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Momentum and ESG Integration: A Strategy for Sustainable Returns

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Resumo

A presente dissertação investiga a integração de fatores ambientais, sociais e governamentais (*ESG*) na estratégia de *momentum*, visando compreender o seu impacto no desempenho financeiro. Para o efeito, foi utilizada uma amostra de ações ordinárias transacionadas nos Estados Unidos da América, entre janeiro de 2010 e setembro de 2024. Os dados de *ESG* foram obtidos através da plataforma *LSEG Data & Analytics* e os retornos das ações extraídos da base de dados *Datastream*. O estudo aplica a estratégia de custo nulo, analisando as ações, que simultaneamente estão classificadas nos melhores 10% quanto aos retornos e nos melhores 30% em termos de *ESG*, por oposição às que estão nos piores 10% e 30% nas mesmas categorias. A investigação conclui que a integração de métricas sustentáveis não melhora significativamente o desempenho da estratégia de *momentum*, aumentando o risco idiossincrático devido à menor diversificação na seleção de ações, e não às características relacionadas com a inclusão de *ESG*. Os resultados sugerem que os investidores não devem esperar obter retornos anormais ao negociar portfólios diferenciados por características *ESG*. Embora o complemento sustentável não melhore o desempenho geral da estratégia de *momentum* tradicional, revela um adicional poder explicativo de fatores como *HML* (valor) e *RMW* (lucratividade), que se tornam pertinentes na determinação dos retornos. Estas conclusões salientam a complexidade da incorporação sustentável e sugerem a necessidade de explorar detalhadamente as suas implicações no longo prazo, incluindo investigações mais amplas no mercado e abordagens alternativas de *ESG*.

Palavras-chave: *ESG*, *Momentum*, Retornos, Diversificação, Fatores

Título: *Momentum* e Integração *ESG*: Uma estratégia para retornos sustentáveis

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Abstract

This dissertation investigates the integration of environmental, social and governmental (ESG) factors into a momentum strategy, intending to understand their impact on financial performance. To this end, a sample of common shares traded in the United States between January 2010 and September 2024 was used. ESG data was obtained from the LSEG Data & Analytics platform and stock returns were extracted from Datastream database. The study employs a zero-cost strategy, focusing on stocks simultaneously ranked in the best 10% in terms of returns and the best 30% regarding ESG scores, against those in the worst 10% and 30% in the same categories. The research concludes that the integration of sustainable metrics does not significantly improve the performance of the momentum strategy, instead, it increases idiosyncratic risk due to less diversification in stock selection rather than characteristics related to ESG inclusion. The results suggest that investors should not expect to obtain abnormal returns when trading momentum portfolios differentiated by ESG characteristics. Although the sustainable complement does not improve the traditional momentum strategy's overall performance, it reveals additional explanatory power of factors such as HML (value) and RMW (profitability), which become pertinent in determining returns. These conclusions underscore the complexity of sustainable incorporation and suggest the need to explore its long-term implications in detail, including broader market research and alternative ESG approaches.

Keywords: ESG, Momentum, Returns, Diversification, Factors

Title: Momentum and ESG Integration: A Strategy for Sustainable Returns

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1. Introduction

Sustainable investing, which incorporates environmental, social, and governance (ESG) factors into financial decision-making, has experienced remarkable growth over recent decades. Rooted in corporate social responsibility (CSR) principles, ESG investing aims to align financial goals with societal values, assessing companies' sustainability and ethical practices. This shift has been driven by growing regulatory pressures, climate change awareness, and concerns over social inequality, with ESG-focused assets surpassing $35 trillion in 2020 and projected to reach $50 trillion by 2025. Although studies like Amel-Zadeh & Serafeim (2018) suggest that most investors are motivated by financial rather than ethical reasons in using ESG data, the financial performance of ESG investments remains a source of debate. While some studies (e.g., Chen & Yang, 2020; Nagy et al., 2016) argue that ESG integration can enhance returns, others, such as Kaiser & Welters (2019), highlight its limitations in momentum-driven markets.

Momentum investing, first formalized by Jegadeesh and Titman (1993), capitalizes on the tendency for assets with outstanding recent performance to persist. This strategy, which challenges the Efficient Market Hypothesis (EMH), is explained by behavioural finance theories like investor overreaction and underreaction (Hong & Stein, 1999) and cognitive biases such as herding (Barberis et al., 1998). Recent research (Blitz et al., 2020) continues to show momentum's profitability, although it faces risks during market reversals, as Daniel & Moskowitz (2016) discuss.

This thesis explores the momentum integration with ESG scores to determine whether combining these approaches improve performance or reveal new dynamics in explaining returns. The analysis focuses on traded U.S. stocks from January 2010 to September 2024, employing three strategies: **(1)** traditional momentum, **(2)** green momentum, and **(3)** pure ESG-based strategy. The key research questions are: **(1)** Does incorporating ESG scores into momentum strategy enhance performance compared to traditional momentum? **(2)** Are the factors driving returns in green momentum strategy consistent with those explaining traditional momentum returns? Those questions aim to understand if the inclusion of a sustainable metric allows us to achieve at least the same performance as would be realized without it, and to explain the reasoning behind this.

The term "green momentum" is used for simplicity, as the analysis focuses on overall ESG scores rather than exclusively on the environmental (E) component. In this method, stocks for the long portfolio are selected from the top 10% of returns and the top 30% of ESG scores during the formation period. Similarly, the short portfolio includes stocks from the bottom 10% of returns and the bottom 30% of ESG scores in the same formation period.

The results indicate that including ESG scores in the momentum strategy does not lead to statistically significant improvements in performance. While there is a slight increase in returns, the strategy also experiences heightened volatility. This increased volatility is not directly attributable to the inclusion of ESG factors, but rather to a reduction in the number of stocks in the portfolio. The smaller number of stocks leads to higher idiosyncratic risk, thereby diminishing the diversification benefits, as mentioned by (Revelli & Viviani, 2015). Incorporating ESG factors into the momentum strategy enhances its explanatory power when introducing additional risk factors such as HML (value) and RMW (profitability), which were not significant in explaining the traditional momentum model. This indicates that ESG-enhanced outcomes capture more than just momentum effects, they also reflect value and profitability characteristics associated with sustainable, high-performing companies. This diversification of explanatory factors makes the strategy more comprehensive, as it now benefits from the stability offered by companies with better governance and profitability, aligning with stable long-term investment trends focused on sustainability.

A robustness process was conducted to achieve a clearer understanding of the dynamics driving the green momentum. The analysis examined various holding and formation periods, revealing that intermediate formation periods (between 6 and 12 months) combined with shorter holding periods led to better results.

In addition, excluding January from the data reduced the returns of the short leg, which ultimately benefited the strategy. This phenomenon is largely attributed to the rebound in stock prices that typically occurs in January, following the sell-offs in December for tax-related reasons.

When the analysis was segmented into two distinct periods, 2010-2017 and 2018-2024, the strategy remained statistically insignificant in both time frames. However, during the more volatile period from 2018 to 2024, the factors influencing the outcomes were more effectively captured, although they still did not generate significant alpha. Notably, none of these robustness checks changed the overall results of the strategy, the performance continued to be statistically insignificant across all variations of the analysis.

A break-even analysis was conducted to evaluate the transaction costs required to offset the portfolio returns. The findings indicated that both the traditional momentum strategy and the green momentum had similar costs, with approximately 12% for the short leg and 8% for the long leg. However, when stocks were selected solely based on their ESG scores, the break-even transaction cost rose significantly. This increase can be attributed to lower portfolio turnover, as fewer stocks are added to or removed from the portfolio each month.

After clarifying the motivation and key research questions, this thesis will now focus on the empirical analysis of momentum strategies, both with and without ESG factors. The aim is to investigate the impact of sustainability on performance and identify the factors that drive these returns.

2. Literature Review

2.1 Foundations of Momentum Strategies

Momentum research is among the most widely studied phenomena in financial markets. The core idea behind momentum is that stocks that have performed well in the past tend to continue performing well in the near future, while underperforming stocks often maintain their downward trajectory. This concept was first formalized by Jegadeesh and Titman (1993), who found that buying stocks with high recent returns ("winners") and selling those with poor performance ("losers") can generate abnormal returns, challenging the traditional efficient market hypothesis, which posits that stock prices reflect all available information and thus cannot be predicted by past performance. This marked the beginning of momentum strategies as a cornerstone in asset management.

Since this landmark study, momentum has been applied to various asset classes and geographies, showing consistent performance across different market conditions. This broad applicability has made momentum a fundamental strategy in both active and passive investment management. However, the evolving landscape of sustainable investing prompts the question: How can momentum be integrated with Environmental, Social, and Governance (ESG) factors? In recent years, as ESG has gained traction, academic inquiry has increasingly focused on the intersection of momentum results and ESG, exploring how investors can leverage sustainability trends while generating returns. This review examines existing literature on traditional momentum, ESG investing, and their potential synergy to establish a framework for green momentum in stock portfolios.

2.2 Momentum Across Sectors and Global Markets

While early momentum studies focused on individual stocks, Moskowitz and Grinblatt (1999) demonstrated that momentum extends beyond stock-specific performance to the industry level. They showed that investing in top-performing sectors while shorting underperforming ones yielded significant monthly returns, averaging 0.43%. The study focused primarily on U.S. stocks, with a particular emphasis on the performance of industries like technology, manufacturing, and financials, sectors often characterized by cyclicality and price trends. The implication here is that industry dynamics are crucial when applying momentum strategies. This insight is particularly relevant to ESG investing, where specific sectors, such as clean energy or technology companies emphasizing sustainability, could offer additional momentum opportunities. These sectors may benefit from regulatory tailwinds, public sentiment, and long-term global trends, creating fertile ground for ESG-aligned momentum strategies.

Momentum results also prove effective on a global scale. Fama and French (2012) showed that international momentum methods generate returns similar to those observed in U.S. markets. Their analysis spanned developed markets in Europe and Asia, applying momentum to large- and mid-cap stocks across diverse sectors. This global applicability is vital for ESG momentum strategies, as the push for sustainability is a worldwide trend. Additionally, research by Asness, Moskowitz, and Pedersen (2013) reinforced the momentum universality, finding consistent performance across equities, fixed income, commodities, and currencies in various countries. These findings highlight the potential to integrate momentum with ESG principles in global portfolios.

2.3 Stock-Specific Momentum Dynamics and ESG Integration

The dynamics of stock-level momentum have been refined in subsequent studies. Jegadeesh and Titman (2001) revisited their original findings, focusing on price reversals, where past winners underperform, and past losers recover after 12 to 24 months. This study focused on U.S. equities, with a notable representation of large-cap stocks, which tend to exhibit slower price reversals compared to small-cap stocks. This timeframe is critical when considering momentum strategies for ESG stocks. Companies with strong ESG profiles may experience more prolonged periods of positive momentum due to favourable investor sentiment and reduced risk exposure. Conversely, firms with poor ESG ratings may see earlier price reversals, as unsustainable business practices become priced in by the market over time.

A critical contribution to ESG momentum research comes from Nagy, Kassam, and Lee (2016), who analyse the concept of ESG momentum. This study focused on global equities, examining stocks across developed markets with rising ESG scores. The stocks in their sample came from sectors such as technology, healthcare, and industrials, industries that have been early adopters of ESG practices. The results showed that stocks with improving ESG scores outperformed those with declining scores, highlighting the potential synergy between ESG improvements and momentum. By integrating ESG score improvements into momentum strategies, investors can capture the dual benefit of price momentum and ESG-driven outperformance.

In a related context, Albuquerque, Koskinen, and Zhang (2020) examined the resilience of ES (Environmental and Social) stocks during the COVID-19 market crash. They found that firms with high ES ratings earned an extra daily return of 0.45% from February 24 until March 17 relative to firms with low ES ratings, resulting in a cumulative difference of 7.2%. This underscores the protective role of ES factors in turbulent markets, highlighting a potential advantage for momentum strategies that incorporate ESG criteria. Stocks with strong ESG profiles may be less likely to experience sharp reversals in adverse market conditions, emphasizing a synergy between momentum, which depends on trend persistence, and the stability afforded by robust ESG practices.

2.4 Momentum and Sustainable Investing

Kempf and Osthoff (2007) examined socially responsible investing (SRI) by evaluating portfolio performance through positive and negative screening approaches using KLD ratings, which are a set of metrics assessing environmental, social, and governance factors, with a more qualitative focus on ethical considerations and corporate social responsibility, originally developed for socially responsible investing. Their research revealed that portfolios using positive or best-in-class screening achieved an alpha of about 5% annually, demonstrating the financial viability of selecting high-responsibility stocks. However, negative screening did not produce similar results, underscoring the importance of targeting firms with superior ESG performance. These findings complement ESG and momentum by illustrating how rising ESG scores, paired with sustained price trends, can enhance returns.

Eccles, Ioannou, and Serafeim (2014) reinforced the case for ESG-focused investing by demonstrating that companies with robust ESG practices tend to outperform their peers. This outperformance is attributed to their superior operational efficiency, lower capital costs, and

better risk management. Their research suggests that firms can embrace environmentally and socially responsible policies without compromising shareholder value. Additionally, they found that such companies are more resilient in economic downturns, which is crucial for momentum investors seeking to mitigate the risk of price reversals. By investing in ESG stocks, investors may benefit from more stable price trends, reducing the likelihood of sudden reversals that often disrupt momentum strategies. Further evidence supporting ESG integration comes from a meta-analysis by Friede, Busch, and Bassen (2015), which reviewed over 2,000 studies on ESG and financial performance. They found that 63% of studies showed a positive relationship, while only 8% found a negative one, reinforcing the notion that ESG considerations can enhance long-term returns. This indicates that stocks with improving ESG scores are likely to perform well, satisfying both financial and sustainability objectives.

In addition, Bolton and Kacperczyk (2021) provided insights into how carbon risk is priced into financial markets. Contrary to some expectations, their research revealed that firms with higher carbon emissions earn higher returns, suggesting a carbon premium. This finding implies that investors are already demanding compensation for their exposure to carbon emission risk. While this premium exists, the exclusion of high-carbon companies from ESG strategies remains a relevant concern, particularly for investors who aim to align their portfolios with sustainability goals. By avoiding high-carbon firms, ESG-focused portfolios may forego the carbon premium, but they may also mitigate the long-term risks associated with environmental liabilities and the transition to a low-carbon economy.

2.5 ESG Factors and Risk-Return Dynamics

Nofsinger and Varma (2014) are also valuable contributors with their demonstration that socially responsible investing tends to outperform during market downturns. Specifically, their study found that SRI portfolios yielded excess returns of 1.6% during bear markets, as ESG-focused companies were better positioned to weather economic shocks. This defensive quality of ESG stocks is especially relevant for momentum strategies, which typically are threatened during periods of market volatility. By incorporating ESG scores into momentum models, investors may achieve both downside protection and the potential to capitalize on upward trends, enhancing the overall robustness of the strategy.

An optimistic perspective is provided by Pedersen, Fitzgibbons, and Pomorski (2020), who introduced the concept of the ESG-efficient frontier. This framework allows investors to

visualize the trade-offs between ethical considerations and financial performance. Their research suggests that incorporating ESG factors into portfolios can improve risk-adjusted returns, particularly by reducing exposure to companies with unsustainable practices. The ESG-efficient frontier shows that ethical investment goals can be achieved with minimal sacrifices in financial performance. Furthermore, their model captures the practical nuances of ESG integration by identifying optimal portfolios that balance ESG characteristics and financial returns. This enhanced risk-return profile is particularly relevant for this thesis, as it indicates that ESG stocks may exhibit smoother performance patterns, making momentum signals more reliable by mitigating the risk of significant drawdowns.

While integrating ESG factors into momentum strategies presents substantial opportunities, challenges also arise. Geczy, Stambaugh, and Levin (2021) argued that socially responsible investment (SRI) funds often face performance headwinds due to the exclusion of certain high-performing sectors, such as fossil fuels, tobacco, or defense industries. This exclusion can reduce the potential for strong returns, as certain sectors that historically contribute to momentum strategies may be absent from the investment universe. Consequently, sustainable momentum might miss out on lucrative opportunities concentrated in these sectors, creating a trade-off between ethical considerations and maximizing financial performance.

2.6 Summary of Key Contributions

Momentum, while traditionally focused on individual stocks, has demonstrated adaptability across various markets. Integrating ESG-focused stocks offers both opportunities and challenges. While ESG screening may limit exposure to certain high-performing sectors, evidence suggests that stocks with rising ESG scores can deliver competitive long-term returns. This thesis explores how momentum strategies can be adapted to ESG stocks, assessing whether joining ESG score enhances traditional momentum signals. By bridging financial performance with sustainability objectives, this work aims to contribute actionable insights to the evolving field of ESG investing.

3. Hypothesis

Momentum strategies have been widely recognized for their potential to generate excess returns by capitalizing on the persistence of stock price trends. Recent research has explored the possibility of enhancing these results by incorporating Environmental, Social, and Governance (ESG) factors, suggesting that ESG integration may influence stock performance and provide

additional sources of momentum. However, the precise impact of ESG factors on momentum strategies, and whether they alter the key drivers of returns, remains an area of ongoing investigation. To address these gaps, the following hypotheses are formulated:

Hypothesis 1: ***"The inclusion of ESG scores in the momentum strategy leads to higher performance than the traditional momentum strategy".***

Hypothesis 2: ***" The factors driving the momentum strategy incorporating ESG scores are the same as those behind the traditional momentum strategy".***

This work explores the relationship between momentum and ESG factors, aiming to determine whether including ESG scores enhances performance. Additionally, it seeks to identify and compare the key factors that drive the returns of momentum strategies, both with and without ESG integration.

4. Data

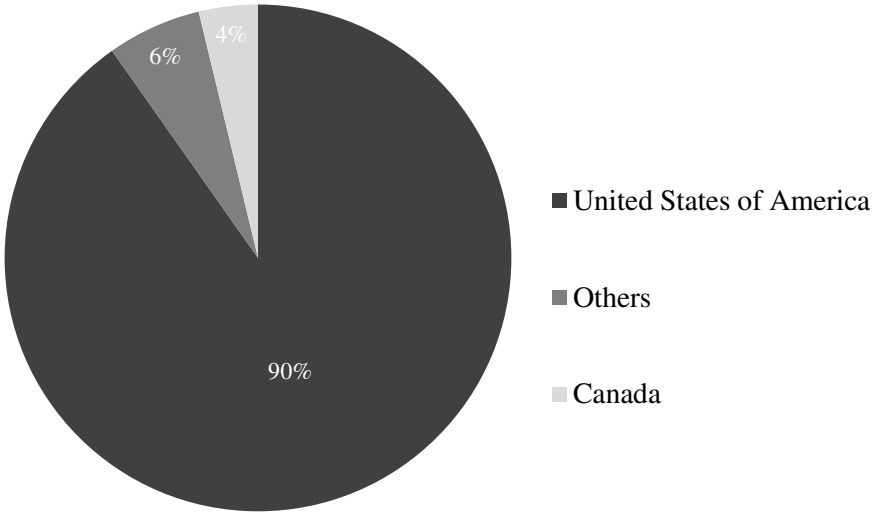
4.1 Dataset and Sample Construction

This study investigates a green momentum strategy, which extends the traditional momentum approach by integrating Environmental, Social, and Governance (ESG) scores alongside past stock returns. This integration allows identifying stocks based on financial performance and sustainability metrics.

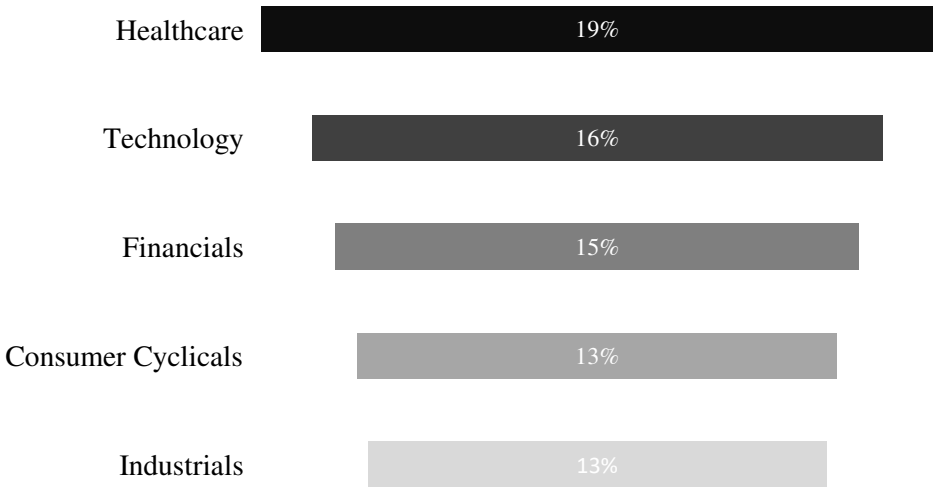
The data for this thesis was collected using LSEG Data & Analytics (formerly Refinitv), with the Advanced Search tool employed to gather a sample of equities traded in the U.S. The selection criteria focused on equities listed on the New York Stock Exchange (NYSE), NYSE American, NASDAQ Global Select Market, NASDAQ Global Market, and NASDAQ Capital Market. This approach ensured the inclusion of actively traded and liquid stocks, aligning with best practices in momentum literature, such as those outlined by Jegadeesh and Titman (2001), which emphasize the importance of a diverse and liquid sample for accurately evaluating momentum. A total of 3,191 equities, denominated in U.S. dollars, were selected. Only ordinary shares were considered, focusing on core securities relevant to the analysis.

Graphs 1 **and 2** present the geographical and industrial composition of the entire sample. The United States and Canada collectively account for 94% of the total, reflecting a sample largely composed of U.S. equities. The industry breakdown shows notable representation from healthcare and technology but remains well-diversified.

Graph 1: Geographical Composition



Graph 2: Top 5 - Industrial Composition



Accordingly with the literature, a cross-sectional approach was applied monthly throughout the study period. To ensure a representative and investable sample, stocks trading below $5 in any given month and those within the bottom decile of NYSE market capitalization were excluded. These criteria mitigate potential biases associated with small and illiquid stocks, which tend to exhibit heightened volatility, limited liquidity, and bid-ask bounce effects. Notably, these

exclusions were implemented dynamically, allowing stocks to re-enter the sample in subsequent months if they no longer met the exclusion thresholds.

4.2 Total Return Index

Following the establishment of the core dataset, total return indexes were obtained for each equity from Datastream, covering the period from January 2010 to September 2024. Total return indexes account for price changes as well as the reinvestment of dividends, offering a complete measure of the returns that would be realized by investors. This approach provides a more accurate representation of equity performance than price returns alone, particularly for dividend-paying stocks, as dividends can constitute a significant portion of total returns over time. The total return index is calculated using the formula:

$$RI_t = RI_{t-1} * \frac{PI_t}{PI_{t-1}} * \left(1 + \frac{DY_t}{100} * \frac{1}{N}\right) \quad (1)$$

Where:

RI_t = Return Index on day t

RI_{t-1} = Return Index on previous day

PI_t = Price Index on day t

PI_{t-1} = Price Index on previous day

DY_t = Dividend Yield % on day t

N = Number of working days in the year (taken to be 260)

4.3 ESG Scores

Once the total return indexes for each stock were obtained, the ESG scores[1] were retrieved from the LSEG Data & Analytics database every month, covering the same period. These scores evaluate a company's performance across environmental, social, and governance (ESG) dimensions. Refinitiv's methodology incorporates over 630 individual ESG metrics, of which 186 were selected for their relevance and comparability across industries. These selected metrics are organized into 10 key categories, which are further aggregated into three main pillars: Environmental (E), Social (S), and Governance (G). The Environmental pillar assesses a company's ecological impact, focusing on factors such as carbon emissions, resource consumption, and energy use. The Social pillar evaluates aspects related to employee welfare,

1 In most cases, reported ESG data is updated once a year in line with companies own ESG disclosure. The data is refreshed more frequently in exceptional cases, usually when there is a significant change in the reporting or corporate structure during the year.

diversity, and community involvement, reflecting the company's relationship with its workforce and broader society. The Governance pillar examines corporate structures and practices, including board composition, transparency, and ethical standards, highlighting the company's commitment to effective and ethical management.

Appendix A outlines key ESG indicators for assessing a company's sustainability. The tailored weighting system considers the materiality of ESG issues by industry, with Environmental and Social pillars using industry-specific weights, while Governance follows a uniform approach across all sectors. LSEG's magnitude matrix establishes the importance of each category, normalizing scores to a 0 to 100 range for each pillar. The final ESG score reflects a company's sustainability performance based on reported data.

Appendix B displays the ESG classification. This classification offers a clear visualization of how companies are distributed across various ESG score ranges.

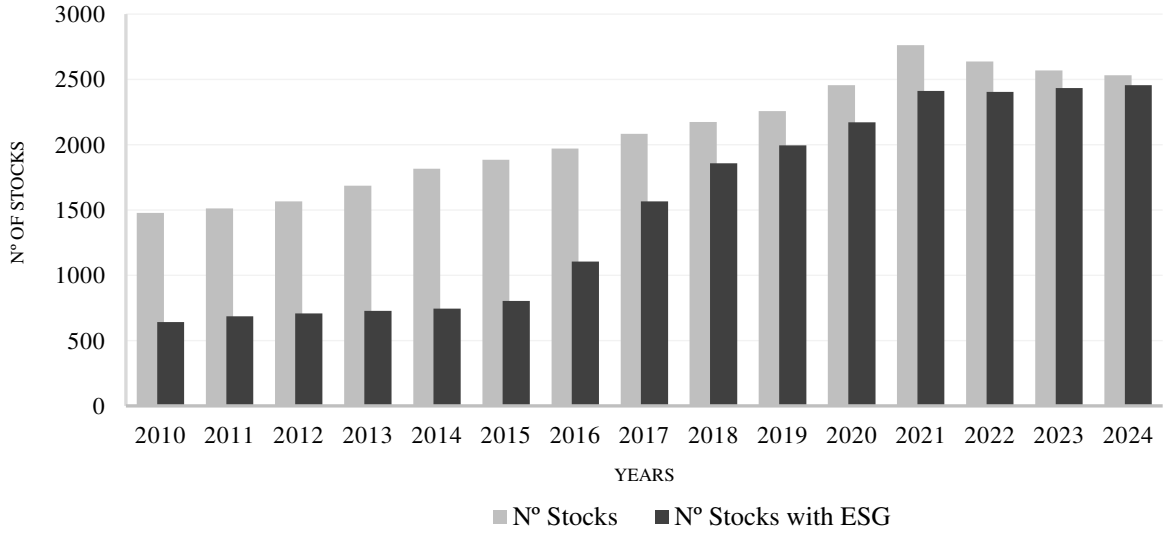
4.4 Data Coverage

Upon completing the dataset, it is crucial to evaluate the consistency of the sample size and the availability of ESG data. ***Graph 3*** illustrates the annual average number of stocks included in the analysis, along with the average number of stocks that have available ESG scores. The results reveal a significant increase in both the total number of stocks considered and the availability of the scores during the study period. This trend highlights the growing robustness of the analysis, reflecting an expanding sample size and enhanced coverage of ESG data.

4.5 Market Benchmarks and Factor Models

To ensure a comprehensive analysis of the strategy, additional data sources were incorporated. The S&P 500 total return index was downloaded from Datastream to serve as a benchmark for this study. This index is primarily used to provide a broad reference for the performance of the U.S. equity market, it is important to note that a direct comparison with the strategy is not entirely appropriate. The S&P 500 is not based on a long-short strategy, it does not fully align with the structure of green momentum, but it offers a general benchmark for understanding broader market trends. In addition, momentum portfolio data from AQR Capital Management was obtained, specifically the U.S. stock selection momentum returns. This data is based on the updated portfolios used in the study by Ilmanen, Israel, Lee, Moskowitz, and Thapar (2021), *How Do Factor Premia Vary Over Time? A Century of Evidence*.

Graph 3: Data Coverage



The inclusion of this momentum portfolio data allows for comparison against established momentum factors, providing insights into how well the green momentum correlates with traditional momentum strategies and whether the incorporation of ESG factors improves or enhances momentum-based performance.

The green momentum was further evaluated through factor regressions using the Fama-French factor models and the q^5 factors, sourced respectively from Kenneth French's data library and the q^5 Global Factors site. These regressions provide a detailed decomposition of returns, identifying the extent to which traditional risk factors or ESG-related factors contributed to performance. By doing so, the analysis clarified whether the strategies delivered genuine alpha or if their returns were simply a byproduct of exposure to well-documented risk factors.

5. Methodology

This study evaluates the performance of three primary strategies: **Momentum**, **Green Momentum**, and **Pure ESG**. The goal is to assess how incorporating ESG metrics into traditional momentum influences returns and whether it contributes to a more sustainable investment framework. The analysis takes a comprehensive approach, considering various time horizons, formation and holding periods combinations, to explore the synergies between momentum investing and ESG integration.

5.1 Returns Calculation

To calculate the returns for each stock, the Total Return Index was used, applying the formula:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} \quad (2)$$

Where:

R_t = Stock Return on month t

P_t = Total Return Index on month t

P_{t-1} = Total Return Index on month t-1

Simple returns were used because they measure the percentage change between two discrete periods, such as monthly returns.

5.2 Formation Periods and Compounded Returns

To construct the portfolios, compounded returns were calculated using monthly return data from January 31, 2010, to September 30, 2024, across varying formation periods of *k* months (3, 6, 9, 12, 24, and 36). Compounding returns ensures a more precise representation of cumulative performance, capturing the effect of returns building upon prior periods.

The final month of each formation period was excluded to account for potential short-term momentum reversals. Compounded returns were calculated only when all months within the formation period contained valid data, excluding stocks with missing values.

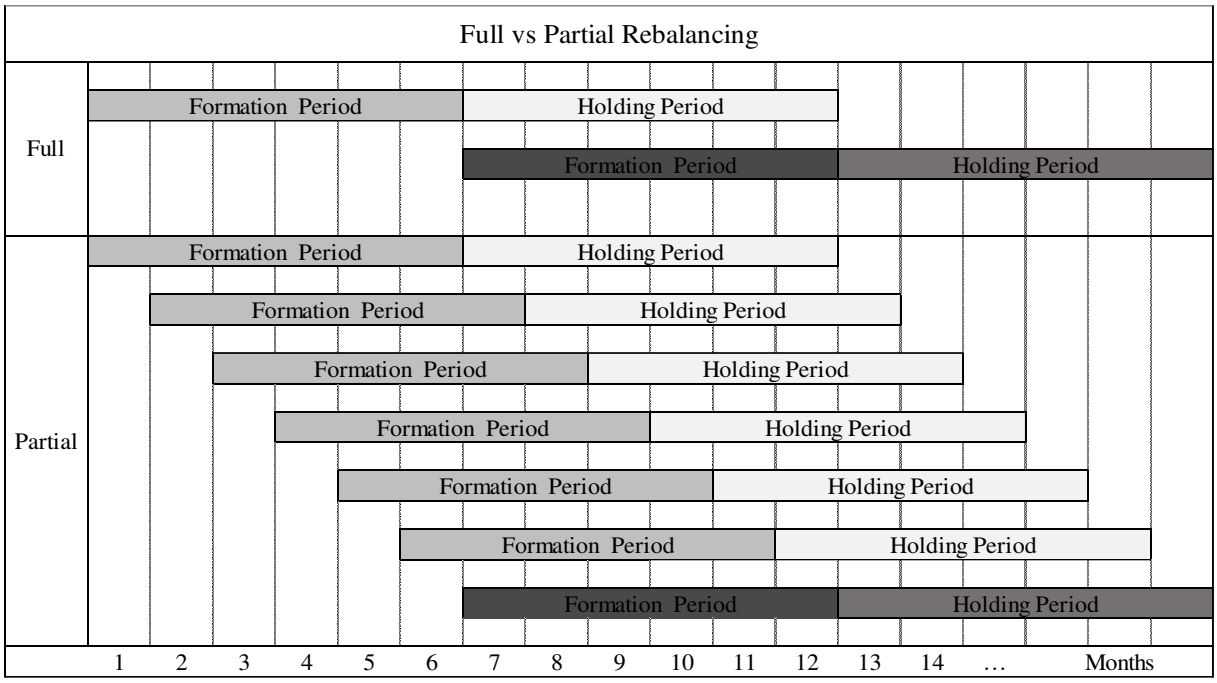
A partial rebalancing strategy, constituted by an overlapping approach, was employed to maximize data utilization, as in ***Graph 4***. This method offers the advantage of increasing the significance of the results by generating a larger number of observations, as formalized by Jegadeesh and Titman (1993). However, the main drawback of partial rebalancing is the significantly higher trading costs associated with it, as it involves more frequent rebalancing than the full rebalancing approach.

5.3 Decile Construction and Stock Allocation

The classification stage involved determining monthly decile boundaries based on the compounded returns from the preceding k-month formation period (excluding the last month). These limits were calculated to divide the dataset into ten equal groups or deciles for each month. Once the boundaries were established, stocks were assigned to their respective deciles based on their compounded returns during the inception period. This distribution ensured that

each stock was placed in the appropriate decile according to its past performance.

Graph 4: Rebalancing Strategy



5.4 ESG Inclusion

A similar procedure was followed for ESG scores. Instead of using compounded returns, the simple average of the scores over the last k months of the formation period was calculated, with no exclusion of the final month, as ESG scores do not exhibit short-term reversals. The average ESG scores were selected, even though ESG scores usually change annually. However, in some instances, the data is updated more frequently to reflect significant changes, such as shifts in a company's reporting or corporate structure. Averaging the scores over several months captures the regular annual updates and any interim changes. After averaging the scores, each stock was assigned to a decile based on its ranking during the formation period, using the same decile boundaries approach.

Nagy, Kassam, and Lee (2016) constructed their ESG momentum portfolio based on the score improvement over 12 months. However, in this analysis, the absolute ESG score was used instead of the change examination. This decision reflects the relatively stable nature of ESG scores, which typically do not exhibit significant variations across months, reducing the relevance of short-term changes in ratings for portfolio construction.

5.5 Strategy Implementation

Three distinct strategies were implemented:

1. **Top 10% & Bottom 10% Returns (Momentum)**

   This traditional momentum strategy focused solely on past returns. Stocks were classified into the top 10% (long portfolio) and bottom 10% (short portfolio) based on their returns over the designated formation periods.
2. **Top 10% & Bottom 10% Returns with Top 30% & Bottom 30% ESG (Green Momentum)**

   This strategy integrated momentum and ESG metrics. Stocks were first classified based on their returns, top 10% (long portfolio) and bottom 10% (short portfolio). Additionally, ESG scores were applied as a co-equal criterion: for the long portfolio, only stocks in the top 30% of ESG scores were included, while for the short portfolio, only stocks in the bottom 30% of ESG scores were selected.
3. **Top 30% & Bottom 30% ESG (Pure ESG)**

   This strategy was based solely on ESG scores. Stocks were classified into the top 30% (long portfolio) and bottom 30% (short portfolio) based entirely on their ESG rankings, without regard to returns.

5.6 Long Short Portfolio

For each approach, an equal-weighted portfolio was constructed with monthly rebalancing. Stocks meeting the defined criteria during the formation period were included, and their monthly returns were incorporated into the calculations across k different holding periods (1, 3, 6, 9, and 12 months).

The average return of all stocks was calculated each month, ensuring equal weighting across all positions. To assess performance, a long-short approach was used by calculating the return difference between the long and short portfolios, which provided a monthly measure for each strategy. All results presented are net of the risk-free rate, ensuring the returns reflect the excess performance. The risk-free rate used in these calculations was retrieved from the Kenneth French Data Library.

5.7 Performance Measurement

The performance evaluation used a rigorous analytical framework. The aim was to gain a thorough understanding of their effectiveness and stability. To assess the strategies' results, mean returns were computed to evaluate their average profitability over time, supported by statistical tests to determine whether the returns were significantly different from zero. Standard deviation was incorporated to account for variations across different periods, while the sharpe

ratio served as a benchmark for assessing returns relative to risk, facilitating direct comparisons among the strategies. Additionally, the minimum and maximum returns illustrated the range of outcomes, offering insight into potential best- and worst-case scenarios during the analysis period. Correlation with the AQR momentum factor was calculated to validate the outcome against a standard momentum benchmark. For ESG strategies, this step assessed whether they aligned with traditional momentum principles or offered diversification benefits, showcasing their unique value and relevance in modern investment frameworks.

Cumulative returns were plotted alongside the S&P 500 to evaluate the strategies' long-term performance relative to a widely recognized benchmark. This comparison provides a visual representation of how the approaches evolve, allowing for an assessment of trends and consistency. For ESG-focused scenarios, it offers insights into the potential relationship between incorporating sustainability metrics and long-term performance.

A drawdown analysis was conducted to examine the extent and duration of losses during market downturns, providing a measure of resilience. This was crucial for understanding the potential impact on investors, particularly during adverse conditions, and assessing how well the strategies could withstand periods of negative results.

For a deeper analysis of risk-adjusted returns and factor exposures, data from Kenneth French's data library were integrated, including the Fama-French three-factor (FF3) model, the Fama-French five-factor (FF5) model, and the Fama-French six-factor (FF6) model:

$$\text{FF3} \quad ER_{it} = \alpha_i + b_i(RM_t - RF_t) + s_i SMB_t + h_i HML_t + \varepsilon_{it} \tag{3}$$

$$\text{FF5} \quad ER_{it} = \alpha_i + b_i(RM_t - RF_t) + s_i SMB_t + h_i HML_t + r_i\, RMW_t + c_i CMA_t + \varepsilon_{it} \tag{4}$$

$$\text{FF6} \quad ER_{it} = \alpha_i + b_i(RM_t - RF_t) + s_i SMB_t + h_i HML_t + r_i\, RMW_t + c_i CMA_t + \varepsilon_{it} + w_i WML_t + \varepsilon_{it} \tag{5}$$

Where:

ER_{it} = Excess return on portfolio i for month t

$RM_t - RF_t$ = Market Risk Premium. Excess return of the market portfolio over the risk free rate

SMB_t = Size Premium. Return difference between small cap stocks and large cap stocks

HML_t = Value Premium. Return difference between stocks with high book to market ratios (value stocks) and low book to market ratios (growth stocks)

RMW_t = Profitability Premium. Return difference between firms with robust (high) and weak (low) operating profitability

CMA_t = Investment Premium. Return difference between firms with conservative (low) and aggressive (high) investment practices

WML_t = Momentum Premium. Return difference between stocks with high past returns (winners) and stocks with low past returns (losers)

The q^5 factors from Hou, Xue, and Zhang (2015) were incorporated because their model offers a more refined explanation of stock returns than the traditional Fama-French factors. The q^5 model has been shown to fully subsume the Fama-French 6-factor model in factor spanning tests, meaning it explains all the variations in stock returns that the Fama-French model does, while adding further explanatory power. This inclusion provides a more comprehensive understanding by accounting for these additional risk factors.

$$q^5 \quad ER_{it} = \alpha_i + b_i MKT_t + s_i ME_t + i_i IA_t + p_i ROE_t + g_i EG_t + \varepsilon_{it} \tag{6}$$

Where:

ER_{it} = Excess return on portfolio i for month t

MKT_t = Market Risk Premium. Excess return of the market portfolio over the risk free rate

ME_t = Size Premium. Return difference between small cap stocks and large cap stocks

IA_t = Investment Premium. Return difference between firms with low and high investment practices

ROE_t = Profitability Premium. Return difference between firms with high and low profitability

EG_t = Expected Growth Premium. Return difference between firms with high and low expected growth

The market factor (MKT) in the q^5 model corresponds directly to the market factor (RM-RF) in the Fama-French models. Both measure the return premium of the market over the risk-free rate, serving as a baseline for evaluating other factors. Similarly, the size factor (ME) in the q^5 model, captures the size effect and is closely related to the Fama-French SMB factor, both targeting the size premium

The q^5 investment factor (IA) is conceptually linked to the Fama-French CMA factor, which captures the return spread between low and high-investment firms. However, IA offers a stronger and more precise measure because it incorporates joint sorting with profitability, revealing interactions that CMA does not account for. This distinction is critical, as profitability and investment are positively correlated but predict returns with opposing signs. Including profitability in the construction allows the q^5 model to provide a more nuanced explanation of return drivers.

Profitability, measured by ROE in the q^5 framework corresponds to RMW in the Fama-French models but offers a significant advantage due to its construction. ROE relies on recent quarterly earnings, making it more sensitive to current firm performance, whereas RMW is derived from annual profitability data, which may be less timely. This methodological difference enables ROE to capture return premiums more effectively, highlighting its superiority as an explanatory factor. The expected growth factor (EG), unique to the q^5 model, represents an additional dimension absent in the Fama-French framework. By capturing expected growth in earnings, EG provides insights into how growth expectations influence returns, further enriching the analysis.

Following the factors assessment, robustness checks were implemented to ensure the reliability of the findings. Below, some of them are referred.
The strategies were computed for different formation and holding periods to evaluate the behaviour under different time frames. This is crucial as the optimal time horizon can vary, and such tests provide a better understanding ensuring robustness across varying periods

The exclusion of January returns tested whether the strategies were influenced by the well-documented seasonal anomaly known as the January effect, as illustrated by George and Hwang (2004) in *The 52-Week High and Momentum Investing*. This phenomenon is often attributed to tax-loss selling, where investors sell underperforming stocks at year-end for tax purposes and subsequently repurchase them in January. By excluding January, the analysis aimed to avoid distortions in momentum signals caused by these tax-related transactions, ensuring a more accurate evaluation of the strategies' performance.

Moreover, the analysis was divided into two subperiods to examine the results under different market conditions. The period from January 2010 to December 2017 represented a phase of lower market volatility, while the period from January 2018 to September 2024 captured a phase of higher market volatility. This segmentation allowed for a more detailed assessment of consistency and adaptability across varying economic environments.

Finally, a breakeven analysis was performed to evaluate the practical feasibility of the results when accounting for transaction costs. The monthly turnover of each portfolio was calculated using the following formula:

$$\text{Turnover (\%)} = \big(\text{Dropouts (\%)} + \text{New (\%)}\big) \tag{7}$$

This turnover calculation provided insight into the frequency of asset trades within the portfolio. The average monthly returns were then divided by the turnover to determine the transaction costs necessary to offset the returns completely. This step identified the level of transaction costs that would neutralize any gains generated by the strategy, offering a deeper understanding of its real-world applicability.

Each of these analyses was carefully chosen to provide a holistic assessment of the strategies, capturing their strengths, weaknesses, and adaptability in different market conditions. Together, they offer a nuanced understanding of the potential for integrating momentum and ESG factors in portfolio construction while addressing key investor concerns regarding risk, performance, and sustainability.

6. Empirical Analysis and Results

6.1 Evolution of ESG Scores and Initial Insights on Returns

Before presenting the results, exploring the evolution of absolute ESG scores over time and their relationship with stock returns is important. This analysis provides valuable context by highlighting trends in corporate sustainability practices and their potential relationship with the financial perspective.

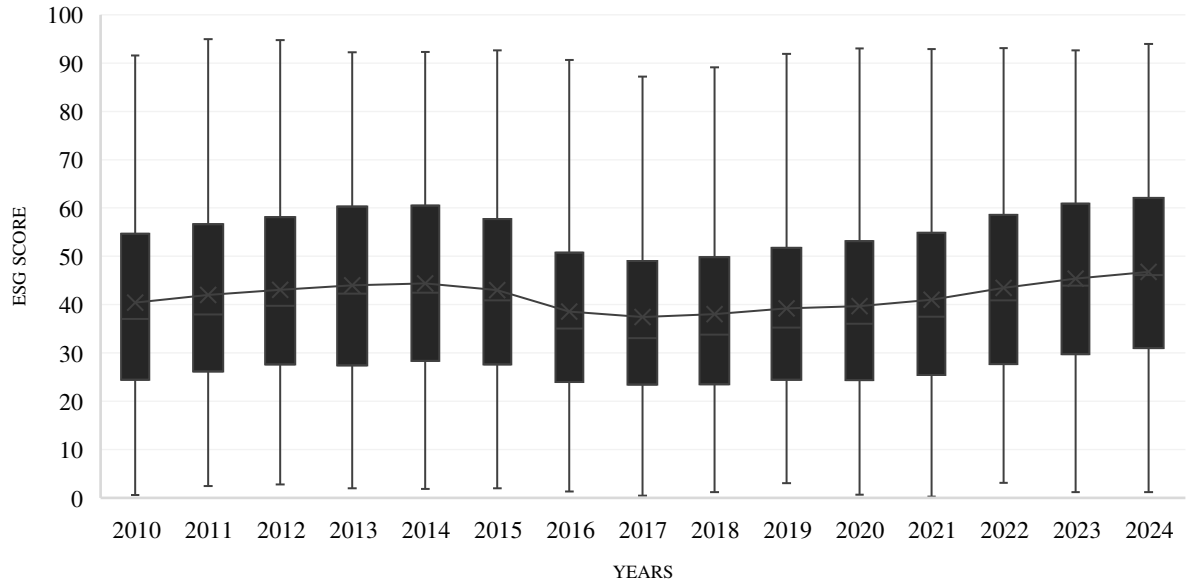
Throughout the analysis period, the lower quartile of ESG scores consistently ranged between 20 and 30, indicating that the least sustainable companies remained within this band. Similarly, the upper quartile was generally between 50 and 60, reflecting the performance of the most sustainable firms. The average ESG scores oscillated between 40 and 50, highlighting the overall balance of sustainability levels across the dataset.

As we can observe in ***Graph 5***, between 2015 and 2016, there was a slight decrease in average ESG scores. This decline is partially attributed to the increased number of stocks in the sample during this period, as more companies began reporting ESG data. Many of these newly added firms initially had lower ESG scores, contributing to the observed average score reduction. Importantly, this trend does not imply that companies already included in the sample reduced their classification, instead, it reflects the expansion of the dataset to include a broader range of firms.

Following 2015, ESG scores exhibited a slight but consistent increasing trend until 2024. This improvement can be linked to companies adopting more robust sustainability practices, the growing influence of investor demand for ESG-aligned investments, and stricter regulatory

pressures. The 2015 Paris Agreement played a pivotal role in shaping corporate ESG strategies, particularly around climate and environmental objectives, encouraging firms to enhance their sustainability efforts. Additionally, advancements in ESG reporting frameworks and standardization have improved the quality of ESG data, enabling firms to address identified gaps and improve their ratings over time.

Graph 5: ESG Evolution



To enhance this analysis, a transition matrix, illustrated in ***Graph 6***, was created to track how stocks moved between ESG deciles throughout the analysis period. This matrix illustrates the dynamic nature of ESG rankings. While some firms consistently maintained their positions in the highest or lowest deciles, others showed significant mobility from January 2010 to September 2024. Notably, stocks generally tend to transition to an equal or higher position, indicating an overall trend toward improvement. This pattern emphasizes the progress and increasing emphasis on sustainability practices by companies over time.

Another observation is that in the earlier years of the dataset, ESG score availability was limited, as fewer companies disclosed this information. However, in years with more comprehensive ESG data coverage, the investigation consistently reveals a clear trend of upward transitions in ESG deciles.

Graph 7 presents the relationship between average ESG scores and stock returns across 10 deciles. Stocks were sorted into deciles based on their ESG scores over a 12-month formation period, with returns observed over a 1-month holding period. Monthly average returns for each decile were calculated and then averaged across all months to determine the overall decile

Graph 6: ESG Transition Matrix

		September 2024									
	Deciles	1	2	3	4	5	6	7	8	9	10
January 2010	1	2%	6%	8%	8%	10%	13%	11%	11%	19%	11%
	2	3%	3%	3%	8%	5%	19%	10%	21%	19%	10%
	3	2%	3%	6%	12%	3%	12%	11%	18%	14%	20%
	4	0%	2%	3%	5%	11%	6%	20%	18%	18%	18%
	5	2%	0%	0%	0%	3%	6%	20%	20%	30%	19%
	6	2%	2%	0%	5%	5%	5%	23%	15%	26%	18%
	7	0%	0%	0%	0%	3%	6%	11%	18%	30%	32%
	8	0%	0%	0%	0%	2%	6%	5%	22%	29%	37%
	9	0%	0%	0%	0%	2%	2%	8%	12%	38%	39%
	10	0%	0%	0%	0%	0%	0%	1%	4%	19%	75%

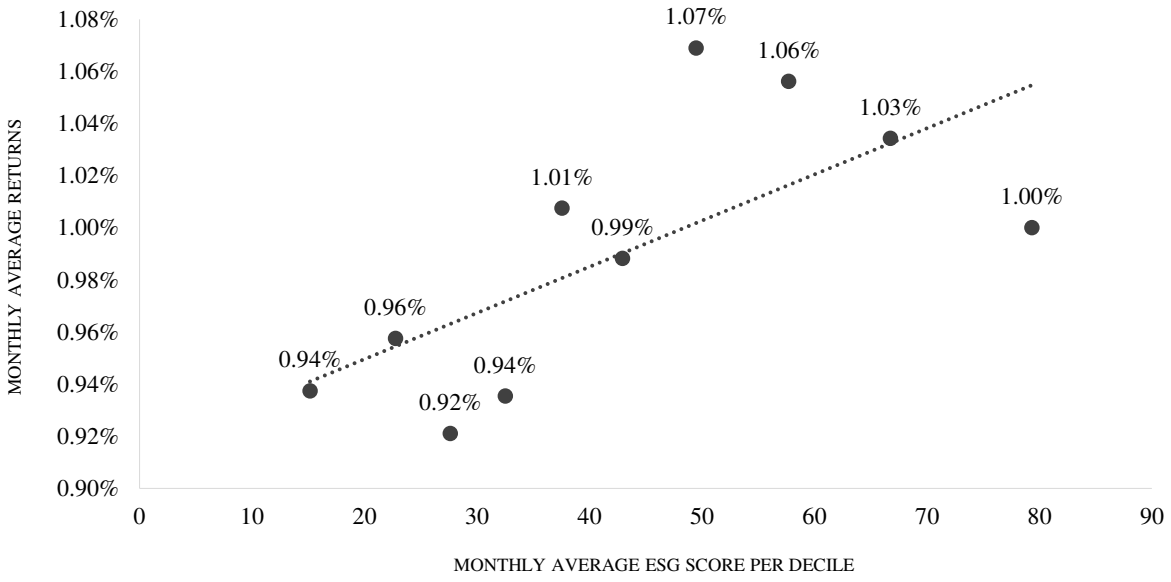
returns. Each point on the graph represents the monthly average ESG score of a decile and the corresponding monthly average return of the stocks within that decile. While no clear pattern emerges for a marginal increase in the decile, companies in the highest ESG deciles appear to exhibit slightly higher returns compared to those in lower deciles. This preliminary observation offers a general indication of the relationship between sustainable performance and stock returns, providing a starting point for further analysis. Several factors could explain this pattern:

1. **Investor Demand for ESG-Aligned Stocks**: Increasing demand for ESG investments over the past decade, driven by growing awareness of sustainability and social responsibility, has likely led to higher capital inflows into companies with higher ESG scores (Eccles & Klimenko, 2019). These inflows could be reflected in stock price appreciation, especially in a market where investors are increasingly prioritizing sustainability.
2. **Lower Risk and Better Long-Term Performance**: Companies with high ESG scores are often viewed as more stable and better prepared for long-term challenges, such as regulatory changes, environmental risks, and social concerns. As such, these companies are seen as lower-risk investments, which may contribute to more favourable market valuations and better performance over time. Studies have suggested that firms with strong ESG practices tend to outperform in terms of risk-adjusted returns because they are better at managing operational and reputational risks (Friede, Busch, & Bassen, 2015).
3. **The "Green Premium" and Policy Influence**: Following key global environmental policies and agreements like the Paris Agreement, companies that align with these sustainability goals are often better positioned to benefit from regulatory incentives or avoid penalties related to environmental practices. This "green premium" may also explain

the slight differences between the companies, as their adherence to these global standards positions them more favourably in the market.

Studies on the relationship between ESG and stock returns have produced mixed findings. Kroll[2] (2023) finds that companies with higher ESG ratings tend to outperform those with lower ratings, especially over the long term, suggesting that strong sustainable practices can drive positive market performance. In a similar vein, Pedersen et al. (2021) argue that governance-related ESG factors have a positive impact on stock returns. However, the effects of environmental and social factors appear to vary depending on the industry and market conditions. These findings highlight the growing importance of ESG in investment decisions, serving as a foundation for further exploration and discussion.

Graph 7: Monthly Average Returns vs Monthly Average ESG Score per Decile



6.2 Performance Analysis of Momentum and ESG Strategies

In assessing the strategies' outcomes, a 12-month formation period coupled with a 1-month holding period was selected as representative in this study. This choice was made due to its consistent results and alignment with existing literature. ***Table 1*** presents descriptive statistics for the long, short, and long-short portfolios. The reported mean, standard deviation, and sharpe ratio are annualized to offer a clearer and more comparable perspective than would be provided by monthly values.

2 Kroll is a leading independent provider of global risk and financial advisory solutions, that examines the relationship between historical returns of publicly traded companies and their ESG ratings globally.

The standard momentum strategy (Top 10% & Bottom 10% Returns) produced an annualized long-short return of **10.51%**, supported by a sharpe ratio of **0.59**. The statistical significance for the long-short portfolio suggests that the results are robust and the mean is different from zero. The standard deviation of **17.75%** in the long-short portfolio reflects the inherent volatility of momentum strategies. While this strategy performed well in terms of returns, its risk-adjusted performance remains moderate.

Incorporating ESG scores (Top 10% & Bottom 10% Returns with Top 30% & Bottom 30% ESG) slightly enhanced long-short returns to **10.74%**. However, this came at the cost of increased volatility (**22.40%**), resulting in a lower sharpe ratio of **0.48**. While the long leg (12.74%) continued to drive performance, the p-value (**0.23**) suggests that the result is not statistically significant. This highlights a trade-off: ESG integration improves absolute returns but reduces diversification, amplifying idiosyncratic risk. These findings are consistent with Pedersen, Fitzgibbons, and Pomorski (2021), which demonstrates that ESG levels in a portfolio lead to minor sharpe ratio reductions, suggesting that ethical investing can align with financial goals at a small cost to efficiency.

The pure ESG strategy, which focused on the top 30% and bottom 30% of ESG performers, generated a long-short return of only **1.64%**. This return is significantly lower than that of momentum-focused strategies. The sharpe ratio of **0.26** indicates weak risk-adjusted performance, and the p-value of **0.52** shows no statistical significance. The long leg produced an annualized return of 10.26%, surpassing the short leg's return of 8.62%. However, the minimal differentiation between high- and low-ESG stocks suggests that ESG alone is not a strong driver of returns in this dataset, particularly when returns are not considered as a classification metric.

The results indicate that momentum is the primary driver of investment returns, with both pure and green momentum strategies outperforming a purely ESG-focused approach. While integrating ESG factors slightly enhances returns, it also introduces trade-offs, such as increased volatility and a lower sharpe ratio, largely due to reduced diversification rather than the ESG factors themselves. This is particularly evident as the pure ESG strategy shows much lower volatility (**6.26%**) compared to momentum and green momentum strategies.

The pure ESG strategy struggles to generate meaningful long-short returns because both high- and low portfolios yield positive returns, reducing the differentiation needed for a profitable long-short strategy. These findings emphasize the dominant role of momentum over ESG factors and highlight the importance of carefully managing the trade-offs between return and risk when incorporating ESG into momentum.

Relying solely on ESG scores to identify high-performing stocks has limitations, as highlighted by Halbritter and Dorfleitner (2015). This underscores the importance of complement sustainable factors with other established indicators, such as momentum, to create potentially more effective investment strategies.

The correlation analysis with AQR momentum portfolio provides valuable insights into their relationships with a well-established momentum benchmark. The pure momentum strategy demonstrated a strong correlation of **89.97%** with AQR, underscoring its close alignment with traditional momentum principles. This high degree of similarity validates the robustness of the approach, suggesting that it effectively captures the same return persistence factors observed in AQR's analysis. Minor differences in outcomes are likely attributable to variations in stock selection criteria.

The green momentum showed a slightly lower correlation of **82.48%**. This reduction reflects the impact of ESG integration on the momentum factor. By filtering out stocks with weak ESG scores, the strategy sacrifices some alignment with traditional momentum portfolios, as certain high-return but low-ESG stocks are excluded. Nevertheless, the relatively high correlation indicates that green momentum retains core momentum characteristics while introducing additional dimensions that subtly reshape portfolio exposures and outcomes.

The pure ESG strategy exhibited a markedly lower correlation of **18.63%** with AQR's momentum portfolio. This divergence is not surprising, highlighting the fundamental differences between an ESG-driven selection process and momentum-based methodologies. While momentum strategies focus on short-term price trends, the ESG-only approach prioritizes sustainability metrics. This leads to portfolios operating outside the momentum framework, consistent with the observed performance.

Table 1: Portfolios: 12-Month Formation and 1-Month Holding

	Momentum			Green Momentum			Pure ESG		
	Short	Long	Long - Short	Short	Long	Long - Short	Short	Long	Long - Short
Mean	1.30%	**11.81%****	**10.51%***	2.00%	**12.74%*****	10.74%	**8.62%****	**10.26%*****	1.64%
T-stat	0.69	2.42	1.67	0.79	2.82	1.20	1.97	2.49	0.65
(p-value)	(0.49)	(0.02)	(0.10)	(0.43)	(0.01)	(0.23)	(0.05)	(0.01)	(0.52)
Stdev	28.34%	20.28%	17.75%	29.84%	17.90%	22.40%	19.02%	16.73%	6.26%
Max	34.40%	20.66%	12.96%	33.94%	20.91%	16.41%	17.47%	17.17%	5.81%
Min	-29.97%	-20.71%	-18.11%	-28.56%	-14.58%	-25.16%	-23.93%	-21.53%	-4.39%
Sharpe	0.05	0.58	0.59	0.07	0.71	0.48	0.45	0.61	0.26
AQR Correlation			89.97%			82.48%			18.63%

*** p≤0.01; ** p≤0.05; * p≤0.1

As presented in ***Graph 8*** and ***Graph 9***, this analysis examines the integration of ESG (Environmental, Social, and Governance) factors when returns are the sole selection criterion. The goal is to explore how the share of stocks within the top 30% and bottom 30% ESG scores evolves across the three portfolios: the top 10%, middle deciles, and bottom 10% regarding returns, over a 12-month formation period with a 1-month holding period. By sorting stocks solely based on historical returns, the central question is: How do the proportions of stocks within the top and bottom ESG scores change when returns are the only factor used to construct the portfolios?

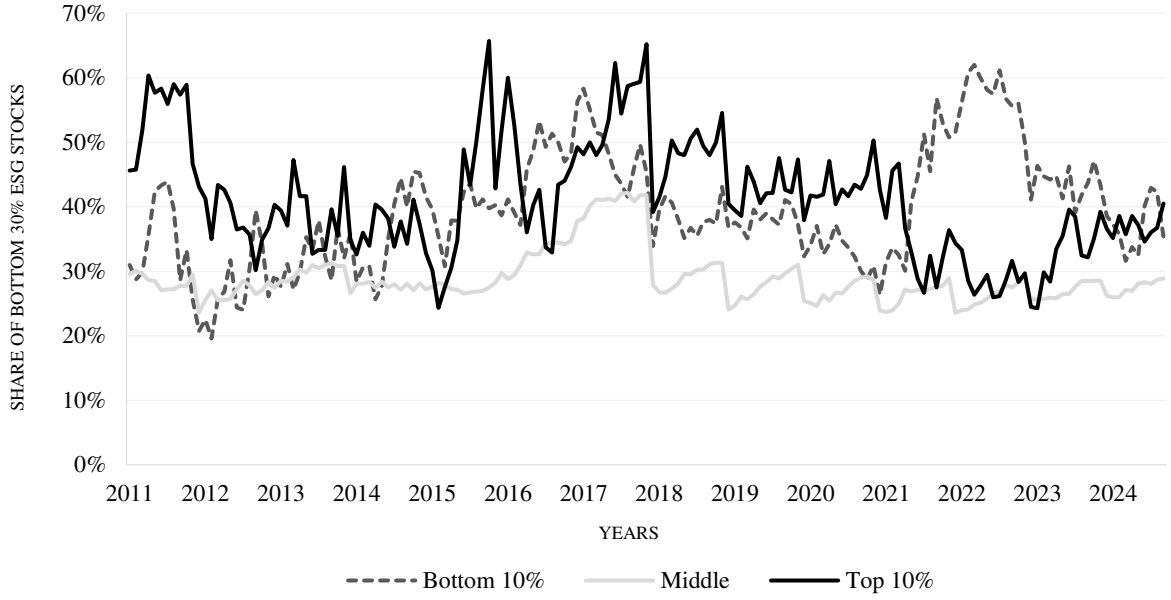
The middle portfolio, which has the largest number of stocks, generally demonstrates slightly stronger ESG characteristics. It features a higher proportion of stocks in the top 30% for ESG scores and a lower share in the bottom 30%. This indicates that stocks with balanced ESG profiles are more likely to be included in this category. Such an alignment supports sustainable investing principles that prioritize both financial performance and ESG criteria.
On the other hand, the portfolio representing the bottom 10% of returns shows a clear preference for stocks with weaker ESG scores. It contains more stocks in the bottom 30% of the ESG category than those in the top 30%. Interestingly, the portfolio with the top 10% of returns exhibits a similar trend, featuring a significant number of stocks with lower ESG scores. This suggests that building portfolios based solely on high or low returns does not necessarily lead to better ESG performance.

Over time, there is no consistent pattern in the distribution of ESG scores between the top and bottom deciles. This variability highlights the inconsistency of ESG representation in portfolios built solely on return, reinforcing the idea that return-driven strategies do not inherently align with ESG priorities.
Starting in 2021, stocks with lower ESG scores in the bottom decile and higher ESG scores in the top decile increased, driven by market trends such as a record $120 billion inflow into sustainable assets in 2021. ESG investing gained popularity for its environmental benefits and strong risk-adjusted returns, attracting both impact-focused and financial investors. However, the findings indicate that aligning return-driven strategies with ESG objectives requires intentional integration.

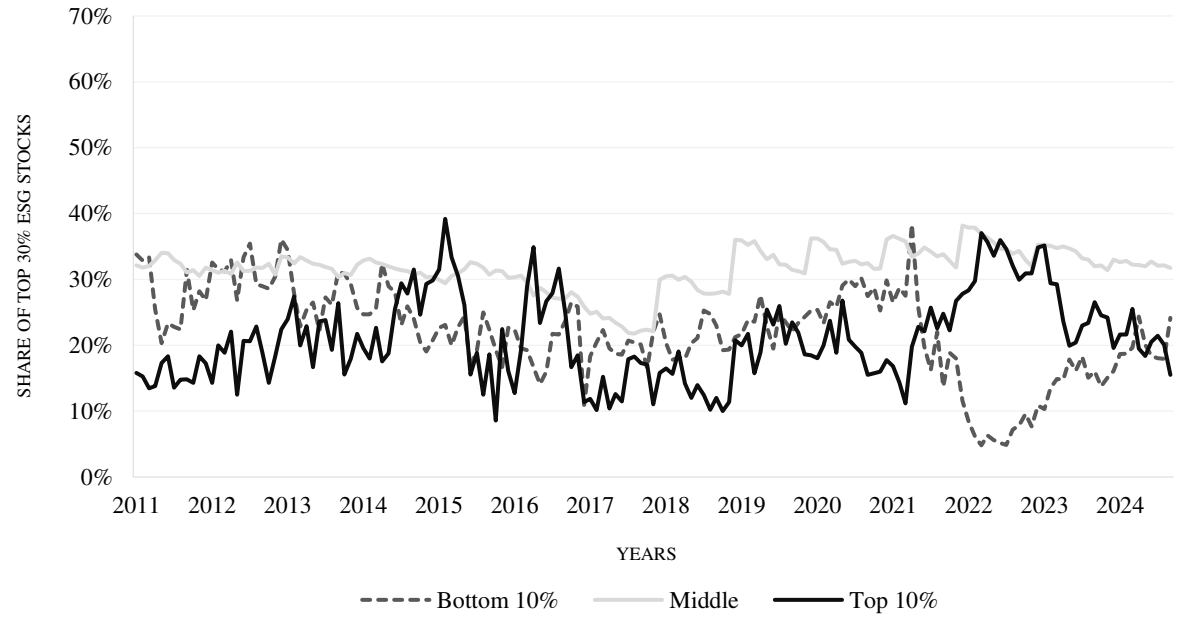
6.3 Cumulative Returns and Drawdown Analysis

Graph 10 shows the three cumulative returns, with the S&P 500 serving as a general benchmark for market performance.

Graph 8: Share Evolution of Bottom 30% ESG stocks across the 3 portfolios



Graph 9: Share Evolution of Top 30% ESG stocks across the 3 portfolios

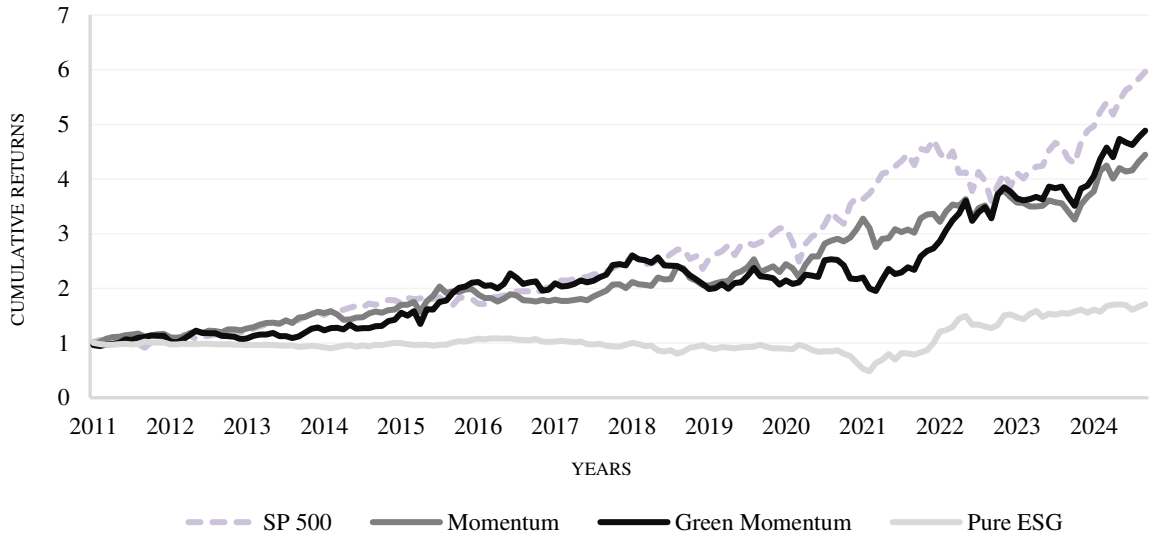


From 2011 to 2021, the pure momentum strategy did not demonstrate significantly higher cumulative returns compared to the green momentum strategy, both performed similarly. However, after 2021, green momentum not only narrowed the performance gap but also surpassed pure momentum. This change likely reflects the increasing importance of ESG (Environmental, Social, and Governance) factors among investors and favourable market conditions that benefit high-ESG stocks. This trend aligns with the findings of Pastor, Stambaugh, and Taylor (2020), which indicated that green assets tend to outperform during

positive ESG shocks, driven by shifts in customer demand for sustainable products and investor preferences for responsible investments. The observed outperformance of the green momentum strategy after 2021 suggests that these positive shifts in market sentiment regarding ESG factors have contributed to its success. This aligns with real-world developments, such as the United States rejoining the Paris Agreement in 2021 and the Inflation Reduction Act in 2022, which have sent a strong signal to global markets about the U.S.'s climate ambitions.

In contrast, the pure ESG strategy has been the weakest performer throughout the entire period, generating minimal cumulative returns compared to the other strategies.

Graph 10: Cumulative Returns

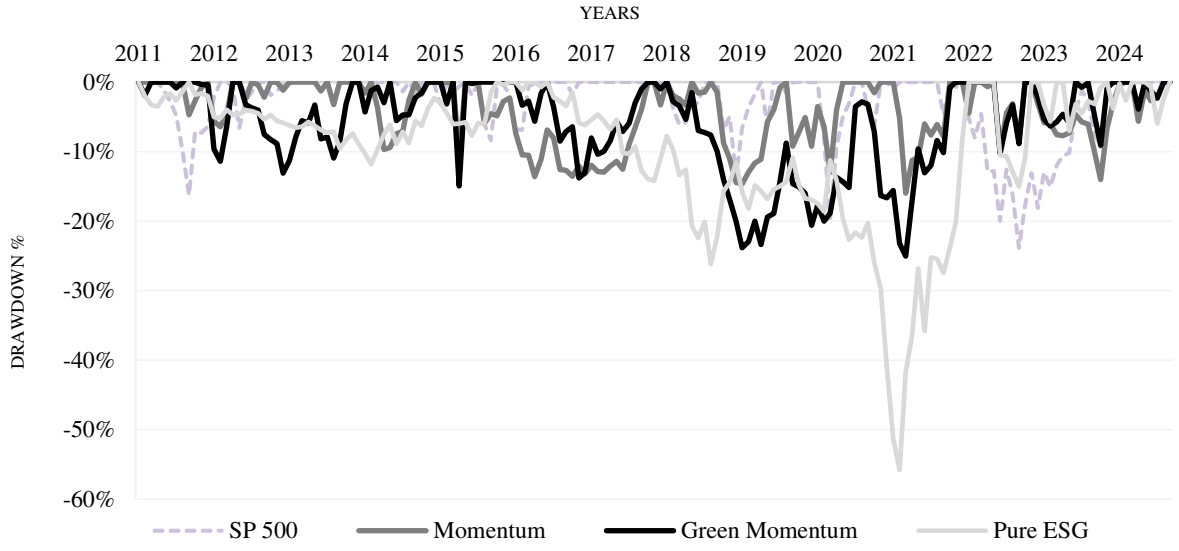


The patterns observed in ***Graph 11*** indicate that the maximum drawdowns occurred in early 2021. During this period, the pure ESG strategy experienced a significant decline of -55%. In comparison, the green momentum faced a drawdown of -25%, while the traditional momentum performed better with a drawdown of -15%. This observation is consistent with the previous analysis, as this timeframe corresponds to a notable decrease in cumulative returns across all strategies.

The severe drawdowns in early 2021 can be attributed to a combination of market-specific phenomena and broader economic trends. A key driver was the speculative surge in "meme stocks" like GameStop and AMC, fueled by retail investors on online platforms, which are typically not considered top ESG stocks. This volatility disrupted market equilibrium, with hedge funds scrambling to cover short positions, triggering broader market instability. Concurrently, concerns about rising inflation and increasing interest rates led to corrections in high-growth sectors such as technology.

While the inclusion of ESG metrics in the momentum strategy did not show a clear protective effect during the 2021 drawdown, we do not have reason to believe that ESG inclusion leads to a worse performance during market downturns. In fact, the COVID-19 period provides an example: during that period of economic uncertainty, ESG strategies did not exhibit significantly larger drawdowns than momentum alone.

Graph 11: Drawdowns



6.4 Fama-French 3-Factors Regression

The Fama-French three-factor (FF3) analysis highlights common traits and unique characteristics among the three strategies. While green momentum is the primary focus, comparing it with momentum and pure ESG offers greater insights into the effects of integrating sustainable factors, as shown in ***Table 2***.

The green momentum strategy exhibits a defensive market orientation, as shown by a negative and significant market factor coefficient of **-0.405**. This finding aligns with Bauer et al. (2005), who suggest that ethical investments tend to be less sensitive to market fluctuations. Furthermore, the significant size factor of **-1.062** indicates a strong preference for larger-cap stocks, which is consistent with the exclusion of smaller-cap stocks from the sample. This is supported by Drempetic et al. (2020), who emphasize that firms with higher ESG scores are often larger, well-established companies capable of adopting and disclosing sustainable practices effectively. The strategy also achieves a significant alpha of **0.009** at the 5% significance level, manifesting its ability to generate excess returns beyond what traditional risk factors can explain. With an adjusted R^2 of 0.324, the model captures a modest portion of the return variance, suggesting that other unexplored factors may also influence the outcome.

The momentum strategy shares many of the same characteristics as the green momentum, including the same alpha of **0.009**. However, a notable difference is the significant negative exposure to the value factor, indicating that the absence of ESG constraints suggests a preference for growth-oriented stocks.

In contrast, the pure ESG demonstrates a robust positive coefficient of **0.150** for the value factor, indicating a distinct preference for value stocks linked to the inclusion of the sustainable metric. This finding aligns with the results of Halbritter and Dorfleitner (2015) when utilizing Bloomberg ESG scores. Meanwhile, the size factor remains significantly negative at **-0.554**, emphasizing the inclination towards large-cap stocks. However, the strategy fails to generate any alpha, suggesting that its returns can be entirely attributed to traditional factors, without any additional value beyond what the Fama-French model captures. The higher adjusted R^2 of 0.666 indicates a stronger correlation with systematic risk factors than the green momentum.

Table 2: Fama French 3 Factors Regressions (12/1)

	Momentum			Green Momentum			Pure ESG		
	Short	Long	Long - Short	Short	Long	Long - Short	Short	Long	Long - Short
RMRF	**1.369*** **	**1.079*** **	**-0.291*** **	**1.398*** **	**0.993*** **	**-0.405*** **	**1.037*** **	**1.030*** **	-0.007
	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.762)
SMB	**1.210*** **	**0.673*** **	**-0.537*** **	**1.176*** **	0.114	**-1.062*** **	**0.690*** **	**0.136*** **	**-0.554*** **
	(0.000)	(0.000)	(0.001)	(0.000)	(0.221)	(0.000)	(0.000)	(0.001)	(0.000)
HML	**0.288*** **	-0.052	**-0.341** **	**0.199** **	0.066	-0.132	**0.176*** **	**0.326*** **	**0.150*** **
	(0.000)	(0.475)	(0.011)	(0.029)	(0.377)	(0.308)	(0.000)	(0.000)	(0.000)
ALPHA	**-0.008*** **	0.001	**0.009** **	**-0.008** **	0.001	**0.009** **	-0.001	-0.001	0.000
	(0.001)	(0.771)	(0.018)	(0.020)	(0.610)	(0.040)	(0.196)	(0.234)	(0.643)
Adjusted R^2	0.862	0.852	0.226	0.775	0.711	0.324	0.951	0.956	0.666

*** p≤0.01; **p≤0.05; *p≤0.1

6.5 Fama-French 5-Factors Regression

There are similarities when the investigation extends to the Fama-French five-factor (FF5) model in ***Table 3***, but the additional factors of profitability (RMW) and investment (CMA) provide important insights into how these strategies interact with these extra explanatory variables.

The green momentum strategy aligns with conservative investment profiles, as evidenced by the positive and statistically significant CMA coefficient of **0.595**. This result suggests that the approach tends to favour firms exhibiting prudent investment behaviours. This finding aligns with the argument made by Eccles et al. (2014) that short-termism, where executive

compensation is closely tied to immediate performance metrics, often incentivizes managers to prioritize short-term gains at the expense of strategic investments critical for long-term growth. In contrast, firms that prioritize Environmental, Social, and Governance (ESG) factors tend to focus on creating long-term value and promoting sustainable development. The RMW coefficient of 0.149 is insignificant, indicating no clear preference for selecting either more or less profitable firms. The alpha remains slightly positive at **0.008**, significant at the 10% level, reflecting the strategy's ability to generate modest excess returns, even with the inclusion of the additional explanatory factors. The adjusted R^2 improves slightly to 0.342, without significantly altering the model's overall explanatory power.

The traditional momentum strategy shows a positive and significant CMA coefficient of **0.533**, indicating a similar tendency toward conservative investment practices. The RMW coefficient is slightly negative and insignificant, suggesting that profitability does not significantly influence the portfolio. The alpha remains unchanged at **0.009**, consistent with the FF3 results.

The pure ESG strategy demonstrates a significant positive RMW coefficient of **0.198** at the 1% significance level, indicating a preference for firms with higher profitability. This finding aligns with the research by Khan, Serafeim, and Yoon (2016), which shows that firms with high scores on material ESG issues, those pertinent to their industry, tend to exhibit greater profitability. Additionally, the CMA coefficient for the pure ESG strategy is also positive and significant, at **0.231**, suggesting that these firms generally adopt conservative investment practices. The model's explanatory power increases slightly, reflecting the added relevance of these factors for ESG-driven portfolios. Notably, the lack of alpha indicates that the returns from the pure ESG strategy can be almost entirely explained by these systemic risk factors.

6.6 Fama-French 6 Factors Regression

Incorporating the momentum factor into the analysis of the green momentum strategy highlights its reliance on return persistence. WML explains a significant portion of the returns, but analysing green momentum beyond WML is essential to assess whether ESG considerations provide a meaningful distinction, as presented in ***Table 4***.

The incorporation of WML serves two primary purposes. First, it enables **factor exposure identification**, revealing the extent to which the green momentum aligns with the traditional one. If WML explains most of the returns, it suggests that the green momentum strategy largely mimics the performance of standard momentum, with the ESG overlay providing minimal differentiation.

Table 3: Fama French 5 Factors Regressions (12/1)

	Momentum			Green Momentum			Pure ESG		
	Short	Long	Long - Short	Short	Long	Long - Short	Short	Long	Long - Short
RMRF	**1.325*** **	**1.096*** **	**-0.229** **	**1.373*** **	**1.033*** **	**-0.339*** **	**1.012*** **	**1.024*** **	0.012
	(0.000)	(0.000)	(0.020)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.578)
SMB	**1.109*** **	**0.571*** **	**-0.537*** **	**1.038*** **	0.091	**-0.947*** **	**0.660*** **	**0.216*** **	**-0.443*** **
	(0.000)	(0.000)	(0.002)	(0.000)	(0.373)	(0.000)	(0.000)	(0.000)	(0.000)
HML	**0.246*** **	**-0.212** **	**-0.458*** **	0.117	-0.105	-0.222	**0.129** **	**0.247*** **	**0.118*** **
	(0.010)	(0.022)	(0.005)	(0.333)	(0.253)	(0.205)	(0.011)	(0.000)	(0.000)
RMW	**-0.202***	**-0.343** **	-0.141	**-0.316***	-0.167	0.149	-0.059	**0.139** **	**0.198*** **
	(0.092)	(0.002)	(0.466)	(0.066)	(0.149)	(0.494)	(0.249)	(0.004)	(0.000)
CMA	**-0.345** **	0.188	**0.533** **	-0.200	**0.395*** **	**0.595** **	**-0.166*** **	0.065	**0.231*** **
	(0.028)	(0.143)	(0.034)	(0.336)	(0.003)	(0.039)	(0.009)	(0.297)	(0.000)
ALPHA	**-0.007*** **	0.001	**0.008** **	**-0.006***	0.001	**0.008***	-0.001	**-0.001***	-0.000
	(0.003)	(0.454)	(0.019)	(0.051)	(0.603)	(0.072)	(0.336)	(0.088)	(0.634)
Adjusted R^2	0.871	0.865	0.248	0.779	0.724	0.342	0.957	0.960	0.721

*** p≤0.01; **p≤0.05; *p≤0.1

Second, it facilitates **disentangling ESG effects**. By examining whether the green momentum strategy retains alpha or exhibits significant coefficients for other factors even after accounting for WML, it becomes possible to evaluate the unique contribution of ESG considerations. If these additional effects persist, they indicate that ESG factors enhance the results in a way that goes beyond merely capturing the traditional momentum effect.

The market risk premium becomes insignificant, indicating that the returns of this strategy are not primarily driven by broad market movements but rather by specific factors beyond systemic market risk. The Small-Minus-Big (SMB) factor remains significant, although its coefficient decreases to **-0.573**. This decline reflects the influence of other factors, particularly the momentum factor, which absorbs part of SMB's explanatory power.

The High-Minus-Low (HML) factor turns significantly positive with a coefficient of **0.290**, a notable change from its previously negative insignificance in the Fama-French 5-factor model. This shift indicates that when momentum (WML) is modelled, its effect is isolated, revealing HML's true contribution. It suggests that some value stocks with high ESG scores may exhibit momentum-like behaviour. Additionally, multicollinearity tests confirmed that the factors remain distinct and interpretable.

The Robust-Minus-Weak (RMW) factor gains significance at the 1% level, with a coefficient of **0.427**, highlighting the importance of profitability in the green momentum strategy. Although value stocks are typically found in sectors such as energy, banking, and utilities, areas often associated with poorer ESG performance, research by Stagnol, Lopez, Roncalli, and Taillardat (2021) suggests that value portfolios can still achieve high ESG scores, particularly when stock

picking is prioritized. Conversely, the Conservative-Minus-Aggressive (CMA) factor shows no significant explanatory power, indicating that the effects previously captured by CMA are now accounted for by the momentum factor.

The Winners-Minus-Losers (WML) factor, which captures the momentum effect, is highly significant at the 1% level with a coefficient of **1.298**. The substantial magnitude of this coefficient reaffirms that momentum is a dominant factor in explaining the strategy's performance, irrespective of ESG criteria.

In the Fama-French 6-factor model, the disappearance of alpha suggests that the green momentum strategy is entirely explained by the included factors, particularly WML, and does not yield excess returns. This indicates that the strategy's returns are attributable to traditional risk factors rather than a unique source of alpha. Furthermore, the increase in adjusted R^2 to 0.728 signifies that the Fama-French 6-factor model provides a significantly better fit, effectively capturing both traditional risk factors and momentum-driven effects, thereby demonstrating the strategy's reliance on well-established factors.

Unlike traditional momentum, the green momentum strategy involves more complex dynamics by integrating additional explanatory factors. While standard momentum is mainly influenced by the WML (Winners Minus Losers) and SMB (Small Minus Big) factors, the green strategy also demonstrates significant exposure to the RMW (Robust Minus Weak) and HML (High Minus Low) factors. This indicates that considerations of profitability and value are essential in shaping sustainable returns.

The pure ESG strategy, in contrast, emphasizes factors such as SMB, HML, RMW, and CMA, while WML is found to be insignificant. This indicates that the pure ESG strategy focuses more on fundamental ESG characteristics rather than on momentum-driven dynamics. This distinction highlights that the green momentum effectively integrates traditional momentum principles with ESG factors, while the pure ESG strategy does not depend on momentum as a driving force.

6.7 q^5 Global Factors Regression

In ***Table 5***, the results from the q^5 factor model for the green momentum strategy are consistent with the ones from the FF5 model, but with a notable difference: the profitability factor (ROE) plays a much more significant role, with a coefficient of **0.824**. This suggests that profitability is an important explanatory factor for the strategy's returns. Importantly, in q^5, ROE tends to capture both profitability and momentum dynamics, meaning it reflects aspects of both the

firm's financial health and its momentum characteristics. In other words, firms with high ROE are also likely to benefit from momentum.

Additionally, the expected earnings factor shows a positive correlation with the strategy, reinforcing the idea that green momentum stocks are likely to have favourable growth prospects.

The absence of significant alpha in the q^5 model can be understood as a result of the model's broader factor coverage, which captures the key drivers behind green momentum returns in other dimensions, reducing the likelihood of excess returns after accounting for these factors.

Table 4: Fama French 6 Factors Regressions (12/1)

	Momentum			Green Momentum			Pure ESG		
	Short	Long	Long - Short	Short	Long	Long - Short	Short	Long	Long - Short
RMRF	**1.167*****	**1.196*****	0.029	**1.188*****	**1.119*****	-0.070	**0.996*****	**1.002*****	0.006
	(0.000)	(0.000)	(0.588)	(0.000)	(0.000)	(0.323)	(0.000)	(0.000)	(0.762)
SMB	**0.890*****	**0.709*****	**-0.181***	**0.782*****	**0.210****	**-0.573*****	**0.638*****	**0.186*****	**-0.452*****
	(0.000)	(0.000)	(0.069)	(0.000)	(0.022)	(0.000)	(0.000)	(0.000)	(0.000)
HML	-0.053	-0.023	0.030	**-0.233***	0.057	**0.290****	**0.099***	**0.206*****	**0.107*****
	(0.497)	(0.719)	(0.732)	(0.037)	(0.433)	(0.020)	(0.089)	(0.000)	(0.002)
RMW	**-0.364*****	**-0.241*****	0.123	**-0.506*****	-0.079	**0.427****	-0.075	**0.116****	**0.192*****
	(0.000)	(0.005)	(0.315)	(0.000)	(0.429)	(0.004)	(0.140)	(0.012)	(0.000)
CMA	-0.041	-0.004	0.037	0.155	**0.230****	0.075	**-0.135***	**0.107***	**0.242*****
	(0.689)	(0.957)	(0.748)	(0.313)	(0.032)	(0.664)	(0.051)	(0.095)	(0.000)
MOM	**-0.759*****	**0.479*****	**1.238*****	**-0.887*****	**0.412*****	**1.298*****	**-0.076****	**-0.104*****	-0.028
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.020)	(0.000)	(0.306)
ALPHA	**-0.004****	-0.001	0.003	-0.003	-0.001	0.002	-0.001	-0.001	-0.000
	(0.012)	(0.576)	(0.107)	(0.274)	(0.732)	(0.458)	(0.531)	(0.253)	(0.748)
Adjusted R^2	0.953	0.929	0.808	0.880	0.784	0.728	0.959	0.965	0.721

*** p≤0.01; **p≤0.05; *p≤0.1

Table 5: q^5 Global Factors Regressions (12/1)

	Momentum			Green Momentum			Pure ESG		
	Short	Long	Long - Short	Short	Long	Long - Short	Short	Long	Long - Short
R_MKT	**1.208*****	**1.005*****	**-0.204****	**1.221*****	**0.994*****	**-0.227****	**0.958*****	**1.019*****	**0.061****
	(0.000)	(0.000)	(0.027)	(0.000)	(0.000)	(0.019)	(0.000)	(0.000)	(0.017)
R_ME	**0.717*****	**0.655*****	-0.063	**0.523*****	0.149	**-0.374***	**0.501*****	0.075	**-0.425*****
	(0.000)	(0.000)	(0.737)	(0.001)	(0.249)	(0.063)	(0.000)	(0.114)	(0.000)
R_IA	**-0.282****	-0.144	0.138	**-0.358****	0.160	**0.518****	**-0.206*****	**0.149****	**0.356*****
	(0.012)	(0.197)	(0.485)	(0.021)	(0.153)	(0.011)	(0.000)	(0.017)	(0.000)
R_ROE	**-0.634*****	-0.067	**0.568****	**-0.596*****	0.228	**0.824*****	-0.075	**0.101***	**0.176*****
	(0.000)	(0.563)	(0.014)	(0.001)	(0.113)	(0.000)	(0.130)	(0.088)	(0.005)
R_EG	**-0.434*****	-0.067	0.367	**-0.644*****	-0.199	**0.445***	**-0.322*****	**-0.352*****	-0.031
	(0.003)	(0.630)	(0.154)	(0.002)	(0.188)	(0.077)	(0.000)	(0.000)	(0.658)
ALPHA	-0.003	0.001	0.004	-0.002	0.000	0.002	0.001	-0.000	-0.001
	(0.275)	(0.527)	(0.322)	(0.629)	(0.851)	(0.651)	(0.480)	(0.948)	(0.452)
Adjusted R^2	0.892	0.857	0.272	0.812	0.732	0.415	0.962	0.956	0.650

*** p≤0.01; **≤0.05; *p≤0.1

7. Robustness Analysis

7.1 Formation and Holding Period Dynamics

The robustness of the methodology was evaluated by testing different formation periods (3, 6, 9, 12, 24, and 36 months) and holding periods (1, 3, 6, 9, and 12 months), as detailed in **Appendices D to I**. As the holding period increases, the profitability of both momentum and green momentum strategies tends to decrease. This decline is largely due to increasing returns from the short-leg portfolios, offsetting gains from the long leg, ultimately reducing overall performance. Furthermore, longer holding periods are associated with decreased volatility, as the strategy captures a wider range of price movements, smoothing out short-term fluctuations. Research by Jegadeesh and Titman (1993) shows that shorter holding periods in momentum strategies yield higher returns by capturing price trends before mean reversion occurs. Lee and Swaminathan (2000) further emphasize that shorter periods effectively exploit momentum gains while reducing the risks associated with reversal pressures. These findings highlight the importance of balancing holding and formation periods to optimize the outcomes. While longer periods may reduce volatility, they often decrease profitability and weaken the strategy's risk-return profile.

Regarding formation periods, Bird and Whitaker (2003) indicate that both formation and holding periods significantly influence momentum performance, with intermediate formation periods (e.g., 6-12 months) proving to be the most effective. This conclusion aligns with the provided results and broader literature: short formation periods (e.g., 3 months) tend to be too sensitive to market noise and may fail to capture sustained trends, while longer formation periods (e.g., over 12 months) risk incorporating outdated information, which diminishes the strategy’s effectiveness. Intermediate formation periods strike a balance by identifying persistent trends while avoiding the early reversals that are commonly associated with shorter periods.

7.2 January effect

The strategies' resilience was evaluated by excluding January from the dataset to account for the well-documented "January effect." This phenomenon, as described by Jegadeesh & Titman (1993) and George & Hwang (2004), suggests that stock prices, particularly those of underperforming stocks, often rebound in January after being suppressed in December due to tax-loss selling.

The exclusion of January resulted in improved outcomes (***Appendix C***). Specifically, returns increased, volatility decreased, and sharpe ratios moved positively across all strategies. This enhancement was primarily driven by the reduced performance of the short portfolio, which is disproportionately influenced by the January effect. By removing this month, the temporary rebound that artificially inflates the returns of the short leg was eliminated, aligning with the findings in the existing literature. Despite these improvements, the returns for green momentum and pure ESG remained statistically insignificant, showing no meaningful deviation from zero. Referring to ***Table 6***, excluding January, manifests that the factors remained significant in explaining green momentum. This persistence highlights the model's robustness, demonstrating its validity and stability. Furthermore, the results confirm that the model is not influenced by seasonal biases, such as the January effect, reinforcing its reliability in capturing fundamental return drivers.

Table 6: Fama French 6 Factors Regressions (12/1) – Excluding January

	Momentum			Green Momentum			Pure ESG		
	Short	Long	Long - Short	Short	Long	Long - Short	Short	Long	Long - Short
RMRF	**1.160*** **	**1.195*** **	0.035	**1.189*** **	**1.130*** **	-0.058	**1.000*** **	**1.005*** **	0.005
	(0.000)	(0.000)	(0.519)	(0.000)	(0.000)	(0.432)	(0.000)	(0.000)	(0.813)
SMB	**0.842*** **	**0.722*** **	-0.120	**0.773*** **	**0.250** **	**-0.524*** **	**0.631*** **	**0.189*** **	**-0.441*** **
	(0.000)	(0.000)	(0.203)	(0.000)	(0.015)	(0.000)	(0.000)	(0.000)	(0.000)
HML	-0.027	-0.020	0.007	**-0.229** **	0.064	**0.293** **	**0.133** **	**0.224*** **	**0.091** **
	(0.709)	(0.779)	(0.932)	(0.044)	(0.403)	(0.016)	(0.020)	(0.000)	(0.019)
RMW	**-0.401*** **	**-0.232** **	0.169	**-0.522*** **	-0.061	**0.461*** **	-0.057	**0.129*** **	**0.186*** **
	(0.000)	(0.012)	(0.174)	(0.000)	(0.571)	(0.003)	(0.291)	(0.008)	(0.001)
CMA	-0.018	0.005	0.023	0.145	**0.217***	0.072	**-0.137** **	**0.124***	**0.260*** **
	(0.866)	(0.955)	(0.848)	(0.363)	(0.061)	(0.687)	(0.043)	(0.055)	(0.000)
MOM	**-0.811*** **	**0.501*** **	**1.312*** **	**-0.939*** **	**0.472*** **	**1.411*** **	-0.041	**-0.080*** **	-0.039
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.241)	(0.004)	(0.259)
ALPHA	**-0.003** **	-0.001	0.002	-0.003	-0.002	0.001	-0.001	**-0.001***	0.000
	(0.030)	(0.396)	(0.269)	(0.279)	(0.311)	(0.765)	(0.178)	(0.090)	(0.963)
Adjusted R^2	0.952	0.927	0.800	0.873	0.793	0.710	0.958	0.965	0.686

*** p≤0.01; **p≤0.05; *p≤0.1

7.3 Period Split

The sample was divided into two subperiods: January 2010 to December 2017, characterized by lower market volatility, and January 2018 to September 2024, marked by higher volatility. In the first subperiod, the pure momentum strategy underperformed due to superior results from losing stocks, which negatively impacted returns. The green momentum strategy showed slight improvement, while pure ESG strategies declined as a result of strong returns from low-ESG stocks. In the second subperiod, the pure momentum strategy strengthened, thanks to weaker

returns from short positions, which benefited the zero-cost portfolio. However, green momentum declined as increased volatility outweighed the benefits of ESG considerations. Conversely, pure ESG strategies improved, supported by weaker performance from low-ESG stocks. Overall, the results remained insignificant regardless of the period.

This analysis aligns with the findings of Wang, K. Q., and Xu, J. (2015), which suggest that the time variation in momentum profits arises mainly from loser stocks rather than winner stocks. Their study highlights that the predictability of momentum profits stems largely from the behavior of losing stocks, which tend to deviate more significantly across different market conditions. Integrating ESG factors into the strategy helps smooth changes in the short leg, reducing its overall impact on the portfolio. This effect becomes particularly evident during periods of high market volatility when investors aggressively price risks, leading to sharper sell-offs in stocks. In the green momentum strategy, the short leg specifically targets underperforming stocks with low ESG scores. By focusing on already vulnerable stocks, the strategy naturally mitigates extreme volatility. As a result, ESG integration produces more stable relative performance compared to traditional momentum strategies, which may include more speculative stocks.

Table 7 demonstrates that during periods of lower market volatility, the green momentum is predominantly driven by the size and momentum factors. The size factor exhibits a negative coefficient of **-0.405**, while the momentum explains nearly the entire strategy's dynamics, with a coefficient of **1.472**. However, as shown in ***Table 8***, the explanatory framework evolves during periods of higher volatility. While size and momentum remain significant, additional factors such as HML (value), with a coefficient of **0.317**, and RMW (profitability), with a coefficient of **0.352**, emerge as critical in explaining the performance of the green momentum. In contrast, the pure momentum strategy relies solely on size and momentum, with the size factor becoming relevant only in high-volatility conditions.

The heightened significance of the HML and RMW factors in the green momentum during volatile periods highlights the interaction between ESG attributes and fundamental market factors. ESG criteria often prioritize stocks with characteristics such as stability, profitability, and sustainable practices, which closely align with the value and profitability dimensions represented by the HML and RMW factors. This alignment becomes particularly evident in turbulent market environments, where ESG considerations act as a stabilizing force, enhancing the explanatory power of these factors. Consequently, the green momentum distinguishes itself

from the pure momentum under volatile conditions, emphasizing the added value of incorporating ESG attributes into investment strategies.

Table 7: Fama French 6 Factors Regressions (12/1) – 2010/2017

	Momentum			Green Momentum			Pure ESG		
	Short	Long	Long - Short	Short	Long	Long - Short	Short	Long	Long - Short
RMRF	**1.064*** **	**1.159*** **	0.095	**1.244*** **	**1.184*** **	-0.060	**1.048*** **	**0.998*** **	-0.050
	(0.000)	(0.000)	(0.207)	(0.000)	(0.000)	(0.704)	(0.000)	(0.000)	(0.191)
SMB	**0.724*** **	**0.667*** **	-0.057	**0.411** **	0.006	**-0.405** **	**0.358*** **	0.008	**-0.349*** **
	(0.000)	(0.000)	(0.599)	(0.024)	(0.975)	(0.046)	(0.000)	(0.821)	(0.000)
HML	**-0.239** **	-0.103	0.136	**-0.379***	-0.285	0.094	-0.047	-0.048	-0.001
	(0.020)	(0.319)	(0.276)	(0.065)	(0.194)	(0.677)	(0.516)	(0.327)	(0.987)
RMW	**-0.278** **	**-0.220***	0.058	-0.264	-0.000	0.264	-0.030	0.008	0.038
	(0.034)	(0.059)	(0.732)	(0.345)	(1.000)	(0.383)	(0.704)	(0.884)	(0.541)
CMA	0.004	-0.101	-0.105	**0.661** **	**0.532** **	-0.129	0.063	**0.217*** **	**0.154** **
	(0.977)	(0.465)	(0.570)	(0.013)	(0.032)	(0.712)	(0.442)	(0.001)	(0.045)
MOM	**-0.951*** **	**0.396*** **	**1.347*** **	**-1.156*** **	**0.316** **	**1.472*** **	**-0.105***	**-0.097*** **	0.008
	(0.000)	(0.000)	(0.000)	(0.000)	(0.019)	(0.000)	(0.056)	(0.000)	(0.865)
ALPHA	-0.002	-0.001	0.001	-0.005	-0.001	0.004	-0.000	-0.000	-0.000
	(0.237)	(0.611)	(0.616)	(0.200)	(0.755)	(0.348)	(0.869)	(0.636)	(0.915)
Adjusted R^2	0.943	0.900	0.808	0.820	0.639	0.640	0.938	0.967	0.544

*** p≤0.01; ** p≤0.05; * p≤0.1

Table 8: Fama French 6 Factors Regressions (12/1) – 2018/2024

	Momentum			Green Momentum			Pure ESG		
	Short	Long	Long - Short	Short	Long	Long - Short	Short	Long	Long - Short
RMRF	**1.255*** **	**1.234*** **	-0.021	**1.228*** **	**1.119*** **	-0.109	**1.007*** **	**1.010*** **	0.003
	(0.000)	(0.000)	(0.796)	(0.000)	(0.000)	(0.217)	(0.000)	(0.000)	(0.908)
SMB	**1.098*** **	**0.754*** **	**-0.343***	**1.143*** **	**0.314*** **	**-0.830*** **	**0.836*** **	**0.269*** **	**-0.568*** **
	(0.000)	(0.000)	(0.057)	(0.000)	(0.009)	(0.000)	(0.000)	(0.000)	(0.000)
HML	-0.022	0.005	0.027	**-0.168***	**0.149***	**0.317** **	**0.121*** **	**0.249*** **	**0.128*** **
	(0.788)	(0.948)	(0.825)	(0.081)	(0.079)	(0.012)	(0.007)	(0.000)	(0.002)
RMW	**-0.403*** **	**-0.285** **	0.118	**-0.525*** **	-0.173	**0.352***	**-0.098** **	0.096	**0.194*** **
	(0.001)	(0.021)	(0.543)	(0.000)	(0.143)	(0.063)	(0.048)	(0.121)	(0.009)
CMA	-0.058	0.007	0.065	-0.073	0.125	0.198	**-0.181** **	**0.115***	**0.296*** **
	(0.663)	(0.948)	(0.687)	(0.676)	(0.284)	(0.331)	(0.011)	(0.093)	(0.000)
MOM	**-0.595*** **	**0.538*** **	**1.132*** **	**-0.595*** **	**0.492*** **	**1.087*** **	0.007	**-0.104*** **	**-0.111*** **
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.866)	(0.002)	(0.002)
ALPHA	**-0.006** **	0.000	**0.006***	-0.002	0.001	0.004	-0.002	-0.001	0.001
	(0.022)	(0.996)	(0.093)	(0.509)	(0.549)	(0.384)	(0.158)	(0.332)	(0.678)
Adjusted R^2	0.968	0.940	0.820	0.938	0.887	0.830	0.984	0.978	0.827

*** p≤0.01; ** p≤0.05; * p≤0.1

7.4 Break-Even Transaction Costs

Accurately estimating transaction costs presents a significant challenge due to their variability across exchanges, brokers, trade sizes, and market conditions. Several factors add to this complexity, including bid-ask spreads, brokerage fees, market impact for large trades, and

regional regulations, making the precise calculation of transaction costs difficult without detailed data.

To address this issue, a break-even analysis was performed rather than directly computing transaction costs. For each leg of the strategy, both long and short, turnover was evaluated by determining which stocks entered or exited the portfolio each month. By dividing the average monthly return by the turnover, we established a transaction cost threshold that would entirely offset the strategy's returns for each month. After calculating these values for all months in the sample period, we derived an overall average break-even transaction cost. This figure offers a representative threshold for the costs that the strategy can absorb while maintaining profitability.

The analysis yielded the following conclusions: For the pure momentum, an average transaction cost of **12.3%** would negate the gains from the short leg, while a cost of **8%** would offset the positive returns from the long leg. When introducing ESG into the strategy, the breakeven costs remained relatively similar, with figures of **12.1%** for the short leg and **7.4%** for the long leg. In contrast, the pure ESG s revealed significantly higher breakeven costs due to lower turnover each month, indicating fewer stocks were entering or exiting the portfolio. Specifically, the short leg had a breakeven cost of **91.9%**, and the long leg had a breakeven cost of **183.2%**.

Table 9: Break-Even Transaction Costs (12/1)

	Momentum			Green Momentum			Pure ESG		
	Short	Long	Long - Short	Short	Long	Long - Short	Short	Long	Long - Short
Break Even Transaction Costs	12.3%	8.0%	20.3%	12.1%	7.4%	19.5%	91.9%	183.2%	275.1%

8. Limitations and Future Research

The limitations of this study primarily stem from data selection, methodology, and inherent issues with ESG scoring. The dataset is restricted to U.S.-traded ordinary stocks reported in U.S. dollars, which affects the generalizability of the findings, especially regarding ESG and green investment strategies. Regional differences in market conditions, regulatory frameworks, and ESG integration (Capelle-Blancard & Monjon, 2014; Lins et al., 2017) indicate that the dynamics observed in the U.S. may not be applicable globally. Additionally, the exclusion of

other asset classes, such as green bonds or ETFs limits the analysis. These instruments could provide valuable insights into the performance of ESG and momentum strategies across a broader financial ecosystem. Furthermore, focusing on green momentum may produce different results when applied to other regions and financial instruments. For instance, emerging markets, with their unique ESG regulatory environments, may experience different dynamics that impact momentum outcomes (Giese et al., 2019). Expanding the scope to include diverse regions and asset classes would offer a more comprehensive understanding of global performance.

The analysis commenced in January 2010, with only 642 out of an average of 1,478 companies reporting available ESG scores at that time. The limited availability of ESG data prior to 2015, as noted by Berg, Kölbel, and Rigobon (2020), posed challenges in making robust comparisons or tracking the performance of ESG-related strategies over an extended period. This data scarcity in the early years constrained the analysis, making it difficult to fully explore the long-term dynamics of ESG-focused strategies or their behaviour across varying market conditions. Furthermore, the issue of limited ESG data availability during the initial years aligns with the observations of Eccles and Klimenko (2019), who highlight the significant expansion of ESG disclosures over the past decade. This growth has been driven by rising investor demand and evolving regulatory requirements, which have enhanced the accessibility and reliability of ESG metrics in recent years.

The classification of stocks into the top 30% and bottom 30% based on ESG scores, rather than utilizing more granular deciles, introduced limitations to the precision of the analysis. This broader segmentation was chosen to mitigate the risk of smaller sample sizes, as using deciles would have significantly reduced the number of stocks included in the portfolio each month. However, this approach meant that some companies in the top 30% might not represent the highest ESG performers, potentially diminishing the effectiveness of integrating ESG factors into the investment strategy. This methodology differs from studies such as Nagy et al. (2015), which analysed ESG momentum, measuring year-over-year changes in ESG scores, to provide a more dynamic perspective on ESG performance. In contrast, this study relied on absolute ESG scores to avoid complications arising from instances of zero changes in ESG scores during the formation periods. This decision was particularly relevant given the monthly overlapping formation periods employed for the green momentum, which required consistency in data handling.

ESG scoring presents several challenges that affect the reliability of this study's findings. One major issue is that ESG scores often emphasize internal company processes rather than the real-world impact of a company's products and services (Kotsantonis & Serafeim, 2019). Furthermore, ESG ratings lack consistency across providers due to variations in methodologies and data collection practices, leading to significant discrepancies in a company's ratings depending on the provider (Chatterji et al., 2016). This inconsistency is further compounded by the use of estimates when actual data is unavailable, particularly for smaller or emerging market companies. Additionally, there is a bias favouring larger, developed-market companies, as they are typically better equipped to meet ESG reporting standards. Consequently, these firms tend to achieve higher scores, which limits the diversity of companies represented and skews results in favour of well-established organizations.

These limitations highlight the need for better standardization and transparency in ESG data to ensure more accurate and equitable assessments across different company sizes and sectors.

9. Final Conclusions

This study explores the potential value-added of incorporating ESG criteria into momentum investment strategy. By leveraging the foundational framework of Jegadeesh and Titman (1993), this research expands the traditional zero-cost momentum strategy with ESG scores, aiming to achieve not just strong returns but also sustainable outcomes that consider environmental, social, and governance factors.

The analysis focuses on combining momentum and ESG for ordinary stocks traded on U.S. markets. Traditional momentum and pure ESG strategies serve as benchmarks to understand the impact of including ESG metrics. Previous research offers mixed evidence regarding the relationship between ESG scores and abnormal returns. Studies such as Derwall et al. (2005) and Kempf & Osthoff (2007) report positive alphas in sustainability-screened portfolios, while others, including Diltz (1995) and Halbritter & Dorfleitner (2015), find no significant relationship.

To examine whether ESG scores influence risk-adjusted returns, this study applies established performance evaluation methods and multifactor models. Portfolios were constructed as follows: two equally weighted portfolios, one comprising stocks in the top 10% by returns with the top 30% ESG scores, and the other in the bottom 10% by returns with the bottom 30% ESG scores. Additionally, a long-short portfolio was created, taking a long position in the top metrics

and a short position in the worst metrics. These portfolios were analysed over the period from January 2010 to September 2024.

The empirical results indicate that incorporating ESG criteria into a momentum strategy produces statistically insignificant outcomes. However, the broad evidence presented in this paper provides valuable insights. Notably, green momentum closely mirrors the behaviour of pure momentum, as evidenced by similar results. While the annualized average returns slightly increase with ESG inclusion, this comes at the cost of heightened volatility, which undermines the statistical significance of the outcomes. Examining a pure ESG strategy, where stock selection is based solely on ESG scores without considering returns, reveals substantially lower volatility. This suggests that the observed increase in volatility in the green momentum strategy may not stem directly from ESG dynamics. Instead, it likely arises from reduced portfolio diversification and restricted investment opportunities, as noted by Revelli and Viviani (2015). ESG screening excludes stocks in industries classified as unsustainable, such as oil, gas, mining, gambling, tobacco, and alcohol, thereby limiting the pool of investable assets. This reduced diversification can be detrimental, as a well-diversified portfolio generally minimizes risk (Markowitz, 1952).
A drawdown analysis further highlights the trade-offs involved. The green momentum strategy experiences slightly higher drawdowns compared to pure momentum strategies. This observation reinforces the idea that ESG introduces additional volatility and exposure, albeit to a limited extent. These findings underscore the importance of balancing sustainability goals with diversification and risk management in ESG-focused investment strategies.

When examining the factor exposures, two factors consistently emerge as significant: Size (SMB) and Investment (CMA). The size factor shows a negative relationship, meaning larger firms tend to outperform smaller firms, which aligns with the typical behaviour of momentum strategies that favour established companies. Additionally, the investment factor has a positive relationship, suggesting that conservative firms with lower investment rates outperform more aggressive ones. When considering the strategy performance, we find that the Fama-French 3-Factor (FF3) and 5-Factor (FF5) models yield significant alpha, demonstrating that the strategy outperforms the market after accounting for common risk factors. However, when the q^5 factor model is introduced, this alpha becomes insignificant. This suggests that the q^5 factor model, which focuses on profitability and investment factors, captures much of the performance

explained by other models, reducing the additional explanatory power seen in the earlier regressions.

A key part of this analysis is the inclusion of the Momentum (MOM) factor in the Fama-French 6-Factor (FF6) model. The green momentum is indeed captured by the momentum factor, as expected. However, in contrast to traditional momentum strategies, two additional factors, HML (Value) and RMW (Profitability), play a significant role in explaining the strategy's returns. These factors suggest that the strategy leans toward value and profitable stocks, which can be partly attributed to the ESG inclusion. Specifically, ESG-compliant firms tend to be undervalued or exhibit higher profitability, which aligns with the characteristics of stocks selected by this method. Despite the lack of alpha when combining momentum and ESG, as confirmed by the findings of Halbritter and Dorfleitner (2015), the analysis suggests that joining ESG factors with momentum does lead to the emergence of additional explanatory factors. This highlights that the green momentum strategy is shaped by factors beyond simple momentum dynamics. The strategy's returns can be improved by enhancing the portfolio's exposure to the Value (HML) and Profitability (RMW) factors. This can be achieved by selecting stocks that exhibit momentum characteristics while also aligning with these factors. Reallocating the portfolio to emphasize sectors historically linked to value and profitability could further optimize performance. Additionally, focusing on undervalued stocks that are ESG-compliant and demonstrate strong profitability metrics offers an opportunity to balance financial performance with sustainable investing objectives.

For future research, it would be valuable to examine how ESG factors affect momentum strategies under different market conditions. Expanding the analysis to cover longer time periods could offer insights into the long-term effects of ESG integration, especially in diverse economic environments. Additionally, exploring the impact of sustainable metrics across different geographic regions could enhance our understanding of how ESG criteria influence investment strategies globally. A broader approach, incorporating various ESG rating sources, could also provide a more comprehensive and reliable assessment of the role ESG plays in shaping investment outcomes.

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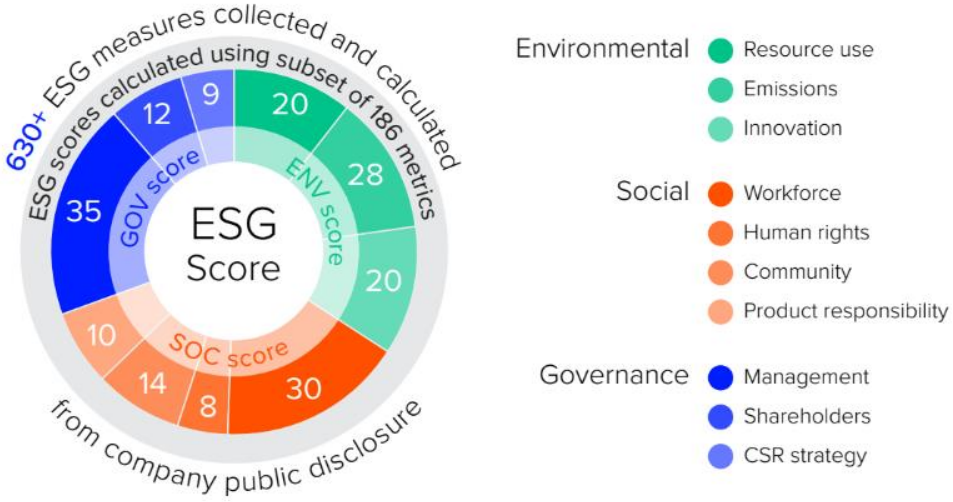
Appendices

Appendix A: ESG Metrics



Source: (LSEG Data & Analytics)

Appendix B: ESG Classification

Score range	Grade	Description
0.0 <= score <= 0.083333	D -	'D' score indicates poor relative ESG performance and insufficient degree of transparency in reporting material ESG data publicly.
0.083333 < score <= 0.166666	D	
0.166666 < score <= 0.250000	D +	
0.250000 < score <= 0.333333	C -	'C' score indicates satisfactory relative ESG performance and moderate degree of transparency in reporting material ESG data publicly.
0.333333 < score <= 0.416666	C	
0.416666 < score <= 0.500000	C +	
0.500000 < score <= 0.583333	B -	'B' score indicates good relative ESG performance and above-average degree of transparency in reporting material ESG data publicly.
0.583333 < score <= 0.666666	B	
0.666666 < score <= 0.750000	B +	
0.750000 < score <= 0.833333	A -	'A' score indicates excellent relative ESG performance and high degree of transparency in reporting material ESG data publicly.
0.833333 < score <= 0.916666	A	
0.916666 < score <= 1	A +	

ESG laggards

ESG leaders

Source: (LSEG Data & Analytics)

Appendix C: Portfolios: 12-Month Formation and 1-Month Holding – Excluding January

	Momentum			Green Momentum			Pure ESG		
	Short	Long	Long - Short	Short	Long	Long - Short	Short	Long	Long - Short
Mean	0.61%	**11.67%****	**11.06%***	0.24%	**11.55%****	11.30%	**7.89%***	**9.37%****	1.83%
T-stat	0.56	2.30	1.85	0.54	2.46	1.37	1.78	2.28	0.80
(p-value)	(0.57)	(0.02)	(0.07)	(0.59)	(0.02)	(0.17)	(0.08)	(0.02)	(0.43)
Stdev	27.22%	20.20%	16.85%	28.83%	18.19%	21.27%	18.64%	16.73%	6.00%
Max	34.40%	20.66%	12.96%	33.94%	20.91%	16.41%	17.47%	17.17%	5.33%
Min	-29.97%	-20.71%	-18.11%	-28.56%	-14.58%	-25.16%	-23.93%	-21.53%	-4.39%
Sharpe	0.02	0.58	0.66	0.01	0.63	0.53	0.42	0.58	0.31
AQR Correlation			89.11%			81.42%			11.42%

*** p≤0.01; ** p≤0.05; * p≤0.1

Appendix D: Portfolios: 3-Month Formation and K-Month Holding

	Momentum			Green Momentum			Pure ESG		
	Short	Long	Long - Short	Short	Long	Long - Short	Short	Long	Long - Short
Mean	5.10%	**9.81%****	4.71%	3.59%	**12.32%*****	8.73%	**9.4%****	**10.68%*****	1.28%
T-stat	1.22	2.10	0.90	1.01	2.57	1.31	2.13	2.60	0.42
(p-value)	(0.22)	(0.04)	(0.37)	(0.31)	(0.01)	(0.19)	(0.03)	(0.01)	(0.68)
Stdev	25.73%	21.07%	14.08%	26.92%	20.29%	19.14%	19.53%	17.07%	6.57%
Max	23.03%	24.65%	14.08%	21.90%	24.13%	18.02%	18.49%	17.64%	6.97%
Min	-24.78%	-22.26%	14.08%	-23.86%	-20.76%	-16.11%	-23.43%	-21.70%	-5.23%
Sharpe	0.20	0.47	0.14	0.13	0.61	0.46	0.48	0.63	0.20
Mean	5.60%	**10.51%****	4.91%	4.77%	**9.63%****	4.86%	**9.16%****	**10.61%*****	1.45%
T-stat	1.33	2.26	1.58	1.20	2.25	0.87	2.12	2.59	0.57
(p-value)	(0.18)	(0.02)	(0.11)	(0.23)	(0.03)	(0.39)	(0.04)	(0.01)	(0.57)
Stdev	23.50%	20.38%	9.37%	24.19%	18.51%	14.72%	19.14%	17.01%	6.32%
Max	23.23%	20.33%	11.99%	20.39%	19.85%	16.18%	18.19%	17.60%	6.83%
Min	-23.98%	-23.57%	-8.50%	-22.47%	-24.59%	-12.83%	-23.31%	-21.62%	-4.90%
Sharpe	0.24	0.52	0.52	0.20	0.52	0.33	0.48	0.62	0.23
Mean	6.93%	**9.45%****	2.52%	6.65%	**9.11%****	2.46%	**9.16%****	**10.59%*****	1.43%
T-stat	1.59	2.09	1.36	1.53	2.18	0.50	2.14	2.59	0.60
(p-value)	(0.11)	(0.04)	(0.18)	(0.13)	(0.03)	(0.62)	(0.04)	(0.01)	(0.55)
Stdev	21.67%	20.28%	5.78%	22.32%	18.13%	11.15%	18.85%	16.99%	6.16%
Max	21.60%	18.39%	5.70%	19.91%	17.12%	11.82%	17.69%	17.59%	6.64%
Min	-23.73%	-22.52%	-5.29%	-22.68%	-20.62%	-11.08%	-23.05%	-21.61%	-5.38%
Sharpe	0.32	0.47	0.44	0.30	0.50	0.22	0.49	0.62	0.23
Mean	**6.97%***	**9.74%****	**2.78%****	6.82%	**9.52%****	2.70%	**9.13%****	**10.55%*****	1.42%
T-stat	1.64	2.17	2.02	1.59	2.29	0.74	2.15	2.58	0.64
(p-value)	(0.10)	(0.03)	(0.05)	(0.11)	(0.02)	(0.46)	(0.03)	(0.01)	(0.52)
Stdev	20.68%	19.85%	4.57%	21.19%	17.82%	9.56%	18.57%	16.97%	6.01%
Max	20.86%	17.71%	3.16%	19.23%	16.59%	8.42%	17.31%	17.52%	6.46%
Min	-23.01%	-22.29%	-4.70%	-22.09%	-20.37%	-9.14%	-22.52%	-21.49%	-5.26%
Sharpe	0.34	0.49	0.61	0.32	0.53	0.28	0.49	0.62	0.24
Mean	**8.04%***	**9.22%****	1.18%	**7.41%***	**8.74%****	1.33%	**9.18%****	**10.56%*****	1.39%
T-stat	1.86	2.09	1.14	1.73	2.14	0.33	2.18	2.59	0.66
(p-value)	(0.06)	(0.04)	(0.26)	(0.09)	(0.03)	(0.74)	(0.03)	(0.01)	(0.51)
Stdev	19.93%	19.65%	3.49%	20.38%	17.72%	8.38%	18.35%	16.92%	5.84%
Max	19.78%	17.75%	2.63%	18.54%	17.28%	7.80%	17.04%	17.25%	5.99%
Min	-22.37%	-22.19%	-3.67%	-22.07%	-19.85%	-5.68%	-22.28%	-21.43%	-4.75%
Sharpe	0.40	0.47	0.34	0.36	0.49	0.16	0.50	0.62	0.24

*** p≤0.01; **p≤0.05; *p≤0.1

Appendix E: Portfolios: 6-Month Formation and K-Month Holding

	Momentum			Green Momentum			Pure ESG		
	Short	Long	Long - Short	Short	Long	Long - Short	Short	Long	Long - Short
Mean	4.07%	**12.93%*** **	**8.86%***	2.43%	**11.32%****	8.89%	**10.05%****	**11.68%*** **	1.63%
T-stat	1.06	2.61	1.65	0.85	2.44	1.14	2.25	2.79	0.62
(p-value)	(0.29)	(0.01)	(0.10)	(0.39)	(0.02)	(0.26)	(0.03)	(0.01)	(0.54)
Stdev	27.01%	20.89%	15.57%	28.49%	19.69%	20.89%	19.30%	16.96%	6.46%
Max	23.88%	21.09%	13.76%	23.30%	18.36%	17.80%	18.04%	17.61%	6.40%
Min	-24.56%	-25.53%	-12.77%	-24.31%	-27.15%	-18.75%	-23.67%	-21.68%	-4.74%
Sharpe	0.15	0.62	0.57	0.09	0.57	0.43	0.52	0.69	0.25
Mean	5.62%	**12.49%*** **	**6.87%***	5.91%	**10.98%*** **	5.07%	**10.04%****	**11.70%*** **	1.66%
T-stat	1.31	2.56	1.82	1.33	2.48	0.72	2.27	2.80	0.68
(p-value)	(0.19)	(0.01)	(0.07)	(0.19)	(0.01)	(0.47)	(0.02)	(0.01)	(0.50)
Stdev	24.29%	20.56%	11.46%	25.62%	18.59%	16.68%	19.01%	16.90%	6.26%
Max	24.78%	20.19%	9.99%	23.27%	17.08%	13.02%	17.88%	17.58%	6.30%
Min	-25.02%	-23.96%	-10.85%	-24.85%	-22.50%	-18.40%	-23.41%	-21.43%	-4.57%
Sharpe	0.23	0.61	0.60	0.23	0.59	0.30	0.53	0.69	0.26
Mean	6.24%	**12.39%*** **	6.16%**	6.65%	**11.63%*** **	4.98%	**9.96%****	**11.63%*** **	1.67%
T-stat	1.44	2.59	2.13	1.48	2.71	0.94	2.27	2.79	0.72
(p-value)	(0.15)	(0.01)	(0.03)	(0.14)	(0.01)	(0.35)	(0.02)	(0.01)	(0.47)
Stdev	22.63%	20.04%	9.10%	23.48%	17.59%	13.61%	18.81%	16.88%	6.14%
Max	23.93%	18.82%	7.96%	22.30%	15.93%	9.36%	17.48%	17.55%	6.27%
Min	-25.34%	-22.33%	-8.83%	-24.53%	-20.57%	-15.61%	-23.23%	-21.48%	-4.88%
Sharpe	0.28	0.62	0.68	0.28	0.66	0.37	0.53	0.69	0.27
Mean	7.01%	**11.89%*** **	**4.89%****	6.95%	**11.88%*** **	4.94%	**10.08%****	**11.56%*** **	1.48%
T-stat	1.60	2.55	2.20	1.57	2.81	1.16	2.31	2.78	0.65
(p-value)	(0.11)	(0.01)	(0.03)	(0.12)	(0.01)	(0.25)	(0.02)	(0.01)	(0.52)
Stdev	21.39%	19.60%	7.11%	22.08%	17.12%	11.70%	18.57%	16.84%	6.01%
Max	21.85%	18.34%	6.35%	19.44%	15.31%	8.59%	17.21%	17.51%	6.12%
Min	-23.76%	-22.31%	-7.38%	-22.62%	-20.29%	-12.47%	-22.69%	-21.48%	-4.68%
Sharpe	0.33	0.61	0.69	0.31	0.69	0.42	0.54	0.69	0.25
Mean	**8.38%***	**11.40%*** **	3.02%	**7.86%***	**11.89%*** **	4.03%	**9.97%****	**11.68%*** **	1.70%
T-stat	1.86	2.48	1.62	1.75	2.83	1.05	2.31	2.81	0.83
(p-value)	(0.06)	(0.01)	(0.11)	(0.08)	(0.01)	(0.29)	(0.02)	(0.01)	(0.41)
Stdev	20.67%	19.39%	5.87%	21.16%	16.95%	10.39%	18.36%	16.83%	5.81%
Max	21.24%	18.26%	4.59%	18.96%	16.10%	7.87%	17.07%	17.28%	5.80%
Min	-23.47%	-21.75%	-5.67%	-22.41%	-19.51%	-8.76%	-22.35%	-21.38%	-4.11%
Sharpe	0.41	0.59	0.52	0.37	0.70	0.39	0.54	0.69	0.29

*** p≤0.01; **p≤0.05; *p≤0.1

Appendix F: Portfolios: 9-Month Formation and K-Month Holding

	Momentum			Green Momentum			Pure ESG		
	Short	Long	Long - Short	Short	Long	Long - Short	Short	Long	Long - Short
Mean	3.63%	**13.17%*** **	9.54%	2.74%	**11.47%*** **	8.73%	**9.42%** **	**10.91%*** **	1.49%
T-stat	0.99	2.67	1.52	0.88	2.55	0.94	2.14	2.64	0.56
(p-value)	(0.32)	(0.01)	(0.13)	(0.38)	(0.01)	(0.35)	(0.03)	(0.01)	(0.58)
Stdev	28.07%	20.34%	17.37%	29.67%	18.58%	22.47%	19.02%	16.77%	6.39%
Max	35.19%	21.90%	13.48%	38.04%	16.19%	17.17%	17.60%	17.33%	6.48%
Min	-28.38%	-21.86%	-18.81%	-27.84%	-19.27%	-26.93%	-23.70%	-21.59%	-4.42%
Sharpe	0.13	0.65	0.55	0.09	0.62	0.39	0.50	0.65	0.23
Mean	3.46%	**13.64%*** **	**10.17%** **	3.25%	**12.06%*** **	8.81%	**9.65%** **	**10.92%*** **	1.26%
T-stat	0.98	2.79	2.22	0.94	2.78	1.27	2.13	2.64	0.67
(p-value)	(0.33)	(0.01)	(0.03)	(0.35)	(0.01)	(0.20)	(0.03)	(0.01)	(0.50)
Stdev	25.25%	19.92%	13.92%	26.34%	17.47%	18.63%	18.77%	16.71%	6.25%
Max	31.03%	20.35%	11.61%	32.01%	17.48%	12.56%	17.64%	17.31%	6.34%
Min	-27.27%	-21.17%	-15.76%	-25.32%	-17.37%	-22.44%	-23.46%	-21.48%	-4.27%
Sharpe	0.14	0.68	0.73	0.12	0.69	0.47	0.51	0.65	0.20
Mean	4.84%	**12.30%*** **	**7.46%** **	4.70%	**11.49%*** **	6.79%	**9.25%** **	**10.86%*** **	1.60%
T-stat	1.20	2.60	2.00	1.16	2.74	1.14	2.14	2.63	0.68
(p-value)	(0.23)	(0.01)	(0.05)	(0.25)	(0.01)	(0.26)	(0.03)	(0.01)	(0.50)
Stdev	23.33%	19.51%	11.43%	24.10%	16.84%	15.95%	18.60%	16.68%	6.13%
Max	28.26%	19.58%	10.23%	27.55%	17.03%	10.59%	17.31%	17.28%	6.18%
Min	-25.87%	-19.85%	-13.58%	-23.98%	-15.30%	-17.18%	-23.23%	-21.50%	-4.21%
Sharpe	0.21	0.63	0.65	0.20	0.68	0.43	0.50	0.65	0.26
Mean	5.94%	**11.95%*** **	**6.01%** **	5.69%	**12.04%*** **	6.35%	**9.36%** **	**10.87%*** **	1.52%
T-stat	1.39	2.57	1.95	1.34	2.86	1.25	2.17	2.64	0.68
(p-value)	(0.17)	(0.01)	(0.05)	(0.18)	(0.00)	(0.21)	(0.03)	(0.01)	(0.50)
Stdev	22.16%	19.24%	9.49%	22.72%	16.77%	14.12%	18.38%	16.66%	5.97%
Max	24.56%	19.25%	7.18%	22.65%	20.28%	8.49%	17.14%	17.39%	6.03%
Min	-25.19%	-19.72%	-10.16%	-23.65%	-15.64%	-12.13%	-22.79%	-21.46%	-4.10%
Sharpe	0.27	0.62	0.63	0.25	0.72	0.45	0.51	0.65	0.25
Mean	7.01%	**11.20%** **	4.20%	**5.80%**	**11.55%*** **	5.76%	**9.30%** **	**10.95%*** **	1.65%
T-stat	1.59	2.45	1.59	1.38	2.80	1.26	2.18	2.66	0.79
(p-value)	(0.11)	(0.02)	(0.11)	(0.17)	(0.01)	(0.21)	(0.03)	(0.01)	(0.43)
Stdev	21.29%	19.03%	8.05%	21.86%	16.47%	12.76%	18.21%	16.63%	5.79%
Max	23.41%	18.37%	6.37%	21.55%	18.40%	8.86%	17.11%	17.25%	5.83%
Min	-25.04%	-19.86%	-8.10%	-24.35%	-15.49%	-10.97%	-22.45%	-21.28%	-4.04%
Sharpe	0.33	0.59	0.52	0.27	0.70	0.45	0.51	0.66	0.28

*** p≤0.01; **p≤0.05; *p≤0.1

Appendix G: Portfolios: 12-Month Formation and K-Month Holding

	Momentum			Green Momentum			Pure ESG		
	Short	Long	Long - Short	Short	Long	Long - Short	Short	Long	Long - Short
Mean	1.30%	**11.81%****	**10.51%***	2.00%	**12.74%*****	10.74%	**8.62%****	**10.26%*****	1.64%
T-stat	0.69	2.42	1.67	0.79	2.82	1.20	1.97	2.49	0.65
(p-value)	(0.49)	(0.02)	(0.10)	(0.43)	(0.01)	(0.23)	(0.05)	(0.01)	(0.52)
Stdev	28.34%	20.28%	17.75%	29.84%	17.90%	22.40%	19.02%	16.73%	6.26%
Max	34.40%	20.66%	12.96%	33.94%	20.91%	16.41%	17.47%	17.17%	5.81%
Min	-29.97%	-20.71%	-18.11%	-28.56%	-14.58%	-25.16%	-23.93%	-21.53%	-4.39%
Sharpe	0.05	0.58	0.59	0.07	0.71	0.48	0.45	0.61	0.26
Mean	2.43%	**11.32%*****	**8.88%***	2.28%	**10.00%****	7.72%	**8.45%****	**10.21%*****	1.76%
T-stat	0.82	2.38	1.80	0.80	2.35	1.08	1.96	2.48	0.76
(p-value)	(0.41)	(0.02)	(0.07)	(0.42)	(0.02)	(0.28)	(0.05)	(0.01)	(0.45)
Stdev	25.47%	19.89%	14.64%	26.37%	17.52%	18.51%	18.77%	16.69%	6.09%
Max	30.51%	19.93%	11.61%	29.74%	19.66%	12.94%	17.38%	17.14%	5.67%
Min	-27.28%	-20.82%	-15.72%	-23.75%	-15.25%	-17.92%	-23.70%	-21.49%	-4.16%
Sharpe	0.10	0.57	0.61	0.09	0.57	0.42	0.45	0.61	0.29
Mean	4.04%	**10.98%****	**6.93%***	4.53%	**11.66%*****	7.13%	**8.40%****	**10.17%*****	1.77%
T-stat	1.06	2.34	1.65	1.12	2.72	1.12	1.96	2.47	0.80
(p-value)	(0.29)	(0.02)	(0.10)	(0.26)	(0.01)	(0.26)	(0.05)	(0.01)	(0.43)
Stdev	23.91%	19.56%	12.45%	24.73%	17.07%	16.68%	18.60%	16.67%	5.98%
Max	28.73%	18.95%	9.93%	27.98%	21.50%	11.73%	17.13%	17.18%	5.52%
Min	-27.73%	-19.83%	-13.73%	-25.68%	-15.13%	-17.29%	-23.48%	-21.53%	-3.97%
Sharpe	0.17	0.56	0.56	0.18	0.68	0.43	0.45	0.61	0.30
Mean	4.94%	**10.46%****	5.53%	5.17%	**11.18%*****	6.01%	**8.36%****	**10.18%*****	1.82%
T-stat	1.21	2.28	1.56	1.24	2.65	1.09	1.96	2.48	0.87
(p-value)	(0.23)	(0.02)	(0.12)	(0.22)	(0.01)	(0.28)	(0.05)	(0.01)	(0.39)
Stdev	22.53%	19.24%	10.61%	23.21%	16.84%	14.72%	18.44%	16.66%	5.84%
Max	25.11%	18.94%	7.98%	23.58%	20.40%	11.17%	16.99%	17.23%	5.49%
Min	-26.28%	-19.79%	-11.51%	-24.84%	-15.08%	-12.79%	-23.18%	-21.55%	-3.88%
Sharpe	0.22	0.54	0.52	0.22	0.66	0.41	0.45	0.61	0.31
Mean	5.86%	**9.82%****	3.96%	5.01%	**10.89%*****	5.88%	**8.33%****	**10.32%*****	1.99%
T-stat	1.38	2.17	1.30	1.23	2.60	1.24	1.97	2.51	1.01
(p-value)	(0.17)	(0.03)	(0.20)	(0.22)	(0.01)	(0.22)	(0.05)	(0.01)	(0.31)
Stdev	21.48%	19.28%	9.23%	22.13%	16.78%	13.25%	18.28%	16.64%	5.68%
Max	23.52%	18.68%	6.63%	22.45%	19.44%	9.35%	17.01%	17.16%	5.31%
Min	-25.87%	-20.45%	-9.29%	-24.80%	-15.44%	-10.76%	-23.00%	-21.34%	-3.97%
Sharpe	0.27	0.51	0.43	0.23	0.65	0.44	0.46	0.62	0.35

*** p≤0.01; **p≤0.05; *p≤0.1

Appendix H: Portfolios: 24-Month Formation and K-Month Holding

	Momentum			Green Momentum			Pure ESG		
	Short	Long	Long - Short	Short	Long	Long - Short	Short	Long	Long - Short
Mean	7.09%	**13.03%*** **	5.94%	7.01%	**15.86%*** **	8.86%	**10.01%** **	**11.40%*** **	1.39%
T-stat	1.41	2.51	0.86	1.39	3.04	1.01	2.20	2.66	0.60
(p-value)	(0.16)	(0.01)	(0.39)	(0.17)	(0.00)	(0.32)	(0.03)	(0.01)	(0.55)
Stdev	25.80%	20.47%	17.62%	26.34%	19.68%	23.07%	18.24%	16.37%	5.61%
Max	31.61%	18.83%	13.04%	31.51%	16.32%	17.94%	17.05%	16.56%	4.65%
Min	-31.04%	-18.00%	-15.56%	-31.09%	-16.35%	-23.32%	-23.84%	-21.11%	-4.47%
Sharpe	0.27	0.64	0.34	0.27	0.81	0.38	0.55	0.70	0.25
Mean	7.90%	**12.01%** **	4.11%	6.82%	**14.36%*** **	7.53%	**9.82%** **	**11.34%*** **	1.52%
T-stat	1.57	2.37	0.72	1.42	2.88	1.07	2.18	2.65	0.71
(p-value)	(0.11)	(0.02)	(0.47)	(0.16)	(0.00)	(0.29)	(0.03)	(0.01)	(0.48)
Stdev	23.66%	20.28%	14.96%	23.64%	18.95%	19.62%	18.07%	16.35%	5.48%
Max	28.01%	18.23%	11.30%	28.08%	15.84%	16.41%	17.03%	16.85%	4.65%
Min	-29.46%	-18.16%	-13.53%	-29.40%	-15.93%	-20.30%	-23.63%	-21.18%	-4.23%
Sharpe	0.33	0.59	0.28	0.29	0.76	0.38	0.54	0.69	0.28
Mean	**8.41%***	**10.94%** **	2.53%	**8.89%***	**14.58%*** **	5.70%	**9.86%** **	**11.37%*** **	1.51%
T-stat	1.69	2.21	0.50	1.75	2.99	0.88	2.20	2.65	0.73
(p-value)	(0.09)	(0.03)	(0.62)	(0.08)	(0.00)	(0.38)	(0.03)	(0.01)	(0.47)
Stdev	22.45%	20.10%	13.10%	22.67%	18.36%	17.21%	17.99%	16.37%	5.38%
Max	26.10%	18.26%	9.06%	25.42%	14.99%	15.56%	17.03%	16.81%	4.52%
Min	-28.20%	-19.14%	-12.34%	-27.66%	-15.34%	-16.80%	-23.50%	-21.15%	-4.09%
Sharpe	0.37	0.54	0.19	0.39	0.79	0.33	0.55	0.69	0.28
Mean	**9.10%***	**9.97%** **	0.87%	**9.19%***	**13.59%*** **	4.40%	**9.86%** **	**11.43%*** **	1.57%
T-stat	1.84	2.06	0.16	1.84	2.81	0.77	2.21	2.66	0.79
(p-value)	(0.07)	(0.04)	(0.88)	(0.07)	(0.01)	(0.44)	(0.03)	(0.01)	(0.43)
Stdev	21.44%	20.03%	11.69%	21.62%	18.41%	15.42%	17.91%	16.38%	5.22%
Max	24.03%	18.03%	7.60%	24.54%	14.87%	13.12%	17.04%	17.03%	4.34%
Min	-26.57%	-18.97%	-11.76%	-26.36%	-15.16%	-14.35%	-23.44%	-21.11%	-4.08%
Sharpe	0.42	0.50	0.07	0.43	0.74	0.29	0.55	0.70	0.30
Mean	**9.43%***	**9.86%** **	0.42%	**8.88%***	**12.74%*** **	3.86%	**9.92%** **	**11.47%*** **	1.55%
T-stat	1.93	2.04	0.09	1.83	2.68	0.74	2.22	2.68	0.79
(p-value)	(0.06)	(0.04)	(0.93)	(0.07)	(0.01)	(0.46)	(0.03)	(0.01)	(0.43)
Stdev	20.70%	20.07%	10.58%	21.03%	18.31%	14.39%	17.85%	16.36%	5.17%
Max	22.73%	17.98%	6.70%	23.18%	14.30%	11.54%	16.73%	17.01%	4.28%
Min	-25.57%	-19.42%	-12.16%	-26.16%	-14.92%	-12.60%	-23.38%	-21.06%	-4.06%
Sharpe	0.46	0.49	0.04	0.42	0.70	0.27	0.56	0.70	0.30

*** p≤0.01; **p≤0.05; *p≤0.1

Appendix I: Portfolios: 36-Month Formation and K-Month Holding

	Momentum			Green Momentum			Pure ESG		
	Short	Long	Long - Short	Short	Long	Long - Short	Short	Long	Long - Short
Mean	5.73%	**10.85%****	5.12%	4.66%	**9.56%***	4.90%	**9.39%****	**11.04%****	1.64%
T-stat	1.19	2.07	0.77	1.05	1.91	0.51	1.99	2.46	0.73
(p-value)	(0.24)	(0.04)	(0.44)	(0.30)	(0.06)	(0.61)	(0.05)	(0.02)	(0.47)
Stdev	25.18%	20.63%	16.56%	26.21%	20.00%	21.27%	18.47%	16.55%	5.44%
Max	29.30%	19.56%	11.75%	30.54%	15.76%	17.68%	17.12%	16.43%	3.92%
Min	-30.08%	-18.33%	-16.26%	-33.43%	-15.97%	-22.80%	-24.45%	-20.61%	-5.04%
Sharpe	0.23	0.53	0.31	0.18	0.48	0.23	0.51	0.67	0.30
Mean	5.98%	**10.52%****	4.54%	5.08%	**9.77%****	4.69%	**9.20%****	**11.02%*****	1.82%
T-stat	1.25	2.03	0.81	1.12	2.00	0.59	1.97	2.46	0.85
(p-value)	(0.21)	(0.04)	(0.42)	(0.26)	(0.05)	(0.56)	(0.05)	(0.01)	(0.40)
Stdev	23.58%	20.56%	14.92%	24.61%	19.20%	18.45%	18.38%	16.51%	5.34%
Max	28.14%	19.87%	11.40%	28.39%	19.60%	17.13%	17.08%	16.46%	3.84%
Min	-29.99%	-18.60%	-15.02%	-33.71%	-16.58%	-16.59%	-24.40%	-20.56%	-4.71%
Sharpe	0.25	0.51	0.30	0.21	0.51	0.25	0.50	0.67	0.34
Mean	6.50%	**10.10%****	3.60%	**5.74%**	**11.01%****	5.26%	**9.39%****	**10.97%****	1.58%
T-stat	1.35	1.97	0.75	1.24	2.22	0.85	2.01	2.46	0.74
(p-value)	(0.18)	(0.05)	(0.45)	(0.22)	(0.03)	(0.40)	(0.05)	(0.02)	(0.46)
Stdev	22.41%	20.51%	13.31%	22.91%	18.91%	16.26%	18.24%	16.50%	5.26%
Max	25.05%	19.31%	10.44%	24.28%	18.35%	13.00%	16.99%	16.40%	3.82%
Min	-29.07%	-18.63%	-13.21%	-30.25%	-17.24%	-14.00%	-23.71%	-20.52%	-4.60%
Sharpe	0.29	0.49	0.27	0.25	0.58	0.32	0.51	0.66	0.30
Mean	7.11%	**9.72%***	2.61%	5.56%	**10.99%****	5.43%	**9.33%****	**11.02%*****	1.70%
T-stat	1.47	1.90	0.62	1.23	2.23	0.99	2.00	2.47	0.83
(p-value)	(0.14)	(0.06)	(0.53)	(0.22)	(0.03)	(0.33)	(0.05)	(0.01)	(0.41)
Stdev	21.49%	20.55%	12.15%	22.14%	18.82%	15.03%	18.19%	16.51%	5.18%
Max	23.23%	19.31%	9.06%	22.91%	17.27%	12.21%	17.00%	16.53%	3.91%
Min	-27.37%	-18.64%	-12.41%	-30.02%	-17.81%	-13.14%	-23.48%	-20.52%	-4.39%
Sharpe	0.33	0.47	0.22	0.25	0.58	0.36	0.51	0.67	0.33
Mean	7.83%	**9.78%***	1.94%	6.49%	**10.96%****	4.48%	**9.47%****	**11.12%*****	1.65%
T-stat	1.60	1.92	0.52	1.38	2.22	0.84	2.03	2.48	0.81
(p-value)	(0.11)	(0.06)	(0.60)	(0.17)	(0.03)	(0.40)	(0.04)	(0.01)	(0.42)
Stdev	20.85%	20.49%	11.27%	21.45%	18.88%	14.72%	18.17%	16.52%	5.16%
Max	22.88%	19.14%	8.78%	23.57%	17.33%	10.78%	17.23%	16.49%	3.96%
Min	-26.26%	-18.66%	-11.92%	-28.36%	-17.57%	-12.77%	-23.26%	-20.52%	-4.70%
Sharpe	0.38	0.48	0.17	0.30	0.58	0.30	0.52	0.67	0.32

*** p≤0.01; **p≤0.05; *p≤0.1