440   S.E. of regression   0.035496
R-squared            0.817232   Adjusted R-squared   0.804770
F(3, 44)             65.58075   P-value(F)           2.83e-16
Log-likelihood       94.21888   Akaike criterion    -180.4378
Schwarz criterion   -172.9529   Hannan-Quinn        -177.6092
rho                 -0.245682   Durbin-Watson        2.447897

Excluding the constant, p-value was highest for variable 2 (SMB)
```

Figure 19: FF3FM regression output for portfolio 1 (CCC) (Source: Own contribution)

```
Model 8: OLS, using observations 2017:07-2021:06 (T = 48)
Dependent variable: Portfolio_0_NON_ESG

             coefficient   std. error   t-ratio    p-value
  ---------------------------------------------------------
  const      -0.00158123   0.00401315   -0.3940   0.6955
  MKTRF       1.31547      0.0814545    16.15     4.14e-020 ***
  SMB         0.551848     0.144027      3.832    0.0004    ***
  HML         0.620879     0.101137      6.139    2.11e-07  ***

Mean dependent var   0.013740   S.D. dependent var   0.086604
Sum squared resid    0.029290   S.E. of regression   0.025801
R-squared            0.916909   Adjusted R-squared   0.911243
F(3, 44)             161.8456   P-value(F)           8.77e-24
Log-likelihood       109.5316   Akaike criterion    -211.0633
Schwarz criterion   -203.5785   Hannan-Quinn        -208.2347
rho                 -0.382752   Durbin-Watson        2.733954
```

Figure 20: FF3FM regression output for portfolio 0 (Non-ESG) (Source: Own contribution)