ESG vs. ESG Momentum as risk premia: A multi-factor asset pricing study in the U.S. stock market

Bachelor Thesis IBEB

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Abstract

In financial markets, environmental, social, and governance (ESG) considerations have gained prominence as key drivers of investment decisions. This thesis extends the asset pricing literature by extending the renowned Fama-French three-factor model to incorporate ESG and ESG momentum factors. By building upon the foundation of the market, size, and value factors, this study explores the potential significance and impact of ESG-related metrics on a handful of portfolios with various construction methods. Additionally, the investigation evaluates the influence of ESG and ESG momentum portfolios to generate abnormal returns. With empirical data from the U.S. stock market for roughly 14-year period from 2008 to 2021, this research aims to provide insights into the potential role of ESG-related factors in enhancing the explanatory power of asset pricing models and shedding light on the evolving relationship between financial performance and sustainability factors.

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1. Introduction

In recent years, attention has shifted towards integrating environmental, social, and governance (ESG) considerations into asset pricing models, reflecting a growing awareness of non-financial risk factors. Researchers have explored the inclusion of ESG-related variables as potential factors that influence asset returns, addressing the broader concerns of ethical investing and sustainable finance. The development of asset pricing model refines the understanding of how financial markets operate, adapt to changing economic landscapes, and incorporate a diverse array of risk factors to explain asset pricing and returns more comprehensively. Moving into the early 2000s, CSR programs in many firms started to move towards full integration with strategic management and corporate governance (Carroll, 2008). This implied that firms are starting to be more socially conscious, starting by developing management and organizational mechanisms for reporting and control on business' socially conscious policies and practices. As the idea of responsible business grows, new methods to quantify the impact of a business also grows. Several global indices have been made to quantify the impact of a business to the society and environment. Sustainability reporting itself is the practice of measuring and disclosing organizational performance towards the goal of sustainable development. In 2015, the United Nations adopted what we know today as SDGs, or Sustainable Development Goals, which consists of 169 targets to meet the 17 Sustainable Development Goals. Today, one of the most significant quantifying method of businesses' performance towards social and environmental goals is called ESG, or Environmental Social and Governance. Environmental, social, and governance, or ESG measures describe the environmental, social, and governance issues that are considered to influence corporate behavior in their investment decisions (IFAC, 2012).

In research done by Amel-Zadeh & Serafeim (2018), they find that the main reasons that investors and portfolio managers are starting to use and incorporate ESG factors to their financial decisions is mostly because the relevance of ESG factors to investment performance and also the increase in clients' demand for sustainable practices. ESG itself can be divided into three pillars, Environmental, Social, and Governance. ESG raters such as Bloomberg, Thomson Reuters, and MSCI uses these three factors to derive ESG ratings for each company. With the practice of socially responsible investing became more significant, many studies find significant correlation between ESG ratings and returns (Nagy et al., 2016; Pollard et al., 2018; Jin, 2018; Chen & Yang, 2020; Maiti, 2020; Berg et al., 2022). In a study by Nagy, Kassam, and Lee (2016) that focuses on two main investment strategies that incorporate ESG factors, they find that ESG tilt and ESG momentum strategy are able to generate significant return relative to the market. Both approaches use ESG scores of stocks but with different methods. While ESG tilt focuses more on weighting the portfolio more towards high ESG stocks, ESG momentum takes advantage of the return generated by stocks that has been improving their ESG scores in the last 12 months. On the contrary, study by Hong and Kacperczyk (2009) suggests otherwise. They find evidence that "sin" stocks, or stocks that generally have low socially responsible rating such as alcohol, tobacco, and gaming, gives higher premium for investors that holds them, which in turn could lead to higher expected return on these stocks. Maiti (2020) in a multifactor asset pricing study with ESG factor, also finds multiple negative coefficients on ESG factor loadings. Ultimately, studies regarding ESG application in investment strategies and finance are still filled with mixed results.

Altogether, this thesis aims to contribute to the literature by giving strengthening evidence of the significance of ESG risk factor in stock returns using a multifactor asset pricing approach. The main findings of this thesis, utilizing the ESG ratings from Refinitiv EIKON, is that it supports the growing notion of how significant ESG-related factors in pricing assets and driving returns, as we constructed a new ESG and ESG momentum risk factor alongside the Fama-French original three factors, and then regress them on portfolios with different characteristics. In most of the portfolios we constructed, we find that the ESG factor loadings are all strongly significant in explaining the returns. On top of that, the majority of ESG factor loadings are strongly negative, which is in line with Maiti (2020), and supports the notion of by Hong and Kacperczyk (2009) that on average, low ESG stocks or "sin" stocks gives higher premium since they are exposed to more social and environmental risks compared to high ESG stocks.

However, we find no significant evidence that ESG momentum, as a risk factor, has a strong and significant power in explaining stock returns. Studies from Nagy et al. (2016) and Chen & Yang (2020) provide evidence that, with the rise of socially responsible investing (SRI), ESG momentum portfolio strategy could be a profitable investment strategy. From there, we question that if ESG momentum could be a significant systematic risk factor that help explains stock returns and improve the efficiency of asset pricing models. Nevertheless, our findings suggest that when regressed on multiple portfolios, ESG momentum factor loadings are only significant in explain returns on portfolio sorted by ESG momentum but cannot explain the returns of portfolios with different characteristics and sorting methods.

2. Literature Review

This section discusses about the relevant concepts and findings about the literature that has been made up until today. The chapter itself is divided into three sections, where in the first section, we discuss the literature around asset pricing models. In the second section we present an overview of literature that studies the relationship between ESG and returns in the stock market. Lastly, the third section we present an overview of the development of literature around ESG momentum and its relationship with stock returns.

2.1. Background

Sustainable finance is the after product of the early concept of Corporate Social Responsibility (CSR), which started in the 1950s where businesses start to notice concerns about the society. Starting from what we call the “corporate” period, which is around 1930 to present day, firms started to be seen more as institutions that has social obligation to fulfill (Carroll, 2008). Further into the mid 1900s, CSR starting to take shape. Carroll (2008) defined the period 1953 through 1967 as the “awareness” era, where companies, especially in the U.S., started to gain awareness of their responsibility towards the society, not only in profitability. In this era, more companies are starting to donate sums to charities. Later, the 1968 to 1973 was called the “issue” era, where companies started to address more specific issues such as pollution problems, racial discriminations, and urban decay. The 1974 to 1978 was called the ”responsiveness” era, where CSR programs are taken more seriously by companies, and they were taking serious actions around their management to address social issues. The popularity of the term CSR itself was popularized by Howard R. Bowen in 1953 by his publication of “Social Responsibilities of the Businessman”, which he emphasized the idea that businesses have broader responsibilities beyond their primary economic goals. He discussed the ethical and moral obligations of business to consider the well-being of society, employees, customers, and other stakeholders. His work was instrumental in understanding the roles of businesses in society and sparking discussions about ethical dimensions of corporate behavior.

2.2. Asset Pricing Models

Along the years, there has been many significant new contributions to the literature. There have been many advancements over the years on asset pricing models. Among these literatures, there are a few notable studies that are able to identify significant new risk factors in asset pricing models. One of the earliest contributions to the literature was the study by William F. Sharpe’s in his paper “Capital Asset Prices: A theory of market equilibrium under conditions of risk” in 1964. In this paper, he presented a groundbreaking framework for understanding the relationship between risk and return in financial markets. The paper lays the foundation for the Capital Asset Pricing Model (CAPM), which has become a cornerstone of modern finance theory. Later, the model was perfected by Black, Scholes, and Jensen (1972). It is the first study that introduces the concept of systematic risk and beta, suggesting that in expected return, market risk acts as the main systematic risk that could not be diversified away. Later, Fama and French (1993) was able to come up with the Fama-French three-factor model, expanding from the simple CAPM. Fama and French identified the size and value effect as systematic risk that drives excess returns alongside market factor. This model gained substantial empirical support and provided a basis for understanding the role of additional risk factors beyond market beta. The subsequent years we saw the emergence of multifactor models like the Fama-French Five-Factor Model

(2015), which added profitability and investment factors to the original three, providing a more comprehensive explanation for cross-sectional returns.

2.3. ESG Ratings

The popularity Environmental, Social, and Governance (ESG) ratings has been on the rise recently, especially following the increasing popularity of sustainable and socially responsible investing. More and more investment managers today are incorporating ESG factors and metrics into their decision-making process. The usage of ESG itself has been formally proposed in 2004, and today the practice of ESG has been done in Europe, America, and other developed countries (Li et al., 2021). The environmental pillar evaluates each company's compliance towards environmental factors that may have an impact towards a company's financial performance, such as emissions reduction, energy consumption and efficiency, air pollutants, and waste management. The social pillar includes social matters that may have an impact on a company's financial performance, such as workforce freedom and equality, child labor, workplace health and safety, human right compliance, and product responsibility. Lastly, the governance pillar evaluate a company from governance matters such as codes of conduct and business principles, accountability, transparency and disclosure, bribery and corruption, and stakeholder engagement. Nowdays, there are multiple ESG rating agencies, and they scrutinize and assess corporate sustainability performance by using their respective metrics and methodologies (Escrig-Olmedo, 2019). Among these rating agencies that issue their ESG ratings, some of them are Morgan Stanley Capital International (MSCI), FTSE, Bloomberg, and Refinitiv. Although they have different methodologies in evaluating a company sustainability score, their methodologies revolves around the main three pillars.

2.4. ESG Ratings and Expected Return

Over the years, there are increasing literature on ESG investing as there are increasing concerns about environment and social issues. While the trend of sustainability reporting has started from as early as 1970s, the same thing happened with sustainable investing. Nevertheless, the majority of research in ESG investing and financial performance resulted in ambiguous relationship (Friede, Busch, and Bassen, 2015). Therefore, the debate whether ESG or sustainable investing could bring higher returns for investors is still debatable. Only 42.7% of studies in North America and 26.1% of studies in Europe found a non-negative relationship between ESG and corporate financial performance. Among these studies, the non-negative relationship became less significant in portfolio-based studies. Additionally, Friede, Busch, and Bassen (2015) also studied the ESG effect over time, in which they hypothesized that if ESG awareness kept increasing within investment strategies, a decreasing ESG alpha would be expected due to learning effects in capital markets. Derwall et al. (2005) is among the first who study socially responsible investing strategy which contains the top U.S. companies with high social and environmental scores. Using the Carhart four-factor model, the strategy obtained a positive alpha of 4.15% per year. Kempf and Osthoff (2007) also found evidence of positive abnormal returns on ESG best-in-class portfolio strategy when regressed on four-factor model. Pollard, Sherwood, and Klobus (2018) also finds a positive ESG risk premia when regressed on Fama-French factors model. Jin (2018) found that ESG-related risk factors are significant to returns for mutual funds, but their effect varies over time. ESG-weighted portfolio seems to be outperforming the market pre-2010 but outperformed by the market post-2010. Nevertheless, Jin found significant evidence of the contribution of ESG-related factors when incorporated to the Fama-French's five-factor model. Maiti (2021) also suggest that ESG-related risk factor will be more significant in asset pricing models towards the future, and incorporated ESG risk and factors into the Fama-French three-factor model with size and value effect. Maiti found that the new model obtained a slightly lower GRS F-statistics, which imply better performance in explaining returns in the constructed portfolios. However, the coefficients on the ESG-related factors are mainly negative.

2.5. ESG Momentum and Expected Returns.

Furthermore, most studies regarding the relationship between ESG and asset returns are done with ESG absolute scores. However, some recent studies have identified the impact of incorporating the so-called "ESG momentum" effect into portfolio construction to increase returns (Nagy et al, 2016; Chen & Yang, 2020; Galema & Gerritsen, 2022; Berg et al., 2022; Cauthorn et al., 2023). The ESG momentum effect is hypothesized that as investors pay more attention to ESG scores due to increasing concerns about social and environmental issues, an improvement of ESG score on such a short period could lead to higher valuations of firms. Chen and Yang (2020) found that investors in the Chinese stock market tend to exhibit optimistic responses to good news about a company's improving ESG score, and pessimistic responses to bad news about a company's deteriorating in their ESG score. Nagy, Kassam, and Lee (2016) studied two distinct strategies that are aimed to increase alphas by utilizing ESG scores, ESG tilt and ESG momentum. While ESG tilt strategy focuses more on traditional ESG portfolio strategy that overweight stocks with higher ESG, the ESG momentum strategy utilizes the improvement of ESG scores over 12 months. They found that on average the ESG momentum portfolio strategy was able to obtain 2.7% active return compared to the benchmark portfolio, higher than the active return for ESG tilt portfolio, 1.06%. Galema and Gerritsen (2022) didn't find any significant abnormal returns that can be attributed to short-term ESG changes, i.e., a few days before and after the ESG score changes. However, Galema and Gerritsen were able to find significant evidence of negative buy-and-hold returns due to deteriorating ESG score in medium-term, which is 6 months. Furthermore, Berg at al. (2022) found evidence of significant positive buy-and-hold returns for firms that upgraded their ESG scores and vice versa. Cauthorn et al. (2023) also found evidence of significant stock price reaction to ESG score changes in the medium-term and long-term timespan, affecting returns. However, they conclude that there is no short-term effect to portfolio return that can be attributed to changing ESG scores. Kempf & Osthoff (2008) and Derwall et al. (2005) found that portfolios that are constructed based on ESG scores could obtain significant positive abnormal returns. However, Friede et al. (2015) argues that due to the learning effect, the capability of ESG portfolios in generating abnormal return would diminish as more investors incorporate ESG factors into portfolio-making.

2.6. Hypothesis Construction

Among the wide literature that studied the impact of ESG on firm performances and returns, there are still minimum attention on the role of ESG momentum as a risk factor that could drive stock returns. The aim of this thesis is to uncover if ESG and ESG momentum can offer superior performance in explaining stock returns, when incorporated to the renowned asset pricing model, the Fama-French three-factor model.

Main Hypothesis:

1. **The inclusion of ESG and ESG momentum factors in the Fama-French three-factor model will significantly improve the model's explanatory power in explaining stock returns.**

Secondary Hypothesis:

1. **The return on ESG portfolio strategy outperforms the market.**
2. **The return on ESG momentum portfolio strategy outperforms the market.**

The main hypothesis aims to answer the main questions of this study, of whether ESG factor and ESG momentum factor can be attributed as a significant risk factor in the Fama-French three-factor model. As discussed in the previous chapter, Jin (2018) and Maiti (2021) were able to construct asset pricing models by integrating new ESG-related risk factors, and they both find evidence that shows ESG-related factors actually can be contributed to explain stock returns. Jin (2018) finds ESG-related factor's betas are significant, but the coefficients changes over time. Maiti (2021) also finds small improvement in asset pricing models when incorporated with ESG, but the coefficients on ESG factors are mostly negative. Just as Friede, Busch, and Bassen (2015) stated in their meta-analysis, most of the study around ESG and firm performance are inconclusive. There are mixed results between positive and negative relationship between the two. Furthermore, the effect of ESG momentum as a risk factor when integrated to asset pricing models is not widely studied yet. Most studies around ESG momentum lies around generating positive alpha with ESG momentum portfolio strategies. In addition, we construct two additional comparative hypotheses to further analyze the potential of ESG and ESG momentum strategy in generating positive returns.

Additionally, many recent studies (Nagy et al., 2016; Chen & Yang, 2020; Galema & Gerritsen, 2022; Cauthorn et al., 2023) has identified that portfolios sorted on ESG-related factors could generate significant abnormal return compared to the market. Our secondary hypotheses aim to contribute to this growing body of literature in the research of generating returns with ESG, which we utilize ESG and ESG momentum portfolios to analyze the returns they generate. We do this by constructing our own ESG and ESG momentum portfolios that represent the characteristics of ESG-sorted portfolio in the U.S. market.

3. Methodology and Data

3.1. Data and Sample Selection

In undergoing this research, the stock price data are obtained from Refinitiv EIKON, which provides monthly closing price for stocks. Furthermore, to ensure that our sample fully represents the U.S. stock markets, we collect stocks from two major U.S. stock exchanges: NYSE and NASDAQ. Historically, stocks traded on NYSE are associated with larger and more established companies, while stocks traded on NASDAQ are usually considered growth-focused and technology-focused, therefore associated with a lot more small-growth companies. Both exchanges represents the U.S. stocks market, since these are two of the biggest stock markets in the United States. Which is why we chose to take representative companies from these two exchanges. We obtain 687 companies from NYSE, and 693 companies from NASDAQ. Due to data size limitations and the necessity to work with manageable sample size, we only include companies that are active up to this day, and those that are established before the year 2000. Therefore, this may introduce survivorship bias. It is important to consider this limitation when interpreting the study's findings. We obtained the total return index for 1380 companies from January 2008, up until December 2022, which take into account all returns attributed to capital return, dividends, and stock splits. For the market capitalization data, we obtain the data from Worldscope, taking the monthly market capitalization from January 2008 up to December 2022. For the book-to-market equity ratio data, we take the yearly book value per share data from Worldscope for each firms, and then divide it by each firms' monthly closing price. ESG score data is obtained from Datastream by Refinitiv EIKON for the same 1380 companies. The dimensions of each pillars of Refinitiv's ESG rating can be seen in **Table A.1**. For excess market return and risk-free rate data, we obtain the CRSP value-weighted returns and 1-month U.S. treasury bills from Kenneth French's website. This market return and risk-free rate data has been proven to be reliable and representative of the whole U.S. market. We only use the rate from January 2008 up to December 2022, which is the intended study period for this paper.

Table 2.1. Data Sources

Data Series	Source	Frequency	Observations
Total Return Index	Datastream	Monthly	223272
Book Value Per Share	Worldscope	Monthly	248011
Market Capitalization	Worldscope	Monthly	245687
ESG Score	Datastream	Yearly	159840
U.S. Treasury Bill Rate (4-Weeks)	Kenneth French Website	Monthly	180
CRSP Value-Weighted Returns	Kenneth French Website	Monthly	180

Following Fama and French (1993), we excluded banks and financial services stocks from our sample. This is due to the characteristics of financial stocks themselves. They have higher financial leverage compared to other stocks, which can distort the book-to-market ratio figures and the value effects of the model. There are also multiple cases of missing data in our sample. A small subset of companies also does not have market capitalization and closing price data available for certain periods in the sample. These stocks do not necessarily need to be excluded from the sample. As our portfolio construction method requires monthly rebalancing of stocks, we simply exclude the stocks which have missing data only in the corresponding periods of when the data is missing. We use the same method to deal with missing ESG score. For ESG score, the case of missing data is more severe. Although the U.S. stock market from NASDAQ and NYSE alone consist of thousands of stocks and is one of the biggest stock markets in the world, the U.S. government hasn't yet issued any mandatory law regarding ESG reporting for companies, therefore not all company disclose their ESG report. This is much more severe in periods before 2010. Based on our sample, in 2008, there are only 487 companies with ESG score report, although the figure kept increasing in later periods. In 2020, there are 1200 firms with complete ESG scores. Additionally, due to incomplete ESG score reporting in significant portion of firms in the sample within 2022, we decide to limit our sample up to 2021. Furthermore, we decide to exclude any firms that have negative book value. Firm with negative book value is a rare occasion where the company liabilities exceed its assets, which may signal that the company is in a bad financial shape. This could lead to negative book-to-market equity ratio and distort the coefficient of HML.

3.2. Methodology

From the sample, we proceed to construct the right-hand side factors to create our multi-factor asset pricing model. This model is based on the theoretical framework of the Fama and French three factor asset pricing model (1993), which incorporate excess market return (Rm-Rf), size factor (SMB), and value factor (HML), which goes as follows:

$$R_{it} - R_{ft} = \alpha + \beta(R_{mt} - R_{ft}) + \gamma SMB_t + \delta HML_t \qquad (1)$$

The model is essentially a time series regression, which $R_{it} - R_{ft}$ stands for excess return of portfolio i at time t, $R_{mt} - R_{ft}$ stands for the excess market return at time t, SMB_t stands for small-minus-big, or we can say the excess return of the portfolio created to mimic the size effect, and HML_t stands for high-minus-low, or the excess return of the portfolio created to mimic the value effect. If assets are priced rationally, variables that are related to average returns such as size and book-to-market equity ratio, which are depicted by SMB and HML, will act as proxies to common and undiversifiable risk factors in returns (Fama and French, 1993). From the three-factor model, there are a lot of significant breakthroughs in the literature of multifactor asset pricing models, one of them being the Fama and French five-factor model (2015). The five-factor model incorporate RMW and CMA, which are profitability factor and level of investment factor, respectively. But fitting the model with too many factors could lead to overfitting problems, which adding another factor could distort the significance of another factor in the model. Therefore, we proceed with the three-factor model as our base framework. In this study, we are interested how ESG momentum and ESG will act as a proxy for common risk factor in the U.S. stock market returns, therefore we developed two new models that we will use for this study, as seen in **Equation 2** and **Equation 3.**

$$R_{it} - R_{ft} = \alpha + \beta(R_{mt} - R_{ft}) + \gamma SMB_t + \delta HML_t + \theta ESGM_t \qquad (2)$$

$$R_{it} - R_{ft} = \alpha + \beta(R_{mt} - R_{ft}) + \gamma SMB_t + \delta HML_t + \theta ESG_t \qquad (3)$$

3.3. Right-hand side portfolio

3.3.1. The Market Return Factor

To construct the excess market return factor, we are using data provided from Kenneth French website, which is the value-weighted returns for all stocks in the CRSP database, that are listed on NYSE, NASDAQ, or AMEX, that has CRSP share code of 10 or 11. Kenneth French's market return factor proved to be a great representative of market return of the whole U.S. stock market. Taking the CRSP value-weighted return, we deduct them by the 1-month U.S. treasury bills rate.

3.3.2. The Size Factor

In constructing the SMB and HML factors, we use value-weighted returns. We do this by assigning weights for each stock in the portfolios for each month. Shown in **Equation 4** is how we construct the weighting for each stock, and **Equation 5** shows how we derive the value-weighted returns. MVrepresent the total market value or market capitalization of stock i at month t, ER'_{it} represent the excess return of stock i at month t, and w_{it} represent the weights assigned for stock i at month t. Since the portfolios are rebalanced per month, the weights could be different for one portfolio in different points of time. The portfolios themselves does not always have the same number of stocks between portfolios and across each month. We assign the weighting themselves using market capitalization of the stocks. We take the market capitalization for each stock and divide it by the sum of market capitalization of all stocks in that portfolio at time t. Then, to obtain the value-weighted excess return, we take the respective excess return of each stock and multiply them by their respective weights. This approach puts more weight on bigger stocks, or stocks with bigger market capitalization, which helps reflect the true performance of the market since bigger stocks tend to have bigger influence in the stock market. This is also in line with the approach Fama and French (1993) used to construct the SMB and HML factors.

$$w_{i,t}^{value} = \frac{MV_{i,t}}{\sum_{i=1}^{n} MV_{i,t}} \tag{4}$$

$$ER_{i,t}^{value} = (R_{i,t} - R_{f,t}) * w_{i,t}^{value} \tag{5}$$

We then create two market capitalization categorization (big and small), and three B/M ratio categorization (growth, neutral, and value). We divide between small and big firms by taking the median value of all firms' market capitalization in our sample, and then putting the firms in the upper-half to the big portfolios, and firms in the lower-half in the small portfolios. We then proceed to sort the portfolios to 3 groups based on B/M ratio. We simply take the excess returns of the stocks that are group in the small portfolios (small-value, small-neutral, small-growth), take the average, and then deduct it with the average excess returns of the stocks in the big portfolios (big-value, big-neutral, big-growth). Therefore, the SMB factor is just the difference between excess return of the portfolio constructed to mimic small stocks, and the excess return of the portfolio constructed to mimic big stocks. **Equation 6** shows how we construct the SMB factor.

$$SMB_t = \frac{(SG_t + SN_t + SV_t)}{3} - \frac{(BG_t + BN_t + BV_t)}{3} \tag{6}$$

Where:

SG_t = value-weighted return of Small-Growth portfolio at month t.

SN_t = value-weighted return of Small-Neutral portfolio at month t.

SV_t = value-weighted return of Small-Value portfolio at month t.

BG_t = value-weighted return of Big-Growth portfolio at month t.

BN_t = value-weighted return of Big-Neutral portfolio at month t.

BV_t = value-weighted return of Big-Value portfolio at month t.

3.3.3. The Value Factor

Book-to-market equity ratio is constructed by taking the book value per share of stock i at month t (BV_{it}) and divide it by the corresponding closing price of stock i at month t (P_{it}), as shown in **Equation 7.** To construct the HML factor, we use the same 6 portfolios sorted on size and B/M ratio. The lower 30% of stocks in terms of B/M ratio are put into the growth stocks group, and the upper 30% of stocks in terms of B/M ratio are put into value stocks group, and stocks in between are put in neutral stocks group. Growth stocks are stocks that have low book-to-market equity ratio, implying that their market valuation is significantly higher than book value, and value stocks are stocks with high book-to-market equity ratio. The intuition is that value stocks generally hold a higher premium for those who holds them. This is known as the value premium. These stocks generally are viewed underperforming by investors, therefore holds higher level of risk. We then take the difference between the value-weighted excess return of value portfolios (big-value and small-value) minus the growth portfolios (big-growth and small-growth), as shown in **Equation 8**.

$$BM_{it} = \frac{BV_{i,t}}{P_{i,t}} \tag{7}$$

$$HML_t = \frac{(SV_t + BV_t)}{2} - \frac{(BG_t + SG_t)}{2} \tag{8}$$

Where:

SV_t = value-weighted return of Small-Value portfolio at month t.

BV_t = value-weighted return of Big-Value portfolio at month t.

SG_t = value-weighted return of Small-Growth portfolio at month t.

BG_t = value-weighted return of Big-Growth portfolio at month t.

3.3.4. The ESG Factor

For the ESG factor, we take the ESG score of each company from Refinitiv EIKON. Then we construct 6 portfolios based on size and ESG scores. The cut-off point for size is the median market capitalization for all firms in the dataset, taking into account all firms that have sufficient ESG reporting for all of the study periods. For the ESG scores, we create 2 cut-off points to create three groupings for ESG scores. We group them by 30% lowest, 40% middle, 30% highest, following to how Fama and French (1993) constructed the SMB and HML factor. After that, we create a weighting for each firm in each of the 6 groupings based on each firm market capitalization. We then take the value-weighted excess returns for each portfolio and create the ESG factor as shown in **Equation 9.**

$$ESG_t = \frac{\left(SH_t^{esg} + BH_t^{esg}\right)}{2} - \frac{\left(SL_t^{esg} + BL_t^{esg}\right)}{2} \tag{9}$$

Where:

SH_t^{esg}= value-weighted return of Small-High portfolio at month t.

BH_t^{esg}= value-weighted return of Big- High portfolio at month t.

SL_t^{esg} = value-weighted return of Small-Low portfolio at month t.

BL_t^{esg}= value-weighted return of Big-Low portfolio at month t.

3.3.5. The ESG Momentum Factor

There is no clear methodology as for the holding period to construct ESG momentum portfolios. Nagy, Kassam, and Lee (2016) constructed their ESG momentum portfolio based on ESG score improvement over 12 months. Chen & Yang (2020) find that the returns of ESG momentum portfolios peaked at around 12-18 months.

$$esgm_{i,t} = esg_{i,t} - esg_{i,t-1} \tag{10}$$

Therefore, we decide to use 1-year ESG score change as the basis in constructing ESG momentum portfolio. We first calculate ESG momentum by subtracting the current ESG score by the ESG score last year, as shown in **Equation 10**. Then to construct the ESG momentum factor, we construct 6 new portfolios that are based on size and ESG momentum, separately from the 2x3 size and B/M ratio portfolios. We do this by creating a cutoff point in terms of market capitalization to divide the stocks in our sample. We used the median market cap of all stocks in the sample and put the stocks with market capitalization above the median in the "big" portfolios, and stocks with market cap below the median in the "small" portfolios. Then, we create three distinct groupings for ESG momentum by creating two cutoff points. The lowest 30% in terms of ESG momentum are put into the two “low” portfolios, the upper 30% are put into the two “high” portfolios, and the middle 40% are put into the middle grouping of ESG momentum. We calculate them by taking the average return from small-high plus big-high portfolios and deduct it by the average return of small-low and big-low portfolios. Furthermore, we utilize the value-weighting method, as with our previous method in constructing SMB and HML. We take the value-weighted returns of each portfolio and create the ESGM factor shown by **Equation 11.**

$$ESGM_t = \frac{\left(SH_t^{esgm} + BH_t^{esgm}\right)}{2} - \frac{\left(SL_t^{esgm} + BL_t^{esgm}\right)}{2} \tag{11}$$

Where:

SH_t^{esgm}= value-weighted return of Small-High portfolio at month t.

BH_t^{esgm}= value-weighted return of Big- High portfolio at month t.

SL_t^{esgm} = value-weighted return of Small-Low portfolio at month t.

BL_t^{esgm}= value-weighted return of Big-Low portfolio at month t.

In this next section, we are going to dissect how we construct the *left-hand side* (LHS) portfolios used for the regression. In order to test the significance of ESG and ESG momentum in explaining stock returns in the U.S. market, we test our new four-factor model, both with ESG and with ESG momentum, on a handful of portfolios. By constructing multiple portfolios with different sorting techniques, we can analyze the impact of the ESG and ESG momentum factor in explaining stock returns.

3.4. Left-hand side portfolios

3.4.1. ESG Momentum Portfolios

We rank firms based on the change of their ESG scores over one year, and then we sort them into 5 low to high ESG momentum portfolios. Regarding the cutoff points construction, there are no perfect benchmark at what percent the portfolios should be divided. Therefore, we divided the stocks into 5 quantiles grouping based on ESG momentum. In **Table 3.1,** we can see how the ESG momentum score is grouped across the 5 groups. Quantile 1 mostly consist of firms that have deteriorate in their ESG score across one year, as much as 69.96 points in one year. They inhibit a negative ESG momentum score. The middle quantiles, quantile 2 and 3, consists of firms that didn’t go through significant changes in ESG scores. Quantile 4 consists of firms that improve their ESG scores by moderate amount, and quantile 5 consists of firms with the highest ESG score improvement across one year.

Table 3.1. Descriptive statistics of the absolute ESG score change per month for each of ESG momentum grouping.

ESGM Grouping	ESG score change			
	Mean	Std. Deviation	Min.	Max.
1 (Low)	-5,64	3,36	-69,96	-2,44
2	-0,92	0,79	-2,43	0,38
3	1,62	0,74	0,39	2,96
4	4,72	1,11	2,97	6,85
5 (High)	12,33	5,55	6,86	58,18

We create the 5 portfolios by dividing the firm sample by into three by two cutoff points based on market cap, and further divide them into nine by two cutoff points based on ESG momentum. As seen in **Table 3.3**, we are able to see the average number of firms per period for each portfolio we have constructed. To obtain the excess return, we use the value-weighting method for each firm in the portfolio. Bigger firms with higher market capitalization are given bigger weight, which mimics the volume of stocks traded in the stock market.

3.4.2. ESG Portfolios

Similar to the 5 portfolios sorted on ESG momentum, we also 5 portfolios sorted on ESG scores. Regarding the cutoff points, there are no specific guidelines in the literature on how to construct your ESG portfolios. Kempf and Osthoff (2007) uses a 10% cutoff point to construct the best-in-class ESG portfolio strategy, while Halbritter and Dorfleitner (2015) uses 20% as their cutoff point. We use the absolute ESG score for each firm in our dataset and decide to divide them into five quantiles based on each firm ESG scores, the top 20% being the portfolio with the highest ESG score. Then we further group the firms into three grouping for size. In **Table 3.2,** we can see how firms with different ESG scores being grouped into five ESG quantiles. The first group with the lowest ESG scores has an average ESG score of 19,22, while the high ESG group has an average ESG score of 75,01. The five groupings sorted on ESG score should allow us to further dissect the characteristics of firms with different ESG scores when regressed on the multi-factor model.

Table 3.2. Descriptive statistics of the absolute ESG score for each of ESG grouping.

ESG Grouping	ESG score			
	Mean	**Std. Deviation**	**Min.**	**Max.**
1 (Low)	19,22	5,42	0,71	26,79
2	32,20	3,08	26,8	37,68
3	43,52	3,43	37,69	49,82
4	57,47	4,52	49,83	65,36
5 (High)	75,01	6,59	65,38	95,16

3.4.3. Double-sorted size and B/M ratio portfolios

To further dissect the role of ESG and ESG momentum as risk factors in the Fama and French three-factor model, we created 4x4 double-sorted portfolio based on size and B/M ratio. Here, we want to test the performance of ESG and ESG momentum as a risk factor when used aligned with the Fama and French's three-factor model. Double-sorted portfolios on size and B/M ratio allow for capturing variations in both size and value characteristics simultaneously. The use of double-sorted portfolios became common practice following Fama and French original work (1993). This enables a better understanding of how different combinations of size and B/M ratio characteristics affect asset returns, especially how ESG-related factor would react to each of the portfolios with different characteristics.

Table 3.3. Average number of firms per month in each LHS portfolio, from January 2008 to December 2021 (168 months)

Panel A. 5 ESG Portfolios + 5 ESG Momentum Portfolios

Portfolio	**ESG**	**ESG Momentum**
1 (Low)	153,18	144,46
2	154,63	143,23
3	153,08	142,90
4	154,58	143,48
5 (High)	156,63	143,60

Panel B. 4x4 Size & B/M Portfolio

Size	B/M Ratio			
	1 (Growth)	**2**	**3**	**4 (Value)**
Small (1)	70,69	53,38	72,06	132,01
2	62,09	75,37	98,89	100,40
3	77,61	104,55	93,30	67,05
Big (4)	127,53	104,63	73,67	38,46

Shown in **Table 3.3** are the average number of firms in each grouping of portfolio. We derive this by taking the total number of observation and divide it by the number of periods in the dataset. As we can see, all of the portfolios sorted on ESG and ESG momentum have balanced number of firms. On the other hand, the average number of firms in our double-sorted portfolios on size and B/M ratio varies. These differences in the average number of firms reflects the availability of stocks in the specified categories.

4. Results and Discussions

4.1. Summary Statistics of Portfolio Returns

In this section, we present our main findings and discussions. Our analysis is performed over the study period from February 2008 through December 2021 for a handful of left-hand side portfolios, constructed with different methodologies. This is done to study the effect and role of ESG-related factor as systematic risk in the multi-factor model to portfolios with different characteristics.

Table 4.1. Summary statistics of factors' returns for February 2008 to December 2021 (167 months)

Factors	Mean	Std. Deviation	Minimum	Maximum	Observation
Rm-Rf	1,00%	4,66%	-17,23%	13,65%	167
SMB	0,21%	2,36%	-5,04%	7,25%	167
HML	-1,71%	2,79%	-9,73%	6,24%	167
ESGM	0,02%	1,36%	-4,94%	5,81%	167
ESG	-0,42%	1,89%	-8,86%	4,32%	167

The descriptive statistics for all factors (Rm-Rf, SMB, HML, ESGM) are shown in **Table 4.1**. We can see that the market return factor has a mean of precisely 1 percent. SMB has a positive mean, as expected that small firms tend to outperform big firms in terms of stock returns. ESG momentum has a slightly positive mean, we cannot take conclusion yet on whether there is a further trend that firms that significantly improved their ESG score in recent year tend to outperform firms that are degrading in ESG scores. But on the other hand, ESG factor has a negative mean. This may serve as preliminary evidence that on average firms with lower ESG scores outperforms firms with higher ESG scores, in line with Hong & Kacperczyk (2009). However, more evidence is needed to draw a robust conclusion.

Table 4.2. Value-weighted excess returns for each RHS portfolios, from January 2008 to December 2021 (168 months)

Panel A. 2x3 Size-B/M Portfolios

Portfolio	Mean
ME1/BM1	1,45%
ME1/BM2	0,85%
ME1/BM3	-0,46%
ME2/BM1	1,21%
ME2/BM2	0,32%
ME2/BM3	-0,31%

Panel B. 2x3 Size-ESG Portfolios

Portfolio	Mean
ME1/ESG1	0,44%
ME1/ESG2	0,39%
ME1/ESG3	0,37%
ME2/ESG1	1,35%
ME2/ESG2	0,82%
ME2/ESG3	0,57%

Panel C. 2x3 Size-ESG Momentum Portfolios

Portfolio	Mean
ME1/ESGM1	0,45%
ME1/ESGM2	0,40%
ME1/ESGM3	0,41%
ME2/ESGM1	0,71%
ME2/ESGM2	0,58%
ME2/ESGM3	0,78%

Furthermore, we can notice an anomaly in the HML factor, which has a highly negative mean. This implies that there might be evidence that growth stocks tend to outperform value stocks. This might be caused be several factors, mainly economic conditions during those times. **Table 4.2** further breaks down the statistics of value-weighted excess return for each portfolio we use to create the right-hand side factors. All ME2 portfolios tend to be outperformed by ME1 portfolios, but all the BM3 portfolios are outperformed by BM1 portfolios. This furthers our findings that there is a reversed relationship between the performance of value and growth portfolios. Throughout these periods, the central bank has taken measures to boost demand and inflation (Borio & Gambacorta, 2017). Growth firms are volatile to interest rate changes due to their valuation method and cost of capital. Growth stocks are often valued based on their expected future cash flow, which is discounted at the WACC, the cost of debt and the cost of equity. Both are affected by the risk-free rate. In a low interest rate environment, cost of debt and cost of equity are lower. This, in turn, also discounts the cash flow at a lower rate, hence higher valuation. This effect is much more severe in growth firms due to them having longer-term cash flow horizon in their valuation. This is because growth-oriented activities done by growth firms require investments that may not generate immediate cash flows but are expected to generate substantial returns in the future. On the other hand, **Table 4.2 Panel C** shows the performance difference between high ESG momentum portfolios and low ESG momentum portfolios seems to be quite indistinguishable. ME1/ESGM1 portfolio outperforms ME1/ESGM3 portfolio with higher ESG momentum, but ME2/ESGM1 portfolio is outperformed by ME2/ESGM3 portfolio. Nevertheless, neutral ESG momentum portfolios seem to be outperformed by both low and high ESG momentum portfolios. For size and ESG sorted portfolios, we can see that on average portfolios with lower ESG scores have higher mean excess returns than portfolios with higher ESG scores. Portfolio ME1/ESG1 has a higher mean excess return than portfolio ME1/ESG3, and portfolio ME2/ESG1 also has a higher mean excess return than portfolio ME2/ESG3.

Table 4.3. Value-weighted excess returns for each LHS portfolios, from January 2008 to December 2021 (168 months)

Panel A. 5 ESG Portfolios + 5 ESG Momentum Portfolios

Portfolio	ESG	ESG Momentum
1 (Low)	1,00%	0,66%
2	0,98%	0,63%
3	0,74%	0,73%
4	0,99%	0,66%
5 (High)	0,41%	0,74%

Panel B. 4x4 Size & B/M Portfolio

Size	B/M Ratio			
	1 (Growth)	2	3	4 (Value)
Small (1)	0,43%	0,84%	0,46%	-1,05%
2	1,63%	1,18%	0,62%	-0,54%
3	1,50%	1,00%	0,37%	-0,37%
Big (4)	1,30%	0,50%	0,11%	-0,42%

We present the excess return statistics for all of our left-hand side portfolios in **Table 4.3.** In **Table 4.3 Panel A,** we lay out the mean excess returns for the 5 quantiles of ESG portfolios and 5 quantiles of ESG momentum portfolios. The evidence further strengthens Hong & Kacperczyk (2009) findings. Low ESG stocks seem to outperform high ESG stocks. However, the difference between excess returns of the top quantile of ESG momentum and lowest quantile of ESG momentum is almost indistinguishable, just as we find in the double-sorted portfolios on size and ESG momentum we use to construct the ESG momentum risk factor. Although top quantile slightly outperforms the lowest quantile, further evidence using the multi-factor model is needed.

We also observed a further anomaly between small cap portfolios and big cap portfolios in our 4x4 double-sorted portfolios on size and B/M ratio. There is a tendency of big cap portfolios outperforming small cap portfolios. As we discussed earlier, this might be due to the same reasons for the anomaly between growth and value stocks. The low interest environment has pushed stocks that are growth oriented to be higher in valuation due to their longer-term cash flow horizon.

Figure 4.1. Cumulative returns of portfolios with respect to market returns from February 2008 to December 2021.

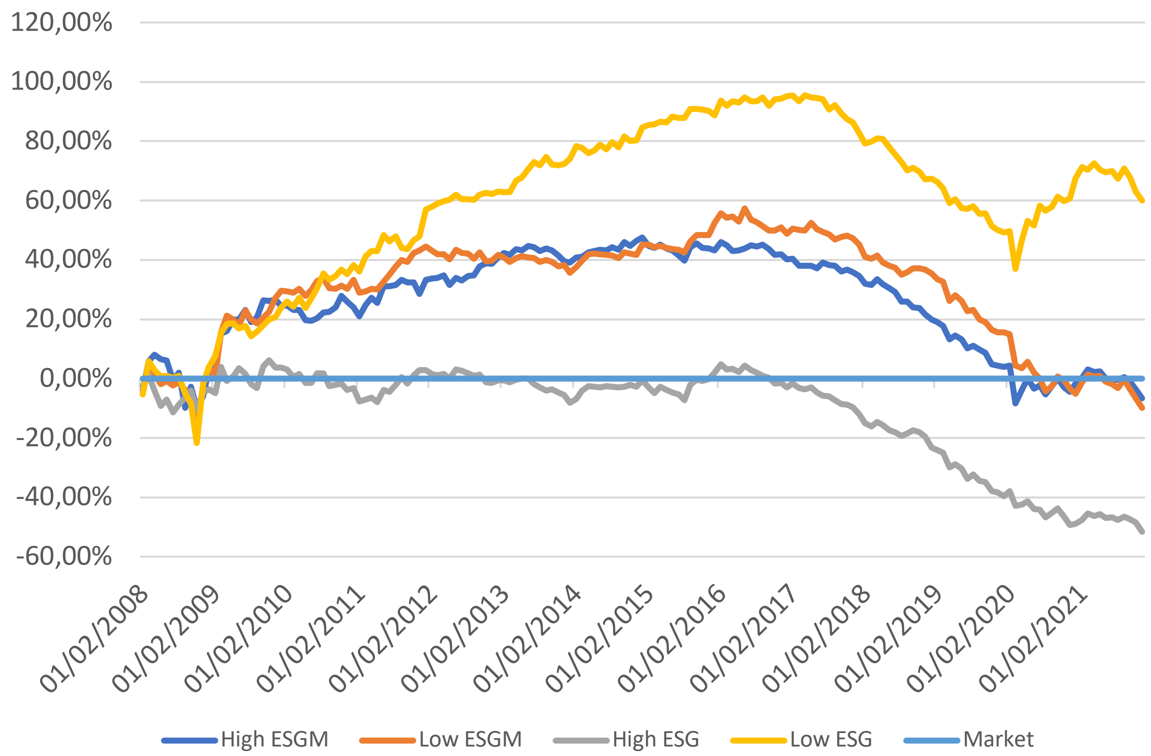

Figure 4.1 depicts the cumulative returns relative to market return of 4 portfolios: High ESGM, Low ESGM, High ESG, Low ESG. We use the extreme quantiles of ESG momentum and ESG portfolios for this. The top quantile ESG momentum portfolio represents the high ESGM portfolio, while the lowest quantile ESG momentum portfolio represents the low ESGM portfolio in this figure, similar with ESG portfolios. As we can observe, the cumulative returns of these portfolios' changes over time. During 2008 up to 2010, high ESG momentum portfolio outperforms the other four portfolios. In period after 2010, we can see that the return of low ESG portfolio skyrocketed, outperforming the market and high ESG momentum portfolio. This confirms the findings of Hong & Kacperczyk (2009) and Bauer et al. (2005), where low ESG stocks or "sin" stocks tend to outperform high ESG stocks as a premium for holding riskier stocks that are more prone to environmental and social risks. On the other hand, the difference between cumulative returns of low ESG momentum portfolios and high ESG momentum portfolios seems to be very small, and always varying. While throughout 2008 to 2010 high ESG momentum outperforms low ESG momentum, throughout 2013 to 2016, low ESG momentum outperforms high ESG momentum. Nevertheless, the difference between cumulative returns of high ESG portfolio and low ESG portfolio is very significant. The low ESG portfolio constantly outperforming the market while high ESG portfolio constantly outperformed by the market. Furthermore, entering 2017, we see a decreasing trend of cumulative returns of all of the portfolios. The reversing trend is also visible on ESG portfolios, both high and low. We can see how the cumulative

returns of high and low ESG momentum portfolio, which outperforms the cumulative market return until mid-2018, reversed and being outperformed by the market.

4.2. Asset pricing model results and discussions

In **Table 4.4,** we present the regression results of the 5 ESG portfolios and 5 ESG momentum portfolios with the three-factor Fama and French asset pricing model (1993). As we can see, all of the market betas are strongly significant. High ESG momentum portfolio inhibits a higher market beta, while the lowest ESG momentum portfolio has a market beta below one This difference is significant by 1% significance level. It implies the portfolio is more market sensitive compared to the lowest quantile of ESG momentum. On the other hand, the market betas for lowest ESG score portfolio seems to have a higher market beta compared to the highest ESG score portfolio, although only significant at 10% level. This is in line with the notion that higher ESG stocks are safer and less volatile in the market to lower ESG stocks (Hong & Kacperczyk, 2009; Bauer et al., 2005).

However, The SMB or small-minus-big factor are only significant in 3 out of 10 portfolios. The coefficients on the SMB factor are strongly significant in ESG 1 and ESG 5 portfolios. In ESG 1 portfolio, the coefficient is strongly positive, and in the ESG 5 portfolio the coefficient is strongly negative. This could imply that low ESG portfolio is dominated by smaller firms while high ESG portfolio is dominated by bigger firms, which we will discuss further in **Table 4.7**. Nevertheless, the negative coefficients do not necessarily mean that big cap firms on average outperform small cap firms.

Furthermore, analyzing the high-minus-low (HML) factor as we can observe from the table seems to lose significance when regressed on portfolios sorted on ESG and ESG momentum. The coefficients on HML are only significant in 4 out of 10 portfolios. Two lowest ESG momentum portfolios have significant negative coefficients, which could imply they are dominated by value stocks.

The alphas of the three-factor regression show no significant abnormal returns, except in one portfolio. The lowest ESG momentum portfolio generates a weakly significant positive alpha at 0.63%, which is the only portfolio able to generate significant alpha with the three-factor model.

Table 4.4. Regression results of four-factor model with ESG on 5 portfolios sorted on ESG momentum and 5 portfolios sorted on ESG, from February 2008 to November 2021 (166 months).

Factors	ESG Momentum					Difference	ESG					Difference
	ESGM 1	ESGM 2	ESGM 3	ESGM 4	ESGM 5	(High - Low)	ESG 1	ESG 2	ESG 3	ESG 4	ESG 5	(High - Low)
Rm - Rf	0.97***	1.04***	1.04***	0.97***	1.06***	0.09***	1.01***	1.00***	1.07***	1.11***	0.92***	-0.09*
	(0.060)	(0.048)	(0.052)	(0.065)	(0.057)	(0.021)	(0.065)	(0.071)	(0.063)	(0.066)	(0.043)	(0,048)
SMB	-0.018	-0.052	0.0025	-0.020	-0.093	-0.075**	0.32***	0.20*	0.11	-0.13	-0.13**	-0.45***
	(0.089)	(0.070)	(0.077)	(0.096)	(0.083)	(0,031)	(0.095)	(0.104)	(0.094)	(0.098)	(0.063)	(0,071)
HML	0.32***	0.16**	0.031	-0.030	0.11	-0.21***	0.16	0.080	0.28***	0.13	0.13*	-0.03
	(0.099)	(0.078)	(0.085)	(0.107)	(0.093)	(0,034)	(0.106)	(0.116)	(0.104)	(0.109)	(0.070)	(0,079)
Constant	0.0063*	0.0023	-0.00015	-0.00092	0.0018		0.0051	0.0025	0.0031	0.0049	0.0010	
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)		(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	
Observations	166	166	166	166	166		166	166	166	166	166	
R^2	0.728	0.812	0.775	0.648	0.750		0.735	0.668	0.750	0.706	0.799	
Adjusted R^2	0.723	0.809	0.771	0.641	0.745		0.730	0.662	0.745	0.701	0.795	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the difference column, we test the difference of each factor loadings, when regressed on the highest quantile portfolio vs. the lowest quantile portfolio. To determine the significance of the difference on the respective factor loadings, we estimate the difference between estimator A and estimator B, and divide them by the standard error of the difference between estimator A and B. Therefore, we are able to derive the T-statistics of the difference between respective factor loadings on highest quantile portfolio and lowest quantile portfolio.

On **Table 4.5,** we present the regression results for the four-factor model with ESG, regressed on our 9 double-sorted portfolios on size & ESG momentum. The table reports each factor coefficients, alphas, and the R-squared of the four-factor model of ESG momentum.

It can be observed that all of the market betas are strongly significant. We can also observe the difference among market betas of the portfolios. The top ESG momentum quantile has 1.08 market beta, while the lowest ESG momentum quantile has 0.99 market beta, and the difference is very significant. This implies that top ESG momentum stocks are more market sensitive. On the other hand, the top ESG quantile portfolio has the lowest market beta, standing at 0.93. This is in line with the popular trend that high ESG stocks are less volatile relative to the market, due to them offering less exposure to risks, mainly environmental and social risks (Hong & Kacperczyk, 2009; Bauer et al., 2005).

Surprisingly, none of the small-minus-big (SMB) factor loadings is significant on the 5 portfolios sorted on ESG momentum. The majority of coefficients on SMB are negative, but none are significant. We can imply from the strongly negative coefficients, that these 5 portfolios are mostly consist of relatively big cap firms. Furthermore, the SMB factor loadings in the 5 portfolios sorted on ESG score are only significant in the 1st, 2nd, and 5th ESG quantile portfolios. The first ESG quantile has a strongly significant positive relationship with the SMB factor. But on the contrary, the top ESG quantile has a strong negative coefficient. This could serve as preliminary evidence that top ESG stocks are dominated by bigger firms, while the lower ESG stocks are dominated by smaller firms, similar to our findings on **Table 4.4.**

The high-minus-low (HML) factor loadings shown quite strong explanatory power. On the ESG momentum portfolios, 3 out of 5 coefficients are significant, and all of them are positive. The coefficients are strong especially in the lowest or highest ESG momentum quantiles. On the other hand, the HML coefficients are all significant on ESG portfolios. All of them are positive.

Furthermore, the ESG factor loadings, as can be observed from the table are strongly significant in explaining the returns. The ESG risk factor is significant in all of the portfolios sorted on ESG momentum. The signs of the coefficients are all negative. This imply that the ESG momentum portfolios consists of stocks with low ESG scores. This is not surprising, due to stocks that are volatile in terms of their ESG score changes are mostly stocks with lower ESG, while stocks with higher ESG are mostly less volatile and less likely to experience significant changes of their ESG scores. On the other hand, the ESG factor loadings are strongly significant in 4 out of 5 portfolios sorted on ESG scores, and all of them is negative. The lowest ESG quantile has the strongest negative coefficient, showing 1.02 can be attributed to the ESG risk factor. However, the ESG risk factor seems to be unable to explain the returns on the top ESG portfolio.

Table 4.5. Regression results of four-factor model with ESG on 5 portfolios sorted on ESG momentum and 5 portfolios sorted on ESG, from February 2008 to November 2021 (166 months).

Factors	ESG Momentum					Difference	ESG					Difference
	ESGM 1	ESGM 2	ESGM 3	ESGM 4	ESGM 5	(High - Low)	ESG 1	ESG 2	ESG 3	ESG 4	ESG 5	(High - Low)
Rm - Rf	0.99***	1.05***	1.05***	1.00***	1.08***	0.09***	1.06***	1.05***	1.09***	1.13***	0.93***	-0.13***
	(0.059)	(0.047)	(0.051)	(0.062)	(0.054)	(0.054)	(0.053)	(0.061)	(0.061)	(0.064)	(0.043)	(0.030)
SMB	-0.036	-0.064	-0.014	-0.048	-0.12	-0.08**	0.27***	0.15*	0.080	-0.15	-0.13**	-0.40***
	(0.087)	(0.069)	(0.075)	(0.091)	(0.079)	(0.037)	(0.077)	(0.089)	(0.090)	(0.095)	(0.063)	(0.044)
HML	0.38***	0.19**	0.081	0.056	0.19**	-0.19***	0.31***	0.23**	0.36***	0.20*	0.14*	-0.17***
	(0.099)	(0.078)	(0.084)	(0.103)	(0.089)	(0.042)	(0.087)	(0.101)	(0.101)	(0.107)	(0.072)	(0.049)
ESG	-0.37***	-0.23**	-0.33***	-0.57***	-0.52***	-0.15***	-1.02***	-0.98***	-0.51***	-0.47***	-0.072	0.95
	(0.123)	(0.097)	(0.105)	(0.128)	(0.111)	(0.053)	(0.109)	(0.126)	(0.126)	(0.133)	(0.089)	(0.619)
Constant	0.0057*	0.0019	-0.00069	-0.0019	0.00098		0.0034	0.00087	0.0023	0.0042	0.00091	
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)		(0.003)	(0.003)	(0.003)	(0.004)	(0.002)	
Observations	166	166	166	166	166		166	166	166	166	166	
R^2	0.743	0.819	0.788	0.687	0.780		0.828	0.758	0.773	0.727	0.800	
Adjusted R^2	0.736	0.814	0.783	0.679	0.775		0.824	0.752	0.767	0.720	0.795	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the difference column, we test the difference of each factor loadings, when regressed on the highest quantile portfolio vs. the lowest quantile portfolio. To determine the significance of the difference on the respective factor loadings, we estimate the difference between estimator A and estimator B, and divide them by the standard error of the difference between estimator A and B. Therefore, we are able to derive the T-statistics of the difference between respective factor loadings on highest quantile portfolio and lowest quantile portfolio.

The alphas are of the regressions are insignificant in 9 out of 10 of all portfolios**.** This shows that the model successfully explains the majority of variations in excess returns of the portfolios, except in the first ESGM quantile portfolio. The alpha is positive although weakly significant at 10 percent level. This implies that the four factors including ESG risk factor are able to explain significant amount of returns in the majority of the portfolios.

Ultimately, we can observe the R-squared of each of the 10 regressions in **Table 4.5** is slightly higher than their respective regressions on the same portfolio in **Table 4.4.** with FF 3-factor. Although we cannot determine whether the differences in R-squared are significant or not, this finding might serve as preliminary evidence that including ESG risk factor could increase the explanatory power of the Fama-French 3-factor model.

In **Table 4.6,** we present the regression results for the four-factor model with ESG momentum on the same 5 + 5 portfolios. As seen from the table, the market beta slightly changes when we use ESG momentum factor instead of ESG factor. Nevertheless, we see the similar trends between highest and lowest quantiles portfolios. The top ESG quantile portfolio has the lowest beta, which means it is less market sensitive when compared to lower ESG portfolios. On the other hand, highest ESG momentum quantile portfolio seems to be more market sensitive compared to the lowest ESG momentum quantile portfolio.

None of the SMB factor loadings are significant when regressed on 5 portfolios sorted on ESG momentum. However, the SMB factor loadings are significant on 3 out of 5 portfolios sorted on ESG score. We can see significant difference between the SMB factor loadings on the lowest ESG quantile and the highest ESG quantile. The lowest ESG quantile has a strong positive SMB factor loading, while the top ESG quantile has a strong negative SMB factor loading, in line with our previous regressions.

The HML factor loadings also differs when we incorporate ESG momentum rather than ESG as a risk factor. It seems to have much less significance in explaining returns when used with ESG momentum risk factor. Only 4 out of 10 HML factor loadings that are significant, at least at the 10% level. On top of that, all of the HML factor loadings are positive.

Table 4.6. Regression results of four-factor model with ESG momentum on 5 portfolios sorted on ESG momentum and 5 portfolios sorted on ESG, from February 2008 to November 2021 (166 months).

Factors	ESG Momentum					Difference	ESG					Difference
	ESGM 1	ESGM 2	ESGM 3	ESGM 4	ESGM 5	(High - Low)	ESG 1	ESG 2	ESG 3	ESG 4	ESG 5	(High - Low)
Rm - Rf	0.98***	1.04***	1.03***	0.97***	1.05***	0.07***	1.01***	0.99***	1.06***	1.11***	0.92***	-0.09*
	(0.058)	(0.047)	(0.052)	(0.065)	(0.054)	(0,021)	(0.065)	(0.070)	(0.064)	(0.066)	(0.043)	(0.048)
SMB	-0.082	-0.078	0.0089	0.011	-0.029	0.05*	0.33***	0.25**	0.11	-0.11	-0.13**	-0.46***
	(0.087)	(0.071)	(0.078)	(0.098)	(0.081)	(0,032)	(0.097)	(0.105)	(0.096)	(0.099)	(0.065)	(0.073)
HML	0.23**	0.12	0.040	0.013	0.20**	-0.003	0.18	0.15	0.29***	0.16	0.13*	-0.05
	(0.098)	(0.080)	(0.088)	(0.110)	(0.092)	(0,035)	(0.110)	(0.118)	(0.108)	(0.112)	(0.073)	(0.082)
ESGM	-0.62***	-0.25*	0.062	0.30	0.62***	1.24***	0.12	0.47**	0.077	0.21	-0.030	-0.15
	(0.164)	(0.133)	(0.147)	(0.184)	(0.153)	(0,059)	(0.183)	(0.197)	(0.180)	(0.187)	(0.122)	(0.137)
Constant	0.0045	0.0016	0.000022	-0.00011	0.0035		0.0054	0.0038	0.0033	0.0055	0.00094	
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)		(0.004)	(0.004)	(0.004)	(0.004)	(0.002)	
Observations	166	166	166	166	166		166	166	166	166	166	
R^2	0.751	0.816	0.776	0.653	0.773		0.736	0.679	0.750	0.708	0.799	
Adjusted *R^2*	0.744	0.811	0.770	0.645	0.768		0.729	0.671	0.744	0.701	0.794	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the difference column, we test the difference of each factor loadings, when regressed on the highest quantile portfolio vs. the lowest quantile portfolio. To determine the significance of the difference on the respective factor loadings, we estimate the difference between estimator A and estimator B, and divide them by the standard error of the difference between estimator A and B. Therefore, we are able to derive the T-statistics of the difference between respective factor loadings on highest quantile portfolio and lowest quantile portfolio.

The ESG momentum factor loadings, as we can observe, on average has less coefficients that are significant in explaining the 10 portfolios. The ESG momentum factor is significant in explaining 3 of the 5 portfolios sorted on ESG momentum. As expected, the first ESG momentum quantiles, which consists of stocks that has degraded their ESG scores over the term of one year, has significantly negative coefficient, while in the top ESG momentum quantiles the coefficients are positive. On the portfolios that are sorted on ESG scores, ESG momentum risk factor has less significance in explaining returns. The factor loading is only significant on the second quantile of ESG portfolio.

The alphas are all insignificant across all portfolios, which means that taking into account ESG momentum risk factor, these portfolios are unable to generate abnormal returns. The R-squared of the regressions with ESG momentum risk factor only differs slightly from the regressions with ESG risk factor.

Table 4.7. Descriptive Statistics of Market Capitalization and B/M Ratio for each top and bottom quantile of single-sorted portfolios.

Portfolio	Statistics	Market Capitalization ($ million)	B/M Ratio
ESG 1	Mean	4916.54	0.59
	Median	1306.06	0.46
ESG 5	Mean	50306.2	0.34
	Median	21444.33	0.34
ESGM 1	Mean	21916	0.50
	Median	5965.79	0.40
ESGM 5	Mean	17907.14	0.50
	Median	4223.98	0.41
Whole Sample	Mean	11525.93	0.59
	Median	1386.05	0.46

As we can see in **Table 4.7,** we can confirm our findings in previous regressions**.** By observing the mean and median of market capitalization of the lowest and highest ESG quantiles, we are able to see size characteristics of the majority firms in each portfolio. The median market capitalization value for portfolio ESG 5 is far higher compared to the median market capitalization in portfolio ESG 1. This confirm our finding that top ESG portfolio is dominated by bigger firms, while bottom ESG portfolio is dominated by smaller firms. But when we compare mean and median market capitalization of the top ESG quantile, they are far above the whole sample mean and median. However, the lowest ESG quantile is only slightly lower in mean and median market capitalization when compared to the whole sample. On the other hand, the B/M ratio median for top ESG quantile seems significantly lower than the sample median, implying that most stocks in the top ESG quantile are leaning towards value stocks. However, the lowest ESG quantile has similar mean and median B/M ratio for the whole sample, therefore we cannot determine whether they are dominated by value or growth stocks.

On the other hand, the top and lowest ESG momentum portfolios have no significant gap in median B/M ratio, implying that both portfolio ESGM 1 and ESGM 5 have similar mix of value and growth stocks. However, the difference in mean and median of market capitalization still can be seen between ESGM 1 and ESGM 5, although the difference is not as big as portfolio ESG 1 and ESG 5. Nevertheless, we can observe that both top and bottom quantile of ESGM portfolio is dominated by relatively bigger firms, based on the mean and median market capitalization that are higher than the whole sample. However, in **Table 4.4, Table 4.5, and Table 4.6,** we see no significant coefficient on the SMB factor loading. This is most likely due to value-weighted excess return, which gives higher weighting for bigger firms. We can see the difference in the significance of the factor loadings in the equally weighted portfolio regressions in section 4.3.

In **Table 4.8**, we use our own four-factor model with ESG as an additional risk factor to explain the returns on the same 16 double-sorted portfolios by size and B/M ratio. This 4x4 double-sorted portfolios are meant to mimic the 5x5 double-sorted portfolio by Fama and French (1993), which mimics different characteristics of stocks with different level of market cap and B/M ratio in the market.

The market risk factor is strongly significant in 16 out of 16 portfolios. However, there is no clear trend that the market betas of small capitalization portfolios are higher than the big capitalization portfolios. All market betas revolve around one.

On the other hand, the majority of SMB factor loadings are significant. We can see that first to third market cap quantiles, the coefficients of the SMB factor loadings are all strongly positive, while on the fourth market cap quantiles, the coefficients are negative, although the significance is very weak. This confirms the SMB effect among stocks, in line with Fama and French findings (1993 & 2015). However, the effect of smaller stocks seems stronger compared to the effect of bigger stocks.

Furthermore, the HML or high-minus-low factor loadings shows the significance of the value effect in explaining stock returns. On the third and fourth B/M ratio quantiles, we can see all of the coefficients on the HML factor loadings are strongly significant at one percent, and positive. On the other hand, we can see the reversed value effect in the first quantiles of HML. Nonetheless, we cannot imply through negative and positive coefficients that value portfolios are significantly outperforming growth portfolios. We can only imply that portfolios with significantly positive coefficients are dominated with value stocks, therefore tend to move in line with the HML factor.

Table 4.8. Regression results of four-factor model with ESG on 16 double-sorted portfolios on size and B/M ratio, from February 2008 to November 2021 (166 months).

Size Quantiles	B/M Ratio Quantiles							
	1 (Low)	2	3	4 (High)	1 (Low)	2	3	4 (High)
	Mkt-Rf				SMB			
1 (Small)	0.97***	1.02***	0.84***	0.99***	1.26***	0.95***	0.87***	0.77***
2	1.03***	0.90***	0.89***	1.05***	1.08***	0.91***	0.96***	0.98***
3	0.96***	0.96***	0.99***	1.10***	0.57***	0.50***	0.43***	0.58***
4 (Big)	1.01***	0.97***	0.89***	0.95***	-0.085	-0.11	-0.048	0.021
	HML				Alpha			
1 (Small)	-0.13	0.11	0.25**	0.59***	0.016*	0.0048	0.0019	-0.0063*
2	-0.22**	0.18**	0.42***	0.87***	0.0051*	0.0051*	0.0038	-0.00014
3	0.025	0.29***	0.54***	0.91***	0.0066**	0.0065**	0.0051*	0.0037
4 (Big)	-0.26***	0.11	0.51***	0.83***	0.00053	0.00034	0.0057*	0.0061**
	R-Squared							
1 (Small)	0.476	0.687	0.780	0.832				
2	0.860	0.848	0.875	0.902				
3	0.804	0.849	0.834	0.859				
3 (Big)	0.699	0.758	0.774	0.831				

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

On the other hand, we can see the reversed value effect in the first quantiles of HML. Nonetheless, we cannot imply through negative and positive coefficients that value portfolios are significantly outperforming growth portfolios. We can only imply that portfolios with significantly positive coefficients are dominated with value stocks, therefore tend to move in line with the HML factor, while portfolios with significantly negative coefficients are dominated with growth stocks, therefore they tend to move inversely with the HML factor.

There are quite a few significant alphas on the 16 portfolios regressed on Fama-French's three factor model. 8 out of 9 alphas that are significant are positive. This implies that in these portfolios, the model is not able to capture some of the returns generated. On the other hand, R-squared, which depicts how much variation that the model is able to capture in each portfolio, varies in values. Portfolio ME1/BM1 has the lowest R-squared value, which means the model performs relatively poorer compared when used on the other portfolios.

Table 4.9. Regression results of four-factor model with ESG momentum on 16 double-sorted portfolios on size and B/M ratio, from February 2008 to November 2021 (166 months).

Size Quantiles	B/M Ratio Quantiles							
	1 (Low)	2	3	4 (High)	1 (Low)	2	3	4 (High)
	Mkt-Rf				SMB			
1 (Small)	0.98***	1.06***	0.85***	1.01***	1.25***	0.92***	0.85***	0.75***
2	1.05***	0.92***	0.91***	1.08***	1.07***	0.89***	0.94***	0.96***
3	0.98***	0.98***	1.02***	1.12***	0.55***	0.48***	0.41***	0.56***
4 (Big)	1.03***	0.99***	0.91***	0.97***	-0.11	-0.13*	-0.065	0.0085
	HML				ESG			
1 (Small)	-0.11	0.21	0.29***	0.64***	-0.15	-0.71***	-0.29**	-0.31**
2	-0.17*	0.23***	0.48***	0.93***	-0.34***	-0.36***	-0.44***	-0.41***
3	0.083	0.36***	0.62***	0.98***	-0.39***	-0.44***	-0.50***	-0.46***
4 (Big)	-0.19**	0.16*	0.57***	0.86***	-0.49***	-0.34***	-0.34***	-0.26**
	Alpha				R-Squared			
1 (Small)	0.016*	0.0037	0.0014	-0.0068*	0.477	0.714	0.787	0.838
2	0.0046	0.0045	0.0031	-0.00082	0.869	0.858	0.888	0.910
3	0.0059**	0.0057**	0.0043	0.0029	0.819	0.867	0.852	0.869
3 (Big)	-0.00027	-0.00021	0.0052*	0.0057*	0.732	0.773	0.787	0.837

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In **Table 4.9.**, we are able to observe how the four-factor model with ESG risk factor performs when regressed on the same 16 portfolios sorted on size and B/M ratio. All of the 16 portfolios obtain similar market betas when regressed with ESG factor. There are also no significant changes on the SMB factor loadings, except for one factor loadings on portfolio ME2/BM4, which is now significantly negative, although only at the 10% level. The HML factor loadings are also similar to when we regress the portfolios with the Fama-French three-factor model. It seems that the value effect is very strong across 3 quantiles of B/M ratio, but the growth stocks effect is only strong in the first B/M ratio quantile.

The ESG risk factor, which we add as an extension to the Fama and French's three-factor model, seems to have quite a strong significance in explaining returns of the 16 portfolios. In total, the ESG risk factor are able to explain, with at least 5 percent significance, the excess returns of 15 out of 16 portfolios. Among these significant coefficients, all of them are strongly negative and economically significant. From this, we can imply that our evidence is in line with the findings of Hong & Kacperczyk (2009), which states there are higher premium involved in holding "sin" stocks, or lower ESG stocks. The negative coefficients imply that lower ESG stocks evidently tend to outperform higher ESG stocks, because of the nature of how we construct the ESG risk factor. By looking at the strength of the ESG risk factor in explaining the majority of returns in all portfolios, may serve as preliminary evidence that ESG risk factor is actually a systematic risk factor in the majority of portfolios with different characteristics, therefore should be taken into account in further asset pricing literature.

The R-squared of the first size quantile seems to be the lowest among all of the 16 portfolios, being able to explain 47.7% of the excess return variations in the portfolio, similar to our findings on previous regression. This may imply that the ME1/BM1 portfolio has a unique variation of excess return that, in general, is harder to explain with these models. One plausible explanation for this unique excess return characteristics is that the sample size for this portfolio is limited, leading to higher abnormal return. On the other hand, the alphas seem to be insignificant on average. Only portfolios ME3/BM1 and ME3/BM2 that have significant and positive alphas.

Table 4.10. Regression results of four-factor model with ESG momentum on 16 double-sorted portfolios on size and B/M ratio, from February 2008 to November 2021 (166 months).

Size Quantiles	B/M Ratio Quantiles							
	1 (Low)	2	3	4 (High)	1 (Low)	2	3	4 (High)
	Mkt-Rf				SMB			
1 (Small)	0.97***	1.01***	0.83***	0.99***	1.27***	1.01***	0.90***	0.77***
2	1.03***	0.90***	0.89***	1.05***	1.08***	0.92***	0.97***	0.99***
3	0.96***	0.95***	0.99***	1.10***	0.58***	0.51***	0.43***	0.54***
4 (Big)	1.00***	0.97***	0.89***	0.95***	-0.070	-0.11	-0.053	0.032
	HML				ESG Momentum			
1 (Small)	-0.12	0.19	0.29***	0.59***	0.11	0.57**	0.29	0.013
2	-0.22**	0.19**	0.43***	0.88***	-0.017	0.089	0.072	0.048
3	0.045	0.31***	0.55***	0.85***	0.14	0.11	0.034	-0.41**
4 (Big)	-0.24**	0.12	0.51***	0.84***	0.15	0.061	-0.049	0.11
	Alpha				R-Squared			
1 (Small)	0.016**	0.0064	0.0027	-0.0062*	0.477	0.696	0.784	0.832
2	0.0051*	0.0053*	0.0040	-0.000013	0.861	0.848	0.875	0.902
3	0.0069**	0.0067**	0.0052*	0.0025	0.805	0.850	0.834	0.864
3 (Big)	0.00093	0.00051	0.0056*	0.0064**	0.700	0.758	0.774	0.832

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

On **Table 4.10,** we observe how our four-factor model with ESG momentum perform when regressed on 16 double-sorted portfolios on size and B/M ratio. The market betas are all significant and converging around one. There are slight differences from our previous regressions, but none that are economically significant. The SMB factor loadings are also strongly significant, but only on the first to third size quantiles. This shows strong size effect in the smaller stocks, but weaker in bigger stocks. The HML factor loadings, on the other hand, are strongly significant and positive in high B/M ratio portfolios, similar to previous regressions.

However, the factor loadings on ESG momentum risk factor are barely significant, namely only significant on 2 out of 16 portfolios. Portfolio ME1/BM2 has a positive ESG momentum factor loading, while portfolio ME3/BM4 has a negative ESG momentum factor loading. This may imply that the stocks on ME1/BM2 have been improving in ESG score, while vice versa on stocks in ME3/BM4. The rest of the portfolios have insignificant ESG momentum factor loadings and mixed with positive and negative coefficients. We do not have enough evidence to conclude that ESG momentum is a systematic risk factor that cannot be diversified away.

4.3. Robustness Tests

To ensure our results are robust and not biased when tested, robustness tests are run to check the limitations of the model's performance. Following the widely accepted method of robustness test in asset pricing literature, we also constructed the left-hand side portfolios with equal-weighting instead of value-weighing.

In **Table A.2.**, we present the results of the Fama-French's three-factor model when regressed on 5 equal-weighted portfolios sorted on ESG and 5 equal-weighted portfolios sorted on ESG momentum. It can be observed that the R-squared are significantly higher compared to the regression with value-weighted portfolios**.** Additionally, all of the SMB and HML factor loadings are significant, contrary to previous regressions where HML and SMB factor loadings have limited significance in explaining the returns on ESG-sorted and ESG momentum-sorted portfolios. One plausible explanation for this is that equal-weighted portfolios have equal weighting of returns, which in turn allows for bigger weighting on smaller stocks, while value-weighted portfolios' returns are mostly driven by bigger stocks. We can observe this by all of the significant and positive SMB factor loadings on all portfolios, indicating that the majority of return are driven by the small-cap premium. On top of that, we can also see the value premium is stronger on the equal-weighted portfolios.

It becomes apparent that ESG risk factor has a strong explanatory power, even in equally weighted ESG momentum-sorted portfolios, generating all significant coefficients, as can be seen in **Table A.3**. The coefficients on all of the ESG momentum portfolios are negative, which means the portfolios mostly consists of low ESG stocks. The ESG factor loadings are also strongly significant in all ESG-sorted portfolios, however, all ESG portfolios from the lowest to the highest have negative ESG factor loadings. The top ESG quantile, has smaller coefficient compared to the lower ESG quantiles, but it is still significantly negative, nevertheless. This shows that the low ESG premium, or "sin" stocks premium (Hong & Kacperczyk, 2009) is very strong, even in the high ESG quantile. **Table A.4.** shows the four-factor model with ESG momentum when regressed on 10 equal-weighted portfolios. It confirms that EGS momentum factor can only explain returns on portfolios sorted on ESG momentum, although weakly. We can observe that the ESG momentum effect is more visible in the bottom ESG momentum quantiles, which are dominated by stocks with degrading ESG scores. The ESG momentum factor does not have any explanatory power in ESG-sorted portfolios.

Furthermore, we also run equal-weighted regressions for the 4x4 double-sorted portfolios on size and B/M ratio. As we can see on **Table A.5.**, the ESG factor loadings explains a significant number of returns, even in equal-weighted portfolios. All 16 portfolios have 5% significant ESG factor loadings, and all of them are negative. This suggests that low ESG stocks dominates all 16 portfolios and significantly have higher return compared to high ESG stocks. **Table A.6.** shows the ESG momentum factor loadings, which are only significant in 3 portfolios. The coefficients on portfolio ME1/BM2 and ME1/BM3 are positive albeit weakly significant, and the coefficient on ME3/BM4 is 5% significant but negative. This further confirms our findings that ESG momentum has little significance as a systematic risk factor in a multifactor asset pricing model.

Table 4.11 shows the results of the Gibbons, Ross, and Shanken (GRS) tests with the Fama and French's three-factor model, four-factor model with ESG, and four-factor model with ESG momentum. The GRS test is a statistical procedure employed to assess the efficiency of an investment portfolio's performance. Lower GRS F-statistics indicates that the factors are able to explain the returns on left-hand side portfolios better, which makes lower GRS statistics desirable for asset pricing models. $A|a_i|$ stands for mean absolute alpha. A mean absolute alpha near zero indicates that there are nearly no abnormal returns in the portfolios that are left unexplained by the factors.

Table 4.11. Gibson, Ross, and Shanken (GRS) tests for portfolio efficiency.

Portfolios	Value-weighted			Equal-weighted		
	GRS	**P-Value**	$A\|a_i\|$	**GRS**	**P-Value**	$A\|a_i\|$
Panel A. 5 ESG portfolios + 5 ESG momentum portfolios						
3-factor	*1,6337*	*0,1019*	*0,0028*	*1,6054*	*0,1098*	*0,0046*
3-factor + ESG	*1,5610*	*0,1234*	*0,0023*	*1,5336*	*0,1324*	*0,0040*
3-factor + ESG(M)	*1,3256*	*0,2214*	*0,0029*	*1,6706*	*0,0924*	*0,0045*
Panel B. 4x4 size-B/M portfolios						
3-factor	*2,2118*	*0,0070*	*0,0048*	*3,2879*	*0,0001*	*0,0057*
3-factor + ESG	*2,1745*	*0,0082*	*0,0044*	*3,2228*	*0,0001*	*0,0052*
3-factor + ESG(M)	*2,1834*	*0,0079*	*0,0051*	*3,1789*	*0,0001*	*0,0059*

As we can see, on the 5 ESG portfolios and 5 ESG momentum portfolios, the 4-factor model with ESG momentum achieve the lowest GRS test statistic. However, the 4-factor model with ESG is able to generate the lowest mean absolute alpha. Moreover, when we try with equal-weighted portfolios, the 4-factor model with ESG obtain the lowest GRS test statistic. With 16 double-sorted portfolios size and B/M ratio, we obtain higher GRS statistics. As expected, the models perform better on portfolios that are sorted on ESG-related factors. Moreover, we also find that the 4-factor model with ESG has the lowest GRS test statistics and lowest mean absolute alpha when tested with value-weighted portfolios. However, when tested on equal-weighted portfolio, the average GRS test statistics among the 3 modes is slightly higher, and the 4-factor model with ESG momentum obtain the lowest GRS statistics. However, 4-factor model with ESG still holds the lowest mean absolute alpha even in equal-weighted portfolios.

5. Conclusion

This thesis aims to amplify the understanding of ESG-related factors, namely ESG scores and ESG momentum, on their role as systematic risk factors in the stock market, therefore improving our understanding in sustainable finance. Based on the handful of multi-factor asset pricing regressions with different sorting method on each portfolio, conclusion can be drawn from our results.

The ESG and ESG momentum factor loadings allow us to study the role of ESG-related factors in the Fama-French three-factor model. First of all, we are able to take the conclusion that ESG factor is substantially a stronger and a more systematic risk factor than ESG momentum. We test the ESG and ESG momentum factors on various single-sorted and double-sorted portfolios, and the ESG factor are able to explain the majority of returns on most portfolios, while ESG momentum factor loadings are weakly significant when tested in portfolios sorted on size and B/M ratio. Nevertheless, ESG momentum factor could explain a significant portion of returns in portfolios sorted on ESG momentum and ESG scores. Nevertheless, ESG momentum may perform well as a portfolio strategy to generate abnormal return, but we cannot conclude that ESG momentum is a systematic risk factor in asset pricing.

Furthermore, our findings suggest the existence of a higher premium for holding stocks with lower ESG rating, shown by strongly significant negative coefficient on ESG factor loadings. This is in line with Hong and Kacperczyk (2009) findings, where they hypothesized that "sin" stocks carries an extra premium for investors to hold due to their exposures to environmental and social risks, whereas high ESG stocks are less exposed to. On the other hand, the returns generated by high ESG momentum stocks, or stocks that has significantly improved their ESG ratings in the past year, is not as significant as returns from low ESG stocks. Moreover, as can be seen in **Figure 4.1.,** the cumulative returns from high ESG momentum stocks are able to outperform market return up until 2018, and then the returns on high ESG momentum stocks starts to diminish and fell below market return in 2020. This is in line with the idea that as ESG scores are improving, there will be a certain period where the majority of firms has maximized their ESG score, which in terms smaller rooms for ESG improvement.

6. Contribution to literature

This thesis acts as an extension to the growing body of literature on asset pricing that mostly focuses on ESG-related factor. The research introduces a new factor into the asset pricing research, namely ESG momentum, and compare the significance of ESG momentum as a risk factor with absolute ESG score. To our knowledge, there are no previous research that has incorporated ESG momentum as a new factor in a multi-factor asset pricing model. Most of studies that focuses on ESG momentum only discuss how could the ESG momentum portfolio strategy generate positive significant alpha (Nagy et al, 2016; Chen & Yang, 2020; Galema & Gerritsen, 2022; Berg et al., 2022; Cauthorn et al., 2023). On the other hand, most studies in asset pricing that incorporated ESG-related risk factor only uses ESG absolute scores and individual E, S, and G scores (Maiti, 2021; Jin, 2018). We incorporated the ESG momentum as a risk factor and compare its performance in explaining returns with absolute ESG score as a risk factor, utilizing the Fama and French's three-factor model.

7. Limitations and Future Research

As in every research, each research has its own limitations. First of all, up to today, not all firms in the U.S. have disclosed their ESG reports. Many companies today have ESG report disclosed publicly, but currently the majority of firms that have ESG reporting are middle to large cap companies. This creates a lack of sample of small-cap and micro-cap firms for studies in sustainable finance. But as sustainable finance kept growing in practice, more companies will start to report their sustainability scores, and future research in sustainable finance could benefit from this.

Our time period selection in our study also acts as one of the limitations. As we are studying monthly stock returns in the U.S., we are dealing with complex stock market data, and the choice to make the cutoff point in January 2008 is to make the study simpler and more focused to current situation in the stock market. Nevertheless, sustainable finance and investing has already been practiced since the 1970s, therefore it might be worthwhile to take longer time periods in future study to uncover more information in earlier periods of the stock market. Moreover, our study is limited to the U.S. stock market, which are different in characteristics from the European stock market, and stock market in other countries. In addition, we test our hypothesis by extending the Fama and French's three-factor asset pricing model. While this is a solid and widely used model in finance practice, there are still a lot of other models that we could incorporate ESG-related factors into.

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9. Appendix

Table A.1. Refinitiv ESG (Environmental, Social, Governance) rating's dimensions.

Dimension	Category
Environmental (E)	Resource use
	Emission reduction
	Innovation
Social (S)	Workforce
	Human rights
	Community
	Product Responsibility
Governance (G)	Management
	Shareholders
	CSR Strategy

Source: ESG Scores Methodology - Refinitiv

Table A.2. Regression results of FF three-factor model on 5 portfolios sorted on ESG momentum and 5 portfolios sorted on ESG (equal-weighted), from from February 2008 to November 2021 (166 months).

Factors	ESG Momentum					Difference	ESG					Difference
	ESGM 1	ESGM 2	ESGM 3	ESGM 4	ESGM 5	(High - Low)	ESG 1	ESG 2	ESG 3	ESG 4	ESG 5	(High - Low)
Rm - Rf	1.08***	1.07***	1.06***	1.08***	1.07***	-0.01	1.03***	1.06***	1.09***	1.11***	0.98***	-0.05
	(0.051)	(0.051)	(0.054)	(0.050)	(0.048)	(0.018)	(0.060)	(0.053)	(0.051)	(0.050)	(0.043)	(0.042)
SMB	0.43***	0.42***	0.42***	0.34***	0.37***	-0.06**	0.63***	0.61***	0.53***	0.32***	0.099	-0.53***
	(0.075)	(0.075)	(0.079)	(0.073)	(0.070)	(0.027)	(0.088)	(0.078)	(0.075)	(0.074)	(0.063)	(0.062)
HML	0.44***	0.50***	0.36***	0.42***	0.39***	-0.05*	0.43***	0.42***	0.40***	0.48***	0.35***	-0.08
	(0.084)	(0.084)	(0.088)	(0.081)	(0.078)	(0.030)	(0.098)	(0.087)	(0.083)	(0.082)	(0.070)	(0.069)
Constant	0.0048*	0.0053*	0.0028	0.0052*	0.0038		0.0077**	0.0042	0.0032	0.0060**	0.0036	
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)		(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	
Observations	166	166	166	166	166		166	166	166	166	166	
R^2	0.864	0.866	0.842	0.862	0.871		0.830	0.864	0.871	0.868	0.858	
Adjusted R^2	0.861	0.863	0.839	0.860	0.868		0.827	0.862	0.869	0.866	0.855	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the difference column, we test the difference of each factor loadings, when regressed on the highest quantile portfolio vs. the lowest quantile portfolio. To determine the significance of the difference on the respective factor loadings, we estimate the difference between estimator A and estimator B, and divide them by the standard error of the difference between estimator A and B. Therefore, we are able to derive the T-statistics of the difference between respective factor loadings on highest quantile portfolio and lowest quantile portfolio.

Table A.3. Regression results four-factor model with ESG on 5 portfolios sorted on ESG momentum and 5 portfolios sorted on ESG (equal-weighted), from February 2008 to November 2021 (166 months).

Factors	ESG Momentum					Difference	ESG					Difference
	ESGM 1	ESGM 2	ESGM 3	ESGM 4	ESGM 5	(High - Low)	ESG 1	ESG 2	ESG 3	ESG 4	ESG 5	(High - Low)
Rm - Rf	1.10***	1.09***	1.09***	1.10***	1.09***	-0.01	1.06***	1.09***	1.11***	1.13***	0.99***	-0.07*
	(0.049)	(0.049)	(0.051)	(0.047)	(0.046)	(0.019)	(0.056)	(0.050)	(0.049)	(0.049)	(0.042)	(0.036)
SMB	0.41***	0.40***	0.40***	0.32***	0.35***	-0.06**	0.60***	0.59***	0.51***	0.30***	0.090	-0.51***
	(0.073)	(0.072)	(0.075)	(0.070)	(0.067)	(0.028)	(0.082)	(0.074)	(0.071)	(0.071)	(0.062)	(0.053)
HML	0.50***	0.56***	0.43***	0.48***	0.45***	-0.05	0.53***	0.50***	0.47***	0.54***	0.38***	-0.15**
	(0.082)	(0.082)	(0.085)	(0.079)	(0.076)	(0.032)	(0.092)	(0.084)	(0.081)	(0.081)	(0.071)	(0.060)
ESG	-0.37***	-0.38***	-0.46***	-0.41***	-0.40***	-0.03	-0.61***	-0.47***	-0.41***	-0.36***	-0.18**	0.43***
	(0.102)	(0.102)	(0.106)	(0.098)	(0.094)	(0.039)	(0.115)	(0.104)	(0.100)	(0.100)	(0.088)	(0.074)
Constant	0.0042	0.0047*	0.0021	0.0045*	0.0031		0.0067**	0.0034	0.0025	0.0054**	0.0033	
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)		(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	
Observations	166	166	166	166	166		166	166	166	166	166	
R^2	0.874	0.877	0.858	0.876	0.884		0.856	0.880	0.883	0.878	0.861	
Adjusted R^2	0.871	0.874	0.855	0.872	0.881		0.852	0.877	0.880	0.875	0.858	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the difference column, we test the difference of each factor loadings, when regressed on the highest quantile portfolio vs. the lowest quantile portfolio. To determine the significance of the difference on the respective factor loadings, we estimate the difference between estimator A and estimator B, and divide them by the standard error of the difference between estimator A and B. Therefore, we are able to derive the T-statistics of the difference between respective factor loadings on highest quantile portfolio and lowest quantile portfolio.

Table A.4. Regression results of four-factor model with ESG momentum on 5 portfolios sorted on ESG momentum and 5 portfolios sorted on ESG (equal-weighted), from February 2008 to November 2021 (166 months).

Factors	ESG Momentum					Difference	ESG					Difference
	ESGM 1	ESGM 2	ESGM 3	ESGM 4	ESGM 5	(High - Low)	ESG 1	ESG 2	ESG 3	ESG 4	ESG 5	(High - Low)
Rm - Rf	1.08***	1.07***	1.07***	1.07***	1.07***	-0.01	1.03***	1.06***	1.09***	1.11***	0.98***	-0.05
	(0.050)	(0.051)	(0.053)	(0.050)	(0.047)	(0.017)	(0.060)	(0.053)	(0.051)	(0.050)	(0.043)	(0.042)
SMB	0.39***	0.39***	0.40***	0.36***	0.39***	0.00	0.64***	0.61***	0.52***	0.31***	0.094	-0.55***
	(0.076)	(0.076)	(0.080)	(0.074)	(0.071)	(0.025)	(0.090)	(0.080)	(0.076)	(0.075)	(0.064)	(0.063)
HML	0.39***	0.46***	0.33***	0.44***	0.42***	0.03	0.44***	0.42***	0.40***	0.46***	0.34***	-0.10
	(0.085)	(0.085)	(0.090)	(0.084)	(0.080)	(0.028)	(0.101)	(0.090)	(0.086)	(0.085)	(0.072)	(0.071)
ESGM	-0.32**	-0.28**	-0.20	0.15	0.20	0.52***	0.068	-0.020	-0.051	-0.12	-0.048	-0.12
	(0.142)	(0.143)	(0.151)	(0.140)	(0.134)	(0.047)	(0.169)	(0.150)	(0.143)	(0.141)	(0.121)	(0.119)
Constant	0.0039	0.0045	0.0023	0.0056**	0.0043		0.0079**	0.0041	0.0031	0.0057**	0.0034	
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)		(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	
Observations	166	166	166	166	166		166	166	166	166	166	
R^2	0.868	0.869	0.844	0.863	0.872		0.830	0.864	0.871	0.869	0.858	
Adjusted R^2	0.865	0.866	0.840	0.860	0.869		0.826	0.861	0.868	0.866	0.854	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In the difference column, we test the difference of each factor loadings, when regressed on the highest quantile portfolio vs. the lowest quantile portfolio. To determine the significance of the difference on the respective factor loadings, we estimate the difference between estimator A and estimator B, and divide them by the standard error of the difference between estimator A and B. Therefore, we are able to derive the T-statistics of the difference between respective factor loadings on highest quantile portfolio and lowest quantile portfolio.

Table A.5. Regression results of four-factor model with ESG momentum on 16 double-sorted portfolios on size and B/M ratio, from February 2008 to November 2021 (166 months).

Size Quantiles	B/M Ratio Quantiles							
	1 (Low)	2	3	4 (High)	1 (Low)	2	3	4 (High)
	Mkt-Rf				SMB			
1 (Small)	0.92***	0.97***	0.87***	0.98***	1.07***	0.75***	0.83***	0.64***
2	1.04***	0.92***	0.90***	1.09***	1.13***	0.92***	0.96***	0.97***
3	0.99***	0.96***	1.01***	1.13***	0.59***	0.52***	0.47***	0.61***
4 (Big)	0.94***	0.98***	0.96***	1.04***	0.084	0.12*	0.016	0.092
	HML				ESG			
1 (Small)	-0.023	0.25	0.28**	0.54***	-0.58**	-0.53***	-0.40***	-0.43***
2	-0.19**	0.21**	0.47***	0.89***	-0.44***	-0.38***	-0.43***	-0.45***
3	0.053	0.35***	0.61***	0.97***	-0.39***	-0.46***	-0.49***	-0.49***
4 (Big)	0.050	0.32***	0.55***	0.86***	-0.29***	-0.40***	-0.39***	-0.33***
	Alpha				R-Squared			
1 (Small)	0.018***	0.0055	0.0014	-0.0100***	0.506	0.650	0.769	0.798
2	0.0042	0.0041	0.0030	-0.0023	0.865	0.859	0.890	0.913
3	0.0055*	0.0057**	0.0040	0.0023	0.830	0.871	0.855	0.880
3 (Big)	0.0043*	0.0040	0.0048*	0.0034	0.832	0.830	0.832	0.846

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6. Regression results of four-factor model with ESG momentum on 16 double-sorted portfolios on size and B/M ratio, from February 2008 to November 2021 (166 months).

Size Quantiles	B/M Ratio Quantiles							
	1 (Low)	2	3	4 (High)	1 (Low)	2	3	4 (High)
	Mkt-Rf				SMB			
1 (Small)	0.89***	0.94***	0.85***	0.96***	1.12***	0.83***	0.88***	0.68***
2	1.01***	0.90***	0.88***	1.07***	1.18***	0.95***	0.99***	1.00***
3	0.97***	0.93***	0.99***	1.11***	0.63***	0.55***	0.50***	0.60***
4 (Big)	0.92***	0.95***	0.94***	1.02***	0.088	0.14*	0.033	0.12
	HML				ESG Momentum			
1 (Small)	-0.081	0.24	0.27**	0.50***	0.20	0.51*	0.32*	0.14
2	-0.22**	0.16*	0.42***	0.83***	0.21	0.051	0.100	0.050
3	0.017	0.30***	0.54***	0.85***	0.15	0.11	0.037	-0.35**
4 (Big)	-0.0076	0.25***	0.49***	0.82***	-0.10	-0.00023	-0.021	0.075
	Alpha				R-Squared			
1 (Small)	0.020***	0.0077	0.0029	-0.0089**	0.492	0.641	0.761	0.786
2	0.0055*	0.0049	0.0040	-0.0014	0.853	0.848	0.877	0.903
3	0.0066**	0.0068**	0.0049	0.0021	0.817	0.852	0.837	0.871
3 (Big)	0.0045*	0.0047*	0.0054*	0.0042	0.820	0.811	0.816	0.837

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$