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Sustainable Investments:
Momentum Investment Strategies for ESG Stocks

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Contents

Abstract

This paper aims at investigating the relationship between ESG-Scores and momentum investment strategies. I develop different sustainable and non-sustainable momentum investment strategies in both the American and European markets and document their difference in profitability and predictability. I document the presence of an 'NON-ESG-Momentum effect': I find that, in terms of returns, the non-sustainable momentum strategies consistently outperformed the sustainable momentum strategies for each formation and holding period analysed. The non-sustainable momentum strategies also generated higher cumulative returns over the sample period 2005 to 2020. However, over the same period, sustainable momentum strategy performed better than the benchmark MSCI-World index and showed less volatility compared to the non-sustainable strategies. Moreover, using ARMA models, I document that the sustainable momentum strategies exhibit better predictability of returns. Using GARCH models, I do not find systematic differences in the predictability of conditional volatility of the strategies. Finally, I document that analyst coverage and risk premia can drive part of the effect, nevertheless many questions remain which I will address in the discussion section.

1 - Introduction

In recent years, environmental, social and governance (ESG) investing has caught the attention of many investors, managers, and policy makers. According to SustainFi (2022), a company that connects investors interested in sustainable investing, in the last decade sustainable funds dramatically increased the amount of asset under management, amounting to 357 billion dollars in 2021. Moreover, the largest 10 sustainable mutual funds managed over 95 billion dollars in March 2022 (SustainFi, 2022). Albeit we are witnessing a significant increase in sustainable investments, most investors still prioritize returns rather than sustainability (Gallup, 2022). Similarly, Amel- Zadeh and Serafeim (2018), who conducted a study aimed at understanding why investors use environmental, social and governance (ESG) factors, showed that investors invest in ESG mostly because sustainability proxies for firms' performance and because this type of investments aligns with the customer's demands rather than for ethical reasons. This shows that for most investors, returns remain the first and most important factor to consider when allocating financial resources.

Moreover, a widely held belief about sustainable investments, is that a firm's increase in costs for compliance to ESG regimentations, will, in turn, increase the product cost and hence, lead to lower firms' competitiveness. For example, Walley and Whitehead (1994) argue that the appealing idea that environmental consideration increase profitability is not realistic due to the high costs and challenges of environmental compliance.

Because of these considerations, it is important to investigate investment strategies that are both sustainable and profitable. In this regard, Kempf and Osthoff (2007) study a simple investment strategy, namely they buy stocks with high ratings of ESG and sell stocks with low rating of ESG. They found that this strategy leads to significant abnormal returns with respect to the Carhart and Fama-French model.

In contrast, Halbritter and Dorfleitner (2015), using ESG scores and returns data from the U.S. market, found that portfolios comprised of stocks with high ESG ratings performed roughly the same as portfolios comprised of stocks with low ESG ratings. Hence, according to their analysis investors might not be able exploit ESG data to generate abnormal returns.

The contradictory results of these studies prove that there is still controversy about the relationship between sustainable investing and returns.

Among the controversies, an important consideration that might explain this discrepancy, is that many researchers or investors use different ESG ratings to assess the sustainability of an investment. As I will discuss in section 2, the rating agencies that provide ESG factors use different methodologies and subjective measures of sustainability, leading to unobjective measures of sustainability. Hence, to conduct academic research focusing on sustainability, it is paramount important to use reliable and transparent ESG data sources.

Another relevant open question in this discussion is which investment strategy (if any) one should apply for sustainable stocks.

In the financial literature, many investment strategies have been proven to be profitable. Among those, one that has caught the attention of many researchers around the globe is momentum. Momentum is the tendency of past stock winners to outperform past losers in both the short and long-run. This 'anomaly' (with respect to conventional financial theory which does not explain momentum returns) was first investigated by Carhart (1997) and since then, it became a widely studied and established anomaly. Jegadeesh and Titman (1993) document a simple momentum strategy in which they buy stocks which have had positive past performance and short stocks which have had negative past performance. They found that this strategy generates sizable and statistically significant abnormal returns over the 3 to 12 months holding period.

The direction that this paper wants to take is toward addressing to what extent momentum strategies are applicable to sustainable (ESG) stocks. The main goal of this paper is to investigate if momentum strategy for sustainable stocks, stocks that have a higher-than-average ESG score, yield positive abnormal returns.

In this paper, I will address the following research question(s):

Do sustainable momentum investment strategies yield higher abnormal returns that non-sustainable momentum strategies? Are the returns of the sustainable momentum strategies better predictable over the sample period, compared to those of the non-sustainable strategies?

This paper contributes to the scientific literature in both sustainable investment and momentum investment strategies. The relationship between momentum and sustainable investing has in fact not been investigated in the literature. Hence, this paper aims to fill this gap in the literature by relating momentum strategies to sustainable investments.

Moreover, this paper aims to be socially relevant for both asset managers and policy makers. Investors and policy makers are in fact recently being pressured in more sustainable investments and, developing investment strategies that can allow for both profitable and sustainable investing, can be beneficial for both investors and stakeholders.

To accelerate the process towards a greener financial industry, it is important to foster future financial research towards sustainable investment strategies.

The structure of the paper is as follows: In section 2, I will present relevant academic literature and theoretical framework about sustainable investments, momentum investment strategies and behavioural explanation of momentum returns. In section 3, I will discuss the datasets used for analysis. In section 4, I will cover the relevant methodology used to answer the research question(s). Finally, in section 5, I will present the results and discuss them in section 6, concluding with limitations of the research, relevant social implications and future research in section 7.

2 - Literature Review

In this section, I will present the main insights from the academic literature about sustainable investing, momentum investment strategies and some behavioural explanation of momentum returns. This section serves as a theoretical framework in which I will present the relevant concept on which I will further develop later in the paper.

2.1 ESG Investing

Environmental, Social and Governance (ESG) investing, is based on many factors related to sustainability to allocate resources to companies or organizations that have positive social and environmental impact. Environmental, refers to the impact that an organization has on the environment, Social refers to the human rights, labour conditions, and safety in the workplace as well as the way in which the company integrates in the local community and, Governmental refers to balancing of incentives and responsibilities of the stakeholders.
ESG investing relies on financial measures to make investments that are both sustainable and profitable for the investor. Nevertheless, as argued by Olmedo et al. (2010), the ESG rating agencies which translate ESG risk into financial measures, rely on their own research and methodologies. Hence, the criteria on which these measures are based depend in part on the rating agency that provides them and thus, are not standardized. The main issue in this regard is that the rating agencies are not fully transparent in their assessment criteria (Olmedo et al., 2010). This outlines the need of a standardized measure of ESG factors and the importance of using reliable ESG information when researching (in section 3 I will develop more on the reliability of the dataset used for analysis).

There are many studies that aim to relate ESG scores to the financial performance of companies. Ashwin Kumar et al. (2016), using a quantitative approach, showed that companies that incorporate ESG measures into their strategy show higher returns and lower volatility compared to other firms in the same industry. Many industries that they analysed, on average, exhibited ESG returns equity returns higher that 6.15%. Accordingly, Eccles et al. (2014) analysed a sample of 90 high-sustainability and 90 low-sustainability companies and found that the former outperformed the latter in both stock performance and accounting performance. In fact, with respect to a four-factors model, the abnormal returns of the sustainable sample significantly exceeded those of the non-sustainable sample.

However positive and insightful the outperformance of sustainable stocks, many academic studies also show the contrary. Bauer et al. (2004), who analysed the relationship between governance standards and firm performance, found no evidence of a statistically significant relationship between governance rating and firm performance. More recently, Dorfleitner (2015), analysed ESG data ratings from the ASSET 4 database and concluded that the high ESG portfolio does not exhibit higher abnormal returns with respect to the Fama-French model compared to the low ESG portfolio.

Risk premia provide a possible explanation on the underperformance of ESG stocks. Bannier et al. (2019) found that a portfolio long in stocks that have high ESG ratings and short in stocks that have low ESG ratings generates negative returns, this is mainly driven by the excessive positive returns of non-sustainable firms. They argue that sustainable firms offer an 'insurance-like' protection because those firms proxy for financial stability especially in periods of downturn whereas non-sustainable firms exhibit higher financial risk. In fact, the authors argue that firms with low ESG scores exhibit higher levels of financial risk but also higher returns, which could be explained as a provision of risk premia. Thus, according to this logic, investors need to be compensated with risk premia to invest in non-ESG stocks and require higher returns. As I will argue in later sections, sustainability risk premia can explain part of the 'Non-ESG-momentum' effect presented in later sections according to which, the non-sustainable investment strategies consistently outperformed the sustainable investments strategies and generated higher cumulative returns.

Researchers have also focused on the impact of ESG news (news related to sustainability) on firms' market value. Capelle-Blancard and Petit (2017) performed an event study to identify the relationship between positive (negative) ESG news and market value. They came to the conclusion that firms that face negate ESG news event, on average, lose around 0.1% of their market value in the next three days from the announcement. Instead, firms facing positive ESG news do not experience any significant change in the market value. Moreover, they hypothesized that this asymmetry in the reaction to negative or positive news, is due to behavioural factors. In fact, researchers in behavioural economics have already studied and reported this asymmetry (Soroka, 2006).

Overall, there is still controversy on the impact of ESG factors on the firms' value and stock performance. As we have witnessed, many studies come to contradictory results and hence, we do not have a coherent explanation of ESG returns.

2.2 Momentum Investment Strategies

Momentum is the tendency of past winner to continue to do well in subsequent periods and the tendency of past losers to continue to do badly. This anomaly (anomaly with respect to conventional financial models) was first thoroughly studied by Jagadeesh and Titman (1993) in the famous paper *Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency.* In this paper, the authors created momentum investment strategies in which they bought stocks which have performed well in the past 3-to-12-month formation period and sold stocks which have performed badly. They found that this strategy generates statistically significant abnormal returns in the period from 1965 to 1989 in the United States. Their paper inspired many researchers around the globe to investigate the momentum anomaly across different asset classes.

For instance, Rouwenhorst (2002) shows that the momentum effect is not limited only to the United States, but evidence of momentum has been found in 12 different countries including Europe. Moreover, the author argues that the European and American momentum strategies share a 'common component' and are thus correlated. Accordingly, Nijman et al. (2004) investigated momentum in Europe and concluded that there are significant abnormal returns to momentum strategies and that this is mainly explained by individual stock effects rather than industry momentum.

Momentum proves to be a profitable investment strategy; however, it is not risk-free rather, can be quite volatile. Daniel and Moskowitz (2014) showed that momentum strategies can experience persistent negative returns. They found that 'momentum crashes' happen especially after periods of market downturn and stress and in periods that exhibit high return volatility. This happens mainly because when the market rebounds, past losers experience great gains since, on average past losers have higher beta (correlation to the market) compared to past winners.

Momentum is a well-establish anomaly in the academic literature an continues to puzzle researchers since no unambiguous and convincing explanation has been found yet.

2.3 Behavioural Explanation of Momentum Returns

Among the many explanations of momentum returns, the one that gathered the most interest in the academic literature is the behavioural explanation. In a nutshell, the behavioural explanation of momentum asserts that momentum returns arise because of some mispricing generated by irrational investors in the market. The behavioural analysis gives some interesting and compelling evidence for the autocorrelation of momentum returns. In other words, momentum investors are simply exploiting the mispricing and earning abnormal returns.

Overreaction is one of the most popular behavioural explanations of the phenomenon. Shefrin (2002), in his famous book *Beyond greed and fear: Understanding behavioural finance and the psychology of investing,* describes overreaction as the tendency of investors to overreact and be confident that stocks that have been doing well in the past will continue to do well in the future. According to many, this behavioural mechanism explains the mispricing that momentum investors exploit. De Bondt and Thaler (1987) also favoured the overreaction hypothesis by claiming that because investors are poor Bayesian decision makers, they tend to overreact to information, overweighting recent information and underweighting the base rate. Menkhoff et al. (2011) provided further evidence of the relationship between momentum returns and overreaction. Albeit they analyse currency momentum, the authors argue that momentum currency returns are partly driven by slow information diffusion in the financial markets. The slow diffusion leads to an underreaction at the beginning and a subsequent overreaction when more information is available.

About the slow diffusion of information, Hong et al. (2000) studied the effect of analyst coverage on the momentum returns. They argue the information diffusion partially explains the momentum anomaly trough overreaction. According to their analysis, overreaction (underreaction) can interact with slow information diffusion and generate continuous overreaction (underreaction) in subsequent periods. Furthermore, the show that firms that exhibit low analyst coverage earn higher abnormal momentum returns compared to firms that exhibit high analyst coverage.

Overall, the behavioural explanation of momentum returns seems the most plausible and backed-up by the literature.

In the context of this research, it becomes interesting to understand if there is an overreaction (underreaction) to ESG news and information. More generally, can there be a behavioural explanation of ESG-Momentum return?
To answer this question, I will test if part of the results can be attributed to the 'analyst coverage effect' documented by Hong et al. (2000).

3 - Data

3.1 Data Sources

To study the relationship between sustainable firms, returns and momentum investment strategies, I will utilize data about ESG factors and returns.
In terms of ESG measures I will use the data provided by the Thomson Reuters ESG Database. This is a comprehensive database that is formed by more that 6000 publicly listed companies around the globe and that includes various ESG measures for each of the companies from 2000 to 2020. Moreover, it represents an enhancement to the already existing ASSET 4 ratings which has been largely used in the literature for sustainable investments and ESG factors.
The most relevant variable that this dataset reports is the yearly ESG score, which is an overall company score based on environmental, sustainable and governance scores. More precisely, the yearly ESG score isa weighted average computed through resource use, emissions, innovation, management, shareholders, strategy, workforce, human rights, community and product responsibility. This higher this score is, the more sustainable the company. Most importantly, this variable is reported as a time series, which, as I will discuss in methodology, will be handy to develop ESG-based momentum strategies.
Another strength of this dataset is that provides information of stocks listed on various exchanges around the world. This allows not only to study the U.S. stocks (as most papers related to ESG investing do) but also study other international markets such as Europe.
As discussed in the introduction, when investigating ESG ratings, it is important to rely on transparent and objective company's measures. In fact, as reported by Halbritter and Dorfleitner (2015), it seems that the impact and magnitude of sustainable ratings on returns depends to the rating provider. In this regard, the Thomson Reuters ESG Scores represent an objective and reliable measure of company's ESG levels: it is in fact a robust indicator of ESG performance in which company's size and transparency biases are minimized.

Returns and company specific data will be retrieved from the Centre for Research in Security Prices (CRSP). This is considered one of the most comprehensive and reliable datasets to analyse security prices.

To measure abnormal returns (alpha) and benchmark the sustainable trading strategy, I will use the Fama-French three-factor model. On the Kenneth R. French website[1], it is possible to access data about the research factors size (SMB), value (HML) and market (MKT). These factors will allow for a regression of the excess returns on the Fama-French factors in which the constant will represent the abnormal returns with respect to the Fama-French three-factor model. Also, factor exposure is reported for different countries including the United States and Europe.

Lastly, to study the effect of analyst coverage on ESG momentum returns, I will utilize data from the Institutional Brokers Estimate System (I/B/E/S). This dataset contains variables that report the number of analyst coverage of different firms around the world. More precisely, I/B/E/S contains a monthly-measured variable that represents the number of analysts that estimate the earnings per share of a certain firm. This can be used as a proxy for analyst coverage as outlined by Hong et al. (2000).

3.2 Summary Statistics

In this section, I will report some summary statistics about returns and ESG-score deciles for firms in the U.S. These will serve as stylized facts which will be further investigated in later sections.

Table 1: Mean returns, standard deviation (SD), and Sharpe Ratio (SR) of publicly listed companies in the US in different ESG score deciles.

	ESG Score Deciles									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Mean	0.014	0.011	0.011	0.008	0.013	0.011	0.011	0.011	0.010	0.009
S.D.	0.156	0.112	0.011	0.111	0.179	0.102	0.102	0.089	0.087	0.084
S.R.	0.091	0.097	0.103	0.077	0.081	0.109	0.107	0.128	0.119	0.113

[1] Data retrieved from: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html

Note: Values rounded to 3 decimals. Risk Free rate assumed to be zero for the computations of the Sharpe Ratios. Mean, Standard Deviations and Sharpe Ratios computed over the full sample from 2005 to 2020. The values represent monthly measures.

Table 1 reports mean returns, standard deviation (SD) and Sharpe Ratios (SR) for returns sorted in different ESG score deciles. Decile 10 includes firms that scored the highest in terms of the overall ESG scores, thus it represents the most sustainable firms. In contrast, the first decile includes the firms that performed the worst in terms of sustainability over the full sample. Overall, we do not witness a monotonic increase or decrease in mean, standard deviation, and Sharpe Ratios over different ESG score deciles. However, in the scope of this paper, it is interesting to point out the differences between extreme deciles in the ESG score distribution. Table 1 in fact shows that there appears to be systematic differences in average returns and risk of sustainable and non-sustainable firms.

We can observe that in terms of returns the decile that scored the highest is the first, with mean monthly returns of around 1.4% over the full sample. This implies that the least sustainable firms, on average, scored the highest monthly returns from 2005 to 2020. In contrast, firms the belonged to the top decile of the ESG score distribution scored the second lowest returns over the full sample, with average returns around 0.9%, 0.5 percentage points less than the least sustainable firms.

Already from summary statistics of mean returns we can witness that there appears to be a systematic difference in the return generating process of sustainable and non-sustainable firms. These statistics are consistent with what found by Brammer et al. (2006), who examined the relationship between corporate social performance and stock returns in the United Kingdom and concluded that social performance factors are negatively correlated to stock performance and that significant abnormal return are present for a portfolio of stocks that holds the least desirable stocks from an ESG and social perspective.

In terms of volatility of returns there also appears to be a systematic difference between top and bottom ESG scores deciles. More precisely, the non-sustainable firms present the highest volatility of returns over the full sample, with standard deviation of around 15.6%. On the other end of the ESG scores distribution, the most sustainable firms belonging to the top decile showed the lowest volatility of returns. These results resonate to what found by Ashwin Kumar et al. (2016) who developed a quantitative model of ESG factors and risk adjusted performance and concluded that stock of firms that score high in ESG factors, show on average lower volatility compared to firms that score low on ESG factors.

As discussed so far, it seems that sustainable stock investments generate lower returns compared to non-sustainable investments, however ESG stocks show lower volatility compared to other stocks. In the scope of this paper, it becomes interesting to investigate the risk-return trade-off of sustainable and non-sustainable momentum investment strategies.

In terms of risk-adjusted performance, overall, the firms belonging to the top decile of the ESG score distribution generate a higher Sharpe Ratio compared to the firms in the firms belonging to the bottom decile. They in fact generated a Sharpe Ratio of around 11.3% compared to 9.1% of the bottom decile, an increase of around 2.2 percentage points. From summary statistics, there seems to be a better risk-return trade-off for sustainable firms compared to non-sustainable firms. On this regard, Derwall et al. (2004), focus on socially responsible investment strategies (SRI) and present robust evidence that the most 'eco-efficient' portfolio outperformed the least 'eco-efficient' portfolio in terms of risk-adjusted returns.

Finally, to investigate the sample more accurately, it is insightful to observe the development of the ESG-Scores over time. Figure 1 shows the time series of yearly ESG scores over the full sample.

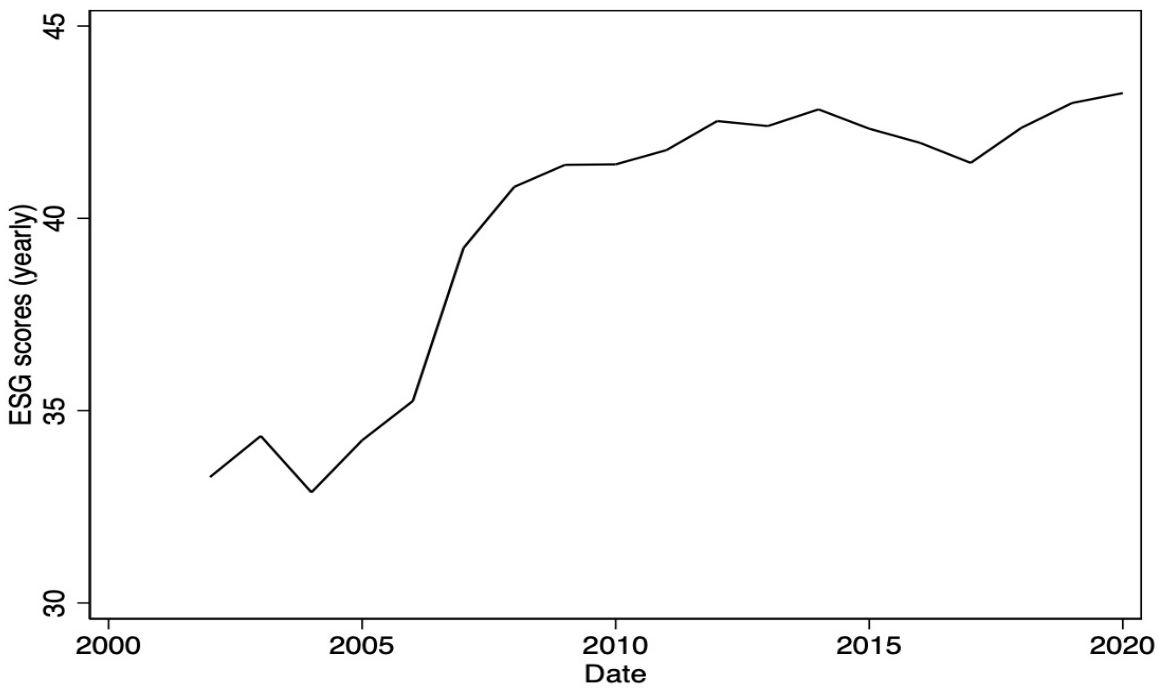

Figure 1: Time series of yearly mean ESG scores 2002-2020

Adapted Source: Thomson Reuters ESG scores

As it is observable from Figure 1, the mean ESG scores have been increasing in the last decades. A dramatic increase followed around 2004/2005 and plateaued around 2010. In fact, the mean ESG scores went from around 33 points in 2004 to around 42 points in 2010, reaching the maximum of 43.26 points in 2020.

Figure 1 shows that on average firms have been improving their ESG profile. This pattern also confirms what has already been outlined in the introduction: in recent years companies and investors have been focusing particularly on sustainability and ESG factors, outlining the need for further investigation for the relationship between ESG scores and financial returns.

4 - Methodology

In this section I will discuss the methodology and relevant theory I will use to successfully answer the research questions reported above.

First, it is important to conceptualize the term 'sustainable firm'. In this research a firm will be defined as sustainable in a certain year if its ESG score belongs to the top decile of the ESG scores distribution. Similarly, a firm will be defined non-sustainable in a certain year if its ESG score belongs to the bottom decile of the ESG score distribution.

The momentum strategy I would like to investigate is the following and relies on a double sort: First, each year the companies will be sorted into deciles based on the overall ESG scores and, the firms that score in the top decile of the ESG score distribution are going to be used for the sustainable momentum strategy (or ESG-Momentum strategy) in the next available year. Here, I take the perspective of an investors that each year investigates which firms performed the best in terms of sustainability and decides to trade only the best sustainability- scoring of those in the following year. Thus, the set of potential sustainable firms traded is rebalanced each year. Second, each month among the firms that have been selected for that year, I will perform another sort based on monthly returns. Here, I apply a momentum strategy and select the 10 best performing firms in terms of returns. These 10 selected firms will then be traded in the next following months based on different formation and holding periods. I hence follow a methodology similar to that of Jegadeesh and Titman (1993). Moreover, I will apply this strategy to both the United States and Europe.

In order to have a measure of comparison, I will also investigate the same momentum strategies for the worst-performing ESG stocks and develop a non-sustainable momentum strategy (Non-ESG-Momentum strategy). The main goal here is to investigate if, keeping the momentum strategy constant, the best-performing ESG stock perform better than the worst-performing ESG stocks.

To measure abnormal returns for each strategy with respect to the three-factor Fama-French model I will run also the following regression:

$$RET_{ESG_t} - R_f = \alpha + \beta_1 SMB_t + \beta_2 HML_t + \beta_3 MKT_t + \epsilon_t \qquad (1)$$

Where RET_{ESG_t} represents the returns of the ESG strategies discussed above, R_f is the monthly risk-free interest rate[2] ,$\beta_1 SMB_t$ represents to exposure to the size factor, $\beta_2 HML_t$ represents exposure to the value factor and $\beta_3 MKT_t$ represents exposure to the market factor. ϵ is what remains unexplained from the model and, most importantly to assess the performance of trading strategies, α is the measure of abnormal returns.

Concerning standard errors of the various specifications, I will take a conservative approach and utilize heteroskedastic robust standard errors. As largely documented in the literature, returns do not usually exhibit constant variance thus, it is important to account for heteroskedasticity. In fact, if the innovations (or errors) are heteroskedastic but homoskedasticity is assumed, the standard errors would be inaccurate and smaller than they should be. This implies that it would be more likely to reject the null hypothesis when, in reality, we should not (type II error).

Another direction which I would like to take in terms of momentum strategies is understanding their predictability of returns and volatility. Are the returns of ESG momentum strategies predictable? How can we model volatility of ESG momentum strategies?

In order to answer these questions, I will take a time series approach and use both the Autoregressive Moving Average Model (ARMA) and the Generalized Autoregressive Conditionally Heteroskedastic (GARCH) model.

Regarding the returns, my goal is to assess the predictability of momentum returns for both sustainable and non-sustainable momentum strategies. In this part, I will use ARMA models to create an in-sample estimation model and test its effectiveness out-of-sample. The amount of lags needed in the ARMA (p,q) model will be identified using the information criterion

[2] The risk-free interest rate is assumed to be 0 in the period between 2010 to 2020. This reflects the fact than during this period the interest rates have been close to 0 or negative. In fact, the risk-free rate in the Kenneth French website is often 0 during the time frame that goes from 2010 to 2020.

(Akaike's and Schwarz's information criterion). Moreover, the effectiveness of the model will be assessed with the Mean Squared Forecast Error (MSE), which is a weighted sum of squares differentials between the actual observation and the forecasted value.
The model that will be estimated is the following:

$$f_{t,s} = \sum_{i=1}^{p} a_i f_{t,s-i} + \sum_{j=1}^{q} b_j u_{t+s-j} \qquad (2)$$

Where $f_{t,s}$ is the forecast made at time t for s steps into the future and the summation terms represents the lagged AR and MA terms respectively.

Regarding volatility, my goal is to investigate the volatility of ESG-momentum strategies. Volatility is interesting because it represents the risk of a certain financial asset. Moreover, many value-at-risk models to measure risk require an estimate of the volatility. In the context of this paper, it is interesting to model the ESG-momentum strategy's volatility over time using a GARCH model.
The model that will be estimated is the following:

$$\sigma_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad (3)$$

Where, σ_t represents current conditional variance which is parametrized by q lags of the squared error and p lags of the conditional variance. Most likely, a GARCH (1,1) will be sufficient to capture the volatility clustering in the data.

Lastly, I will test the robustness the results using a similar methodology developed by Hong et al. (2000). In their paper, the authors provided evidence that the firms that have lower analyst coverage exhibit, on average, higher momentum returns compared to the firms that have high analyst coverage. In other words, the authors showed that information diffusion has an effect on momentum returns due to under or overreaction.
In the context of this research, the higher momentum returns of the non-sustainable strategies can be partly driven by the fact that firms that belong to the lowest decile of the ESG

distribution, have lower analyst coverage compared to firms in the top decile and hence, show higher momentum returns.

The proxy the authors use for information diffusion is analyst coverage. In fact, all else being equal, analyst coverage reflects the diffusion of firm-specific information into the financial markets. Because analyst coverage is highly correlated with firm size, they use residual analyst coverage for their analysis.

Accordingly, I will compute the residual analyst coverage by predicting the residuals of a regression of analyst coverage on firm size. As a proxy of analyst coverage, the I/B/E/S Historical Summary File provides the number of analysts that provided an estimate for the earning per share in a given month. If data entry of the analyst coverage is missing, I set it to 0. As a proxy form firm size, I will use the monthly market capitalization computed as the number of share outstanding multiplied by the price per share in month t.

Similar to Hong et al. (2000), the regression will look as follows[3]:

$$\ln(1 + Cov_{it}) = \alpha_{it} + \beta \ln(MKTCAP_{it}) + \varepsilon_{it} \qquad (4)$$

Where Cov_{it} represent the analyst coverage of a certain firm (i) in a certain month (t), α_{it} represents the constant term, $MKTCAP_{it}$ represents the market capitalization of firm a certain firm (i) in a certain month (t) and ε_{it} represent the residual analyst coverage which is not explained by the firms' size.

Having obtained the residual analyst coverage ($\widehat{\varepsilon_{it}}$) from equation (4), I will use a logistic regression model to test if the residual analyst coverage is predictive of a firm being in the top or bottom decile of the ESG distribution. If that is the case, then part of the results can be driven by the analyst coverage effect documented by Hong et al. (2000).

The logistic regression equation will look as follows:

$$DEC_{it} = \alpha_{it} + \gamma\,\widehat{\varepsilon_{it}} + \upsilon_{it} \qquad (5)$$

Where DEC_{it} is a dummy variable equal to one if a certain firm is in the top ESG decile at time t and equal to zero if a firm is in the bottom ESG decile a time t. $\widehat{\varepsilon_{it}}$ represents the residual analyst coverage predicted in equation (4) and υ_{it} is the error term.

[3] The reason why I add 1 to the logarithm of the dependent variable is that for some of the firms the analyst coverage has been coded as 0. Because the logarithm of 0 is undefined, adding 1 to the analyst coverage solves the issue since analyst coverage is a non-negative continuous variable.

5 - Results

5.1 Momentum Strategy Results in the U.S.

In this section, I will report the results of different momentum strategies over the full sample (without filtering for sustainable and non-sustainable firms) for firms based in the United States. These results will serve as a benchmark for the sustainable momentum strategies results that I will present later in the results section. The results refer to momentum strategies with different formation (J) and holding periods (K). More specifically, I will focus on formation periods of 1,3,6,12 months and corresponding holding periods of 1,3,6,12 months. For example, 3-3 momentum strategy relies on 3 months of formation period, in which stocks with the highest (top decile) cumulative returns are selected, and 3 months holding period, in which the cumulative returns of the best performing firms (top decile) in the following 3 months represent momentum returns. In Table 2 regression results of the momentum returns of the winner (W) and loser (L) portfolio (first decile) are presented. More specifically, Table 2 shows the abnormal returns (α) generated by the winner and loser portfolio with respect to the Capital-Asset-Pricing-Model (CAPM) and the Fama-French Three-Factors-Model (F-F).

Table 2: Abnormal returns of momentum strategy (α) with respect to the CAPM and Fama-French Three factors model.

	W	**L**	**W**	**L**	**W**	**L**	**W**	**L**
			Formation and Holding Periods *(J- K)*					
	1-1	1-1	3-3	3-3	6-6	6-6	12-12	12-12
CAPM α	0.010**	0.018***	0.015**	0.014**	0.016***	0.016**	0.012***	0.015*
	(0.046)	(0.007)	(0.001)	(0.007)	(0.005)	(0.008)	(0.005)	(0.008)
F-F α	0.011**	0.019**	0.015**	0.014**	0.016***	0.017**	0.012***	0.015*
	(0.005)	(0.008)	(0.006)	(0.007)	(0.006)	(0.008)	(0.005)	(0.008)

Note: Table 2 shows the constant term (alpha) from for different winning and losing momentum strategies in the time frame from 2005 to 2020 for American stocks. The alphas represent monthly calculated alphas. Heteroskedastic-Robust Standard Errors are in parentheses; P-Values *p<0.10, **p<0.05, ***p<0.01.

As we can see from the abnormal returns (α) reported in Table 2, buying the past winners generates positive and statistically significant abnormal returns with respect to both the CAPM model and the Fama-French-Three-Factors model over all the different specification of formation and holding period. Moreover, in contrast to the results of Jagadeesh and Titman (1993) who find that the losers portfolio generates significant negative returns in the period from 1963 to 1989, we can witness that the losing portfolio generates positive and statistically significant returns over the full sample period from 2005 to 2010. This is consistent to what found by Daniel and Moskowitz (2014) who show that past losers can outperform past winners for prolonged periods of time, especially following periods of financial distress and high market volatility. This also implies that a long-short strategy in which one buys the past winners and shorts the past losers would most likely not yield abnormal returns from the period from 2005 to 2020. In fact, as we can observe in the Appendix in Figure A1, during the period which goes from 2010 to 2020, the returns of the long-short momentum strategy have been negative with mean value of around -0.2%. These results derive from the fact that the past losers have at times outperformed past winners over that period and hence, this explains the negative sign of the winner-minus-loser strategy. This is observable in Figure A2 in the appendix which shows the time series of cumulative returns of the winner and loser portfolio. From the figure, it is evident that the strategy of buying winners and selling losers would have yielded negative returns in the relevant period.

Moreover, it is noticeable that the momentum strategies that generate the highest long momentum returns are the medium-run (6-6) strategy and the long-run (12-12) strategy, with abnormal returns of 1.6% and 1.2%, abnormal returns statistically significant at the 1% level. These insights resonate to what found by Novy-Marx (2012) who investigated momentum returns in the U.S. equity market and concluded that momentum strategies based on intermediate time horizons generate higher average returns compared to momentum strategies based on short past horizons.

Overall, consistent with the academic literature on momentum returns, past winners still in recent times, seem to generate abnormal returns (winner momentum). However, in contrast to what found by Jagadeesh and Titman (1993), the winner minus loser strategy does not seem to yield positive abnormal returns.

In the scope of this paper, it becomes interesting if the momentum returns of past-winner sustainable stocks generates higher abnormal returns compared to the momentum returns of past-winners non-sustainable stocks. Furthermore, do the ESG-Momentum strategies perform better than the benchmark strategies presented in Table 2?

5.2 ESG-Momentum Strategy Results in The U.S.

In Table 3, results or the ESG-Momentum and Non-ESG-Momentum strategies are presented. To reiterate, for these investment strategies I applied momentum strategies based on yearly

ESG scores. More precisely, each year the firms that score in the top decile of the ESG score distribution will be selected for trading the next available year. Among those selected stocks than I apply momentum strategies based on different formation and holding periods and hence, buy only the stocks that score in the top decile of the cumulative monthly return distribution over the formation period. This represents the ESG-Momentum investment strategy. On the other hand, I apply the same momentum strategies but for the firms that each year score in the bottom decile of the ESG-score distribution. Hence, yearly rebalancing the firms that score the lowest in terms of ESG-scores and apply monthly momentum strategies. The results in Table 3 are presented for different formation and holding period.

Table 3: Abnormal returns (α) of momentum strategy for ESG and non-ESG portfolios with respect to the CAPM and Fama-French Three factors model.

ESG Deciles	**1st**	**10th**	**1st**	**10th**	**1st**	**10th**	**1st**	**10th**
			Formation	**and**	**Holding**	**Periods**	***(J- K)***	
	1-1	1-1	3-3	3-3	6-6	6-6	12-12	12-12
CAPM α	0.018**	0.008*	0.019**	0.010**	0.021***	0.011***	0.016**	0.010**
	(0.007)	(0.005)	(0.007)	(0.005)	(0.007)	(0.004)	(0.007)	(0.004)
F-F α	0.018**	0.008	0.019**	0.009**	0.021***	0.011***	0.016**	0.010**
	(0.007)	(0.005)	(0.007)	(0.005)	(0.008)	(0.004)	(0.007)	(0.004)

Note: Table 3 shows the constant term (alpha) from for different portfolios formed by the best performing stocks in terms of sustainability (10th decile) and the worst performing stocks (1st decile) in the time frame from 2005 to 2020. The alphas represent monthly calculated alphas. Heteroskedastic-Robust Standard Errors are in parentheses; P-Values, *p<0.10, **p<0.05, ***p<0.01.

From the Table 3 we can observe that over all the formation and holding periods, the firms that belong to the 1st decile of the ESG-score distribution (the non-sustainable stocks) consistently outperformed the firms that scored in the 10th decile of the ESG-score distribution (the sustainable stocks). From this analysis it emerges that non-sustainable stocks seem to generate higher momentum returns compared to sustainable stocks in the United States. The formation and holding period in which the non-sustainable stocks seem to generate the highest returns is the 6 months formation and holding period. Again, this is consistent to what found by Novy-Marx (2012) who provided concluded that momentum strategies based on intermediate time horizons seem to generate higher momentum returns compared to stocks with shorter time horizons. Moreover, these results are consistent with respect to both the CAPM model and the Fama-French-Three-Factors model and for all the formation and holding periods analysed. Comparing these results to those presented in the Table 2 in the previous section we can also observe that the momentum strategies for the non-sustainable stocks belonging to the 1st decile seem to outperform the overall momentums strategies performed with no sorts based on ESG-scores. This happens consistently for all the formation and holding periods and with respect to both the CAPM model and the Fama-French-Three-Factors model.

5.3 Momentum Strategy Results in Europe

The previous analysis was performed on companies based in the United States. To have results that are more robust to country specific effects, in the following section I will replicate the results, but I will include only companies that are based in Europe[4]. As previously stated, in this section I will conduct an analysis of abnormal returns with respect to the CAPM and Fama-French-Three-Factors model. Here, I perform a momentum strategy over the full sample of firms based in Europe. The results presented in Table 4 refer to momentum strategies with different formation (J) and holding periods (K). More specifically, I will focus on formation periods of 1,3,6,12 months and corresponding holding periods of 1,3,6,12 months. The time frame of the momentum strategies is from 2010 to end of 2020.

Table 4: Abnormal returns of momentum strategy (α) with respect to the CAPM and Fama-French Three factors model.

	W	**L**	**W**	**L**	**W**	**L**	**W**	**L**
			Formation	**and**	**Holding**	**Periods**	***(J- K)***	
	1-1	1-1	3-3	3-3	6-6	6-6	12-12	12-12
CAPM α	0.003	0.010	0.008	0.007	0.010	0.006	0.011	0.007
	(0.006)	(0.009)	(0.005)	(0.009)	(0.005)	(0.009)	(0.005)	(0.009)
F-F α	0.005	0.011	0.005	0.002	0.010	0.005	0.011	0.005
	(0.006)	(0.010)	(0.006)	(0.008)	(0.005)	(0.009)	(0.005)	(0.009)

Note: Table 4 shows the constant term (alpha) from for different winning and losing momentum strategies in the time frame from 2005 to 2020. The alphas represent monthly calculated alphas. Heteroskedastic-Robust Standard Errors are in parentheses; P-Values *p<0.10, **p<0.05, ***p<0.01.

[4] The countries that have been included for this analysis are Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Luxemburg, Netherlands, Norway, Poland, Portugal, Romania, Spain, Sweden, Switzerland, and United Kingdom

As we can observe from Table 4, in Europe I do not find evidence of statistically significant abnormal momentum returns with respect to both the CAPM and Fama-French-Three-Factors model. In fact, across all formation and holding period, I find no statistically significant alpha that signals abnormal returns. Hence, for the major European markets, the size, value, and market factor seem to completely explain the momentum returns observed in the sample. In the next section I will compare the results of the overall momentum strategy to the ESG-Momentum and Non-ESG-Momentum strategies.

5.4 ESG-Momentum Strategy Results in Europe.

In the following section I will present the results of the ESG-Momentum and Non-ESG-Momentum investment strategies for European stocks. In table 5, we can observe abnormal returns (α) for both investment strategies.

To reiterate, for these investment strategies I applied momentum strategies based on yearly ESG scores. Each year the firms that score in the top decile of the ESG score distribution will be selected for trading the next available year. Among those selected stocks than I apply momentum strategies based on monthly returns and hence, buy only the stocks that score in the top decile (10th) of the cumulative monthly return distribution over the formation period. On the other hand, I apply the same momentum strategies but for the firms that each year score in the bottom decile (1st) of the ESG-score distribution.

The results in Table 5 are presented for different formation period of 1,3,6,12 month and corresponding holding periods of 1,3,6,12 months.

Table 5: Abnormal returns (α) of momentum strategy for ESG and non-ESG portfolios with respect to the CAPM and Fama-French Three factors model.

ESG Deciles	**1st**	**10th**	**1st**	**10th**	**1st**	**10th**	**1st**	**10th**
			Formation	**and**	**Holding**	**Periods**	***(J- K)***	
	1-1	1-1	3-3	3-3	6-6	6-6	12-12	12-12
CAPM α	0.019**	0.001	0.018**	0.018***	0.023**	0.009	0.019**	0.012*
	(0.009)	(0.009)	(0.009)	(0.007)	(0.011)	(0.007)	(0.009)	(0.007)
F-F α	0.021**	-0.002	0.016**	0.015**	0.021*	0.006	0.021**	0.011*
	(0.010)	(0.009)	(0.081)	(0.001)	(0.011)	(0.007)	(0.010)	(0.007)

Note: Table 5 shows the constant term (alpha) from for different portfolios formed by the best performing stocks in terms of sustainability (10^{th} decile) and the worst performing stocks (1^{st} decile) in the time frame from 2005 to 2020. The alphas represent monthly calculated alphas. Heteroskedastic-Robust Standard Errors are in parentheses; P-Values *p<0.10, **p<0.05, ***p<0.01.

Some interesting patterns emerge from table 5. First, if we compare it to the Table 4 in the previous section we notice, that momentum strategies especially for Non-ESG-Portfolios generate positive and statistically significant abnormal returns with respect to the CAPM and the Fama-French-Three-Factors model. Moreover, this insight is consistent for almost all the formation and holding period analysed. Thus, momentum strategies in Europe do not seem to generate abnormal returns but, ESG-Momentum and Non-ESG-Momentum strategies seem to generate statistically significant abnormal returns. Comparing the performance of the ESG-Momentum and Non-ESG-Momentum strategies, we can observe that the non-sustainable momentum investment strategies consistently outperformed the sustainable momentum strategies for all formation and holding periods analysed. Again, consistent with what found by Novy-Marx (2012), the strategies that generate the highest returns for both investment strategies are the ones with intermediate time horizons of formation and holding period. In fact, the highest abnormal monthly returns belong to the six months formation and six months holding strategy for non-sustainable firms, namely 2.3% with respect to the CAPM model and 2.1% with respect to the Fama-French-Three-Factors model.

5.5 Comparison of Results Across Countries

Comparing the results for U.S. portfolios and European portfolios we can paint a similar picture for sustainable and non-sustainable momentum investment strategies. In both countries, there is a consistent outperformance of non-sustainable momentum investment strategies across all formation and holding periods. One main difference is that, compared to the U.S., in Europe the sustainable momentum investment strategy does not generate statistically significant abnormal returns over all the formation and holding periods. More precisely, the sustainable strategy is statistically significant only for the three month formation and holding period, generating 1.8% abnormal monthly returns, higher than the 1% abnormal returns for the same strategy in the United States. About the performance of non-sustainable strategies, whose abnormal returns are statistically significant in both countries, we can observe that in Europe, they generate higher returns for all formation and holding periods except the three-months formation and holding period strategy. Hence, we can conclude that in Europe the non-sustainable investment strategy seems to outperform those in the United States. However, from the perspective of an in investor who is interested only in sustainable investments, the United States momentum sustainable strategies generate significant abnormal returns however lower compared to the non-sustainable.

Taking the perspective of a global investors, who wants to have a diversified portfolio, in this paragraph I will investigate the correlations between the non-sustainable and sustainable investment strategies in the United States and Europe. As a reference strategy for the correlations, I will use the six months formation and holding period strategy since it showed the highest abnormal monthly returns compared to other formation and holding periods.
As we can observe from Figure A3 in the appendix, which plots the time series of returns of both investment strategies in both Europe and United States, the European non sustainable momentum strategies seem to exhibit the highest volatility followed by the European sustainable momentum strategy.
Table 6, shows mean monthly returns, standard deviations, and Sharpe Ratios of the sustainable and non-sustainable momentum investment strategies in the EU and U.S. As graphically evident from Figure A3 in the appendix, the European non-sustainable momentum strategy exhibits higher volatility over the time frame analysed, followed by the American non-sustainable momentum strategy. Non-sustainable momentum strategies exhibit higher volatility than sustainable momentum strategies. Nevertheless, those strategies also exhibit higher monthly mean returns. This is consistent to what found in the summary statistics section in which I calculated the mean returns and volatility of firms in different ESG score deciles. However, in contrary to what found in the summary statistics section, the sustainable momentum strategies have slightly lower risk-return trade-offs compared to the non-sustainable investment strategies. This is in fact evident by the lower Sharpe Ratio presented in Table 6. In fact, the Sharpe Ratio of the sustainable momentum is 20.4% opposed to 20.5% in the U.S. and 11.5% opposed to 17.6% in Europe. The results found in this section are consistent to what found by Lean and Nguyen (2014), who, by analysing sustainable investments from 2004 to 2013 concluded that the returns on Socially Responsible Investments (SRIs) are lower compared to conventional investments. Moreover, similar to what found in this section, they also show that in their sample Europe has the lowest Sharpe Ratio for sustainable investments.

Table 6: Means, standard deviations (S.D.) and Sharpe Ratios (S.R.) of monthly returns of the sustainable and non-sustainable momentum investment strategies in the E.U. and U.S., 2005-2020

	US ESG	US NON-ESG	EU ESG	EU NON-ESG
MEAN	0.009	0.017	0.009	0.023
S.D.	0.046	0.084	0.080	0.128
S.R.	0.204	0.205	0.115	0.176

Note: Table 6 shows the mean monthly returns, standard deviations, and Sharpe Ratios of the sustainable and non-sustainable momentum investment strategies in the E.U. and U.S. The values in the table represent monthly measures and they have been rounded to three decimals.

Diversification is another parameter on which investors rely to balance their portfolio. Optimally an investor should be well diversified so that during times of recession or negative returns, other assets increase in value to compensate for the losses. In this paragraph, I will investigate the correlations between the different momentum investment strategies presented earlier. Table 7 is a correlation matrix of the different momentum strategies.

Table 7: Correlation matrix of ESG and NON-ESG momentum strategies in the United States and Europe.

	US ESG	US NON-ESG	EU ESG	EU NON-ESG
US ESG	1	-	-	-
US NON-ESG	0.6930	1	-	-
EU ESG	0.6093	0.5618	1	-
EU NON-ESG	0.4754	0.4590	0.3882	1

Note: Table 7 shows the correlation between the time series of monthly return of the sustainable and non-sustainable momentum investment strategies in both the United States and Europe.

Overall, as we can observe from the correlation matrix, the momentum strategies are positively correlated with each other. An interesting pattern emerges from the correlation matrix: the sustainable strategies are more highly correlated across countries compared to the non-sustainable strategies. In fact, U.S. ESG-Momentum strategy has a correlation coefficient of 60.93% with the E.U. ESG-Momentum strategy whereas the U.S. NON-ESG-Momentum strategy has a much lower correlation coefficient with the E.U. NON-ESG-Momentum strategy of around 45.90%. Moreover, in Europe, the sustainable and non-sustainable momentum strategy are less correlated compared to those in the U.S., 38.82% correlation coefficient in Europe compared to 69.30% correlation coefficient in the United States. These results resonate to what found by Lean and Nguyen (2014) who showed the returns correlation between social responsible investments (SRI) and conventional investments of the same region are highly positively correlated.

Finally, over the full sample period, it is insightful to investigate the compounded returns of the different momentum strategies in both the United States and Europe. Figure 2 shows the equity curves of the different momentum strategies.

As evident from the equity curves, the non-sustainable investment strategies generated higher compounded returns in both the United States and Europe. One dollar investment in January of 2005 in the non-sustainable momentum strategy would have yielded around 11 dollars by the end of 2020 in the United States. One dollar investment in the non-sustainable momentum strategy would have yielded around 15 dollars by the end of 2020 in Europe. The sustainable momentum strategies would have yielded around 4.50 dollars and 3 dollars in the United States and Europe respectively by the end of 2020, considerably lower compared to the non-sustainable momentum strategies over the same time frame.

However, if we compare the sustainable momentum strategies to the Morgan Stanley Capital International world index (MSCI index), which reflects large and mid-cap stocks around 23 developed market countries, we can see that the sustainable momentum strategies outperformed the index. For instance, the U.S. ESG-Momentum strategy consistently outperformed the index from 2007 to the end of 2020. Moreover, the European ESG-Momentum strategy outperformed the index from 2007 to 2015 and again, more recently, in 2020.

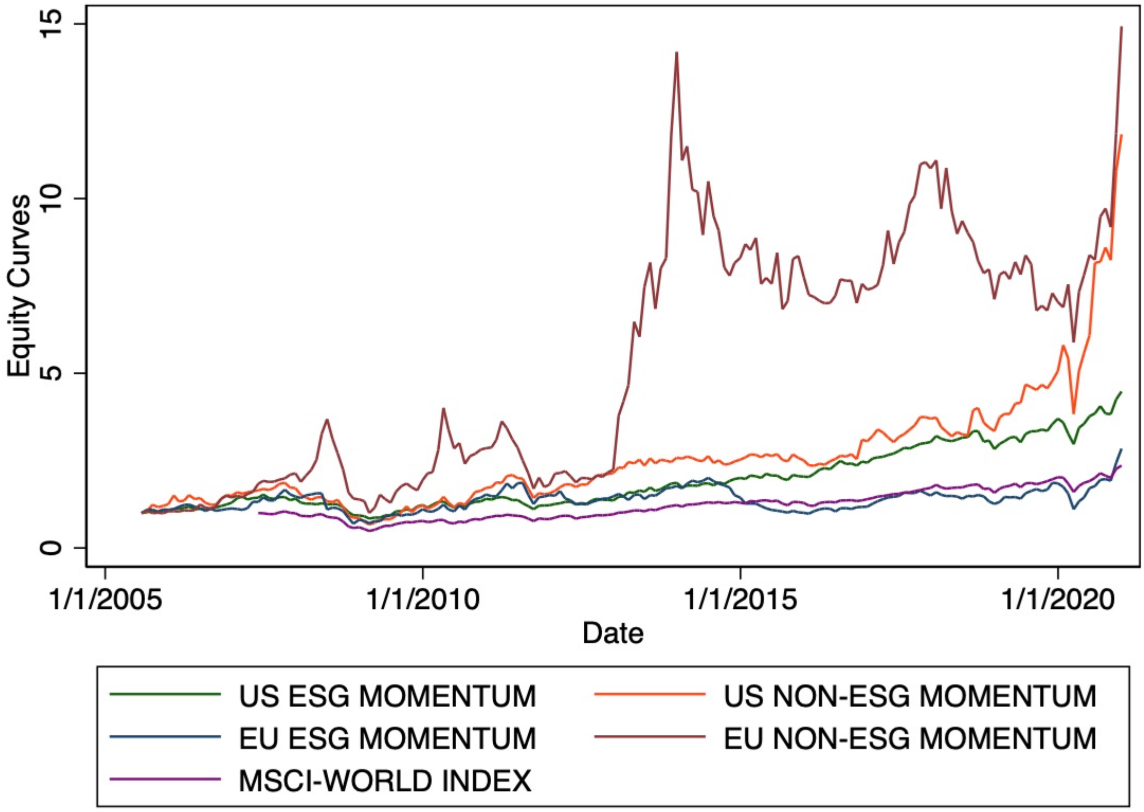

Figure 2: Equity curves of the sustainable and non-sustainable momentum investment strategies in Europe, United States and MSCI-World Index, 2005-2020

Note: Figure 2 shows the equity curves of the sustainable and non-sustainable momentum investment strategies and the MSCI-World index in Europe and United states. The first return has been normalized to one and then compounded from January 2005 to the end of December 2020.

In conclusion, it is evident from the results in this section that the non-sustainable momentum strategies consistently outperformed the sustainable momentum strategies momentum in both Europe and the United States. Hence, we witness an 'Non-ESG-Momentum effect'.
However, if we compare the sustainable momentum strategies to the MSCI-World index, in most years they outperformed the benchmark index.

5.6 Predictability of ESG-Momentum Returns

In this section, I will test the predictability of the ESG-momentum returns. I will seek to answer the following question: *are the ESG-momentum returns better forecastable compared to non-ESG-momentum returns?*

To answer this question, I will take an out-of-sample approach in which I will train a model based on half of the data points available and hold the remaining observations back to estimate the forecast. The in-sample estimation period runs from January 2005 to the end of 2012, the out-of-sample forecast evaluation period runs from January 2013 to the end of 2020. Moreover, as benchmark models I will use the all the momentum investment strategies investigate in the previous section.

As mentioned in the methodology, I will use an Autoregressive Moving Average model (ARMA) to forecast the returns based on the in-sample model.

First, it is important to determine the lags on which the model best forecasts ahead. To this purpose, I will utilize use the model that minimizes the Akaike's (AIC) and Schwarz's (SBIC) Information Criteria[5]. The SBIC involves a more rigid penalty to each marginal term added to the model compared to the AIC[6].

As we can observe from Table A1 in the appendix, the model that minimizes both AIC and SBIC information criteria is the ARMA (3,3) models. Namely, the model with three lags of autoregressive terms and three lags of moving average terms. Moreover, this in consistent for each investment strategy in both Europe and the United States.

To evaluate the forecast, I will compute the Mean Squared Error (MSE) for each investment strategy. Table 8 shows the results of the MSEs of sustainable and non-sustainable investment strategies, in both Europe and the United States, for different formation and holding periods (J-K).

Table 8: Mean Squared Errors (MSEs) of different sustainable and non-sustainable momentum strategies, 2005-2020

	US ESG	US NON-ESG	EU ESG	EU NON-ESG
MSE (1-1)	0.0083	0.0183	0.0148	0.0734
MSE (3-3)	0.0061	0.0136	0.0100	0.0275
MSE (6-6)	0.0040	0.0132	0.0122	0.0331
MSE (12-12)	0.0047	0.0118	0.0171	0.0277

[5] The information criteria involve to main factors: the residual sum of squares and a penalty for adding extra factors to the model. Hence, adding an extra term will create a tradeoff between the decrease in the sum of squares provided by the term and the increase in the penalty term.

[6] The SBIC is in fact computed as follows: $SBIC = \ln(\hat{\sigma}^2) + \frac{k}{T}\ln(T)$. Whereas the AIC is computed as follows: $AIC = \ln(\hat{\sigma}^2) + 2\frac{k}{T}$. Where $\hat{\sigma}^2$ is the residual variance of the fitted model, T is the number of observations and k is the number of parameters.

Note: Table 8 shows the mean squared errors of different momentum strategies in Europe and the United States over the sample period from 2005 to 2020. The in-sample estimation period runs from January 2005 to the end of 2012, the out-of-sample forecast evaluation period runs from January 2013 to the end of 2020. Formation and holding periods (J-K) are in parenthesis. The values presented in the table are rounded to four decimal places.

As hypothesized, Table 8 shows that the MSEs of sustainable momentum strategies are considerably lower than compared to the non-sustainable momentum strategies. This is consistent for each formation and holding periods (J-K) and in both the United States and Europe. In fact, lower MSEs imply that the forecast error is smaller for sustainable strategies than non-sustainable strategies. Hence, this provides evidence for the better predictability of sustainable momentum returns over the sample period.

In the following section, I will present the results of conditional volatility models. In fact, according to the Efficient Market Hypothesis (EMH), there is an absence of autocorrelation in returns. This implies that all the information available in the market are already included in the prices and hence, today's price will not be informative of tomorrow's returns. Nevertheless, ARMA type models are widely used in the literature to predict returns. Moreover, as Cont (2007) shows, stock returns exhibit volatility clustering, namely, changes in prices tend to cluster together.

As it is often done in empirical studies that focus on financial returns and conditional volatility, I will also use the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models to comply with the numerous stylized facts known about financial returns[7]. The main question I will address here is the following: *Is the conditional volatility of the ESG-Momentum better predictable compared to the NON-ESG-Momentum strategies?*
I will test a GARCH (1,1) model against a GJR-GARCH (1,1) model which accounts for the leverage effects of returns[8]. I will perform a Likelihood Ratio Test (LRT) to test if the additional GJR-GARCH parameters add statistically significant increases in likelihoods. The test statistic[9] is Chi-Square distributed with degrees of freedom equal to the number of restrictions from the unrestricted model to the restricted model. For each specification, if the

[7] Those include volatility clustering, absence of autocorrelation, heavy tails (kurtosis) and leverage effects.
[8] The leverage effect of returns reflects the tendency of the market to react more strongly to negative returns. GJR-GARCH accounts for this empirical result by including an indicator function (TARCH term) which activates when the returns are negative.
[9] The LRT test statistics is the following: L = -2*$(l_r - l_u)$ where l_r is the log-likelihood of the restricted model and l_u is the log-likelihood of the unrestricted model.

P-Value coming from the likelihood ratio test is statistically significant at the 5% significance level, and hence the variables in the unrestricted model added statistically significant explanatory power, I will use the GJR-GARCH model, otherwise, I will use the GARCH model. Table A2 in the appendix, shows the P-Values for each specification.

Table 9: Coefficients from the GARCH/GJR-GARCH models for different ESG-momentum strategies.

	US ESG	US NON-ESG	EU ESG	EU NON-ESG
GARCH (1-1)	0.892***	0.841***	0.795***	0.852***
	(0.090)	(0.050)	(0.133)	(0.031)
ARCH (1-1)	0.199*	0.283***	0.130**	0.000
	(0.111)	(0.105)	(0.062)	(0.012)
TARCH (1-1)	-0.254**	-0.262**	-	-
	(0.109)	(0.109)	-	-
GARCH (3-3)	0.617***	0.293	-0.274	-0.907***
	(0.233)	(0.260)	(0.348)	(0.051)
ARCH (3-3)	0.2334**	0.425*	0.206*	0.177***
	(0.140)	(0.227)	(0.115)	(0.046)
TARCH (3-3)	-	-	-	-0.150***
	-	-	-	(0.048)
GARCH (6-6)	0.892***	0.644***	0.846***	0.888***
	(0.090)	(0.117)	(0.074)	(0.109)
ARCH (6-6)	0.199*	0.268**	0.119**	0.064
	(0.111)	(0.135)	(0.054)	(0.047)
TARCH (6-6)	-0.254**	-	-	-
	(0.110)	-	-	-
GARCH (12-12)	0.287	0.711***	0.518***	0.610***
	(0.214)	(0.109)	(0.087)	(0.088)
ARCH (12-12)	0.510*	0.242***	0.592**	0.259***
	(0.275)	(0.091)	(0.252)	(0.089)
TARCH (12-12)	-0.632**	-	-0.419	-
	(0.265)	-	(0.276)	-

Note: Table 9 shows the coefficients from the GARCH/GJR-GARCH models for different ESG-momentum strategies. Specification in which there is no TARCH reported are the ones with insignificant P-values from the Likelihood Ratio Test. Formation and holding periods (J-K) are in parenthesis in the first column. Heteroskedastic-Robust Standard Errors are in parenthesis; P-Values, *p<0.10, **p<0.05, ***p<0.01.

As we can observe from Table 9, most of the specification of sustainable momentum strategies and non-sustainable momentum strategies exhibit significant ARCH, GARCH and TARCH coefficients (TARCH when applicable). Hence, both investment strategies can be significantly predicted using GARCH-type models. However, we witness no significant difference between the sustainable and non-sustainable strategies. In fact, there seems to be no identifying pattern in the significance and magnitude of the coefficients between ESG and NON-ESG momentum strategies. Thus, in this sample, the hypothesis that the conditional volatility of the sustainable momentum strategies is better predictable compared to the non-sustainable strategies is rejected for both the United States and Europe. These results contrast to what found by Ashwin Kumar et al. (2016), who analysed the annualized volatility of stock returns and concluded that companies that achieve higher ESG scores, show lower and more predictable volatility compared to other companies in the same industry.

5.7 Robustness, Residual Analyst Coverage

In this section, I test the hypothesis that the results can be partly driven by the effect of the residual analyst coverage investigated by Hong et al. (2000). In their paper, the authors showed that firms that have low analyst coverage exhibit higher momentum returns compared to firms that have low analyst coverage. Thus, I hypothesize that part of the of the Non-ESG effect individuated in previous section can be explained by the lower analyst coverage of firms belonging to the bottom decile of the ESG distribution.

In this section, I will present the results of the logistic regression outlined in the methodology section. Moreover, I will run the regression for both the United States and Europe. Table 10 shows the output results of the logistic regression.

Table 10: Logistic Regression, analyst coverage

	(1) DEC	(2) DEC
γ	0.2967***	0.3219***
	(0.0269)	(0.0273)
Pseudo R-Square	0.0054	0.0061

Note: Table 10 presents the coefficients of logistic regression of ESG deciles (DEC), which is one for firms that belong to the dop decile of the ESG distribution and 0 for the firms that are in the bottom decile of the ESG distribution, on analyst coverage. Specification (1) refers to the United States and specification (2) refers to

Europe. Robust standard errors are in parenthesis. Pseudo R-Square in presented in the bottom row; P-Values, *p<0.10, **p<0.05, ***p<0.01.

As we can observe from Table 10, the coefficient of the residual analyst coverage is statistically significant at the 1% level for both the United States and Europe and economically sizeable, 29.67% and 32.19% for the United States and Europe respectively. Hence, I find statistically significant evidence to say that higher values of the analyst coverage are associated with a higher probability of belonging to the top decile of the ESG distribution. I other words, there is evidence that part of the ESG effect investigated in previous section can be explained by the lower analyst coverage of firms that belong to the bottom decile of the ESG score distribution. As hypothesized, these results resonate to what found by Hong et al. (2000).

6 – Discussion

In this section, I will discuss the results gathered in the previous section, investigating the possible causes and societal implications. The research question I aimed to answer in this paper, concerned the comparison of sustainable and non-sustainable momentum strategies.

6.1 The NON-ESG-Momentum Effect

As we have witnessed in the results section, the sustainable momentum strategies consistently underperformed the non-sustainable momentum strategies in both Europe and the Unites States. In fact, they exhibited lower abnormal returns with respect to both the CAPM and Fama-French model. In fact, contrary to what I hypothesized, the results point to towards the conclusion that ESG-Momentum strategies do not yield the higher returns compared to the NON-ESG Momentum strategy.
Thus, we witness a 'Non-ESG momentum effect' of momentum strategies, namely the non-sustainable momentum strategies perform better compared to the sustainable momentum strategies. In other words, keeping constant the momentum strategy, there appear to be a systematic difference between the abnormal returns of sustainable and non-sustainable firms. This effect can be the result of many factors: First, as discussed by Walley and Whitehead (1994) compliance to ESG standards can be extremely costly for a firm, also in terms of operational efficiency. In fact, higher regulatory costs can translate to higher product or service

prices and thus, lower competitivity in the market. This, in turn, translates to worse stock performance compared to the firms that do not comply with environmental standards. According to their analysis, this effect could drive part of the Non-ESG momentum effect.

However reasonable this explanation is, it does not consider that compliance to regulatory standards can be costly and lead to underperformance in the short-run but, in the long-run, firms can benefit from a more sustainable and operationally efficient approach. For example, Kotsantonis et al. (2016) in their paper tried to debunk old myths about ESG investing and proved that, in reality, companies that commit to sustainability show better performance in the long-run in terms of product, labour and capital markets. Furthermore, they showed that in the long-run, portfolios that take into account ESG metrics yield higher average returns and lower risk compared to portfolios that do not.

A more reasonable explanation of this systematic difference between sustainable and non-sustainable momentum investment strategies concerns the analyst coverage. As outlined by Hong et al. (2000), all else being equal, firms that have low analyst coverage, exhibit higher momentum returns compared to firms that have a high analyst coverage. Consequently, part of the 'Non-ESG Momentum' effect can be explained by analyst coverage. In other words, the firms that belong to the lowest decile of the ESG score distribution likely exhibit low analyst coverage triggering the effect investigated by Hong et al. (2000). To test this hypothesis, I conducted a logistic regression approach and verified if high analyst coverage is predictive of being in the top decile of the ESG score distribution.

The results show that firms that have high analyst coverage are more likely to belong to the top decile of the ESG distribution, providing evidence in favour of the explanation outlined by Hong et al. (2000). It is also important to notice that low analyst coverage might explain a small part of the variation in the ESG score decile. In fact, as we can observe from Table 10, the percentage of variation explained by the model (Pseudo R-Square) is only 0.54% and 0.61% for the United States and Europe respectively. Thus, a large portion of the Non-ESG-Momentum effect seems still to be unexplained.

As argued in the literature review, part of the Non-ESG-momentum effect can be also explained by the sustainability risk premia: non-sustainable firms exhibit higher firm-specific volatility and hence higher returns. Firms with low ESG rating need to offer risk premia to investors to compensate for the additional default risk as argued by Bannier et al. (2019).

To summarise, the outperformance of the non-ESG momentum strategies is most likely the result of an interaction effect of a momentum component and an ESG component, namely analyst coverage and non-sustainable risk premia: firm that belong to the lowest decile of the

ESG distribution show lower analyst coverage and consequently higher momentum returns as showed by Hong et al. (2000). Also, non-sustainable firms require risk premia for the additional financial risk they imply, generating higher returns as shown by Bannier et al. (2019). This interaction effect can explain both (1) why the non-sustainable momentum strategies consistently outperformed the sustainable momentum strategies and (2) why the non-sustainable momentum strategies generated higher cumulative returns over the sample period. In the conclusion section I will suggest research directions to investigate more on these insights.

6.2 Social Implications

As discussed in the introduction, recently, asset managers are being pressured in more sustainable investments. It is paramount important to further develop research in sustainable investments strategies that aims to maximise both sustainability and profits. The main goal of this paper was to investigate the relationship between momentum returns and ESG investing. The results show that, in terms of returns, the momentum strategy works best for non-sustainable socks. Although, as we have seen in the predictability section of the results, sustainable investment strategies seem to be more predictable and show lower volatility compared to non-sustainable momentum strategies.

Hence, from the perspective of an asset manager who wants to maximise returns and sustainability and minimise volatility, these sustainable strategies still offer interesting dynamics to exploit. In fact, as many of the paper discussed above showed, sustainable investment strategies often offer better risk-return trade-offs, especially in the long-run. Furthermore, as we have seen from Figure 2, the ESG-Momentum strategies outperformed the MSCI-World index in both the United States and Europe.

7 - Conclusion

7.1 The Research Question

Applying different methodologies, this paper investigates the relationship between ESG investing and momentum investment strategies. Previous literature did not investigate this relationship and this paper wants to fill this gap in the literature. In fact, previous research focused mainly on the relationship between ESG indicators and firm performance, arriving at contradictory conclusions.

Computing the abnormal returns of different sustainable and non-sustainable momentum strategies, I provide evidence that, in terms of returns, sustainable strategies underperform the non-sustainable momentum strategies. However, using ARCH models, the sustainable momentum strategies show lower volatility and higher predictability of returns in the sample period from 2005 to 2020. Hence, they can be applied by investors that are interested in both returns and sustainability. Moreover, I do not find evidence of systematic differences in the predictability of volatility using GARCH models.

A possible explanation of the consistent difference in abnormal returns of the sustainable and non-sustainable momentum strategies is that the firms that belong to the bottom decile of the ESG score distribution (the ones that are used for the non-sustainable momentum strategies) show lower analyst coverage and, as Hong et al. (2000) showed, firms that have low analyst coverage tend to exhibit higher momentum returns.

Although this result seems to explain part of this systematic difference in returns, many questions remain.

7.2 Limitations and Future Research

In this section I will address the limitations of the research and possible future research directions.

First, to practically implement the ESG momentum strategy, it is important to account for trading costs of rebalancing the portfolios each month/year. Due to the scope of this short paper and unavailability of reliable data about commission costs, in the analysis conducted above I did not account for transaction costs. However, market frictions such as transaction costs can increase with frequent trading and can hamper the profitability of the investment strategies. In fact, the momentum strategies I developed require frequent rebalancing depending on the formation and holding period. Korajczyk and Sadka (2004) investigate the profitability of momentum strategies after accounting for transaction costs. The authors, using bid/ask spreads and non-proportional trading cost models showed that after accounting for transaction costs, the profitability of momentum strategies significantly decreased but some of the strategies still yielded significant abnormal profits. Future research could focus on the profitability of ESG-Momentum strategies after accounting for transaction costs. For instance, following Korajczyk and Sadka (2004), future researchers can develop a liquidity-weighted-strategy engineered to minimise transaction costs.

Second, the analysis discussed above has been conducted only in Europe and the United States. The literature on momentum strategies has documented contradictory results in different countries. For example, Asness et al. (2013) who analysed momentum returns across different markets and asset classes, showed that in Japan, momentum premia are insignificant.

Third, future research can focus on quantifying the influence of sustainability risk premia on the Non-ESG-Momentum effect. As argued above, the Non-ESG-Momentum effect is most likely influenced by the interaction effect between analyst coverage and non-sustainable risk premia and would be interesting to quantify the contribution of both analyst coverage and risk premia on the Non-ESG-Momentum effect.

Moreover, the effectiveness of the strategies might depend also on national environmental regulations. Hence, future research can replicate the analysis above in different countries.

Finally, this paper is that is purely empirical. Following the increasing interest in sustainable investments, future researchers could develop a microeconomic model of an investor who gains utility from both sustainable investment and returns. In that model ESG-Momentum strategies can be used to predict the invertor's utility from different types of sustainable investment strategies including the ones discussed in this paper.

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9 - Appendix

Figure A1: Time series of returns of the long-short momentum strategy 6-6 in the U.S., 2010-2020

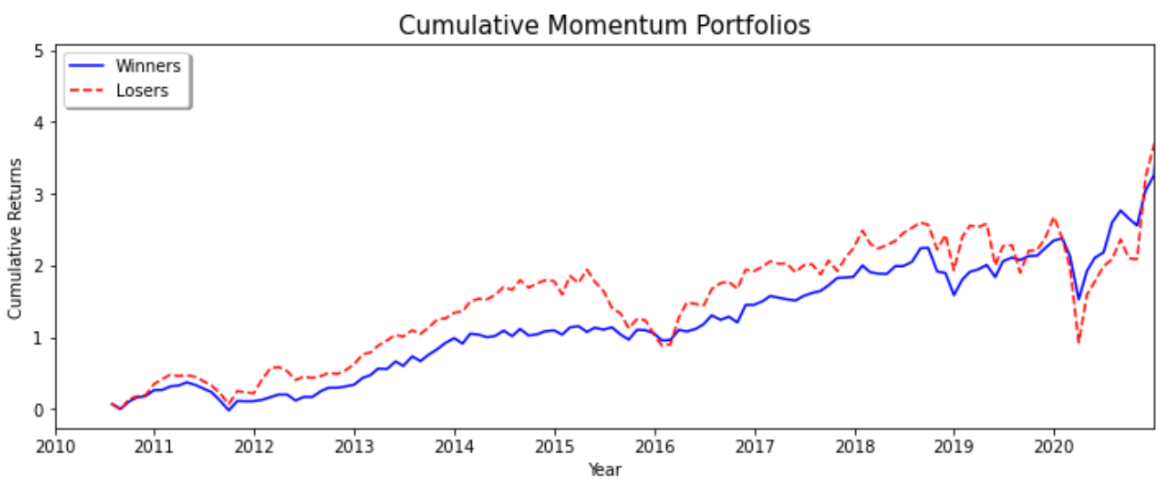

Figure A2: Cumulative returns of the winner and loser portfolio for six months formation and holding period in the U.S., 2010-2020

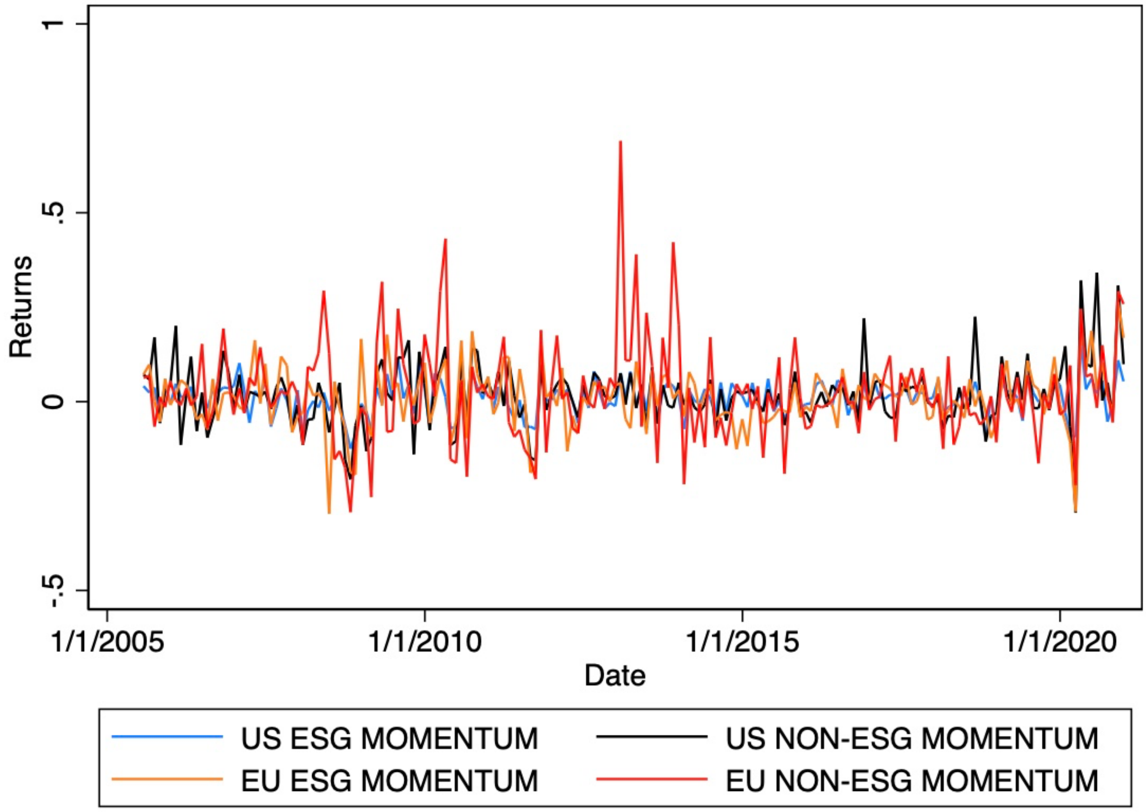

Figure A3: time series of returns of ESG and NON-ESG momentum strategies, 2005-2020

Table A1: AIC and SBIC information criteria for different ARMA type models.

	ARMA (1,1)	ARMA (2,2)	ARMA (3,3)
AIC	-612.1815	-612.3432	-612.8107
SBIC	-586.3755	-586.9077	-596.2145

Note: Table A1 shows the Akaike's and Schwarz's information criterion for the returns of the U.S. ESG-momentum 6 months formation and holing period strategy. -586.9077

Table A2: P-values from the Likelihood Ratio Test.

	US ESG	US NON-ESG	EU ESG	EU NON-ESG
P-Value (1-1)	0.003	0.015	0.552	0.330
P-Value (3-3)	0.445	0.435	0.003	0.017
P-Value (6-6)	0.002	0.523	0.665	0.669
P-Value (12-12)	0.000	0.154	0.022	0.889

Note: Table A2 shows the p-values from the Likelihood Ratio Test. The null hypothesis is that the extra parameters in the unrestricted model do not add significant explanatory power.