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Short-term reaction to extreme returns in ESG and non-ESG stocks: evidence from the US

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SHORT-TERM REACTION TO EXTREME RETURNS IN ESG AND NON-ESG STOCKS: EVIDENCE FROM THE US

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Abstract

The present study aims at comparing the short-term reaction to extreme returns in ESG and non-ESG stocks on the US market, specifically on the S&P 500 index. Stocks with particularly high and low ESG scores were selected for every year between 2010 and 2019 with a total of 91 ESG stocks and 88 non-ESG stocks being used at some time during the period.

Results show that, although statistically significant average CARs occur in a number of days following the initial price shock, there is no discernible difference in the returns of ESG and non-ESG stocks in the S&P 500 up to 10 days post-shock. After positive shocks, ESG stocks present evidence of mean reversion between the eighth and tenth trading days post-shock. This outcome is, however, time-varying, since it is magnified by a large negative abnormal return in 2010 and 2011. After negative shocks, the same stocks present support to the price continuation hypothesis in the first two days post-shock. Among non-ESG stocks, evidence is much weaker, with a single statistically significant average CAR showing in the second day post-negative shock, also pointing towards price continuation. A multivariate analysis finds standard deviation (a proxy of shock size) to be positively related with price reversals in negative shocks.

In conclusion, ESG and non-ESG stocks in the S&P 500 present high levels of price efficiency, with no apparent difference between both sets of stocks being found. This research provides regulators and market practitioners with information on the short-term behaviour of ESG and non-ESG stocks in the highly liquid American index, adding to the extensive literature about short-term predictability of stocks after large price changes.

Keywords: Short-term reaction; Extreme returns; ESG; non-ESG; US stock market; S&P 500

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1. Introduction

Socially Responsible Investing (SRI) is "an investment process that integrates social, environmental, and ethical considerations into investment decision making", according to Renneboog et al. (2008, pp. 1).

A report from the US SIF (2020) estimates that, as of December 2019, one out of every three dollars under professional management in the United States - $17.1 trillion - was managed according to sustainable investing strategies. According to Morningstar data, as of 31st March 2022, 31.5% of funds available for sale in the EU (excluding money market funds, funds of funds and feeder funds) were classified as either Article 8 (27.9%) or Article 9 (3.6%). EUR-Lex (2019) includes, in such categories, funds that promote environmental or social characteristics (article 8) or funds that have sustainable investment as their objective (article 9). The huge presence of socially responsible/sustainable finance is also noticed in the literature, per Luo et al. (2022).

SRI invariably involves subjective determinations about ethics and morality (Bruyn, 2010). In fact, to evaluate companies according to their social responsibility is a challenging task. There are various indices and ratings that are employed by investors to evaluate financial and SRI portfolios (Scalet & Kelly, 2009).

One of such ratings is the Refinitiv ESG Score. According to Refinitiv's methodology framework, this rating captures over 630 company-level ESG (Environmental, Social and Governance) measures, and is "a transparent, data-driven assessment of companies' relative ESG performance and capacity, integrating and accounting for industry materiality and company size biases". This allows the classification of assets in a certain universe of stocks as "relatively responsible" or "relatively irresponsible" (Refinitiv, 2022, pp. 6).

Widyawati (2019) claim that SRI should be approached from two different perspectives: ethical and financial. The ethical paradigm looks at SRI as a tool to pressure companies into changing their procedures and operating in a more sustainable manner. From the financial view, SRI is a financial service offered to investors, and, therefore, it retains characteristics of traditional financial products. This assumption provides the fundamental motivation for this research: to understand whether the short-term reaction pattern observed in ESG stocks differs from that observed in non-ESG stocks and, accordingly, if these securities behave as expected from previous studies on short-term reaction of stocks (an extensive literature review is conducted on the sub-chapter "Short-term reaction to extreme returns in stocks and indices").

Given the comparison made between stocks with high socially responsible ratings and stocks with low socially responsible ratings, as Kempf & Osthoff (2007), we focus on one single market – the US. We discover that, among the large and highly liquid stocks present in the Standard & Poor's 500 index between 2010 and 2019, the short-term behaviour of ESG and non-ESG stocks after large price movements is not significantly different from one another. This occurs despite finding statistically significant abnormal returns following both positive and negative extreme price changes. Our multivariate analysis detects a positive relationship between standard deviation and the 10-day cumulative abnormal return (CAR10) after negative shocks. Negative price shocks in December or January ("tax effect") are found to negatively influence the CAR10.

Apart from this chapter, this dissertation is organized as follows: chapter 2 presents the literature review about this subject, focusing on previous research about the short-term reaction to extreme returns of US stocks and indices, and the impact of SRI and ESG on firm performance. Chapter 3 presents data description and statistics, and the methodology followed. Subsequently, results can be found in chapter 4, and the conclusion of this dissertation is presented in chapter 5.

2. Literature Review

2.1. Short-term reaction to extreme returns in stocks and indices

According to Amini et al. (2013), the study of the short-term reaction of stock prices has found some evidence of predictability after extreme price movements, consistent across different markets and asset classes. Most research finds reversals after both large price rises and large price drops, with price continuations also detected, more typically after relatively smaller moves. As for causes of such predictability, behavioural factors are the most widespread explanation suggested by the literature, with overreaction, leading to price reversals, being especially relevant.

Overreaction is a market anomaly that questions the efficient market hypothesis proposed by Fama (1970) and has been an important topic in the field of Behavioural Finance since the study by De Bondt & Thaler (1985). The authors define overreaction as movements in one direction following extreme asset price movements in the opposite direction. They found that, in periods of up to thirty-six months, prior losers outperformed prior winners, which is consistent with the presence of overreaction. As Hong & Stein (1999) demonstrate, this market anomaly allows for the existence of contrarian strategies. There is robust literature available indicating that such strategies can be profitable in the US stock market (see, for example, Zarowin (1989) and, more recently, Caporale et al. (2018)).

Numerous studies focus on the short-term predictability of prices conditional on large prior price changes in the US market, examining both individual stocks and indices. Early papers by Jegadeesh (1990) and Lehmann (1990) provide evidence of shorter-term return reversals. These studies show significant abnormal returns produced by contrarian strategies that choose stocks based on their performance over the previous month (Jegadeesh, 1990) or week (Lehmann, 1990).

However, Lo and MacKinlay (1990) argue that a large part of the abnormal returns documented by Jegadeesh (1990) and Lehmann (1990) is attributable to a delayed stock price reaction to common variables rather than to overreaction. They suggested that less than 50 percent of the expected profits from a contrarian strategy may be attributed to overreaction. Jegadeesh & Titman (1993) state that because these tactics rely on intensive transactions and short-term price movements, their efficacy may indicate the existence of short-term pricing pressure or a lack of market liquidity. The research by Jegadeesh & Titman (1993) is also the first major evidence indicating underreaction in the stock market, in particular underreaction to firm-specific information.

The wide diversity of approaches employed in the study of the short-term reaction of stock prices after large price movements makes it hard to draw broad conclusions, and there is no defined consensus around them (Amini et al., 2013). In fact, most research selects a large price movement based upon a predefined percentage trigger, but some literature defines the "price shock" with a wide range of different criteria.

Cox & Peterson (1994) study one-day price losses of at least 10% and disprove the overreaction hypothesis by attributing reversals in the subsequent three days to the bid-ask bounce as well as a lack of market liquidity. The researchers find that stock size in negatively correlated with the bid-ask spread, and smaller stocks experience larger reversals. Conrad et al. (1997) used bid returns (which do not include bid-ask spread) in their research and corroborated that a significant portion of the profits from short-term price reversion pertains to bid-ask errors in transaction prices. Very low transaction cost levels eliminate any residual abnormal returns.

On the other hand, Pritamani & Singal (2001) and Lasfer et al. (2003) define price shocks based on a multiple of the standard deviation of the asset's daily returns over a certain period preceding the shock. This method takes account of the volatility of specific markets, but it usually results in a mean absolute value of a large shock which is not particularly large in the context of these studies (Amini et al., 2013).

Pritamani & Singal (2001) find that post-event abnormal returns are found to be unimportant. The 20-day abnormal returns become large as conditioning on volume of information and public announcements is introduced, particularly when the news relates to earnings or analyst recommendations. An out-of-sample trading strategy confirms investor underreaction and generates significant abnormal returns. Lasfer et al. (2003) findings, using daily market indexes from 39 stock exchanges, also point to underreaction. They show positive (negative) abnormal price performance in the short-term window (up to 10 days) following positive (negative) price shocks. Greater post-shock price movements are observed in less liquid markets.

Nevertheless, not all studies defining price shocks based on a multiple of the standard deviation of the asset's daily returns Nam et al. (2006) consider all daily returns and those two standard deviations away from the mean and discover that, on average, a negative return reverted to a positive return more quickly and with a larger reversing magnitude than positive returns reversed to negative returns. This asymmetry is verified in both the index returns, and the individual stock returns.

Choi & Jayaraman (2009) also use a fixed percentage trigger of 10% and find evidence, by comparing the stock and option markets, of a significantly positive reversal over two days after a large price decline for non-optionable firms. Also, in line with the idea that informed traders favour trading in the option markets, stock price reversals cannot be attributed to overreaction or exclusively to the bid-ask bounce: such as Peterson (1995), Choi & Jayaraman (2009) find evidence that more informed traders will tend to choose more liquid markets to make their transactions, making such market react more efficiently than less liquid markets.

A paper by Urquhart & Zhang (2019) finds evidence in FTSE4Good indices for Europe, the UK, and the US of significant returns on SRI when following mean-reverting technical trading rules. Cui & Docherty (2020), by focusing on ESG controversies, obtain a more evident overreaction within smaller firms and stocks that were held by more transient investors before the news announcement. When bad ESG news is released, contrarian strategies are found to be profitable.

By analysing the demand for mutual funds in the US market from 1999 to 2016, Matallín-Sáez et al. (2021) find evidence consistent with the presence of disposition effect among SR investors, since they obtain a negative correlation between outflows and previous performance for conventional funds and a neutral or positive correlation for SR funds.

There is also some literature on emerging markets worth mentioning. Firstly, in Lasfer et al. (2003), the relationship between market liquidity and post-shock abnormal returns appears to hold true for emerging markets, who exhibit more significant price continuation patterns than developed markets. In other words, these results suggest lower price efficiency in emerging markets.

Furthermore, in line with Fama (1998), the evidence on short to long-term market anomalies such as overreaction can be model dependant. For example, Mazouz et al. (2009) look at the short-term price behaviour of ten Asian stock market indices and finds support for overreaction after shocks of over 10% (more prominent after negative shocks) under the usual OLS regression. The GJR-GARCH method's results offer stronger evidence in favour of market efficiency, which is consistent with the stronger support for market efficiency under the GARCH-based techniques.

Reddy et al. (2020) in their study covering the Shanghai Stock Exchange in the period between 2009 and 2015, find evidence pointing towards overreaction, confirming De Bondt & Thaler's (1985) results since losers outperformed winners in both 3-month and 6-month horizons. The study's conclusions point to uneven overreactions in the stock market, particularly for loser portfolio. The greatest winning and loser portfolios' before-after tests reveal that losers quickly recovered and outperformed the market. The authors suggest that such findings may be related to the frequency of trading and experience of Chinese investors. Approximately 85% of investors in China's stock market are novices who trade more frequently than their overseas counterparts, while in developed nations large institutional investors have much more importance.

Chen & Yang (2020) found evidence suggesting that stock prices overreact to ESG information, specifically indicating that investors react positively to favourable news about companies with higher ESG scores, but negatively to unfavourable news about companies with lower ESG scores. The empirical findings for the Taiwanese stock market support the overreaction hypothesis proposed by De Bondt & Thaler (1985) by explaining that an ESG momentum tactic can yield significant short-term gains and long-term reversals. This strategy does not hold for cycles longer than 18 months. Meanwhile, the environmental element's relevance is more exaggerated by investors than the social or governance factors.

Finally, Shen & Shen (2022) propose the disposition effect as an alternative explanation for short-term contrarian profits. By examining the Chinese stock market, authors argue that investors tendency to realize gains from stocks with unrealized profits relatively quickly, while holding onto stocks with unrealized losses for extended periods is a major driving element of stock price overreaction. Such findings are consistent with the previously mentioned evidence of disposition effect among SR investors found by Matallín-Sáez et al. (2021) in the US market.

2.2. Performance of ESG and non-ESG stocks

Although, to our knowledge, there is no literature comparing the short-term reaction after extreme price movements of ESG stocks and non-ESG stocks, several studies focus on the performance and risk of such securities.

Galema et al. (2008) expect that excessive demand for socially responsible stocks and insufficient demand for non-SRI stocks will cause overpricing of the first and underpricing of the latter. This research builds on previous findings by Heinkel et al. (2001), who demonstrate that negative screening results in fewer investors holding shares of polluting companies since green investors avoid their stock. Because non-green investors don't share the risk, the stock prices of polluting companies decline, increasing the cost of capital for those businesses.

More recently, Nofsinger et al. (2019) made similar discoveries in regard to institutional investors. They appear to be indifferent to positive environmental and social (ES) indicators but tend to underweight stocks with negative ES indicators. The presence of negative ES indicators signals downside risks, such as higher stock return skewness and a greater likelihood of eventual bankruptcy or delisting. Positive ES indicators seem to have little relevance in this context.

Accordingly, Belghitar et al. (2014) find that risk averse investors can increase their utility by reducing their holdings in SR companies and increasing purchases of traditional ones. Their results suggest that socially responsible investing entails a financial cost. The non-financial utility that SRI investors gain from the ethical quality of their investments is thought to make up for the loss in financial utility. This is in line with the findings of Nilsson (2009), who shows SRI investors are looking for more than just decent returns on their investments, as they may be sincerely interested in making a positive impact in their society.

Moreover, Riedl & Smeets (2017) show that investors are less likely to make socially responsible investments if they anticipate that SRI funds will perform worse than traditional equity funds, although investors who have strong social motivations are typically prepared to sacrifice financial gains to make investments that reflect their social preferences.

As for research revealing overperformance, Kempf & Osthoff (2007) test a simple strategy of buying stocks with high socially responsible ratings (best-in-class) and selling stocks with low socially responsible ratings. They find that such approach leads to abnormal returns of up to 8.7% per year. A positive screening technique also leads to abnormal returns, even after accounting for transaction costs, while a negative screening technique does not yield abnormal returns after transaction costs.

With research focusing on US SRI funds, Nofsinger & Varma (2014) claim that ethical funds are less risky in market crisis periods, overperforming conventional funds. SRI funds were composed by less volatile stocks, but, after controlling for such difference, the outperformance was found to be related to the socially responsible attributes. However, Demers et al. (2021) did reveal that ESG presented no positive explanatory power for returns during the COVID-19 crisis period in 2020.

Regarding geographical differences, Hill et al. (2006) discover that European SR-conscious corporations perform differently from Asian and US ones. They conclude that there may be cultural differences between these nations and that European investors appear to regard SRI more highly than Asian and American investors. However, Deng & Cheng (2019) did conduct an empirical analysis of China's A-share listed companies, with the empirical results indicating a positive correlation between a firm's ESG indices and its stock market performance.

Von Wallis & Klein (2014), in their meta-study, conclude that most research publications found SRI funds to perform equally to conventional investments, although a wide range of studies have acknowledged the outperformance of SR investments, and some have even discovered a negative association between SR investments and conventional investments. Jedynak (2017) also establish that there is no consensus over the impact of such investments in portfolio performance.

Derwall et al. (2011) propose an explanation for this "puzzling evidence" that both SRI and non-SRI stocks can yield higher returns. The hypothesis states that orientation towards "profit" means investors will prefer using positive screens and achieve superior performance due to the market systematically undervaluing the importance of corporate social responsibility in influencing the firm's future cash flows. Meanwhile, orientation towards "value" results in investors using negative screens, which can lead to overvaluation of socially responsible portfolios.

This research intends to fill the gaps identified in the literature, by comparing the short-term reaction of ESG and non-ESG stocks after extreme price movements and examining whether factors detected in the literature can be considered a cause for the observed reaction. We expect to find price reversals in both ESG and non-ESG stocks. However, in the line of Chen & Yang (2020), we expect more significant price reversals in ESG stocks post-positive shocks and more significant price reversals in non-ESG stocks post-negative shocks.

We also expect, following Cox & Peterson (1994), a high negative correlation between liquidity and the size of the stock (market capitalization), and a negative relationship between both these variables and the amount of reversal. Accordingly, a negative correlation between trading volume and the amount of reversal is also presumed, following Choi & Jayaraman (2009). Regarding stock performance, we conjecture that ESG stocks perform better than non-ESG stocks (Deng & Cheng, 2019) and exhibit lower volatility than their non-ESG counterparts (Nofsinger & Varma, 2014).

3. Data and Methodology

3.1. Data

The data consists of close prices between January 1st, 2010 and December 31st, 2019[1] for stocks in the S&P 500 index whose firms were among the 5% with higher or lower ESG score according to Refinitiv DataStream[2]. The S&P 500 universe of companies was compiled for each year between 2010 and 2019, always reporting to 31st of December of such year. For each of those groups of companies, we found the ESG Combined Score for the respective year and proceeded to rank them and select the top and the bottom 5%.

Following Auer & Schuhmacher (2016), the strategy to retrieve ESG data reporting to the end of each period allows the database to ensure a high degree of ESG persistence. Annex I compiles the list of selected companies for each year.

Between 2010 and 2019, a total of 177 companies were subject to analysis: 91 appeared, at some point, among the 5% with higher ESG Combined Score, and 88 were among the 5% with lower classification at some time during the period. Two stocks appeared in both the higher and lower groups (Kinder Morgan Inc. and Trane Technologies PLC). By comparing the market capitalization of selected stocks (including repeated occurrences among the ESG or non-ESG samples)[3], we found that, in the context of the S&P 500, the size of ESG stocks was significantly higher than the size of non-ESG stocks (t-stat = 2.00).

Stocks with insufficient price information on the respective period and duplicate stocks (different class stocks from the same company) were excluded from the data. We did not exclude companies that left the index, that went private or defaulted in subsequent years, thus protecting against the survivorship bias.

Table 1 provides the descriptive statistics of every daily return in ESG and non-ESG stocks (ESG+ and ESG−, respectively) in the S&P 500 index between 2010 and 2019.

[1] The data spans from 2010 to 2019 to isolate from the direct effects of the Great Recession and the COVID-19 pandemic on financial markets. Most research on the topic also determines a 7-to-10-year interval.

[2] The platform makes historical coverage of ESG scores for approximately 1000 companies, with a model that is fully automated and data-driven and captures over 630 company-level ESG measures. To this research, we used the ESG combined scores, which overlay the ESG score with ESG controversies and negative media stories. This classification also protects against a possible industry bias (as mentioned by Kempf & Osthoff, 2007) by comparing each company with their industry peers.

[3] The market capitalization of each stock was reported, such as its ESG score, to 31st of December (or the last trading day) of the year under analysis. Information was retrieved from Refinitiv DataStream.

Table 1. Descriptive Statistics of Daily Returns in ESG and non-ESG Stocks

	ESG+	ESG-
Average daily returns (%)	0.029	0.043
Median daily returns (%)	0.067	0.057
Daily standard deviation (%)	1.685	2.099
Skewness	-0.569	-0.879
Kurtosis	9.597	30.897
Total daily observations	60384	59127

Firstly, since more stocks were excluded from the non-ESG database due to the criteria described above, the number of total daily observations is slightly higher in ESG stocks, surpassing 60000.

On the one hand, the average daily return for non-ESG stocks in our sample stands higher than ESG stocks at 0.043%, although the difference is not statistically significant (*t*-stat = -1.26). On the other hand, median daily returns are higher in ESG stocks, which is consistent with the relatively higher negative skewness observed in non-ESG stocks. Negative skewness indicates a longer left tail in the distribution, implying more frequent negative returns. Therefore, both sets of stocks have negative skewness, but "ESG−" has a higher degree of asymmetry.

ESG stocks have a kurtosis of 9.6, while non-ESG stocks have a much higher kurtosis of 30.9. Higher kurtosis indicates "fatter" tails, implying a higher likelihood of extreme returns (both positive and negative). This value suggests that non-ESG stocks have a greater potential for extreme returns when compared to ESG stocks. Since non-ESG stocks present a higher standard deviation, we can conclude that those stocks have a higher variability in returns, and that its data points are spread out over a wider range.

3.2. Methodology

The methodology is based on the work by Lasfer et al. (2003). Whereas these authors compared the short-term reaction of prices after extreme price movements in developed vs. emerging financial markets, this research will compare the behaviour (in the short-term) of ESG vs. non-ESG stocks in the US market.

We conduct an analysis of the performance of the selected assets following a price shock, up to 10 days after the event. The large price movement necessary to be considered a positive (negative) "shock" is one where the return on a certain day is higher (lower) than two standard deviations the daily average return of the security computed in the period of 50 days ending 11 days before the shock ([-60 to -11]) (Lasfer et al., 2003). The option for this trigger is based on the belief that a threshold related to the standard deviation provides a better fit than an arbitrary percentage value.

Price shocks that followed within 10 days of each other were excluded, to avoid conflicting effects, as well as observations in the last 10 days of each calendar year.

After computing the price shocks, the post-shock abnormal returns, AR_t, was computed as follows:

$$AR_t = R_t - E(R_t)$$

where R_t is the daily return and $E(R_t)$ is the average return of a 50-day window ending 11 days before the price shock. This definition was also based on the work by Lasfer et al. (2003). This window allows us to detach from any possible unusual price movement immediately prior to the price shock. The cumulative abnormal returns (CARs) are computed by simply summing the daily abnormal returns following the price shock and the respective test statistic is computed using a student's t-distribution. Table 2 compiles summary statistics about the price shocks in the ESG and non-ESG samples.

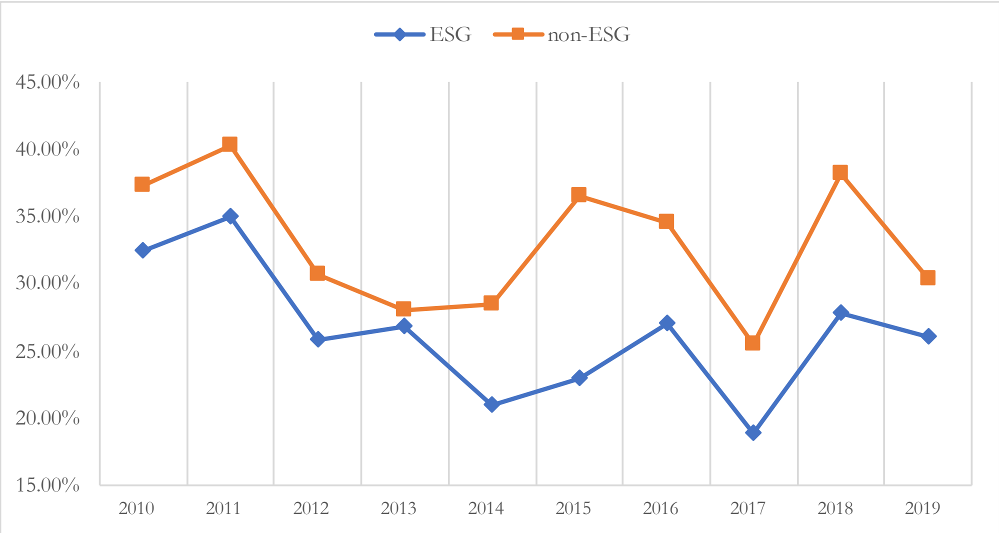
Table 2. Descriptive statistics of price shocks in ESG and non-ESG stocks

ESG+	Annual standard deviation (%)	Total number of shocks	Selected shocks: Maximum negative shock (%)	Maximum positive shock (%)	Positive shocks N	Positive shocks Mean (%)	Negative shocks N	Negative shocks Mean (%)
2010	32.39	360	-23.54	9.41	92	4.70	87	-4.96
2011	34.96	439	-19.21	11.12	93	4.23	108	-5.01
2012	25.76	305	-17.42	12.87	78	3.86	89	-4.09
2013	26.79	324	-22.31	13.96	94	4.00	89	-4.26
2014	20.86	418	-13.41	8.45	90	3.30	99	-3.15
2015	22.92	372	-15.15	11.82	82	3.89	107	-3.48
2016	26.95	401	-10.65	11.33	83	4.14	123	-4.17
2017	18.82	316	-9.92	7.42	92	2.99	82	-3.14
2018	27.77	460	-15.74	8.99	75	3.85	126	-4.40
2019	26.04	295	-17.37	15.00	76	4.67	99	-4.60
All years	26.75	3690			855	3.95	1009	-4.14
ESG-								
2010	37.32	376	-24.97	19.84	87	5.80	86	-6.02
2011	40.26	402	-42.92	14.71	88	5.63	94	-5.87
2012	30.62	270	-28.79	21.14	86	4.85	74	-4.75
2013	27.98	338	-32.00	35.22	109	4.65	80	-3.92
2014	28.44	401	-21.53	15.25	83	4.25	107	-4.32
2015	36.45	372	-14.39	22.74	85	5.74	85	-5.09
2016	34.54	359	-28.51	17.42	85	5.47	101	-5.75
2017	25.47	325	-26.43	15.05	82	4.17	97	-4.81
2018	38.20	439	-22.99	19.61	75	5.94	116	-5.66
2019	30.30	243	-32.00	14.53	58	5.47	89	-5.66
All years	33.32	3525			838	5.17	929	-5.21

The trigger (equal to two times the standard deviation of returns in a period of 50 days starting 60 days before the event) produces 7215 shocks (~6% of total observations), around 50% of which are excluded due to happening less than 10 days after another large price change or in one of the last 10 trading days of the respective year. Among the resulting "selected shocks" there is a higher prevalence of negative shocks than positive shocks: "ESG+" stocks register 855 positive shocks and 1009 negative shocks, while "ESG−" stocks register 838 positive shocks and 929 negative shocks.

The average and maximum (positive and negative) shocks are also higher for non-ESG stocks, in almost every period, as expected. Figure 1 compiles the average annual standard deviation throughout the period.

Fig. 1. Annual standard deviation for ESG and non-ESG stocks



The standard deviation is higher in stocks with low ESG Combined Score in every period, with the average annual standard deviation between 2010 and 2019 being 6.5 percentual points higher in these stocks than in stocks with high ESG Combined Score, therefore confirming the findings of Nofsinger & Varma (2014) stating that SR funds possess, on average, less volatile assets than conventional funds.

Finally, the years in which these assets present the highest standard deviation are 2010, 2011 and 2018, meaning that, in these periods, the volatility was higher which reflected in higher mean price shocks.

Furthermore, we test a multivariate model for both sets of stocks in order to understand whether common factors mentioned in the literature may explain the short-term reaction after extreme price movements in ESG and non-ESG stocks.

In Cox & Peterson (1994), the bid-ask bounce accounts for the majority of the observed price reversal. Additionally, size and bid-ask spread are found to be strongly negatively related, with smaller stocks exhibiting higher bid-ask spreads. This is an indication of size as a proxy for bid-ask spread (such finding is well established in, for example, Stoll (2000)).

Given that ESG stocks are found to be significantly larger than non-ESG stocks, one should expect that the former display lower bid-ask spread and, in consequence, lower reversion than the latter. However, in our sample, the correlation between size and bid-ask spread is insignificant[4], and we chose not to select size as an independent variable in our multivariate regression. Regarding bid-ask spread, we follow Atkins & Dyl (1990), by estimating the bid-ask spread for each stock in our sample as the average of the May and December spreads surrounding the date that the stock experienced the large price change. Another measure of liquidity cited in the literature is trading volume. We obtain turnover by dividing the daily trading volume by the number of shares outstanding of firm i's common stock, as Choi & Jayaraman (2009).

Regarding volatility, our definition of "price shock" is dependent on the standard deviation: the price trigger on a determined trading day is equal to two times the standard deviation of returns between 60 and 11 trading days before that. As a result, the size of the shock and the standard deviation display moderate to large correlation coefficients[5]. To prevent multicollinearity, we estimate two different models: one where both standard deviation and the price shock are independent variables and another where the variable with lower explanatory power is removed. Additionally, we include a dummy variable to capture the tax effect of CARs observed in December or January, and the year of the abnormal return as a different dummy variable.

We apply the following multivariate model:

$$\begin{aligned} CAR_i = \beta_0 &+ \beta_1 NEGDUM_i + \beta_2 SHOCK_i + \beta_3 BIDASK_i + \beta_4 VOLUME_i \\ &+ \beta_5 VOLATILITY_i + \beta_6 ESGDUM_i + \beta_7 TAXDUM_i + \beta_8 Year10 \\ &+ \beta_9 Year11 + \beta_{10} Year12 + \beta_{11} Year13 + \beta_{12} Year14 \\ &+ \beta_{13} Year15 + \beta_{14} Year16 + \beta_{15} Year17 + \beta_{16} Year18 + \varepsilon_i \end{aligned} \tag{3.1}$$

Dependent variable, CAR, represents the cumulative abnormal return after the trigger occurs. NEGDUM is a dummy variable equal to 1 in case of negative extreme price movement and 0 otherwise. SHOCK variable measures the extreme price movement

[4] The correlation between the market capitalization of each stock (in absolute terms) and its daily bid-ask spread on the day of the price shock turned out to be -0.115 for ESG stocks and -0.041 for non-ESG stocks.

[5] The daily standard deviation as described in the definition of price shocks presents the following correlation coefficients with price shocks: 0.747 (positive shocks in ESG stocks); 0.642 (negative shocks in ESG stocks); -0.646 (positive shocks in non-ESG stocks); -0.564 (negative shocks in non-ESG stocks).

experienced by the stock. Moreover, BIDASK is the average of the May and December bid-ask spreads surrounding the date that the stock experienced the large price change, and VOLUME is the daily trading volume divided by the number of shares outstanding on the date of the price shock. VOLATILITY is the standard deviation of returns observed over the [-60, -11] period before an extreme price movement occurs. ESGDUM is a dummy variable that equals to 1 in case of an ESG stock and 0 otherwise (non-ESG stock) and TAXDUM is another dummy variable that equals 1 if the price shock is observed in December or January and 0 otherwise.

With the purpose of running the model for each individual set of stocks, we adapt the regression through the exclusion of the NEGDUM and ESG dummy variables, separately.

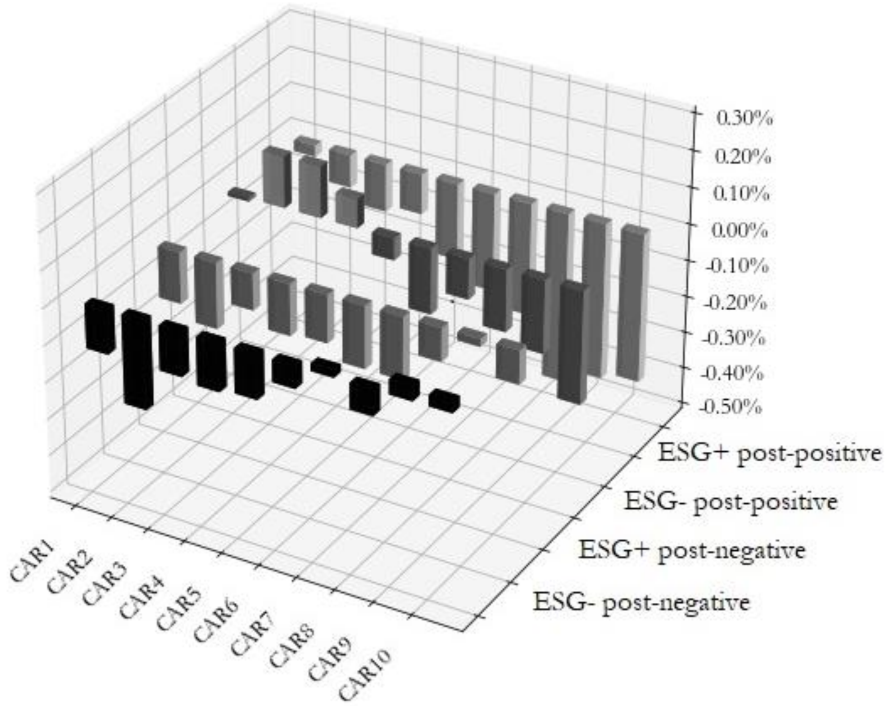
This model is tested according to the ordinary least squares model (OLS) since it is suitable for our sample, as exposed in Appendix I. It is also testing for heteroscedasticity and corrected using White's test (1980).

4. Results

4.1. Short-term reaction to extreme returns in ESG vs. non-ESG Stocks

In Figure 2, it is possible to observe the average cumulative abnormal returns up to 10 days after the initial shock in ESG+ and ESG− stocks.

Fig. 2. After-shock cumulative abnormal returns



Following positive shocks, both sets of stocks reveal a price reversal pattern since they are followed by negative abnormal returns. CARs for "ESG+" reach -0.47% by day 8 while CARs for "ESG−" reach -0.20% by day 10. Negative shocks are also followed by negative abnormal returns, therefore exhibiting a price continuation trend. However, significant values are observed in the first days with CARs for "ESG+" and "ESG−" totalling -0.18% and -0.24% in day 2, respectively. CARs tend to zero as the post-shock period gets closer to day 10.

Apart from post-positive CARs for "ESG+", the pattern is not consistent, with "ESG−" CARs fluctuating between positive and negative cumulative abnormal returns during the 10 days following the price shock, and post-negative CARs for "ESG+" trending towards zero after day 5. In Table 3, this information is paired with the *t*-stat for each day's CAR (in parenthesis).

Table 3. CARs following the price shocks

	N	Mean Shock	CAR1	CAR2	CAR3	CAR4	CAR5	CAR6	CAR7	CAR8	CAR9	CAR10
Panel A: Post-positive shocks												
ESG+	855	3.87***	-0.03	-0.09	-0.13	-0.11	-0.21	-0.27*	-0.31*	-0.47***	-0.43**	-0.41**
		-(57.69)	(0.58)	(1.03)	(1.29)	(0.92)	(1.59)	(1.85)	(1.95)	(2.65)	(2.28)	(2.04)
ESG-	838	4.98***	-0.01	0.14	0.14	0.08	-0.06	-0.18	-0.11	-0.17	-0.20	-0.31
		-(44.15)	(0.14)	-(1.11)	-(0.97)	-(0.48)	(0.31)	(0.94)	(0.57)	(0.81)	(0.90)	(1.29)
ESG+ vs. ESG-		(8.97)***	-(0.18)	-(1.50)	-(1.53)	-(0.93)	-(0.71)	-(0.39)	-(0.76)	-(1.09)	-(0.78)	-(0.32)
Panel B: Post-negative shocks												
ESG+	1009	-4.05***	-0.14**	-0.18**	-0.10	-0.14	-0.13	-0.17	-0.17	-0.09	-0.02	-0.09
		(51.03)	(2.13)	(2.01)	(0.96)	(1.11)	(0.93)	(1.12)	(1.01)	(0.50)	(0.10)	(0.44)
ESG-	929	-5.03***	-0.12	-0.24**	-0.12	-0.13	-0.12	-0.06	0.02	-0.07	0.04	0.03
		(40.31)	(1.46)	(1.97)	(0.86)	(0.75)	(0.66)	(0.32)	-(0.09)	(0.29)	-(0.18)	-(0.12)
ESG+ vs. ESG-		-(6.98)***	-(0.21)	(0.44)	(0.11)	-(0.05)	-(0.03)	-(0.42)	-(0.69)	-(0.07)	-(0.20)	-(0.36)

The table reports the CARs in percentage following the positive and negative shocks in ESG and non-ESG stocks.
The t-statistics are shown in parentheses.
***, **, * Significant at 0.01, 0.05 and 0.1 levels, respectively.

Post-positive shock mean CARs for “ESG+” are statistically significant at the 0.01 level in day 8, and significant at the 0.05 level in days 9 and 10, with days 6 and 7 also showing weak significance. None of the post-positive shock CARs for “ESG−” are significantly different from zero. Post-negative shock CARs for “ESG+” are statistically significant in the first and second days, while CARs for “ESG−” are only significantly different from zero in the second day.

Although stocks exhibit some statistically significant average CARs across our sample, no discernible difference is found between CARs for “ESG+” and CARs for “ESG−”, in post-positive and post-negative shocks. The *t*-statistic of the differences in means is not significant at the 0.05 level. The two sets of stocks present a high level of efficiency, therefore not confirming the hypothesis that stocks with the highest ESG Combined Score in the S&P 500 have a meaningful difference in their short-term behaviour following a price shock from stocks with the lowest ESG Combined Score in the same index.

The discovery of statistically significant price reversals after positive shocks and continuations following negative shocks is in contrast with most results in the literature. Such asymmetrical drifts could be the result of investor disagreement in the stock market (see, for example, Lu et al., 2014). However, the difference between CARs post-positive and post-negative price shocks is not significant at the 0.05 level[6], so no market anomalies can be validated.

From Table 3, one can also confirm the significant difference in mean shocks between “ESG+” and “ESG−”. Both positive and negative “ESG−” shocks display a mean around 1 percentual point higher than their “ESG+” equivalents. Such difference is significant within a 99% confidence interval. This finding was expected given the criteria (based on the standard deviation) used to define a price shock and the discovery that non-ESG stocks display higher volatility during the sample period.

Table 4 presents the *t*-statistics of the differences in means between selected CARs in the same group of assets.

[6] The sample was divided between positive and negative shocks, with *t*- statistics being estimated for the differences in means post-shocks in CAR1, CAR5, CAR8 and CAR10.

Table 4. Paired t-statistics in differences in means between selected CARs

	Positive shocks		Negative shocks	
	CAR1	CAR5	CAR1	CAR5
ESG+				
CAR5	1.53		-0.05	
CAR10	2.00**	1.45	-0.27	-0.34
ESG-				
CAR5	0.29		0.04	
CAR10	1.38	1.61	-0.60	-0.88

The table provides the t-statistics of the differences in CARs measured at one, five and ten day intervals after the shock.

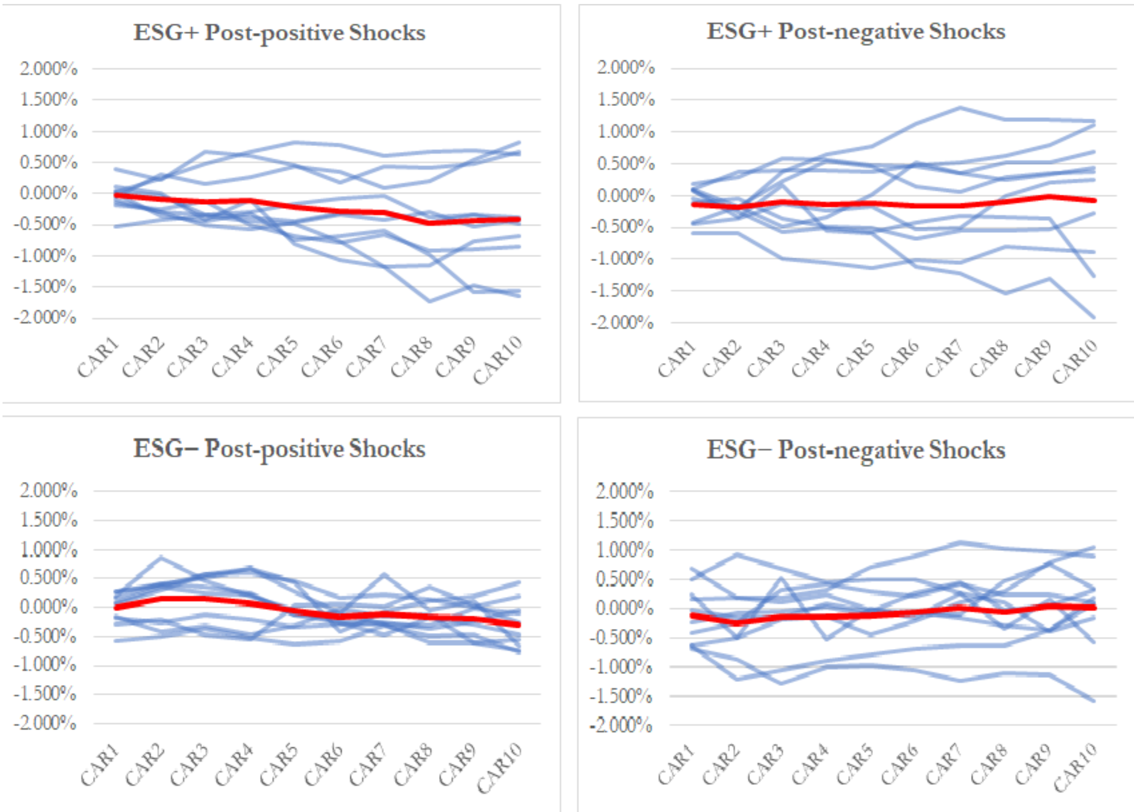
***, **, * Significant at 0.01, 0.05 and 0.1 levels, respectively.

The statistics confirm that a relatively smooth trend throughout the 10 days is only observed in post-positive "ESG+" price shocks. The difference between the mean CARs on day 1 and day 10 is significant at the 0.05 level. Considering differences between CARs on days 1 and 5, days 5 and 10, and days 1 and 10, no other group of assets shows a statistically significant *t*-stat, which is consistent with the graphically observed fluctuation in CARs.

4.2. Time-variance of results

Following Lasfer et al. (2003), we test whether these findings are time-varying, in other words, if there is a significant difference in the observed behaviour on different years of the sample. Figure 3 shows the average cumulative abnormal returns of "ESG+" and "ESG−" after positive and negative price shocks in the entire sample period (in red), as well as the annual average CARs in every year between 2010 and 2019, for each of those categories (in blue).

Fig. 3. Annual Average CARs



This graph illustrates the CAR patterns following a positive or negative price shock for each of the ten years in the sample (in blue) and the average CARs for the whole period (in red).

Globally, individual years have very different average behaviours. A widening gap between the maximum and minimum annual average CARs is noticed in "ESG+" following both positive and negative shocks. The same pattern is not seen in "ESG−" assets, that maintain, in the ten sample years, relatively stable average CARs after displaying statistically significant average jumps on the first two days after the price shock (see Table 3).

In "ESG+" stocks, post-positive shocks display a predominance of negative abnormal returns that contribute to the relatively smooth average CARs after positive shocks observed in Table 3 and Table 4. In the ESG sample, specifically, 2010 and 2011 exhibit highly significant (and negative) average CARs that impact the perceived behaviour of these assets in the full sample. Table 5 shows the average CARs and the respective *t*-statistics for these two years.

Table 5. Annual CARs and *t*-stats for 2010 and 2011

	CAR1	CAR2	CAR3	CAR4	CAR5	CAR6	CAR7	CAR8	CAR9	CAR10
Panel A: Positive shocks – ESG+										
2010	0.114	-0.002	-0.427	-0.105	-0.805	-1.060	-1.165	-1.741**	-1.474**	-1.647**
	-(0.63)	(0.01)	(1.45)	(0.29)	(1.73)	(1.91)	(1.98)	(2.48)	(2.08)	(2.16)
2011	-0.002	-0.350	-0.437	-0.320	-0.744	-0.681	-0.591	-0.976*	-1.581***	-1.548**
	(0.01)	(1.31)	(1.26)	(0.82)	(1.71)	(1.45)	(1.15)	(1.82)	(2.72)	(2.41)
Panel B: Positive shocks – ESG-										
2010	0.169	0.401	0.497	0.682	0.281	-0.111	0.570	-0.052	0.103	-0.669
	-(0.70)	-(1.23)	-(1.31)	-(1.47)	-(0.56)	(0.19)	-(0.85)	(0.07)	-(0.13)	(0.82)
2011	-0.196	-0.255	-0.125	-0.218	-0.351	-0.298	-0.297	-0.612	-0.610	-0.751
	(0.84)	(0.87)	(0.33)	(0.53)	(0.77)	(0.56)	(0.54)	(1.01)	(0.88)	(0.96)
Panel C: Negative shocks – ESG+										
2010	0.086	-0.255	-0.566	-0.501	-0.564	-0.420	-0.318	-0.340	-0.364	-1.257
	-(0.43)	(0.94)	(1.40)	(1.08)	(0.90)	(0.69)	(0.48)	(0.46)	(0.50)	(1.58)
2011	0.074	-0.343	0.169	-0.559	-0.597	-1.110**	-1.220*	-1.534**	-1.298*	-1.906**
	-(0.31)	(0.89)	-(0.43)	(1.07)	(1.24)	(2.00)	(1.86)	(2.36)	(1.94)	(2.62)
Panel D: Negative shocks – ESG-										
2010	0.695**	0.203	0.122	0.240	-0.025	-0.060	-0.093	0.481	0.774	0.361
	-(2.35)	-(0.54)	-(0.29)	-(0.45)	(0.04)	(0.08)	(0.12)	-(0.51)	-(0.76)	-(0.37)
2011	0.256	-0.493	0.530	-0.508	0.015	-0.151	0.283	-0.345	0.176	-0.572
	-(0.85)	(0.94)	-(0.94)	(0.73)	-(0.02)	(0.18)	-(0.32)	(0.37)	-(0.18)	(0.55)

The table reports the CARs in percentage following positive and negative shocks in ESG and non-ESG stocks in 2010 and 2011. The t-statistics are shown in parentheses.

***, **, * Significant at 0.01, 0.05 and 0.1 levels, respectively.

As mentioned, “ESG+” assets are the ones where the 2010-2011 time-variance is most noticeable. After positive shocks, CARs are significant in days 9 and 10 (with day 8 only being significant at a 0.05 level among 2010 observations). After negative shocks, in 2011, CARs are significant in days 6, 8 and 10 (with days 7 and 9 also showing weak significance).

The information for every other sample year is displayed in Annex II. From the annual average CARs, it is possible to conclude that non-ESG stocks (“ESG−”) are consistently efficient after positive shocks since no annual average CAR is statistically significant (at the 0.05 level). The scenario is different among negative shocks, after which there are significant CARs between days 1 and 2 in multiple years. This effect fades and, by day 5, only the 2013 and 2018 observations keep displaying significant average CARs.

In Table 6, one can observe that there is a significant difference between selected CARs in 2010-2011 and the rest of the sample period, particularly in “ESG+” stocks.

Table 6. Shocks and post-shock CARs in the 2010-11 and 2012-19 periods

	2010 - 2011	2012 - 2019	*t*-test of difference
Panel A: Positive shocks – ESG+			
N	185	670	
Mean shocks	4.46	3.81	3.88***
CAR1	0.06	-0.06	0.75
CAR5	-0.77**	-0.06	-2.04**
CAR8	-1.36***	-0.23	-2.35**
CAR10	-1.60***	-0.08	-2.79***
Panel B: Positive shocks – ESG-			
N	175	663	
Mean shocks	5.72	5.03	2.65***
CAR1	-0.01	-0.01	-0.01
CAR5	-0.04	-0.06	0.06
CAR8	-0.33	-0.13	-0.39
CAR10	-0.71	-0.21	-0.81
Panel C: Negative shocks – ESG+			
N	195	814	
Mean shocks	-4.99	-3.94	-4.41***
CAR1	0.08	-0.19***	1.54
CAR5	-0.58	-0.02	-1.36
CAR8	-1.00**	0.13	-2.16**
CAR10	-1.62***	0.28	-3.31***
Panel D: Negative shocks – ESG-			
N			
Mean shocks	-5.94	-5.03	-2.53***
CAR1	0.47**	-0.25***	3.18***
CAR5	0.00	-0.15	0.28
CAR8	0.05	0.07	0.21
CAR10	-0.13	0.07	-0.26

The table reports the average shock and post-shock CARs (in percentage) for the 2010-11 and 2012-19 periods and the *t*-statistics for the difference in means between both samples.
***, **, * Significant at 0.01, 0.05 and 0.1 levels, respectively.

Firstly, the mean shock is higher for 2010-2011 than it is in the rest of the period, in every category. This is a direct consequence of the higher standard deviation observed in the earlier years that produces a higher trigger threshold (a "shock" is a price movement that exceeds two times the standard deviation of asset returns during the [-60, -11] trading days preceding that movement). These differences are statistically significant at the 0.01 level.

Furthermore, for ESG stocks ("ESG+"), the average CARs in 2010-2011 are significantly different (and lower) than the average CARs in 2012-2019, on days 5, 8 (at the 0.05 level), and 10 (at the 0.01 level) after a positive shock. After a negative shock, the same is observed on days 8 (at the 0.05 level) and 10 (at the 0.01 level). The cumulative abnormal return on these stocks for the first two sample years reaches -1.62%, which is very different from the -0.09% found throughout the 10 years of data. As seen in Fig. 1 and Table 2, the first two years of the sample are the ones with higher volatility in this set of stocks, which may explain the unusual behaviour.

On the other hand, "ESG−" stocks display no significant difference of behaviour, in selected days, during the 2010-2011 and 2012-2019 periods, with the only exception being the first day CAR after negative shocks. CAR1 exhibits a pattern of price reversal in 2010-11 and price continuation in the rest of the period, and this difference is significant at the 0.01 level. As expected, since abnormal returns following positive shocks in non-ESG stocks are insignificant, there is no discernible difference between CARs in the aforementioned periods.

From analysing the second column, we can conclude that both sets of stocks achieve a high level of efficiency after positive shocks in the 2012 to 2019 period, since no CAR is significant. ESG and non-ESG stocks display significant price continuations on the first day following negative price shocks between 2012 and 2019.

The same analysis was conducted by dividing both periods equally – the first being comprised by years 2010 to 2014 and the other by years 2015 to 2019. No relevant difference to the previous results was found in "ESG−" assets. Regarding "ESG+" stocks, the diffusion of the 2010 and 2011 CARs causes the difference between both periods to be insignificant for CARs after positive shocks. The statistical significance of the difference in means for CAR8 and CAR10 post-negative shocks also vanishes, although CAR1 gains significance at the 0.05 level. The full table is found on Annex III.

4.3. Multivariate analysis

We present the results from a multivariate model in order to assess the sensibility of CARs following an extreme price movement to different explanatory variables. Table 7 exhibits the overall model results across both ESG and non-ESG stocks, for CAR1, CAR3, CAR5 or CAR10 as a dependent variable.

Table 7. Overall multivariate model for ESG and non-ESG stocks

	1 Day CAR	3 Day CAR	5 Day CAR	10 Day CAR
NEGDUM	-0.001	-0.001	0.000	0.004*
	(0.345)	(0.493)	(0.806)	(0.086)
BIDASK	-0.063	-0.102	-0.026	-0.039
	(0.484)	(0.476)	(0.914)	(0.893)
VOLUME	0.012	0.030	-0.002	-0.011
	(0.576)	(0.417)	(0.958)	(0.902)
STDEV	-0.002	0.199	0.240	0.747***
	(0.981)	(0.171)	(0.187)	(0.004)
ESGDUM	0.000	0.000	0.000	0.001
	(0.905)	(0.804)	(0.982)	(0.618)
TAXDUM	0.001	-0.001	-0.003	-0.004
	(0.188)	(0.762)	(0.222)	(0.264)
Year10	0.001	-0.006**	-0.008**	-0.014**
	(0.600)	(0.029)	(0.041)	(0.016)
Year11	-0.001	-0.005	-0.009**	-0.017***
	(0.463)	(0.116)	(0.017)	(0.002)
Year12	-0.003**	-0.003	-0.003	-0.002
	(0.035)	(0.277)	(0.340)	(0.723)
Year13	-0.001	-0.005**	-0.004	0.000
	(0.549)	(0.026)	(0.215)	(0.927)
Year14	-0.003**	-0.006**	-0.003	-0.001
	(0.046)	(0.028)	(0.332)	(0.907)
Year15	-0.004***	-0.007**	-0.006	-0.004
	(0.006)	(0.045)	(0.127)	(0.436)
Year16	-0.004**	-0.003	-0.004	0.001
	(0.025)	(0.223)	(0.214)	(0.821)
Year17	-0.003**	-0.005*	-0.004	0.000
	(0.032)	(0.051)	(0.186)	(0.953)
Year18	-0.007***	-0.013***	-0.014***	-0.015***
	(0.001)	(0.000)	(0.000)	(0.004)
Constant	0.002	0.002	0.001	-0.010*
	(0.266)	(0.503)	(0.784)	(0.085)

Observations	3631			
Adj R-squared	0.006	0.006	0.003	0.010
F	2.578	2.456	1.630	3.421
Prob>F	0.001	0.001	0.058	0.000

Dependent variable, CAR, represents the cumulative abnormal return after the trigger occurs. NEGDUM is a dummy variable is equal to 1 in case of negative extreme price movement and 0 otherwise. BIDASK is the average of the May and December bid-ask spreads surrounding the date that the stock experienced the large price change, and VOLUME is the daily trading volume divided by the number of shares outstanding on the date of the price shock. VOLATILITY is the standard deviation of returns observed over the [-60, -11] period before an extreme price movement occurs. ESGDUM is a dummy variable that equals to 1 in case of an ESG stock and 0 otherwise. TAXDUM is a dummy variable that equals 1 if the price shock is observed in December or January and 0 otherwise. YEAR represents dummy variables that equals 1 if the trigger occurs during the respective sample year and zero otherwise. Robust p-value in parentheses. *, ** and *** represents significance at the 10%, 5% and 1% levels, respectively.

Initially, this analysis included the SHOCK variable. Nevertheless, as exposed in the methodology chapter and Appendix I, the lower explanatory power of this variable compared to the highly correlated STDEV variable meant that it was removed from the model. By overlooking the "Year" dummy variables, which consistently exhibit significant values across each day's CAR, we can only observe significant coefficients in the model with CAR10 as the dependent variable. This model finds weak significance of NEGDUM and significance at the 0.01 level of STDEV. However, including every positive and negative selected price shock makes interpretation of these coefficients unfeasible.

The model with CAR10 is also overall the more significant (F-stat = 3.421), although the model with CAR1 and CAR3 are also significant at the 0.01 level. CAR10 model also presents the highest explanatory power (Adjusted $R^2 = 0.01$), while still at a very low level. Following these initial results, we chose to proceed with CAR10 and CAR1 as dependent variables. Subsequently, we divide the sample in shocks observed in ESG or non-ESG stocks and positive or negative price shocks. The respective multivariate analysis can be observed in Table 8.

Table 8. Multivariate model for CAR10 in ESG vs. non-ESG stocks and positive vs. negative shocks

	ESG	non-ESG	Positive Shocks	Negative Shocks
NEGDUM	0.003	0.004		
	(0.207)	(0.230)		
BIDASK	0.230	0.163	-0.127	0.079
	(0.534)	(0.755)	(0.739)	(0.854)
VOLUME	0.040	-0.016	-0.015	-0.004
	(0.769)	(0.870)	(0.846)	(0.976)
STDEV	0.812**	0.726**	0.084	1.360***
	(0.029)	(0.035)	(0.825)	(0.000)
ESGDUM			-0.001	0.003
			(0.811)	(0.347)
TAXDUM	-0.005	-0.003	0.006	-0.014***
	(0.227)	(0.644)	(0.207)	(0.007)
Year10	-0.026***	-0.005	-0.017**	-0.012
	(0.002)	(0.565)	(0.039)	(0.169)
Year11	-0.027***	-0.009	-0.017**	-0.019**
	(0.000)	(0.288)	(0.026)	(0.015)
Year12	-0.004	0.000	-0.009	0.004
	(0.577)	(0.996)	(0.233)	(0.539)
Year13	-0.006	0.005	-0.008	0.006
	(0.342)	(0.466)	(0.269)	(0.355)
Year14	-0.002	0.002	-0.003	0.003
	(0.723)	(0.812)	(0.624)	(0.607)
Year15	-0.004	-0.003	-0.011	0.002
	(0.471)	(0.735)	(0.166)	(0.832)
Year16	-0.002	0.005	-0.002	0.004
	(0.737)	(0.506)	(0.808)	(0.513)
Year17	0.000	0.001	-0.011	0.009
	(0.998)	(0.930)	(0.126)	(0.151)
Year18	-0.015**	-0.014*	-0.015*	-0.015**
	(0.017)	(0.091)	(0.081)	(0.023)
Constant	-0.007	-0.014*	0.005	-0.019***
	(0.323)	(0.093)	(0.593)	(0.010)
Observations	1864	1767	1693	1938
Adj R-squared	0.018	0.002	0.001	0.023
F	3.438	1.277	1.141	4.252
Prob>F	0.000	0.214	0.316	0.000

Dependent variable, CAR, represents the cumulative abnormal return after the trigger occurs. NEGDUM is a dummy variable is equal to 1 in case of negative extreme price movement and 0 otherwise. BIDASK is the average of the May and December bid-ask spreads surrounding the date that the stock experienced the large price change, and VOLUME is the daily trading volume divided by the number of shares outstanding on the date of the price shock. VOLATILITY is the standard deviation of returns observed over the [-60, -11] period before an extreme price movement occurs. ESGDUM is a dummy variable that equals to 1 in case of an ESG stock and 0 otherwise. TAXDUM is a dummy variable that equals 1 if the price shock is observed in December or January and 0 otherwise. YEAR represents dummy variables that equals 1 if the trigger occurs during the respective sample year and zero otherwise. Robust p-value in parentheses. *, ** and *** represents significance at the 10%, 5% and 1% levels, respectively.

Firstly, both the estimated models for ESG stocks and Negative shocks are overall significant at the 0.01 level. The estimated model for non-ESG and Positive shocks are not overall significant. Regarding ESG, we observe a significant relationship between CAR10 and STDEV. Dummy variables for 2010, 2011 and 2018 observations also show significant coefficients. As shown in Fig. 1, these are the years where ESG stocks exhibit a larger standard deviation, making this finding consistent with the previous statement that post-shock CARs are larger in years with higher volatility. This model has an adjusted R^2 equal to 0.018.

The model for negative shocks returns a significant STDEV coefficient equal to 1.360, indicating that a 1 percentage point increase in daily standard deviation results in a 1.36 p.p. increase in CAR10, with other factors constant. Such effect indicates that higher CARs post-negative shocks can be linked to higher volatility. Negative shocks also showcase a significant negative coefficient in TAXDUM, suggesting that a pattern of price continuation follows negative shocks occurring in the months of December and January, *ceteris paribus*. These findings contribute to the adjusted R^2 value of 0.023 for this model.

NEGDUM results indicate that there is no significant difference between CAR10 after positive and negative shocks (valid for both ESG and non-ESG stocks). Accordingly, ESGDUM confirms that there is no statistically discernible difference between CAR10 for ESG and non-ESG stocks (valid for post-positive and post-negative shocks).

On theses split samples, no significant differences were found with CAR1 as dependent variable, apart from BIDASK, which shows weak significance on the CAR1 post-negative shocks model. In fact, that is the single model where the bid-ask spread has some degree of significance (only at the 0.1 level). The coefficient of -0.22 points to a decrease of 0.22 percentage points in the post-negative shock CAR1 for every p.p. increase in the bid-ask spread, with other factors constant.

Table 9 explores the multivariate coefficients for positive and negative shocks specific to both ESG and non-ESG stocks (with CAR1 and CAR10 as dependent variables).

Table 9. Multivariate model for CAR1 and CAR10 in positive and negative shocks observed in ESG vs. non-ESG stocks

	ESG				non-ESG			
	1 Day CAR		10 Day CAR		1 Day CAR		10 Day CAR	
	Positive Shocks	Negative Shocks	Positive Shocks	Negative Shocks	Positive Shocks	Negative Shocks	Positive Shocks	Negative Shocks
BIDASK	0.170	-0.024	0.059	0.399	0.017	-0.316	-0.082	0.474
	(0.286)	(0.883)	(0.897)	(0.486)	(0.938)	(0.127)	(0.911)	(0.543)
VOLUME	-0.077	-0.057	0.176	-0.061	0.039	0.005	-0.042	0.002
	(0.256)	(0.406)	(0.451)	(0.708)	(0.382)	(0.811)	(0.607)	(0.990)
STDEV	0.080	0.097	-0.064	1.598***	-0.178	0.076	0.223	1.263***
	(0.644)	(0.517)	(0.913)	(0.001)	(0.534)	(0.600)	(0.655)	(0.005)
TAXDUM	0.000	0.003	0.002	-0.012*	0.002	0.001	0.010	-0.018**
	(0.889)	(0.113)	(0.721)	(0.054)	(0.398)	(0.756)	(0.145)	(0.049)
Year10	0.001	-0.001	-0.025**	-0.025**	0.001	0.002	-0.011	-0.001
	(0.837)	(0.846)	(0.035)	(0.036)	(0.686)	(0.529)	(0.375)	(0.940)
Year11	0.000	-0.001	-0.024**	-0.029***	-0.002	-0.002	-0.011	-0.010
	(0.911)	(0.869)	(0.023)	(0.004)	(0.477)	(0.543)	(0.324)	(0.422)
Year12	-0.005	-0.002	-0.015	0.006	0.002	-0.009***	-0.003	0.002
	(0.138)	(0.496)	(0.161)	(0.543)	(0.604)	(0.006)	(0.785)	(0.879)
Year13	0.001	0.000	-0.012	-0.002	0.000	-0.003	-0.004	0.015
	(0.771)	(0.909)	(0.244)	(0.783)	(0.996)	(0.364)	(0.731)	(0.133)
Year14	0.001	-0.003	-0.002	-0.002	-0.004	-0.005*	-0.005	0.009
	(0.657)	(0.246)	(0.867)	(0.855)	(0.249)	(0.067)	(0.619)	(0.368)
Year15	-0.001	-0.006**	-0.011	0.002	0.001	-0.011***	-0.009	0.002
	(0.835)	(0.029)	(0.230)	(0.829)	(0.709)	(0.001)	(0.480)	(0.888)
Year16	0.004	-0.007**	-0.001	-0.002	0.002	-0.012***	-0.002	0.012
	(0.113)	(0.039)	(0.925)	(0.819)	(0.507)	(0.000)	(0.883)	(0.243)
Year17	-0.001	-0.001	-0.012	0.013	-0.003	-0.007**	-0.008	0.007
	(0.803)	(0.831)	(0.169)	(0.128)	(0.392)	(0.011)	(0.476)	(0.416)
Year18	-0.001	-0.008***	-0.016*	-0.014*	-0.006	-0.012***	-0.012	-0.015
	(0.655)	(0.005)	(0.097)	(0.080)	(0.442)	(0.001)	(0.380)	(0.147)
Constant	-0.001	0.001	0.006	-0.015*	0.003	0.004	-0.001	-0.021**
	(0.778)	(0.778)	(0.550)	(0.087)	(0.624)	(0.206)	(0.933)	(0.036)
Observations	855	1009	855	1009	838	929	838	929
Adj R-squared	0.003	0.010	0.006	0.035	-0.003	0.026	-0.010	0.013
F	1.178	1.782	1.380	3.850	0.776	2.910	0.384	1.913
Prob>F	0.291	0.041	0.163	0.000	0.687	0.000	0.975	0.025

Dependent variable represents the cumulative abnormal return after the trigger occurs. NEGDUM is a dummy variable is equal to 1 in case of negative extreme price movement and 0 otherwise. BIDASK is the average of the May and December bid-ask spreads surrounding the price shock date. VOLUME is the daily trading volume divided by the number of shares outstanding on the date of the price shock. VOLATILITY is the standard deviation of returns observed over the [-60, -11] period before an extreme price movement occurs. ESGDUM is a dummy variable that equals to 1 in case of an ESG stock and 0 otherwise. TAXDUM is a dummy variable that equals 1 if the price shock is observed in December or January and 0 otherwise. YEAR represents dummy variables that equals 1 if the trigger occurs during the respective sample year and zero otherwise. Robust p-value in parentheses. *, ** and *** represents significance at the 10%, 5% and 1% levels, respectively.

From Table 9, we can conclude that there is a clear distinction between results for positive and negative shocks. While no model focusing on CARs post-positive shocks presents overall significance, every model focusing on CARs post-negative shocks is significant at the 0.05 level. Regarding CAR1, such significance after negative shocks is related with the year dummy variables. As we found in chapter 4.1, both sets of stocks exhibit significant CARs in day 1 and/or 2 post-negative shocks. Multiple years display significant negative abnormal returns in the first day after negative shocks, which indicates price continuation.

The individual significance of CARs does not hold for day 10 post-negative shocks. However, from Table 9, we can verify that STDEV and TAXDUM are individually significant in both ESG and non-ESG stocks. These findings are identical to those constants in Table 8 but confirm that the effect of TAXDUM and STDEV over CAR10 reach both ESG and non-ESG stocks. TAXDUM presents a significant negative coefficient (at the 0.1 level among ESG stocks and at the 0.05 level among non-ESG stocks). This suggests that negative shocks in the months of December and January cause CARs in day 10 to be more negative, indicating price continuation, *ceteris paribus.*

Regarding STDEV, among ESG stocks, the STDEV coefficient is equal to 1.598, implying that a 1 percentage point increase in daily standard deviation results in a 1.60 p.p. increase in CAR10 post-negative shocks, with other factors constant. Such value contributes to the explanatory power of this model – the adjusted R^2 is equal to 0.035, the highest of all models. Non-ESG stocks present a similar result, with the STDEV coefficient totalling 1.263.

The standard deviation effect suggests, as mentioned, that higher price reversion post-negative shocks can be related to the presence of higher volatility. Furthermore, the high correlation between standard deviation and the trigger (size of the shock) could mean that the reversal amount depends on the size of the preceding price shock. In fact, Amini et al. (2013) find considerable evidence in the literature that the short-term reaction to extreme returns in stocks may depend on the size of the preceding price move with continuations occurring after relatively smaller moves. The adjusted R^2 of this model is, however, too low at 0.023 to interpret this finding as evidence that the trigger size is one of the primary explanations of post-shock price reversal.

Finally, we discover that VOLUME and BIDASK present no statistical significance in any of the models. This arises as evidence that such variables are not relevant in the context of our sample.

5. Conclusions

Since the beginning of the 21st century, ESG factors have increased their importance in corporate strategy and in financial markets. Although the influence of such factors on firm and stock performance is not certain, most stakeholders have recognized value to including ESG in their strategy.

Despite the growing presence of ESG, there is no research regarding the short-term reaction to extreme returns in ESG stocks and, in particular, comparing its short-term behaviour with the reaction of non-ESG stocks. This study represents a first introduction of this subject and focuses on stocks in the S&P 500 index from 2010 until 2019. Regarding this sample, we discover that stocks with the highest ESG Combined Score show an equivalent daily average return to stocks with the lowest ESG Combined Score but lower return volatility.

We examine price movements larger than two standard deviations in a period of 50 days starting 60 days before the event and find significant price reversals in days 8 to 10 after positive shocks in ESG stocks and significant price continuations post-negative shocks in ESG stocks (days 1 and 2) and non-ESG stocks (day 2). Overall, both groups of stocks exhibit negative cumulative abnormal returns (CARs) after positive or negative price shocks. Despite finding statistically significant price reversals and continuations, there is no statistically discernible difference in the behaviour of ESG and non-ESG stocks across positive or negative assets. Similarly, there is no significant difference on CARs post-positive or post-negative shocks.

Overall, there are no apparent differences between the price efficiency of ESG and non-ESG stocks. Despite finding statistically significant individual CARs in multiple days, both sets of stocks present a high level of efficiency following large price changes. ESG and non-ESG abnormal returns are not significantly different from one another, which means that no market anomaly is consistently found across the sample period.

Furthermore, by dividing the sample in two periods (with the first including only 2010 and 2011) we did find time variance in our results. 2010 and 2011 display the most significant CARs in ESG stocks. By excluding these years from the sample, only the CAR1 for ESG and non-ESG stocks post-negative shocks remains significant.

Our multivariate analysis confirms, through the usage of year dummy variables, the significance of the two first sample years on the behaviour of ESG stocks. In reality, the highest values for standard deviation in the ESG and non-ESG stock samples are shown in both these years, which gave us a logical motive to look for a relationship between standard deviation and the abnormal returns following the price shock. We find a significant positive relationship between the standard deviation and the CAR 10 days after a negative shock. Since standard deviation is considered a proxy of the price shock trigger, this result suggests that the size of the preceding move impacts the amount of reversal observed after negative shocks. Negative shocks in December or January seem to cause more negative CARs in day 10, indicating price continuation. There are no relevant differences in the coefficients of ESG or non-ESG stocks. Interestingly, none of these relationships is found post-positive shocks. Within the S&P 500 index, the short-term reaction to extreme returns of ESG and non-ESG stocks does not appear related to the bid-ask spread or trading volume on the day of the shock.

The focus on one single market (particularly on an index containing some of the largest and most liquid stocks in the world) may be seen as a limitation to this study. Further research should cover different geographical areas, including emerging markets. We believe that researching markets with lower liquidity and reduced presence of institutional investors might affect the significance of post-shock abnormal returns and provide additional insights on the comparative behaviour of ESG and non-ESG stocks. Additionally, the positive relationship found between the size of price triggers and the amount of reversal may present a case to explore different "price shock" definitions. The trigger based upon a multiple of the standard deviation of returns is quite small in the context of the literature on this topic, and a more conventional approach based on a fixed percentage trigger may generate very different results.

6. Appendix

6.1. Appendix I – Econometric Model

The analysis data varies across time, but since the stocks in our sample do not remain the same throughout the period, i.e., most stocks do not display observations for each of the ten sample years, we employ the undated panel in our model.

Furthermore, no significant difference is found between ESG and non-ESG stocks used in our sample, thus ordinary least squares (OLS) is suitable for our analysis. All models presented on this dissertation are corrected for heteroscedasticity using White's test (1980).

The first multivariate model we use, as shown in equation (3.1), is the following:

$$\begin{aligned} CAR_i = {} & \beta_0 + \beta_1 NEGDUM_i + \beta_2 SHOCK_i + \beta_3 BIDASK_i + \beta_4 VOLUME_i \\ & + \beta_5 VOLATILITY_i + \beta_6 ESGDUM_i + \beta_7 TAXDUM_i + \beta_8 Year10 \\ & + \beta_9 Year11 + \beta_{10} Year12 + \beta_{11} Year13 + \beta_{12} Year14 + \beta_{13} Year15 \\ & + \beta_{14} Year16 + \beta_{15} Year17 + \beta_{16} Year18 + \varepsilon_i \end{aligned}$$

After discovering that independent variable SHOCK had lower explanatory power than VOLATILITY, and since both variables presented a high correlation coefficient between them, we tested the model without the variable SHOCK, as follows:

$$\begin{aligned} CAR_i = {} & \beta_0 + \beta_1 NEGDUM_i + \beta_2 BIDASK_i + \beta_3 VOLUME_i + \beta_4 VOLATILITY_i \\ & + \beta_5 ESGDUM_i + \beta_6 TAXDUM_i + \beta_7 Year10 + \beta_8 Year11 + \beta_9 Year12 \\ & + \beta_{10} Year13 + \beta_{11} Year14 + \beta_{12} Year15 + \beta_{13} Year16 + \beta_{14} Year17 \\ & + \beta_{15} Year18 + \varepsilon_i \end{aligned}$$

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8. Annex

Annex I - List of selected companies (2010 – 2019)

Table 10 – Highest and lowest ESG Combined Scores for S&P500 constituents in 2010

Company Name	ESG Combined Score (FY2010)	ESG Score (FY2010)	ESG Controversies Score (FY2010)
	ESG+		
Texas Instruments Inc	88.88	88.88	89.47
Weyerhaeuser Co	85.67	85.67	87.50
Starbucks Corp	85.25	85.25	91.67
Freeport-McMoRan Inc	84.36	84.36	100.00
General Mills Inc	84.19	84.19	89.29
Cleveland-Cliffs Inc	82.59	82.59	100.00
Newmont Corporation	81.68	81.68	84.00
Gap Inc	79.59	79.59	100.00
Pinnacle West Capital Corp	79.17	79.17	100.00
Campbell Soup Co	78.88	78.88	89.29
Trane Technologies PLC	78.17	78.17	84.38
3M Co	78.03	86.84	69.23
Kimberly-Clark Corp	76.13	76.13	91.67
Masco Corp	75.34	75.34	100.00
Nordstrom Inc	75.23	75.23	100.00
Lexmark International Inc	75.10	75.10	86.11
Agilent Technologies Inc	75.00	75.00	100.00
Applied Materials Inc	74.77	74.77	100.00
Analog Devices Inc	74.48	74.48	89.47
Avery Dennison Corp	74.38	77.33	71.43
State Street Corp	73.94	73.94	100.00
Allstate Corp	73.53	76.08	70.97
Peabody Energy Corp	73.37	73.37	87.50
	ESG-		
American International Group Inc	16.74	31.86	1.61
Pioneer Natural Resources Co	16.23	16.23	82.14
Allergan plc	15.99	19.48	12.50
Booking Holdings Inc	15.40	15.40	77.78
Cablevision Systems Corp	15.34	15.34	57.89
Monster Worldwide Inc	15.24	15.24	100.00
Graham Holdings Co	14.77	14.77	50.00
Fiserv Inc	14.53	14.53	100.00
Rowan Companies Ltd	14.28	14.28	100.00
Precision Castparts Corp	14.14	14.14	100.00
Abercrombie & Fitch Co	12.94	23.25	2.63
Coterra Energy Inc	12.82	12.82	15.18
Lorillard LLC	12.76	12.76	46.43
Harman International Industries Inc	12.28	12.28	100.00
Titanium Metals Corp	12.00	12.00	100.00
Expedia Group Inc	11.45	11.45	25.00
Netflix Inc	11.07	11.07	64.71
Kraft Heinz Foods Co	10.67	10.67	
CH Robinson Worldwide Inc	10.31	10.31	100.00
L3 Technologies Inc	8.59	8.59	20.59
Helmerich and Payne Inc	8.17	8.17	64.29
Berkshire Hathaway Inc	6.88	9.91	3.85
SLM Corp	3.41	3.41	57.94
Public Storage	2.81	2.81	100.00

Table 11 – Highest and lowest ESG Combined Scores for S&P500 constituents in 2011

Company Name	ESG Combined Score (FY2011)	ESG Score (FY2011)	ESG Controversies Score (FY2011)
	ESG+		
Texas Instruments Inc	92.54	92.54	100.00
Johnson Controls International PLC	89.49	90.42	88.57
Weyerhaeuser Co	88.07	88.07	100.00
Air Products and Chemicals Inc	85.05	85.05	100.00
Gap Inc	84.86	84.86	100.00
Kimberly-Clark Corp	84.11	84.11	91.67
Campbell Soup Co	83.44	83.44	100.00
State Street Corp	83.07	83.07	85.71
Lexmark International Inc	80.76	80.76	100.00
Staples Inc	80.64	80.64	90.48
Cleveland-Cliffs Inc	79.04	79.04	100.00
Avery Dennison Corp	78.47	78.47	100.00
Agilent Technologies Inc	78.09	78.09	89.29
Entergy Corp	77.94	77.94	100.00
CBRE Group Inc	77.94	77.94	100.00
McDonald's Corp	77.32	77.32	90.00
Waste Management Inc	76.33	76.33	100.00
Analog Devices Inc	75.83	75.83	100.00
Baker Hughes Co	75.72	75.72	100.00
Hasbro Inc	75.7	75.7	91.67
Becton Dickinson and Co	75.58	75.58	100.00
Conagra Brands Inc	75.42	75.42	90.38
Kohls Corp	75.31	75.31	100.00
Marathon Oil Corp	74.28	74.28	82.35
	ESG-		
Genuine Parts Co	17.36	17.36	100.00
ATI Inc	17.02	17.02	100.00
Viatris Inc	16.92	26.03	7.81
Roper Technologies Inc	16.74	16.74	100.00
Federated Hermes Inc	16.56	16.56	100.00
Coterra Energy Inc	16.36	16.36	46.08
L3 Technologies Inc	15.95	15.95	18.75
Titanium Metals Corp	15.93	15.93	100.00
Noble Corporation PLC	15.67	27.76	3.57
Fiserv Inc	14.9	14.9	100.00
Wynn Resorts Ltd	14.54	14.54	100.00
Lorillard LLC	14.12	14.12	42.31
Cablevision Systems Corp	14.06	14.06	60.00
Perrigo Company PLC	13.82	13.82	39.06
Diamond Offshore Drilling Inc	12.46	12.46	100.00
Booking Holdings Inc	11.38	11.38	100.00
UnitedHealth Group Inc	11.3	11.3	37.5
Netflix Inc	11.21	11.21	42.42
Helmerich and Payne Inc	10.74	10.74	100.00
Berkshire Hathaway Inc	10.69	10.69	12.5
Expedia Group Inc	8.66	8.66	18.00
SLM Corp	5.05	5.05	57.75
Public Storage	2.96	2.96	100.00

Table 12 – Highest and lowest ESG Combined Scores for S&P500 constituents in 2012

Company Name	ESG Combined Score (FY2012)	ESG Score (FY2012)	ESG Controversies Score (FY2012)
	ESG+		
Intel Corp	91.31	91.31	95.83
Texas Instruments Inc	89.04	89.04	100.00
3M Co	86.04	86.04	87.50
Air Products and Chemicals Inc	84.43	84.43	100.00
Newmont Corporation	83.65	83.65	85.29
Lexmark International Inc	83.55	83.55	100.00
State Street Corp	82.99	83.63	82.35
Campbell Soup Co	82.41	82.41	100.00
General Mills Inc	81.76	84.95	78.57
Freeport-McMoRan Inc	81.71	81.71	85.29
CBRE Group Inc	81.10	81.10	100.00
General Electric Co	80.91	80.91	87.50
Cleveland-Cliffs Inc	80.68	80.68	100.00
Cisco Systems Inc	80.64	80.64	81.25
Weyerhaeuser Co	80.48	85.96	75.00
Staples Inc	80.47	80.47	100.00
Baxter International Inc	80.46	80.46	100.00
Abbott Laboratories	79.99	80.57	79.41
Hasbro Inc	77.36	77.36	100.00
Agilent Technologies Inc	77.18	77.18	100.00
CA Inc	77.17	77.17	100.00
EIDP Inc	77.01	87.36	66.67
Healthpeak Properties Inc	76.54	76.54	100.00
Conagra Brands Inc	76.40	76.40	92.86
	ESG-		
Kraft Heinz Foods Co	17.79	17.79	
Federated Hermes Inc	17.70	17.70	100.00
Forest Laboratories Inc	17.64	17.64	70.69
Pioneer Natural Resources Co	17.36	17.36	100.00
Diamond Offshore Drilling Inc	16.59	16.59	100.00
Lennar Corp	16.46	16.46	100.00
Lorillard LLC	16.43	16.43	41.43
TFCF Corp	15.95	29.72	2.17
Fiserv Inc	15.71	15.71	100.00
L3 Technologies Inc	15.68	15.68	100.00
Noble Corporation PLC	13.77	22.53	5.00
Cablevision Systems Corp	13.57	13.57	54.35
Genuine Parts Co	12.53	12.53	100.00
Coterra Energy Inc	12.37	12.37	100.00
Wynn Resorts Ltd	11.33	11.33	82.61
Expedia Group Inc	9.91	9.91	21.74
Berkshire Hathaway Inc	8.41	8.41	16.67
UnitedHealth Group Inc	8.41	8.41	50.00
Helmerich and Payne Inc	7.77	7.77	100.00
Trane Technologies PLC	5.87	5.87	100.00
Netflix Inc	5.83	7.11	4.55
SLM Corp	4.33	4.33	63.97
Public Storage	1.90	1.90	100.00

Table 13 – Highest and lowest ESG Combined Scores for S&P500 constituents in 2013

Company Name	ESG Combined Score (FY2013)	ESG Score (FY2013)	ESG Controversies Score (FY2013)
	ESG+		
3M Co	88.23	88.23	100.00
Texas Instruments Inc	87.92	87.92	100.00
Weyerhaeuser Co	87.81	87.81	100.00
Gap Inc	85.50	85.50	100.00
State Street Corp	84.62	84.62	100.00
Campbell Soup Co	84.46	84.46	100.00
CBRE Group Inc	84.27	84.27	100.00
Baker Hughes Co	84.22	84.22	100.00
Baxter International Inc	84.07	84.07	100.00
Analog Devices Inc	79.87	79.87	100.00
Johnson Controls International PLC	79.51	79.86	79.17
Freeport-McMoRan Inc	78.79	78.79	90.00
Cleveland-Cliffs Inc	78.54	78.54	100.00
Qualcomm Inc	77.76	77.76	95.00
Conagra Brands Inc	77.54	77.54	89.39
Agilent Technologies Inc	76.94	76.94	100.00
Old Copper Company Inc	76.34	76.34	100.00
NVIDIA Corp	75.88	75.88	100.00
Allergan Inc	75.87	76.07	75.68
Air Products and Chemicals Inc	75.51	75.51	86.67
Healthpeak Properties Inc	75.41	75.41	100.00
Autodesk Inc	75.21	75.21	100.00
Cummins Inc	74.61	74.61	100.00
Ball Corp	74.55	74.55	100.00
	ESG-		
Genuine Parts Co	18.04	18.04	100.00
Carefusion Corp	17.93	28.36	7.50
Diamond Offshore Drilling Inc	17.89	17.89	100.00
Federated Hermes Inc	17.88	17.88	100.00
Booking Holdings Inc	17.86	17.86	47.83
WPX Energy Inc	17.62	17.62	100.00
Allergan plc	16.56	16.56	39.19
Lorillard LLC	15.27	15.27	27.27
Fiserv Inc	15.15	15.15	100.00
Coterra Energy Inc	15.15	15.15	100.00
Lennar Corp	14.78	14.78	100.00
Berkshire Hathaway Inc	14.61	14.61	26.92
Monster Beverage Corp	14.08	14.08	100.00
H & R Block Inc	13.81	24.28	3.33
Wynn Resorts Ltd	13.28	13.28	91.30
Expedia Group Inc	12.59	12.59	19.57
Cablevision Systems Corp	10.11	10.11	25.00
L3 Technologies Inc	9.85	16.93	2.78
UnitedHealth Group Inc	9.37	9.37	75.00
Tripadvisor Inc	8.00	8.00	100.00
Helmerich and Payne Inc	7.76	7.76	100.00
Netflix Inc	6.57	6.57	89.13
SLM Corp	3.60	3.60	68.52
Public Storage	2.49	2.49	100.00

Table 14 – Highest and lowest ESG Combined Scores for S&P500 constituents in 2014

Company Name	ESG Combined Score (FY2014)	ESG Score (FY2014)	ESG Controversies Score (FY2014)
	ESG+		
Campbell Soup Co	89.29	89.29	100.00
Texas Instruments Inc	83.60	83.60	100.00
Agilent Technologies Inc	82.98	82.98	93.48
Staples Inc	82.88	82.88	100.00
Baxter International Inc	82.48	84.53	80.43
Weyerhaeuser Co	82.14	82.14	100.00
Freeport-McMoRan Inc	80.97	80.97	95.61
Autodesk Inc	79.21	79.21	100.00
Waste Management Inc	79.10	79.10	100.00
Air Products and Chemicals Inc	78.80	78.80	100.00
Humana Inc	78.73	78.73	84.62
Allstate Corp	78.69	82.38	75.00
Hasbro Inc	78.38	78.38	100.00
NVIDIA Corp	78.29	78.29	100.00
NRG Energy Inc	77.61	77.61	100.00
Cisco Systems Inc	77.53	85.06	70.00
Analog Devices Inc	77.25	77.25	100.00
Mosaic Co	77.18	77.18	100.00
Cummins Inc	76.37	76.37	93.06
Johnson Controls International PLC	76.20	81.44	70.97
Conocophillips	76.02	78.71	73.33
CBRE Group Inc	75.98	75.98	100.00
Becton Dickinson and Co	75.93	75.93	93.48
Duke Energy Corp	75.76	75.76	100.00
	ESG-		
Genuine Parts Co	21.06	21.06	100.00
Regeneron Pharmaceuticals Inc	20.87	20.87	100.00
CH Robinson Worldwide Inc	20.81	20.81	100.00
Lennar Corp	19.54	19.54	100.00
L3 Technologies Inc	19.14	19.14	89.29
Wynn Resorts Ltd	18.10	18.10	100.00
QEP Resources Inc	17.38	17.38	100.00
FMC Technologies Inc	17.31	17.31	100.00
Diamond Offshore Drilling Inc	15.94	15.94	100.00
Booking Holdings Inc	15.39	15.39	100.00
Netflix Inc	15.07	15.07	100.00
Airgas Inc	14.55	19.49	9.62
Expedia Group Inc	14.45	14.45	90.48
Monster Beverage Corp	14.45	14.45	66.67
Safeway Inc	14.25	20.60	7.89
Hudson City Bancorp Inc	13.95	13.95	100.00
Cablevision Systems Corp	13.46	13.46	100.00
Helmerich and Payne Inc	12.59	12.59	85.29
UnitedHealth Group Inc	12.45	12.45	34.62
Noble Corporation PLC	10.68	18.42	2.94
Berkshire Hathaway Inc	10.58	11.16	10.00
Tripadvisor Inc	7.87	7.87	90.48
SLM Corp	4.63	4.63	22.00
Public Storage	2.46	2.46	100.00

Table 15 – Highest and lowest ESG Combined Scores for S&P500 constituents in 2015

Company Name	ESG Combined Score (FY2015)	ESG Score (FY2015)	ESG Controversies Score (FY2015)
	ESG+		
Baxter International Inc	88.02	88.02	100.00
Prologis Inc	87.39	87.39	100.00
State Street Corp	87.03	87.03	100.00
Accenture PLC	86.85	86.85	100.00
3M Co	86.51	86.51	100.00
Campbell Soup Co	86.43	86.43	100.00
Weyerhaeuser Co	86.31	86.31	100.00
Waste Management Inc	85.56	85.56	100.00
Johnson Controls International PLC	85.28	85.28	100.00
PG&E Corp	84.87	89.74	80.00
Texas Instruments Inc	84.79	84.79	100.00
Cisco Systems Inc	84.67	84.67	100.00
Hasbro Inc	84.53	84.53	100.00
Intel Corp	84.49	90.42	78.57
Dow Chemical Co	83.89	83.89	85.71
CBRE Group Inc	82.91	82.91	100.00
Gap Inc	82.50	92.09	72.92
Colgate-Palmolive Co	81.53	81.53	100.00
Johnson & Johnson	81.06	91.06	71.05
Best Buy Co Inc	80.75	80.75	100.00
Avalonbay Communities Inc	80.69	80.69	100.00
Autodesk Inc	80.68	80.68	100.00
Healthpeak Properties Inc	80.61	80.61	100.00
	ESG-		
Pepco Holdings LLC	24.95	39.90	10.00
ATI Inc	24.75	37.00	12.50
Helmerich and Payne Inc	24.70	24.70	100.00
UnitedHealth Group Inc	24.64	24.64	100.00
H & R Block Inc	23.67	23.67	100.00
L3 Technologies Inc	23.60	23.60	100.00
Airgas Inc	23.37	23.37	100.00
Meta Platforms Inc	23.27	35.68	10.87
Fossil Group Inc	23.08	23.08	100.00
Amphenol Corp	22.98	22.98	100.00
Cimarex Energy Co	21.93	21.93	100.00
Lennar Corp	21.04	21.04	100.00
Genuine Parts Co	20.90	20.90	100.00
Diamond Offshore Drilling Inc	18.87	18.87	100.00
Windstream Holdings Inc	18.55	18.55	100.00
Booking Holdings Inc	16.59	16.59	81.58
FMC Technologies Inc	16.47	28.78	4.17
Monster Beverage Corp	15.33	15.33	100.00
Netflix Inc	15.04	15.04	100.00
Expedia Group Inc	14.68	14.68	81.58
Berkshire Hathaway Inc	10.98	10.98	72.73
Tripadvisor Inc	10.77	10.77	100.00
Public Storage	5.81	5.81	100.00

Table 16 – Highest and lowest ESG Combined Scores for S&P500 constituents in 2016

Company Name	ESG Combined Score (FY2016)	ESG Score (FY2016)	ESG Controversies Score (FY2016)
	ESG+		
CBRE Group Inc	88.77	88.77	100.00
Agilent Technologies Inc	88.48	88.48	100.00
Campbell Soup Co	87.80	87.80	88.89
Intel Corp	87.48	89.25	85.71
Texas Instruments Inc	86.97	86.97	100.00
Altria Group Inc	86.30	86.30	100.00
Lockheed Martin Corp	82.74	82.74	100.00
Waste Management Inc	82.44	82.44	100.00
Autodesk Inc	82.31	82.31	100.00
Newmont Corporation	81.79	81.79	93.52
Baxter International Inc	81.75	85.72	77.78
Dominion Energy Inc	81.26	81.26	100.00
Ventas Inc	81.24	81.24	100.00
Host Hotels & Resorts Inc	80.99	80.99	100.00
Prologis Inc	80.61	80.61	100.00
Gilead Sciences Inc	80.58	80.58	83.33
PNC Financial Services Group Inc	80.32	80.32	83.33
Becton Dickinson and Co	79.85	81.92	77.78
Northrop Grumman Corp	79.70	79.70	100.00
NRG Energy Inc	79.47	79.47	100.00
PVH Corp	79.27	79.27	100.00
Motorola Solutions Inc	79.02	79.47	78.57
Accenture PLC	78.81	78.81	100.00
Carnival Corp	78.78	78.78	100.00
Ball Corp	78.71	78.71	100.00
	ESG-		
Viatris Inc	24.63	47.17	2.08
Cimarex Energy Co	24.26	24.26	100.00
Monster Beverage Corp	22.85	22.85	100.00
Envision Healthcare Corp (Delaware)	22.82	22.82	66.67
Kinder Morgan Inc	22.37	40.57	4.17
Illumina Inc	22.06	22.06	100.00
L3 Technologies Inc	22.03	22.03	87.50
Meta Platforms Inc	21.61	35.16	8.06
News Corp	20.91	39.65	2.17
Genuine Parts Co	20.86	20.86	100.00
Level 3 Parent LLC	20.83	25.95	15.71
TransDigm Group Inc	20.63	20.63	100.00
Concho Resources Inc	19.98	19.98	100.00
LKQ Corp	19.65	19.65	100.00
Booking Holdings Inc	18.91	18.91	82.50
Helmerich and Payne Inc	18.71	18.71	100.00
Berkshire Hathaway Inc	16.47	16.47	92.31
Netflix Inc	15.92	15.92	100.00
Expedia Group Inc	15.55	15.55	100.00
Charter Communications Inc	15.31	15.31	100.00
Global Payments Inc	14.96	14.96	100.00
Tripadvisor Inc	11.84	11.84	100.00
Extra Space Storage Inc	10.87	10.87	100.00

Table 17 – Highest and lowest ESG Combined Scores for S&P500 constituents in 2017

Company Name	ESG Combined Score (FY2017)	ESG Score (FY2017)	ESG Controversies Score (FY2017)
ESG+			
Gap Inc	90.99	90.99	100.00
Gilead Sciences Inc	90.88	90.88	100.00
Waste Management Inc	90.65	90.65	100.00
Colgate-Palmolive Co	90.29	90.29	100.00
CBRE Group Inc	88.99	88.99	100.00
Agilent Technologies Inc	87.48	87.48	100.00
3M Co	87.47	87.47	100.00
Hasbro Inc	87.44	87.44	100.00
Campbell Soup Co	87.01	91.88	82.14
Humana Inc	85.67	85.67	100.00
Lockheed Martin Corp	85.20	85.20	100.00
Altria Group Inc	84.56	86.97	82.14
S&P Global Inc	84.53	84.53	100.00
Texas Instruments Inc	84.41	84.41	100.00
Baxter International Inc	83.80	83.80	100.00
PepsiCo Inc	83.60	83.60	90.00
Prologis Inc	83.38	83.38	100.00
Philip Morris International Inc	83.23	84.32	82.14
Allstate Corp	83.20	83.20	100.00
CVS Health Corp	82.20	86.63	77.78
Newmont Corporation	82.00	82.00	100.00
Abbott Laboratories	81.99	81.99	86.67
Autodesk Inc	81.75	81.75	100.00
Ventas Inc	81.62	81.62	100.00
ESG-			
Mid-America Apartment Communities Inc	29.56	29.56	100.00
L3 Technologies Inc	29.30	29.30	82.35
Meta Platforms Inc	28.49	53.40	3.57
Loews Corp	28.37	28.37	100.00
SCANA Corp	27.50	30.00	25.00
Navient Corp	27.20	34.54	19.86
H & R Block Inc	26.43	26.43	100.00
TFCF Corp	26.33	49.72	2.94
AMETEK Inc	26.06	26.06	100.00
Booking Holdings Inc	25.03	25.03	100.00
Expedia Group Inc	24.84	24.84	100.00
Align Technology Inc	21.90	21.90	100.00
TransDigm Group Inc	21.38	21.38	82.35
Netflix Inc	20.77	20.77	100.00
Helmerich and Payne Inc	20.00	20.00	100.00
Charter Communications Inc	19.86	19.86	37.84
DISH Network Corp	19.07	19.07	100.00
Equifax Inc	18.67	34.57	2.78
LKQ Corp	14.71	14.71	100.00
Global Payments Inc	14.37	14.37	100.00
Extra Space Storage Inc	11.82	11.82	100.00
Tripadvisor Inc	10.39	10.39	100.00

Table 18 – Highest and lowest ESG Combined Scores for S&P500 constituents in 2018

Company Name	ESG Combined Score (FY2018)	ESG Score (FY2018)	ESG Controversies Score (FY2018)
	ESG+		
Gilead Sciences Inc	92.65	92.65	95.83
CBRE Group Inc	91.94	91.94	100.00
Agilent Technologies Inc	89.37	89.37	100.00
Gap Inc	89.27	89.27	100.00
Johnson Controls International PLC	88.54	88.54	100.00
S&P Global Inc	87.96	88.42	87.50
Waste Management Inc	87.88	87.88	100.00
Colgate-Palmolive Co	87.75	87.75	100.00
Newmont Corporation	87.42	87.42	100.00
Altria Group Inc	87.10	87.10	100.00
Linde PLC	86.54	86.54	86.96
Host Hotels & Resorts Inc	86.41	86.41	100.00
Best Buy Co Inc	86.29	86.29	90.00
Humana Inc	85.99	85.99	100.00
Intuit Inc	85.98	85.98	100.00
Baxter International Inc	85.79	85.79	100.00
Ventas Inc	85.26	85.26	100.00
Air Products and Chemicals Inc	85.10	85.10	100.00
International Business Machines Corp	84.91	84.91	100.00
Texas Instruments Inc	84.69	84.69	100.00
Campbell Soup Co	84.26	87.76	80.77
Freeport-McMoRan Inc	83.64	83.64	100.00
Baker Hughes Co	83.35	83.35	100.00
Halliburton Co	82.87	82.87	100.00
	ESG-		
Helmerich and Payne Inc	29.67	29.67	100.00
Expedia Group Inc	27.51	27.51	78.95
Twitter Inc	27.35	32.87	21.82
Cimarex Energy Co	27.22	27.22	100.00
TFCF Corp	27.02	52.31	1.72
Lennar Corp	25.34	25.34	100.00
Nektar Therapeutics	25.30	25.30	100.00
Global Payments Inc	25.24	25.24	100.00
Paramount Global	22.84	40.50	5.17
Brighthouse Financial Inc	22.41	22.41	100.00
TransDigm Group Inc	22.17	22.17	100.00
Meta Platforms Inc	21.98	43.05	0.91
DISH Network Corp	21.87	21.87	94.83
Fleetcor Technologies Inc	21.01	21.01	87.50
LKQ Corp	20.93	20.93	100.00
ABIOMED Inc	20.51	20.51	83.33
Equifax Inc	20.35	33.20	7.50
Rollins Inc	20.31	20.31	100.00
Netflix Inc	19.91	19.91	27.27
H & R Block Inc	19.84	19.84	100.00
Charter Communications Inc	18.28	18.28	75.00
L3 Technologies Inc	17.97	17.97	100.00
Tripadvisor Inc	14.65	14.65	100.00

Table 19 – Highest and lowest ESG Combined Scores for S&P500 constituents in 2019

Company Name	ESG Combined Score (FY2019)	ESG Score (FY2019)	ESG Controversies Score (FY2019)
	ESG+		
Texas Instruments Inc	89.97	89.97	100.00
CBRE Group Inc	89.84	89.84	100.00
Healthpeak Properties Inc	89.73	89.73	100.00
Agilent Technologies Inc	88.16	88.16	100.00
Xcel Energy Inc	88.14	88.14	100.00
Gap Inc	87.81	87.81	100.00
Waste Management Inc	87.48	87.48	100.00
Best Buy Co Inc	86.89	86.89	100.00
Host Hotels & Resorts Inc	86.84	86.84	100.00
Humana Inc	86.83	86.83	100.00
International Flavors & Fragrances Inc	86.44	86.44	100.00
Newmont Corporation	86.24	86.24	100.00
Halliburton Co	85.81	85.81	100.00
Linde PLC	85.77	85.77	100.00
Johnson Controls International PLC	85.30	85.30	100.00
Elevance Health Inc	84.88	84.88	100.00
Kinder Morgan Inc	84.84	84.84	100.00
3M Co	84.45	88.90	80.00
Hilton Worldwide Holdings Inc	84.22	84.22	100.00
Colgate-Palmolive Co	84.12	84.12	85.71
Boston Scientific Corp	84.12	84.12	100.00
Ventas Inc	83.91	83.91	100.00
Royal Caribbean Cruises Ltd	83.55	83.55	91.84
Campbell Soup Co	83.13	83.13	92.50
Hess Corp	83.08	83.08	100.00
	ESG-		
Cimarex Energy Co	30.48	30.48	100.00
Henry Schein Inc	30.11	45.93	14.29
Broadcom Inc	29.22	47.72	10.71
Sealed Air Corp	28.62	44.74	12.50
Berkshire Hathaway Inc	28.05	28.05	40.00
Coterra Energy Inc	27.37	27.37	100.00
Take-Two Interactive Software Inc	27.31	27.31	100.00
Helmerich and Payne Inc	26.43	26.43	100.00
Rollins Inc	26.20	26.20	100.00
Global Payments Inc	26.02	26.02	100.00
Meta Platforms Inc	25.86	49.33	2.38
Equifax Inc	25.84	33.12	18.57
DISH Network Corp	25.28	25.28	100.00
NVR Inc	25.24	25.24	100.00
LKQ Corp	24.53	24.53	100.00
Fiserv Inc	24.07	24.07	100.00
H & R Block Inc	24.00	24.00	35.71
Lennar Corp	23.90	23.90	100.00
Charter Communications Inc	23.59	23.59	78.57
Twitter Inc	22.85	34.60	11.11
Expedia Group Inc	22.51	22.51	78.57
ABIOMED Inc	20.55	20.55	100.00
T-Mobile US Inc	20.44	39.69	1.19

Annex II - Annual CARs and *t*-statistics

Table 20 – Annual CARs and *t*-stats in "ESG+" post-positive shocks

	CAR1	CAR2	CAR3	CAR4	CAR5	CAR6	CAR7	CAR8	CAR9	CAR10
ESG+ post-positive shocks										
2010	0.11	0.00	-0.43	-0.10	-0.80*	-1.06*	-1.17*	-1.74**	-1.47**	-1.65**
	-(0.63)	(0.01)	(1.45)	(0.29)	(1.73)	(1.91)	(1.98)	(2.48)	(2.08)	(2.16)
2011	0.00	-0.35	-0.44	-0.32	-0.74*	-0.68	-0.59	-0.98*	-1.58***	-1.55**
	(0.01)	(1.31)	(1.26)	(0.82)	(1.71)	(1.45)	(1.15)	(1.82)	(2.72)	(2.41)
2012	-0.52**	-0.42	-0.35	-0.44	-0.48	-0.76*	-1.16**	-1.15*	-0.76	-0.69
	(2.23)	(1.50)	(1.20)	(1.32)	(1.26)	(1.80)	(2.00)	(1.72)	(1.06)	(0.95)
2013	0.05	-0.03	-0.33	-0.38	-0.45	-0.32	-0.30	-0.46	-0.33	-0.37
	-(0.29)	(0.14)	(1.20)	(1.11)	(1.03)	(0.70)	(0.58)	(0.75)	(0.50)	(0.56)
2014	0.04	0.24	0.47	0.67**	0.82**	0.77*	0.62	0.67	0.69	0.63
	(0.21)	(0.92)	(1.66)	(2.07)	(2.14)	(1.79)	(1.42)	(1.46)	(1.46)	(1.24)
2015	-0.10	-0.30	-0.50	-0.57	-0.46	-0.33	-0.41	-0.28	-0.53	-0.42
	(0.54)	(1.25)	(1.61)	(1.66)	(1.13)	(0.71)	(0.86)	(0.57)	(0.96)	(0.73)
2016	0.39**	0.22	0.66*	0.60	0.46	0.19	0.45	0.41	0.47	0.68
	-(2.32)	-(0.73)	-(1.78)	-(1.59)	-(1.10)	-(0.41)	-(0.97)	-(0.88)	-(0.93)	-(1.20)
2017	-0.15	-0.29	-0.34	-0.30	-0.17	-0.09	-0.03	-0.38	-0.33	-0.49
	(0.83)	(1.25)	(1.31)	(1.04)	(0.52)	(0.29)	(0.10)	(0.96)	(0.81)	(1.06)
2018	-0.18	-0.26	-0.13	-0.51	-0.68	-0.80	-0.65	-0.93*	-0.89	-0.86
	(1.04)	(0.92)	(0.44)	(1.56)	(1.65)	(1.66)	(1.28)	(1.72)	(1.46)	(1.33)
2019	-0.06	0.32	0.15	0.27	0.44	0.36	0.10	0.20	0.54	0.82
	(0.27)	-(0.93)	-(0.34)	-(0.51)	-(0.80)	-(0.62)	-(0.17)	-(0.30)	-(0.76)	-(1.07)

The table reports the CARs in percentage following positive shocks in ESG stocks between 2010 and 2019. The t-statistics are shown in parentheses. ***, **, * Significant at 0.01, 0.05 and 0.1 levels, respectively.

Table 21 – Annual CARs and *t*-stats in "ESG−" post-positive shocks

	CAR1	CAR2	CAR3	CAR4	CAR5	CAR6	CAR7	CAR8	CAR9	CAR10
ESG- Post-positive shocks										
2010	0.17	0.40	0.50	0.68	0.28	-0.11	0.57	-0.05	0.10	-0.67
	-(0.70)	-(1.23)	-(1.31)	-(1.47)	-(0.56)	(0.19)	-(0.85)	(0.07)	-(0.13)	(0.82)
2011	-0.20	-0.26	-0.13	-0.22	-0.35	-0.30	-0.30	-0.61	-0.61	-0.75
	(0.84)	(0.87)	(0.33)	(0.53)	(0.77)	(0.56)	(0.54)	(1.01)	(0.88)	(0.96)
2012	0.28	0.40	0.35	0.25	-0.14	-0.11	-0.30	-0.33	-0.01	-0.09
	-(1.15)	-(1.31)	-(0.94)	-(0.68)	(0.34)	(0.23)	(0.57)	(0.60)	(0.02)	(0.14)
2013	0.09	0.36	0.24	0.22	-0.14	-0.27	-0.28	-0.36	-0.24	-0.05
	-(0.44)	-(1.45)	-(0.79)	-(0.68)	(0.36)	(0.64)	(0.56)	(0.70)	(0.46)	(0.09)
2014	-0.30	-0.21	-0.47	-0.57	0.03	0.06	0.00	0.35	0.02	-0.26
	(1.40)	(0.75)	(1.23)	(1.26)	-(0.06)	-(0.11)	(0.01)	-(0.55)	-(0.04)	(0.40)
2015	0.18	0.85	0.45	0.18	-0.06	-0.26	-0.48	-0.19	-0.28	-0.47
	-(0.68)	-(1.53)	-(0.67)	-(0.25)	(0.08)	(0.35)	(0.61)	(0.24)	(0.34)	(0.54)
2016	0.26	0.38	0.58	0.58	0.46	0.16	0.22	0.14	-0.01	0.20
	-(1.10)	-(1.08)	-(1.39)	-(1.43)	-(0.91)	-(0.30)	-(0.36)	-(0.22)	(0.01)	-(0.24)
2017	-0.17	-0.42*	-0.32	-0.48	-0.31	-0.02	-0.15	-0.14	-0.61	-0.55
	(1.16)	(1.86)	(1.05)	(1.55)	(0.86)	(0.05)	(0.32)	(0.31)	(1.15)	(1.00)
2018	-0.59	-0.51	-0.36	-0.52	-0.65	-0.60	-0.33	-0.50	-0.49	-0.78
	(0.76)	(0.64)	(0.49)	(0.56)	(0.66)	(0.59)	(0.33)	(0.48)	(0.46)	(0.75)
2019	0.05	0.30	0.56	0.67	0.42	-0.41	-0.07	0.12	0.19	0.43
	-(0.19)	-(0.72)	-(1.33)	-(1.51)	-(0.86)	(0.58)	(0.09)	-(0.16)	-(0.25)	-(0.48)

The table reports the CARs in percentage following positive shocks in non-ESG stocks between 2010 and 2019. The t-statistics are shown in parentheses. ***, **, * Significant at 0.01, 0.05 and 0.1 levels, respectively.

Table 22 – Annual CARs and *t*-stats in "ESG+" post-negative shock

	CAR1	CAR2	CAR3	CAR4	CAR5	CAR6	CAR7	CAR8	CAR9	CAR10
ESG+ post-negative shocks										
2010	0.09	-0.26	-0.57	-0.50	-0.56	-0.42	-0.32	-0.34	-0.36	-1.26
	-(0.43)	(0.94)	(1.40)	(1.08)	(0.90)	(0.69)	(0.48)	(0.46)	(0.50)	(1.58)
2011	0.07	-0.34	0.17	-0.56	-0.60	-1.11**	-1.22*	-1.53**	-1.30*	-1.91**
	-(0.31)	(0.89)	-(0.43)	(1.07)	(1.24)	(2.00)	(1.86)	(2.36)	(1.94)	(2.62)
2012	-0.04	-0.20	0.38	0.64	0.77	1.12**	1.39**	1.19*	1.19*	1.16*
	(0.23)	(0.77)	-(1.02)	-(1.48)	-(1.55)	-(2.14)	-(2.35)	-(1.84)	-(1.89)	-(1.76)
2013	0.10	-0.18	-0.48*	-0.34	0.01	0.53	0.36	0.25	0.33	0.43
	-(0.59)	(0.75)	(1.80)	(1.07)	-(0.03)	-(1.26)	-(0.72)	-(0.45)	-(0.55)	-(0.73)
2014	-0.12	-0.05	-0.36	-0.50	-0.50	-0.68*	-0.55	-0.55	-0.52	-0.28
	(0.77)	(0.23)	(1.12)	(1.42)	(1.44)	(1.90)	(1.38)	(1.24)	(1.05)	(0.59)
2015	-0.42**	-0.16	0.22	0.55	0.46	0.15	0.06	0.29	0.35	0.36
	(2.24)	(0.56)	-(0.68)	-(1.64)	-(1.25)	-(0.36)	-(0.14)	-(0.58)	-(0.68)	-(0.69)
2016	-0.45*	-0.35	-0.13	-0.24	-0.18	-0.53	-0.51	-0.01	0.20	0.24
	(1.87)	(1.37)	(0.40)	(0.61)	(0.42)	(1.20)	(1.07)	(0.02)	-(0.35)	-(0.43)
2017	0.11	0.37	0.38	0.39	0.37	0.47	0.53	0.63	0.79	1.10**
	-(0.78)	-(1.40)	-(1.20)	-(1.14)	-(0.95)	-(1.15)	-(1.15)	-(1.40)	-(1.63)	-(2.25)
2018	-0.59***	-0.60***	-1.00***	-1.05***	-1.14***	-1.01**	-1.05**	-0.80*	-0.85*	-0.89
	(3.10)	(2.62)	(3.54)	(2.95)	(3.05)	(2.39)	(2.38)	(1.66)	(1.70)	(1.65)
2019	0.19	0.28	0.58	0.56	0.49	0.46	0.35	0.53	0.52	0.69
	-(0.91)	-(1.09)	-(1.60)	-(1.34)	-(1.06)	-(0.89)	-(0.66)	-(0.94)	-(0.87)	-(1.10)

The table reports the CARs in percentage following negative shocks in ESG stocks between 2010 and 2019. The t-statistics are shown in parentheses.
***, **, * Significant at 0.01, 0.05 and 0.1 levels, respectively.

Table 23 – Annual CARs and *t*-stats in "ESG−" post-negative shocks

	CAR1	CAR2	CAR3	CAR4	CAR5	CAR6	CAR7	CAR8	CAR9	CAR10
ESG- Post-negative shocks										
2010	0.69**	0.20	0.12	0.24	-0.03	-0.06	-0.09	0.48	0.77	0.36
	-(2.35)	-(0.54)	-(0.29)	-(0.45)	(0.04)	(0.08)	(0.12)	-(0.51)	-(0.76)	-(0.37)
2011	0.26	-0.49	0.53	-0.51	0.02	-0.15	0.28	-0.35	0.18	-0.57
	-(0.85)	(0.94)	-(0.94)	(0.73)	-(0.02)	(0.18)	-(0.32)	(0.37)	-(0.18)	(0.55)
2012	-0.41*	-0.23	0.34	0.43	0.29	0.23	0.43	0.25	0.25	0.11
	(1.81)	(0.65)	-(0.64)	-(0.80)	-(0.48)	-(0.34)	-(0.61)	-(0.33)	-(0.33)	-(0.14)
2013	0.16	0.18	0.19	0.32	0.72*	0.90**	1.15**	1.03**	0.98	0.91
	-(0.91)	-(0.75)	-(0.74)	-(0.90)	-(1.81)	-(2.17)	-(2.60)	-(2.00)	-(1.69)	-(1.54)
2014	-0.02	-0.15	-0.15	0.09	-0.06	0.28	0.47	-0.03	0.07	0.32
	(0.12)	(0.68)	(0.52)	-(0.21)	(0.12)	-(0.53)	-(0.85)	(0.05)	-(0.11)	-(0.44)
2015	-0.61**	-1.21*	-1.05	-0.88	-0.78	-0.67	-0.61	-0.62	-0.35	0.08
	(2.20)	(1.77)	(1.42)	(1.14)	(0.96)	(0.85)	(0.73)	(0.68)	(0.38)	-(0.08)
2016	-0.63**	-0.50	-0.18	-0.13	-0.43	-0.20	0.11	0.29	0.81	1.06
	(2.48)	(1.63)	(0.45)	(0.24)	(0.76)	(0.37)	-(0.16)	-(0.39)	-(1.07)	-(1.39)
2017	-0.24	-0.07	-0.05	0.04	-0.10	-0.05	-0.14	-0.28	-0.35	0.20
	(1.24)	(0.30)	(0.15)	-(0.08)	(0.22)	(0.11)	(0.27)	(0.53)	(0.65)	-(0.37)
2018	-0.67**	-0.86**	-1.27***	-0.99*	-0.98*	-1.05*	-1.24*	-1.11	-1.12	-1.58**
	(2.41)	(2.31)	(2.75)	(1.79)	(1.68)	(1.74)	(1.82)	(1.58)	(1.55)	(2.01)
2019	0.50**	0.93***	0.68*	0.45	0.52	0.51	0.27	0.11	-0.38	-0.15
	-(2.34)	-(2.73)	-(1.88)	-(0.98)	-(1.02)	-(0.88)	-(0.43)	-(0.16)	(0.55)	(0.20)

The table reports the CARs in percentage following negative shocks in non-ESG stocks between 2010 and 2019. The t-statistics are shown in parentheses. ***, **, * Significant at 0.01, 0.05 and 0.1 levels, respectively.

Annex III – Difference in CARs in the early and late 2010's

Table 24 – Shocks and post-shock CARs in the 2010-14 and 2015-19 periods

	2010 - 2014	2015 - 2019	t-test of difference
Panel A: Positive shocks – ESG+			
N	447	408	
Mean shocks	4.03	3.87	1.12
CAR1	-0.05	-0.02	-0.25
CAR5	-0.33	-0.08	-0.94
CAR10	-0.73**	-0.06	-1.67
Panel B: Positive shocks – ESG-			
N	453	385	
Mean shocks	5.03	5.34	-1.34*
CAR1	0.02	-0.05	0.31
CAR5	-0.07	-0.04	-0.07
CAR10	-0.35	-0.26	-0.18
Panel C: Negative shocks – ESG+			
N	472	537	
Mean shocks	-4.30	-4.01	-1.75**
CAR1	0.02	-0.27***	2.31**
CAR5	-0.20	-0.07	-0.45
CAR10	-0.43	0.21	-1.64
Panel D: Negative shocks – ESG-			
N	441	488	
Mean shocks	-4.98	-5.41	1.65**
CAR1	0.15	-0.35***	3.17***
CAR5	0.16	-0.38	1.47
CAR10	0.21	-0.13	0.66

The table reports the average shock and post-shock CARs (in percentage) for the 2010-14 and 2015-19 periods and the *t*-statistics for the difference in means between both samples.

***, **, * Significant at 0.01, 0.05 and 0.1 levels, respectively.

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