On the Strong Relationship Between ESG Rating Trends and the Evolvement of Equity Prices

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Abstract Investments in sustainable investment vehicles have seen a huge increase in volume over recent years. Thereby, most investment products (e.g. funds and structured products) are constructed on the basis of the sustainability ratings from the same data providers. One such data provider is MSCI, which, in its data offering, provides an Environmental, Social and Governance (ESG) rating trend, indicating whether a company has improved or worsened its ESG score in the last re-evaluation. This project investigates whether this ESG rating trend has a direct influence on a company's alpha. The findings provide strong evidence that a positive ESG rating trend also leads to a more positive development in alpha. A negative ESG rating trend on the other hand leads to a more negative development in alpha.

1. Introduction

In recent years, ESG factors have become an important concept in the global financial landscape. As awareness of sustainability and responsible investing grows, investors and financial institutions are recognising the importance of ESG criteria in assessing the long-term viability and performance of companies. This paradigm shift is driven by the realisation that integrating ESG factors into investment strategies not only aligns with ethical values, but also contributes to improved risk management and financial returns.

1.1 Environmental, Social and Governance

Numerous studies have underscored the value of ESG integration, demonstrating its positive impact on investment performance and risk mitigation[1,2,3,4]. Most notably, Friede, Busch, and Bassen 2015 conducted a comprehensive meta-analysis, encompassing over 2,000 empirical studies, which revealed a positive relationship between corporate sustainability practices and financial performance. Their study provided compelling evidence that companies with strong ESG profiles tend to outperform their counterparts with weaker sustainability credentials in terms of stock market returns, profitability, and operational efficiency. However, they were unable to pin-point clear signals that investors can use to generate alpha based on their findings.

The increasing prevalence of ESG investing has witnessed a growing number of institutional investors embracing ESG portfolios. As a result, there has been a significant surge in the volume of investments being channeled into ESG strategies. Between 2015 and 2020, the assets of funds dedicated to ESG investments have witnessed a remarkable growth of 170%[5]. Bloomberg Intelligence forecasts the total volume in ESG investments by 2025 to 53 trillion USD[6]. The immense potential of the ESG market relies to a substantial extent on the availability and reliability of ESG ratings and data, which are currently sourced from a limited number of data providers. Prominent providers of ESG data include MSCI[7], Sustainalytics[8], and FTSE Russell[9]. It is noted that ratings from different data providers often exhibit relatively low correlation[10]. If more and more Assets under Management (AUM) are invested according to the ESG approach of these data providers, it stands to reason that potential investment opportunities will materialise.

1.2 Common Factors Behind Equity Performance

The evolvement of individual equity prices over time is significantly influenced by factors underlying the stock market as a whole. These common factors are described in several important financial theories that aim to model asset returns. One such theory is the Capital Asset Pricing Model (CAPM), which proposes that the expected return of an asset is determined by its systematic market risk, represented by beta, and the overall

1. Giese, Nagy, and Lee 2021.
2. Alareeni and Hamdan 2020.
3. Velte 2017.
4. Buallay 2019.
5. https://www.ecb.europa.eu/pub/financial-stability/fsr/focus/2020/html/ecb.fsrbox202011_07~12b8ddd530.en.html
6. https://www.bloomberg.com/professional/blog/esg-assets-may-hit-53-trillion-by-2025-a-third-of-global-aum/
7. https://www.msci.com/our-solutions/esg-investing/esg-data-and-solutions
8. https://www.sustainalytics.com/esg-data
9. https://www.ftserussell.com/data/sustainability-and-esg-data
10. consult the graph on page 11:https://www.gpif.go.jp/en/investment/pdf/ESG_indices_selected.pdf

market risk premium[11]. CAPM assumes that movements in the overall market are the only source of risk. The Fama-French Three-Factor Model, developed by Eugene Fama and Kenneth French in 1993, serves as an extention to the CAPM. It expands upon the CAPM by incorporating additional factors that capture systematic risk beyond the market. The three factors include the market risk premium, the size effect (small firms tend to outperform large firms), and the value effect (value stocks tend to outperform growth stocks). In addition to the Fama-French Three-Factor Model, several other asset pricing models have been developed that incorporate more than three factors. One prominent example is the Carhart Four-Factor Model[12], which extends the Fama-French model by including a momentum factor. The momentum factor captures the tendency of stocks with positive past returns to continue outperforming. More recently, quantitative asset managers have explored models with even more factors, such as the Barra Risk Factor Models[13], which include a comprehensive set of factors representing various risk dimensions like industry exposure, interest rate sensitivity, earnings growth, share turnover, senior debt rating and macroeconomic factors[14]. When analyzing the impact of specific external events, such as the increase of an ESG rating on stock prices, it is crucial to distinguish between common factors that affect the entire market and the stock-specific performance, often referred to as alpha.

1.3 Research Question and Experiments

The objective of this project entails the examination whether the MSCI ESG trend bears any implications on the logarithmic alpha returns. The first step thus involves deriving share-specific logarithmic alpha, which measures the excess return of a share over its expected return based on the relevant risk factors and market performance. Logarithmic alpha serves as an indicator of a stock's performance independent of the broader market movements. Subsequently, the potential impact of the MSCI ESG trend on the logarithmic alpha returns is assessed. This entails comparing the logarithmic alpha return *before* vs. *after* the MSCI ESG rating shift has occured.

The results may prove relevant in many aspects. Long-short equity strategies could use the information of the MSCI ESG trend to generate additional alpha. Furthermore, numerous structured products are imaginable, where the retail investor could benefit from the ESG trend. For example, a Barrier Reverse Convertible (BRC) would be conceivable, in which the investor buys a basket of stocks with all positive ESG trends. The investor thereby hedges her/his downside risks through ESG trend upforces.

11. Sharpe 1964.
12. Carhart 1997.
13. https://app2.msci.com/products/analytics/models/
14. Barra risk factor models were developed by Barra Inc., which is now part of MSCI.

2. Definitions

Normalization / Relative Scaling A time series is said to be normalized when it is transformed into a *relative measure of change from the initial value*[15]. Normalisation enables the comparison of time series that originally were on different scales. Thereby, each consecutive value of a time series is divided by the first value, so that the time series starts at 1 (or 0 for log-prices: $\log(1) = 0$). In concrete terms, this means for a time series X_t at time t that $\dot{X}_t = \frac{X_t}{X_1}$ where $\dot{X}_t$ is the normalized value of X_t and X_1 is the first value in the time series.

Returns / Log-Returns Financial asset returns describe the change in the price of a financial asset over a specified period of time[16]. The daily (simple) return $\dot{R}_t$ of the price of a financial asset X_t at time t is the relative change of that asset to the previous day: $\dot{R}_t = \frac{X_t - X_{t-1}}{X_{t-1}}$. As prices of financial assets can be highly skewed and may have heavy tails, log-returns are commonly used for modeling purposes[17]. Given the price of a financial asset X_t at time t, the log-return $R_t = log(\frac{X_t}{X_{t-1}}) = log(X_t) - log(X_{t-1})$.

Risk Adjusted Returns Risk-adjusted returns provide an assessment of the return realized in relation to the risk taken. The Sharpe ratio is commonly used for this purpose. It is defined as: $S = \frac{R_{portfolio} - R_{risk-free}}{\sigma_{portfolio}}$, where $R_{portfolio}$ is the expected return of the portfolio or asset, $R_{risk-free}$ is the risk-free rate of return (typically the yield on a risk-free asset like a Treasury bill or bond) and $\sigma_{portfolio}$ is the standard deviation of the portfolio.

Market Beta Market beta, often referred to as just beta, provides insights into how an asset tends to move in response to market movements (often measured on a market index (e.g. EURO STOXX 50) or benchmark). A beta coefficient of 1 signifies that the asset's returns typically move in tandem, proportionally with the market returns. A beta exceeding 1 indicates higher volatility compared to the market. Conversely, a beta below 1 suggests the asset is comparatively less volatile than the market. According to CAPM[18], market beta can be derived using a regression model $R_t = \alpha + \beta \cdot R_t^{market} + \epsilon_t$, where: R_t represents the returns of a given asset, R_t^{market} represents the returns of the market, α is the intercept i.e. the expected return of the asset when the market return is zero, β is the regression coefficient representing the sensitivity of the asset's returns to the market returns and ϵ_t is the error term or residual, capturing the unexplained variation in the asset's returns not accounted for by the market returns[19]. β_i for share i can be calculated directly by $\frac{Cov(R_i, R_{market})}{Var(R_{market})}$.

15. Mills 2019.
16. Drake and Fabozzi 2010.
17. Mills 2019.
18. Fama and French 2004.
19. Qian, Hua, and Sorensen 2007.

Market Weights Market weights establish the relative significance and inclusion of individual components (e.g. stocks, bonds, ...) in a benchmark or index, often determined by factors like market capitalization or revenue[20]. One approach to benchmark construction is the equal weighting of all underlyings. Let this type of benchmark be called Equal-Weights Benchmark.

Residual Covariance Residual Covariance quantifies the degree to which the residuals ϵ_t of the regression model $R_t = \alpha + \beta \cdot R_t^{market} + \epsilon_t$ are correlated with each other. It indicates whether there is a systematic relationship or pattern in the remaining unexplained variation of a model. According to the Fama-French 3-Factor Model[21], beta-adjusted daily stock prices still contain residual covariance of at least 2 factors: the size factor (SMB) and the value factor (HML). SMB captures the historically measurable outperformance of small-cap stocks compared to large-cap stocks and HML captures the historically measurable outperformance of value stocks compared to growth stocks.

Factor Beta Factor Beta, similar Market Beta, represents the sensitivity of an asset's returns to a specific set of latent factors derived from the residuals covariance. Factor beta extends market beta by quantifying the asset's sensitivity to additional latent factors that explain the remaining variation or patterns in the asset's returns. The process of deriving factor beta involves conducting principal component analysis (PCA) to identify and extract these latent factors from the residual covariance matrix. These latent factors represent systematic sources in the returns that are not captured by the market factor alone.

Factor Weights Similar to market weight, factor weights refer to the coefficients that determine the contribution of each original variable to the latent factors. In PCA, factor weights define the linear combinations used to create the principal components.

Alpha Alpha assesses the excess return generated by a stock beyond what would be expected based on all systematic factors (Factor Beta)[22]. It is often used as a measure of a stocks individual ability to outperform the market or a benchmark. Simply put, alpha is the stock-specific performance after all systematic market drivers are controlled.

20. Drake and Fabozzi 2010.
21. Fama and French 1993.
22. Fabozzi, Focardi, and Kolm 2010.

3 Analysis

In the following, first the data and their origin are declared. Subsequently the data analysis is elaborated.

3.1 Data

3.1.1 MSCI ESG Data

MSCI[23], a leading provider of investment decision support tools and global index benchmarks, provides ESG scores for individual stocks. MSCI's ESG scores[24] capture important information about a company's environmental practices, social impact, and governance structure. Their ESG scores are derived from a variety of sources, including company disclosures, regulatory filings, third-party research, and proprietary research. The data is standardized and normalized to enable comparison across companies and industries.

The data provided by MSCI also includes an ESG rating trend, which indicates whether the ESG rating of a company has improved, deteriorated or remained the same in the recent past. In addition, MSCI also provides for each company the date on which the rating was last re-evaluated[25]. If the rating of a security had improved in the last re-evaluation, the ESG rating trend of that company will be positive (e.g. +1). If the rating worsened in the last re-evaluation, the ESG rating trend will be negative (e.g. -1). If the rating stayed the same during the last re-evaluation, the ESG rating trend will be neutral (0). Changes in the rating may have been triggered by many different factors. Positive improvements can, for example, be due to more women on the board of directors or to the granting of insight (transparency), for example into the supply chain or the waste disposal concept. The ESG rating trend is categorical in nature. This means that a rating improvement/decline of more than one category is possible[26].

3.1.2 Daily Share Prices

Adjusted[27] daily historical share prices of European companies were obtained and collected from Yahoo Finance's database on March 8, 2023. The exact ISINs of the downloaded shares are listed in the appendix. Daily historical share price time series were downloaded for every trading day between February 26, 2019 and March 8, 2023. Three shares were excluded because there was not enough/no data available.

23. https://www.msci.com/
24. https://www.msci.com/our-solutions/esg-investing/esg-data-and-solutions
25. https://www.msci.com/documents/1296102/34424357/MSCI+ESG+Ratings+Methodology+-+Process+%28002%29.pdf
26. e.g., an ESG rating trend of +2 may indicate that a company improved it's rating from A to AAA.
27. The adjusted closing price accounts for any corporate actions, such as dividends, stock splits, or mergers, that may affect the stock's price.

The 251 securities used in the analysis could, in the aggregate, represent an investment universe for a typical institutional investor's Euroland portfolio.

3.2 Data Cleaning

The downloaded historical stock price time series contained "not-available" (NA) prices, which were initially dealt with.

Two types of NA's were identified: The first type occurred "within" known prices. Their cause could not be determined. In this case, the "missing-at-random" assumption was applied, and the NA's were replaced with the last known preceding price.

The second type were leading NA's found at the beginning of the time series. These NAs arise because prices were only available from a point in time after 26 February 2019. To determine their treatment, it was checked if there were at least 180 data points available before the date of the last re-evaluation of the ESG rating. If fewer than 180 data points were available, the respective security was excluded from the analysis, resulting in the exclusion of 2 shares. On the other hand, if at least 180 data points were present, the NA's were replaced with the first known price of the respective time series.

Lastly, to ensure comparability, all time series were normalized and logarithmized (see Definitions).

3.3 Finding the alpha

In the following, the derivation of the security specific alpha is outlined.

3.3.1 Benchmark

The benchmark utilized in the analysis encompassed the specified investment universe, without the consideration of specific market capitalization data. That is, each security within the universe was assigned an equal weight, resulting in an equally weighted benchmark (see Definitions). The log-price of the benchmark at time t

$$log(F_t^{bm}) = \sum_{i=1}^{N_{bm}} \frac{1}{N_{bm}} \cdot log(X_t^i), \tag{1}$$

where N_{bm} indicates the number of individual shares underlying the benchmark and X_t^i is the price of the i^{th} security at time t. The covariance of the logarithmic returns R^i of security i with the logarithmic returns R^{bm} of the benchmark bm

$$Cov(R^i, R^{bm}) = \sum_{j=1}^{N_{bm}} \frac{1}{N_{bm}} \cdot Cov(R^i, R^j), \tag{2}$$

where $R^i = [R_t^i, R_{t-1}^i, \dots, R_1^i]^T$, $R^j = [R_t^j, R_{t-1}^j, \dots, R_1^j]^T$, $R_t^i = log(X_t^i) - log(X_{t-1}^i)$ and $R_t^j = log(X_t^j) - log(X_{t-1}^j)$. The introduced notation will be used throughout this report.

3.3.2 Market Beta

Market Beta β_i for the i^{th} security was derived from (2) using the equality

$$\beta_i = \frac{Cov(R^i, R^{bm})}{Var(R^{bm})}, \tag{3}$$

which is computationally much more efficient than estimating it through the regression equation (see Definitions). Two examples illustrating the market beta for the two stocks "Bayer AG" and "ASML Holding N.V." can be found in Figure 1.

The price $\dot{X}_t^i$ at time t for security i adjusted for the market factor has then been derived using

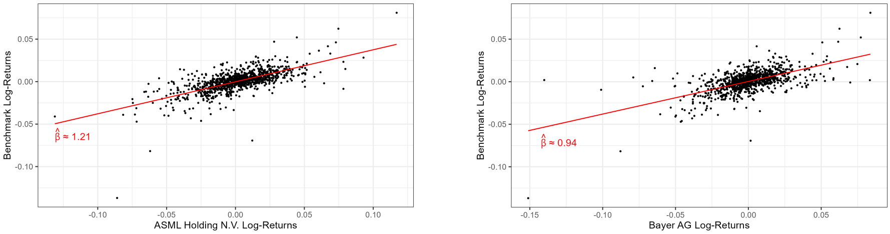
$$log(\dot{X}_t^i) = log(X_t^i) - log(F_t^{bm}) * \beta_i \tag{4}$$

and the market-factor adjusted residual covariance $Cov(\dot{R}^i, \dot{R}^j)$ was straightforwardly estimated from the differentiated beta-adjusted logarithmic return series $\dot{R}^i$ and $\dot{R}^j$. The term *excess return* is used in relation to $\dot{R}^i$.

3.3.3 Factor Beta

As suggested by existing literature[28], it is acknowledged that the beta-adjusted residual covariance and excess returns of securities retain a certain degree of systematic variance within the error term ϵ. To capture this systematic variance, the inclusion of factors such as HML (High Minus Low) and SMB (Small Minus Big) can be used. However, it is worth noting that acquiring factor data for individual securities can be challenging, and for certain shares even impossible. Consequently, a common approach to address this constraint is to employ PCA on the beta-adjusted excess covariance matrix. This approach is sometimes termed "poor man's" factor modeling, in reference to its feasibility without additional fee-based data.

28. Fama and French 1993.



ASML Holding N.V. (Netherlands) Bayer AG (Germany)

FIGURE 1. *Benchmark log-returns plotted against the shares log-returns. β is the slope of the regression*

The variance redistribution resulting from the PCA is presented in Figure 2. In addition, Table A1 in the Appendix illustrates the variance recorded on the first N principal components.

There exist several approaches to determine the "correct" number of principal components. One of which is the Kaiser criterion, in which all principal components larger than 1 are taken into account. As most of the literature uses 3-5 factor models to explain equity returns, for this analysis only the first five principal components in addition to the beta factor are included.

The five selected eigenvectors resulting from the PCA are to be understood as weights of a share on the systematic factors that go beyond the market factor. The factor weights (see Definitions) for share i thus consist of a tuple of five values $W = [W_1^i, \dots, W_5^i]^T$.

Consequently, for factor f at time t, the logarithmic factor price

$$log(F_t^f) = \sum_{i=1}^{N_{bm}} log(X_t^i) * W_f^i. \tag{5}$$

In the following, the term *logarithmic factor performance* is used rather than logarithmic factor price. Logarithmic factor performances, along with the logarithmic market factor performance is displayed in Figure 3. The covariance $Cov(R^f, R^g)$ of the logarithmic returns R^f and R^g of two factors f and g can straightforwardly be derived from their logarithmic factor performance $log(F^f)$ and $log(F^g)$. Similarly, the covariance $Cov(R^i, R^f)$ between the logarithmic return R^i of share i and the logarithmic factor performance R^f of factor f can directly be derived from the logarithmic price series $log(X^i)$ and the logarithmic factor performance $log(F^f)$.

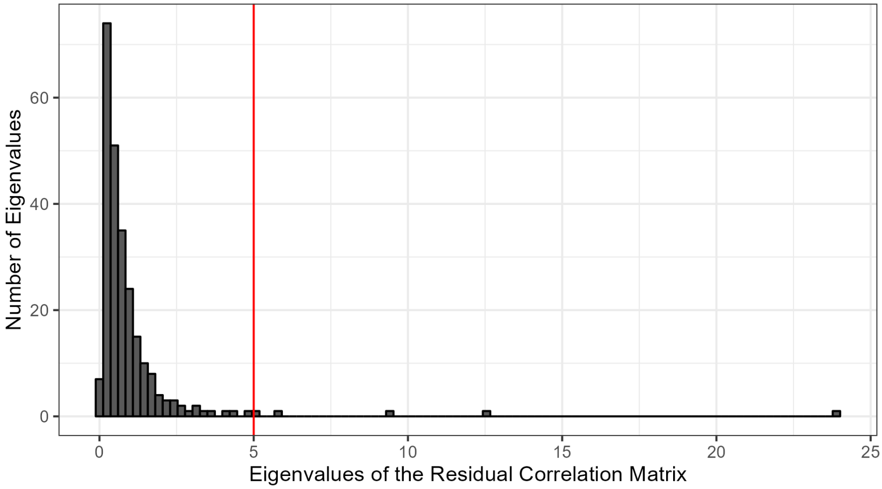
The present juncture beckons to embark upon the derivation of the factor beta. The factor beta for share i and factor f,

$$\beta_i^f = \sum_{g=1}^{N_{factor}} \frac{Cov(R^i, R^g)}{Cov(R^f, R^g)}, \tag{6}$$

where N_{factor} denotes the total number of factors (note that 5 factors are used in the analysis). To avoid any confusion, it is worth noting again that the index i is used to refer to a specific share, and the indices f and g are used to correspond to factors. The origin of (6) in (3) has been noticed by the attentive reader.

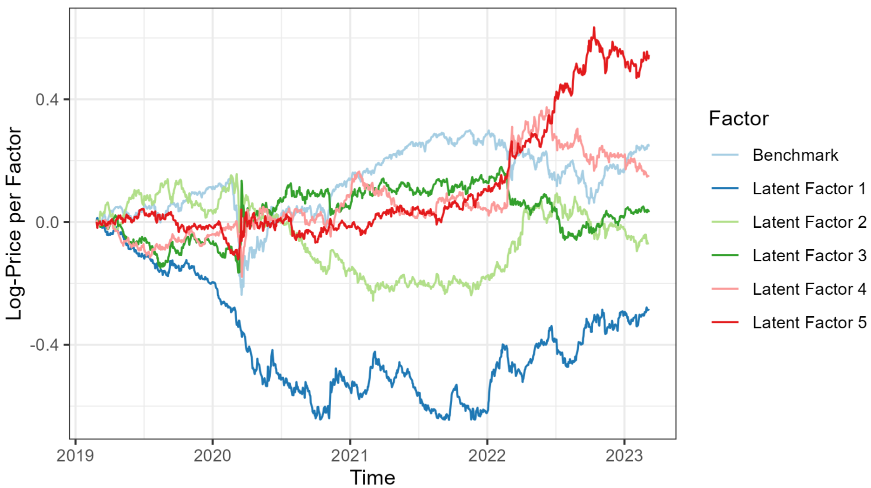
3.3.4 Alpha

In order to calculate the combined factor-specific forces behind the logarithmic price series of an individual share i, equations (1), (5), (3) and (6) can be employed in the following manner: The combined logarithmic factor-specific force $log(F_t^i)$ behind a share i at time t is given by



Notes: The red line indicates the cut-off for the number of factors taken into account. In the analysis, eigenvalues larger than 5 are considered to capture systematic variance.

FIGURE 2. *Histogram of the Eigenvalues resulting from the PCA on the beta-adjusted excess return covariance*



Notes: The benchmark indicates the market factor performance; The latent factors indicate the factor performance resulting from the PCA on the excess covariance matrix.

FIGURE 3. *Factor Performance of all systematic factors.*

$$log(F_t^i) = log(F_t^{bm}) * \beta_i + \sum_{f=1}^{N_{factor}} log(F_t^f) * \beta_f^i \tag{7}$$

Consequently, the logarithmic alpha of an individual share i at time t

$$\alpha_t^i = log(X_t^i) - log(F_t^i), \tag{8}$$

which, evidently, is just the subtraction of (7) from the original logarithmic price of share i. The derived logarithmic price series, logarithmic alpha and combined factor specific forces for the two shares ASML Holding N.V. (Netherlands) and Bayer AG (Germany) are illustrated in Figure 4.

Notes: **Top:** Logarithmic price, logarithmic factor-performance and logarithmic alpha of *ASML Holding N.V.* (Netherlands). **Bottom:** Logarithmic price, logarithmic factor-performance and logarithmic alpha of *Bayer AG* (Germany).

FIGURE 4. *Depiction of the logarithmic alpha of two shares over time. Logarithmic alpha results from the subtraction of the logarithmic factor performance from the logarithmic share price.*

3.3.5 Excursus: Best and worst performance

The derived alpha time series α^i for stock i holds significant implications for constructing an active inverstors portfolio. By analyzing the alpha of share i over a given time period, it becomes possible to determine the appropriate weighting of stock i relative to the weighting within the benchmark.

In the event that α^i is negative over the most recent period, it is prudent to underweight share i compared to the benchmark. This decision is justified by the expectation that share i is under-performing relative to the benchmark.

Conversely, if α^i is positive relative to the benchmark, it is advisable to overweight share i in the portfolio. This action is predicated on the belief that share i exhibits strong performance and is likely to outperform the benchmark in the future.

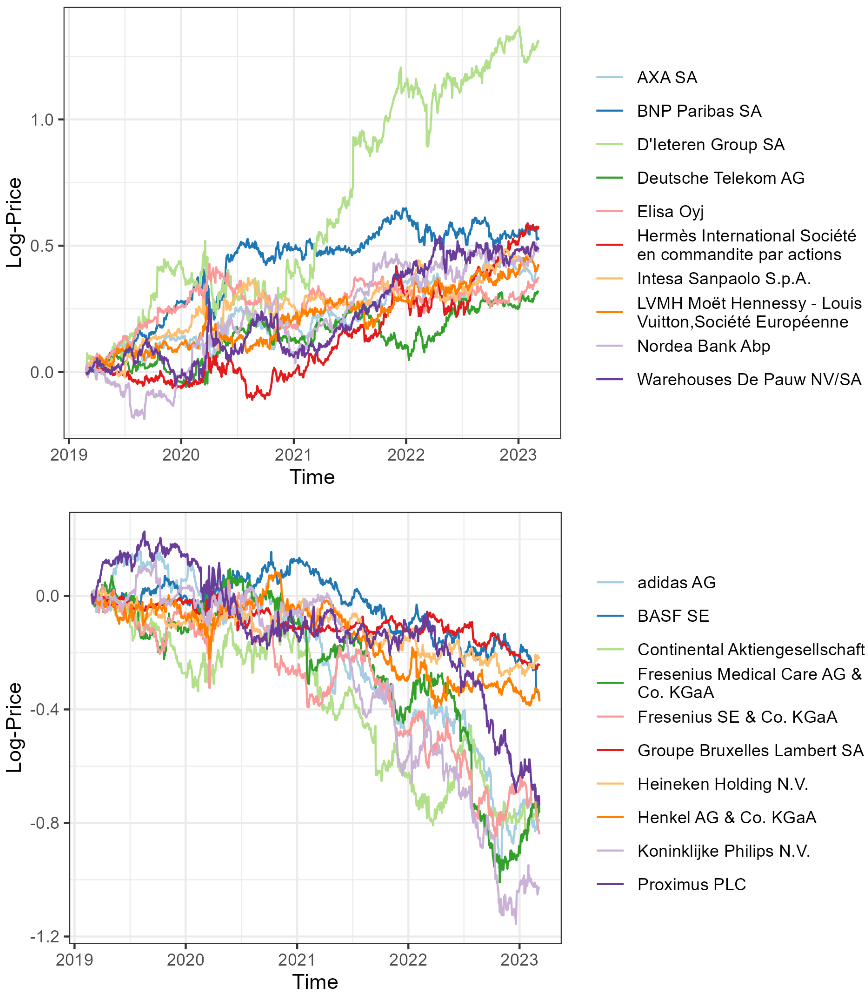
The ten best and worst performers for the time between 26. February, 2019 and 08. March, 2023 according to the above outlined 6-factor model are displayed in Figure 5.

3.4 Examining the ESG Trend Impact

The logarithmic alpha derived in section 3.3 is used to investigate the impact of MSCIs' ESG Trend on equity. For every share i, the six month mean logarithmic alpha return *before* the MSCI ESG rating shift $log(\bar{\alpha}^i_{-6M})$ and the six month mean logarithmic alpha return *after* the MSCI ESG rating shift $log(\bar{\alpha}^i_{+6M})$ was determined. The change in yield $log(\bar{\alpha}^i_{diff})$ for share i was then obtained by

$$log(\bar{\alpha}^i_{diff}) = log(\bar{\alpha}^i_{+6M}) - log(\bar{\alpha}^i_{-6M}) \tag{9}$$

That is, if $log(\bar{\alpha}^i_{diff}) > 0$, the MSCI rating shift had a positive impact on the six month mean logarithmic alpha return, and if $log(\bar{\alpha}^i_{diff}) \leq 0$, the MSCI rating shift had no/negative impact on the six month mean logarithmic alpha return. $log(\bar{\alpha}^i_{diff})$ was calculated for each of the four MSCI ESG rating trend categories that were present in the data: -1, 0, 1, 2.



Notes: **Top:** Logarithmic alpha of the 10 best performing shares. **Bottom:** Logarithmic alpha of the 10 worst performing shares

FIGURE 5. *Depiction of the logarithmic alpha of the top 10 best and top 10 worst performers over the period between 26. February, 2019 and 08. March 2023. Alpha is derived using the 6-factor model outlined in section 3.*

4. Results and Discussion

4.1 Key Findings

The obtained results in Table 1 and Figure 6 provide strong support for the hypothesized relationship between the MSCI ESG trend and the stock-specific alpha returns. Analysis of the data reveals that six month logarithmic alpha returns are substantially higher after an MSCI ESG rating increase of +1 and substantially lower after an MSCI ESG rating decrease of -1. In contrast, there is hardly any change in the six month mean logarithmic alpha returns when the MSCI ESG rating is constant (0). The results in Table 1 manifest themselves particularly strong in the mean over $log(\bar{\alpha}^i_{diff})$ per category, but can also be confirmed in the more outlier robust median. The robustness of the results is especially given in the categories 0 and +1, where the sample size is adequately dimensioned.

The effects in ESG trend category 2 may be perplexing. However, a deeper insight into this category provides clarity. First of all, the sample size of only six observations is too narrow, ruling out any clear findings from this category. Furthermore, it should be noted that the category is peppered with "bad" performers. One of them is Bayer, which has been in the negative headlines for years[29]. Coincidental effects thus seem probable. The severely negative logaritmic alpha of Bayer AG is shown in Figure 4. This category will not be considered further in the analysis. For the sake of completeness, however, it is still displayed in the following tables.

TABLE 1. *$log(\bar{\alpha}^i_{diff})$ per MSCI ESG rating trend category*

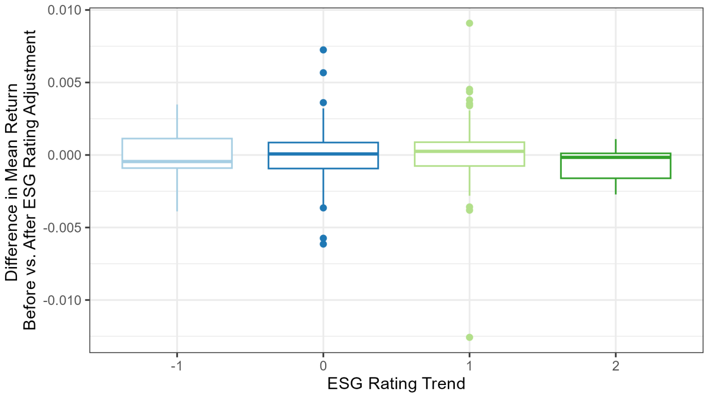
Trend Cat.	Mean*	Median*	SD*	Min*	Max*	N*
-1	-0.000172	-0.000451	0.00198	0.00348	0.00348	14
0	0.00000551	0.0000721	0.00161	-0.00614	0.00725	166
1	0.000176	0.000252	0.00261	-0.0126	0.00909	63
2	-0.000638	-0.000162	0.00144	-0.00272	0.00110	6

Notes: Descriptive statistics for the change in logarithmic mean alpha returns per MSCI ESG trend category.
N denotes the number of observations
* Descriptive statistic calculated on $log(\bar{\alpha}^i_{diff})$

The findings indicate that the MSCI ESG trend has meaningful implications for the performance of stocks in terms of their alpha returns. Possible reasons for these findings may be twofold.

(1) ESG has been considered a growth market with huge potential in the financial

29. https://www.reuters.com/breakingviews/bayer-has-29-bln-reasons-say-bye-bye-ceo-2022-03-29/



Notes: There were no shares in the data that experienced a MSCI ESG rating trend of -2. *Category* = *Observations*; -1 = 14; 0 = 166; 1 = 63; 2 = 6

FIGURE 6. $log(\bar{\alpha}^{i}_{diff})$ *for the MSCI ESG categories -1, 0, 1 and 2*

industry for some time now[30,31]. Many asset managers have thus adopted ESG portfolios. To implement these strategies, they need vast amounts of ESG data. MSCI's ESG data is the industry standard, which means it is purchased by virtually every industrial asset manager. With portfolio managers trying to optimize the overall ESG rating of their portfolio, the tendency arises to buy stocks with a higher ESG rating. As the ESG rating of an individual stock improves, this share becomes more and more attractive to the portfolio manager. This is partly because the share may now meet the minimum ESG requirements of the investment portfolio, and partly because it now contributes stronger to the portfolio managers efforts to improve the overall ESG rating of the portfolio. As a consequence, the demand for a share with a positive ESG trend is enhanced compared to peer shares. Thus, the alpha of this share improves. The same applies in the case of a negative ESG trend. A share with negative ESG trend becomes progressively less attractive to the portfolio manager, as it now negatively impacts the portfolios ESG rating. The demand for such share is reduced compared to peer shares and the alpha of the share declines.

(2) Insurance companies, pension funds and other institutional investors are more and more committed to invest substantial portions of their assets into sustainable investments. One approach that has recently been taken up by many of these large investors is impact investing. By incorporating impact investment principles, investors prioritize companies that exhibit strong ESG practices and positively contribute to

30. https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/the-big-picture-2023-esg-outlook-72802090
31. https://www.bloomberg.com/professional/blog/esg-assets-may-hit-53-trillion-by-2025-a-third-of-global-aum/

society and the environment. If MSCI now communicates a company's positive development in these areas, the demand for this company's shares rises among impact investors, and with it the alpha. The same applies in the opposite case. If the ESG rating of a share falls, the demand among institutional investors with an impact approach falls, and with it the alpha.

The aforementioned interrelationships between the logarithmic alpha of shares and their ESG rating trend raise the question of how investors can capitalize on these insights. Evidently, the identified signals lend themselves well to a long-short ESG strategy. In such strategy, a share exhibiting a positive logarithmic alpha over the past 6 months is assigned a higher weight relative to the benchmark. On the day MSCI publishes an increase in the company's ESG rating, the over-weighting is further increased. Conversely, a share displaying a negative logarithmic alpha over the last 6-month period is under-weighted compared to the benchmark. The under-weighting is further increased on the day MSCI publishes a decrease in the company's ESG rating. Investors could moreover benefit from the ESG trend of a share through a variety of structured products. One conceivable option in this respect might be a tracker certificate that goes short on shares with a negative ESG trend and long on shares with a positive ESG trend. A BRC, consisting of a basket of shares with all positive ESG trends, would be another solution. Here, investors could benefit from the reduced risk of a barrier hit and thus statistically hedge their position. Structured Products of this kind would be eligible to be classified as *Sustainable* by the Swiss Structured Products Association (SSPA), which could turn out to be a positive aspect for marketing as well[32].

4.2 A More Sophisticated Look at the Results

In the following, the results described in section 4.1 are examined in more detail. The aim is to investigate whether there are share-specific attributes for which the link between logarithmic alpha and ESG trend is particularly pronounced. To this end, the effects of the two variables "Cyclical vs. Defensive" and "ESG Controversy Flag" on the relationship between ESG trend and log alpha are investigated.

4.2.1 Cyclical Versus Defensive

A share is said to be *cyclical*, if its performance tends to be closely tied to the overall economic cycle. Cyclical shares belong to companies whose business activities are sensitive to changes in economic conditions, such as fluctuations in consumer spending, interest rates, or industrial production. These shares are often associated with industries like automotive, construction, hospitality, and retail[33].

32. https://sspa.ch/wp-content/uploads/2023/05/sspa-sustainability-guidelines_version-08052023_eng14057980.2615167020.1.pdf
33. Reilly and Brown 2011.

Cyclical shares are characterized by higher volatility, as their fortunes rise and fall with the economic cycle. During periods of economic expansion and prosperity, cyclical shares tend to outperform, as demand for their products or services increases. Conversely, during economic downturns or recessions, these shares may experience declines in revenue and profitability.

On the other hand, *defensive* shares are considered more resilient during economic downturns. They belong to companies whose products or services are considered essential or in demand regardless of the economic climate. Examples include companies in sectors like healthcare, utilities, consumer staples, and essential services[34].

Defensive shares are considered to provide stability and protection during uncertain economic times. These shares tend to exhibit lower volatility and may continue to generate steady revenue and cash flow even when the broader economy is experiencing a downturn. As a result, they are often viewed as a defensive or safe-haven investments.

The MSCI Global Industry Classification Standard[35] (GICS) is a widely recognized framework used to categorize companies into different industry sectors and subsectors based on their primary business activities. Within the GICS framework, there is a distinction made between cyclical and defensive sectors[36]. Table 2 presents the relationship between logarithmic alpha and ESG trend categorized by the MSCI GICS ratings.

TABLE 2. $log(\bar{\alpha}^{i}_{diff})$ *per MSCI GICS Category and per MSCI ESG Rating Trend Category*

GICS Cat.	Trend Cat.	Mean*	Median*	SD*	Min*	Max*	N*
Cyclical	-1	0.000645	0.000749	0.00165	-0.00169	0.00348	7
Cyclical	0	0.0000545	0.0000494	0.00159	-0.00614	0.00725	124
Cyclical	1	0.000266	0.0000987	0.00216	-0.00381	0.00909	45
Cyclical	2	-0.000695	0.0000323	0.00160	-0.00272	0.00110	5
Defensiv	-1	-0.000988	-0.000636	0.00205	-0.00389	0.00250	7
Defensiv	0	-0.000139	0.0000752	0.00167	-0.00574	0.00567	42
Defensiv	1	-0.0000485	0.000370	0.00355	-0.0236	0.00453	18
Defensiv	2	-0.000356	-0.000356	NA	-0.000356	-0.000356	1

Notes: Descriptive statistics for the change in logarithmic mean alpha returns per MSCI ESG trend category. The data from Table 1 is further distinguished by the MSCI GICS categories. N denotes the number of observations
* Descriptive statistic calculated on $log(\bar{\alpha}^{i}_{diff})$

34. Reilly and Brown 2011.
35. https://www.msci.com/our-solutions/indexes/gics
36. https://www.msci.com/documents/1296102/30991361/MSCI+Cyclical+and+Defensive+Indexes.pdf/5e7813d7-957f-e485-7afb-d97a3fe495e5?t=1660056512107

The results of section 4.1 can only be partially replicated in the two MSCI GICS categories Cyclical and Defensive. For means and medians in Table 2, the picture is not clear. It is noteworthy, however, that the patterns from Section 4.1 can still be detected in the trend categories 0 and 1. For both of these categories, and for both Cyclical and Defensive shares, the sample size is more or less appropriate. However, the medians in the Cyclical sector for the trend categories 0 and 1 are only slightly different.

Conclusive statements can hardly be made here due to the sometimes insufficient sample size. Further analysis with more data is needed.

4.2.2 MSCI ESG Controversy

The MSCI ESG Controversies framework is a component of the MSCI ESG Ratings methodology, which assesses the environmental, social, and governance (ESG) performance of companies[37]. The ESG Controversies module focuses specifically on identifying and evaluating controversial incidents or activities associated with companies. The MSCI ESG Controversies framework aims to provide insights into the potential controversies and risks related to the ESG practices of companies. It considers a wide range of criteria, such as environmental accidents, human rights violations, labor disputes, product safety issues and corruption scandals. To construct the ESG Controversies rating, MSCI gathers information from various sources, including media reports, regulatory filings, non-governmental organizations, and other public domain information. The collected data is then analyzed and processed using a systematic methodology to assess the severity and significance of each controversy. Analysed companies are classified into the categories Green, Yellow, Orange and Red. Table 3 presents the relationship between logarithmic alpha and ESG trend categorized by the MSCI ESG Controversy category.

The results are again inconclusive. This is due to the sample size being too small in most of the categories. Strikingly, the median in the ESG Controversy category Green is smaller for category +1 than for category 0. The effects between the two categories in Table 1 thus seem to originate mainly from the categories Yellow and Orange. One can only speculate about possible reasons. One explanation may be that stocks classified as Green under the ESG Controversy score are considered safe and are therefore already present in most ESG portfolios. Stocks rated Yellow and Orange, on the other hand, may not be present in many ESG portfolios. If their ESG rating for one of the yellow, or orange rated shares then improves, many portfolio managers will consider it more attractive and will be more willing to buy it.

37. https://www.msci.com/documents/1296102/14524248/MSCI+ESG+Research+Controversies+Executive+Summary+Methodology+-++July+2020.pdf/b0a2bb88-2360-1728-b70e-2f0a889b6bd4

TABLE 3. *$log(\bar{\alpha}^i_{diff})$ per MSCI GICS Category and per MSCI ESG Controversy Category*

ESG Controversy	Trend Cat.	Mean*	Median*	SD*	Min*	Max*	N*
Green	-1	-0.000786	-0.000486	0.00191	-0.00389	0.00250	9
Green	0	-0.0000376	0.0000781	0.00173	-0.00614	0.00725	99
Green	1	-0.000297	-0.000355	0.00291	-0.0126	0.00909	43
Green	2	-0.000297	0.0000323	0.00159	-0.00202	0.00110	3
Orange	-1	-0.000432	-0.000432	NA	-0.000432	-0.000432	1
Orange	0	0.000176	-0.000198	0.00146	-0.00187	0.00361	19
Orange	1	0.00224	0.00188	0.00161	0.000432	0.00453	6
Orange	2	-0.000108	-0.000108	0.000350	-0.000356	0.000139	2
Yellow	-1	0.00128	0.00131	0.00183	-0.000992	0.00348	4
Yellow	0	0.0000270	0.0000494	0.00141	-0.00365	0.00322	48
Yellow	1	0.000745	0.000545	0.000990	-0.000559	0.00307	14
Yellow	2	-0.00272	-0.00272	NA	-0.00272	-0.00272	1

Notes: Descriptive statistics for the change in logarithmic mean alpha returns per MSCI ESG trend category. The data from Table 1 is further distinguished by the MSCI ESG Controversies categories.
N denotes the number of observations
* Descriptive statistic calculated on $log(\bar{\alpha}^i_{diff})$

5. Limitations

Even if the results seem compelling, alternative explanations for the effects should not be overlooked. One such alternative explanation may be that the 6-factor model described in Section 3 is too conservative. This would imply that other systematic factors are present in the logarithmic alpha time series, and thus that the results may be biased. Another alternative explanation would be that companies that make positive ESG contributions may have better logarithmic alpha in general, i.e. regardless of their MSCI ESG rating. Conversely, the business model of companies that make no or declining ESG contributions may slowly run out of steam. Furthermore, with this sample size, it is also possible that the effects merely arose by coincidence. This is particularly probable in the categories -1 (sample size = 14) and +2 (sample size = 6).

6. Concluding remarks

In conclusion, this project contributes to the growing body of research on the intersection of ESG factors and investment performance. The findings highlight the importance of the MSCI ESG rating trend as a valuable tool for understanding and predicting stock-specific performance. As sustainable investing continues to gain momentum, incorporating ESG considerations and utilizing reliable data sources will play an increasingly crucial role in generating positive financial outcomes while promoting sustainable business practices.

Further research should aim to replicate the findings of this study using different time frames and expanding the analysis to include shares from other markets beyond European stocks. This would provide a broader understanding of the relationship between ESG rating trends and alpha across various regions and market conditions. Additionally, it would be valuable to assess and back-test an investment strategy based on the identified signals to evaluate its effectiveness and potential for generating consistent returns.

7. Supplementary Material

The code (R) of the analysis, the downloaded stock data and the plots in high resolution are available under https://github.com/KilianGitHub97/MSCI-ESG-trends.

8. Appendix

ISIN's of Downloaded Stock Data

NL0010273215, FR0000121014, FR0000120271, DE0007164600, DE0007236101, FR0000120321, FR0000121972, FR0000120073, ES0144580Y14, NL0000235190, DE0005557508, FR0000131104, DE000BAY0017, FR0000125486, FR0000121667, FR0000120628, FR0000052292, BE0974293251, ES0113900J37, DE000BASF111, NL0011821202, FR0000121485, DE0008430026, IT0003128367, DE0006231004, FR0000073272, FR0000120693, DE0005552004, IT0003132476, IT0000072618, ES0113211835, DE0005810055, NL00150001Q9, FR0000120644, NL0012969182, NL0011794037", IE0001827041, FR0000125338, NL0000395903, DE0007037129, FR0010208488, DE0007664039, IT0005239360, FR0014003TT8, IE00BWT6H894, ES0109067019, NL0000009165, DE0006599905, FR0000125007, NL0010832176, NL0000009827, DE000A1EWWW0, FI0009013296, DE0005140008, FR0010307819, ES0173516115, DE000ENAG999, FR0000133308, ES0178430E18, FI0009005987, FR001400AJ45, ES0105066007, FR0000124141, FI0009013403, IE0004906560, DE000SHL1006, FR0000130577, LU1598757687, BE0003565737, FR0010908533, FR0000121329, FR0000051807, ES0118900010, PTEDP0AM0009, NL0000009538, DE000PAG9113, NL0013267909, DE0006048432, NL0000334118, FR0000045072, NL0010773842, DE0005785604, DE000A0D9PT0, NL0012169213 GB00BDCPN049, DE0005200000, AT0000652011, IT0004965148, IT0003153415, BE0003739530, NL0000009082, FR0000120172, IT0000072170, DE000A1DAHH0, ES0105046009, FR0013154002, DE000PAH0038, FR0014000MR3, DE0007165631, IE00B1RR8406, DE000CBK1001, DE0007030009, IT0004176001, NL0012059018, NL0000303709, IE0004927939, FR0000121220, LU0156801721, NL0010801007, FR0010220475, FR0000130452, BE0003797140, FI0009005961, DE0006047004, DE0006062144, FR0006174348, AT0000743059, NL0000008977, BE0974320526, FI0009007884, BE0003470755, FI0009007132, FR0010533075, FR0010242511, DE000ENER6Y0, FR0000131906, FR0000120503, DE000A2E4K43, DE0006048408, NL0000379121, DE000ZAL1111, DE0005439004, ES0127797019, BE0974264930, FR0000127771, NL0006294274, ES0173093024, ES0167050915, DE0005785802, PTGAL0AM0009, PTJMT0AE0001, DE0006602006, FR0013326246, AT0000746409, IE00BD1RP616, FI0009000202, FI0009014377, IT0000062957, DE0005313704, NL0015435975, DE0006969603, FR0010313833, NL0011540547, IT0003796171, IT0005366767, DE0005190037, ES0125220311, FR0000039299, DE0008232125, BE0003822393, DE000LEG1110, BE0974259880, ES0116870314, FR0010340141, FR0000120404, FR0010040865, DE000A12DM80, BE0974349814, FR0013451333, FR0013280286, DE000A161408, NL0012015705, FI0009003727, DE000KBX1006, FR0014004L86, FR0013176526, ES0130960018, IT0004056880, IT0003492391, BE0003717312, FR0004125920, DE0007010803, IT0005090300, ES0171996087, AT0000937503, DE0005158703, NL0014332678, FR0000064578, DE0006452907, FR0000121121, DE000A1J5RX9, IE00BF0L3536, FR0000121204, IT0003497168, FR0000121709, DE0005089031, DE000KGX8881, BE0003810273, DE000UNSE018, NL0011872643, DE000A1PHFF7, IT0005218380, AT0000730007, FI0009014575, IE00BZ12WP82, NL0011821392, DE000A0WMPJ6, NL0012817175, AT0000BAWAG2, ES0124244E34, IT0005211237, NL0012866412, AT0000831706, DE0005664809, FI4000297767, IT0001078911, IT0003856405, IT0001233417, FR0000130403, ES0113679I37, FR0013227113, FR0010451203, ES0113860A34, FI4000074984, IT0005282865, ES0105025003, NL0000852564, FR0000071946, DE000KSAG888, FR0012757854, FI4000312251, NL0006237562, DE0006766504, DE0007500001, DE0005470405, FR0010411983, DE0006095003, ES0139140174, IE0000669501, FR0000121147, FI0009000277, BE0003851681, FR0000050809, FR0012435121, BE0003593044, DE000A0Z2ZZ5, LU0088087324, FR0013269123, BE0003764785, DE000WCH8881, DE0005470306

TABLE A1. *Cumulated Variance of the N Largest Eigenvalues*

Number of Components	Cumulated Variance
5	0.2278548
10	0.3089488
20	0.4128858
30	0.4871777
40	0.5475375
50	0.5993433
60	0.644625

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