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The Impact of the 2014 Oil Price Shock on Corporate Sustainability and Performance

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Abstract

Our thesis aims to study whether high sustainability companies in Europe outperform low sustainability companies in terms of stock performance following the oil price shock in 2014. To conduct this analysis, we employ a data sample consisting of monthly stock returns from publicly listed firms on European stock exchanges, collected from Refinitiv Eikon. We use Refinitiv's ESGC score to measure the companies' degree of environmental and social responsibility effort and divide the top and bottom quartiles into two different groups. We employ a difference-in-differences method and regress the monthly stock returns in the period 2010-2017 on an interaction between a dummy for the post-shock period and a dummy for the group of high sustainability companies. We control for non-diversifiable risk factors and factors proxying for financial health, which previous literature has found to influence returns. Our results suggest the two groups follow a similar trend prior to the shock, before the high sustainability companies significantly outperform their counterparts over the long term following the shock.

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1 Introduction

After four years of high and stable prices at around \$105 per barrel, the average price of Brent crude oil began declining in June 2014. Between June and December, the price fell by \$49, and throughout 2015 the price continued to fall, concluding a cumulative decrease exceeding 70% in January 2016 (Khan, 2017). This price decline is one of the biggest oil price shocks in modern history and many experts argue that we will not experience oil prices close to pre-shock levels ever again (Baffes et al., 2015).

The fact that long-term oil prices may have fallen permanently should be reflected by underlying characteristics driving the shock. Such drivers might be a long-standing tendency of companies moving towards less oil-intensive production technologies (Baffes et al., 2015), increased investments in clean energy and reduced investments in fossil fuels (Khan, 2017) and expectations of an abundance of fossil fuel supplies and low carbon prices (Baffes et al., 2015). Such drivers represent a decarbonisation and a shift towards a greener and more sustainable economy. Thus, the oil price shock might reflect changes in the underlying economics of companies moving towards more sustainable operations, and a broad behavioural shift for consumers towards more sustainable buying patterns. Changes in stakeholders' awareness and knowledge of corporate social responsibility might directly lead to a positive change in the effect that corporate social responsibility has on financial performance (Malik, 2015). This might be due to better employee relations, better access to capital and increased customer loyalty. As a consequence, firms that are superior in terms of environmental and social responsibility should financially outperform less responsible firms. If the firms are publicly listed, the difference in financial performance should be visible in stock prices.

Our thesis aims to study whether European companies with superior environmental and social responsibility efforts outperform companies with low degrees of such efforts in terms of stock performance, following the oil price shock in 2014. To conduct this analysis, we employ a data sample consisting of monthly stock returns from publicly listed firms on European stock exchanges, collected from Refinitiv Eikon. We use ESGC score to measure their degree of environmental and social responsibility effort and group the top quartile of every industry into a *high-ESGC group* and the bottom quartile into a *low-ESGC group*.

We rank the companies by ESGC score from 2013 in order to avoid group membership being affected by the shock. ESGC score is an extension of Refinitiv's ESG score and reflects efforts with regard to the three central factors: environmental, social and corporate governance, in addition to considering controversies covered by the media.

We employ a difference-in-differences method and regress the monthly stock returns in the period 2010-2017 on an interaction between a dummy for the post-shock period and a dummy for the high-ESGC group. We control for non-diversifiable risk factors and factors proxying for financial health, which previous literature has found to influence returns in periods of uncertainty. In addition, we plot the aggregate returns of $1 invested in two equally weighted portfolios consisting of the high- and low-ESGC group to graphically inspect the effect of the shock on returns.

Our results suggest that the high-ESGC group outperforms the low-ESGC group on a long-term basis, following the 2014 oil price shock. The two groups follow a similar trend prior to the shock, while in the four-year period following the shock, the high-ESGC group outperforms by a simple average monthly return of 0.4 percentage points (pp). This indicates a shift in performance that might be due to characteristics reflected by the shock. The result is significant at the 10% level and is supported by the visual analysis of the aggregate returns. The result from 2014 onwards is consistent with similar research suggesting a positive relationship between corporate social responsibility and financial performance (MSCI, 2020).

When investigating the yearly differences between the groups, we find somewhat contradicting results. The results suggest that in 2014, the high-ESGC group significantly outperforms the low-ESGC group by 1.2 pp per month. The result seems to be driven by the low-ESGC group reacting more negatively to the sudden plunge in oil prices in 2014. In 2015, the roles are reversed and the low-ESGC group outperforms the high by 0.9 pp in what seems to be a price correction, neutralising the majority of the effect generated the year before. In 2016 and 2017, the coefficients are positive, however not statistically significant.

Our contribution to the literature is to present estimates on the diverging effect inflicted by the oil price shock on the performance of companies with different degrees of sustainability efforts. Our results provide evidence of a positive effect of high ESGC score on financial performance following the shock and we shed light on the possible drivers behind this shift. Our thesis could make for valuable insight for managers trying to understand the dynamics of environmental and social responsibility and its relationship to corporate financial performance. Moreover, it can add insight to the ongoing debate of drivers of overperformance in environmental and socially responsible assets in 2020.

The remainder of our thesis is structured as follows: Section two presents the background for our hypothesis. In section three we describe our data sample and address concerns in relation to this. Thereafter, we outline our methodology in section four and present the results in section five. We provide a discussion of our results and their implications in section six and conclude the thesis in section seven.

2 Literature review

This section aims to outline the theoretical background and empirical evidence on oil price shocks and how this might relate to the oil price shock in 2014. In addition, we shed light on drivers that relate to a shift towards a greener and more sustainable economy. Thereafter, we discuss the relationship between corporate social responsibility (CSR) and corporate financial performance (CFP) and how one measures CSR.

2.1 Oil price shocks

2.1.1 Theoretical background

Degiannakis et al. (2018) define an oil price shock as a change in the price of oil due to an unanticipated change in oil market fundamentals. Hamilton (2003) maintains that there are two types of oil price shocks: supply-side shocks and demand-side shocks, which are either shocks related to major oil production disruptions or movements in the global business cycles. Kilian (2009) states another classification with three different types of oil price shocks: supply-side shocks, aggregate demand shocks and precautionary demand shocks, where the latter one is caused by geopolitical unrest, diverging from the classification by Hamilton (2003) which explains this as supply-side shocks.

2.1.2 Empirical findings

Oil price shocks have been found to play an important role in affecting stock market returns (Sadorsky, 1999)(Kilian & Park, 2009). However, the subject is debated and Apergis and Miller (2009) find the effect to be too small to draw a conclusion about any relationship between the two.

Kilian and Park (2009) find that the effect an oil price shock poses on stock market returns depends on the cause of the shock. Using the classification by Kilian (2009), they find supply-side shocks not to affect stock markets, which is supported by findings from Kang et al. (2015). Furthermore, Kilian and Park (2009) find a positive correlation between returns and aggregate demand shocks and a negative correlation for precautionary demand shocks (Kilian & Park, 2009). This corresponds with aggregate demand shocks reflecting economic growth and precautionary demand shocks reflecting uncertainty in the oil markets (Degiannakis et al., 2018).

Moreover, the effects of the three oil price shocks are found to be industry specific (Kilian & Park, 2009). This is supported by Sadorsky (1999), El-Sharif et al. (2005) and Arouri and Nguyen (2010) who, for instance, find returns for Petroleum & Natural Gas to be positively correlated with an aggregate demand shock and Automobile & Trucks and Retail industries negatively correlated with a precautionary demand shock, whereas the link between oil price shocks and returns is weak for many industries. Additionally, findings suggest that oil price shocks induce heterogeneous effects depending on whether a country is a net exporter or importer of oil (Wang et al., 2013)(Jung & Park, 2011).

2.1.3 The 2014 oil price shock

As oil prices are essentially determined by the world's supply and demand, in addition to being influenced by macroeconomic, political and climate factors, it can be difficult to capture the underlying causes of a price shock (Jammazi & Aloui, 2012)(Bernabe et al., 2004). However, the literature provides empirical evidence supporting several plausible drivers.

Mănescu and Nuño (2015) conjecture that the increased shale oil and gas production in the US was a major cause for the falling oil prices. From 2010 to 2013, the shale oil production in the US increased by more than 200%, attributed to lower production costs and higher efficiency in the shale oil industry (Baumeister & Kilian, 2016). This led to an unexpected increase in the supply of oil on the global market which eventually contributed to a price reduction. As the oil price started to decrease in 2014, analysts were expecting OPEC to announce an adjustment of their supply to compensate for the high production elsewhere. However, in November 2014, OPEC decided against this, presumably trying to squeeze the shale oil producers out of the market (Khan, 2017), which might have contributed to the magnitude of the shock.

Tokic (2015) suggests that volatility in USD/EUR exchange rates due to economic growth divergences between EU and the US was another primary cause of the shock. When the USD appreciates, oil will be relatively more expensive for countries outside the US, leading to a weakening of the world's demand for oil. He therefore argues that a collapse of the exchange rates in 2014 resulted in inefficient oil prices and eventually contributed to the sudden shock (Tokic, 2015).

In addition, scholars have suggested drivers that might reflect a shift towards a greener and more sustainable economy. Oil demand forecasts were downgraded repeatedly from 2012 up until the summer of 2014, reflecting a change in trends prior to the shock. Baffes et al. (2015) argue this was due to a long-standing tendency of companies moving towards less oil-intensive production technologies, hence putting a downwards pressure on oil-prices. Khan (2017) adds to this by arguing that an important contributor was a global trend of increasing investments in clean energy and alternative fuel sources. In China, investments in renewable energy sources increased by 32% the year prior to the shock (Khan, 2017) and global production of bio fuels had risen sharply since the mid-2000s (Baffes et al., 2015). Combined with an expectation of abundant oil supplies in the future, this might have led to an expectation of lower oil prices.

After the shock in 2014, carbon prices were predicted not to reach similar levels ever again (Baumeister & Kilian, 2016). Assuming an efficient market (Fama, 1970), this signals a lasting shift in preferences (Baffes et al., 2015). The expectation of low carbon prices might partly be attributed to consumer awareness of sustainability concerns and a demand for more sustainable goods and services.

2.2 Socially responsible investments

Socially responsible investments (SRI), also called ethical investments or sustainable investments, refer to investment strategies where both CFP and CSR goals are pursued (Renneboog et al., 2008). Unlike conventional investment strategies, SRI apply a set of environmental, social and corporate governance (ESG) criteria which investments must meet in order to be carried out. In recent decades, SRI have been subject to considerable growth. In 2018, global sustainable investment assets reached $31 trillion, a 34% increase from 2016 (Global Sustainable Investment Alliance, 2018), and even in 2020, when investors pulled record amounts of capital out of the stock market, a new record was set for inflows of capital in ESG investing funds (Elliot, 2020). This signals increasing environmental and social awareness among companies and investors and a demand for sustainable investing.

2.2.1 Theoretical background

Theories regarding the relationship between CSR and CFP remain ambiguous and researchers have presented positive, negative and neutral relationships between the two throughout the years.

Those who provide a critical view of the relationship between CSR and CFP argue that investors who consider CSR in their work account for both financial and social objectives, leading them to incur unnecessary costs which result in a competitive disadvantage (Renneboog et al., 2008). Another perspective points out that the norms inflicted by CSR lead companies and investors to abstain from publicly traded companies involved in alcohol, tobacco, weapons etc (sin-stocks). This results in such stocks being relatively cheaper in terms of valuation metrics than comparable stocks, generating higher expected returns (Hong & Kacperczyk, 2009).

Those who argue for a neutral relationship between CSR and CFP claim there are so many variables working between the two factors, leaving no reason to believe a relationship exists (Ullmann, 1985). Other arguments relate to the problems arising when trying to measure degrees of CSR and highlight the predominant probability of measurement error (Turker, 2009).

Many theories have been proposed in trying to explain a positive relationship between CSR and CFP. The slack resources theory argues that firms with superior financial returns tend to have resources to invest in socially appropriate projects (Miles & Covin, 2000). Another theory suggested by Alexander and Buchholz (1978) argues that CSR works as a proxy for superior management. Thus, a socially aware manager holds the necessary skills to run a superior company in terms of financial performance.

However, the most prominent of the theories is the good management theory (Waddock & Graves, 1997). The theory suggests that the reason for a positive relationship is that superior environmental and social performance will better satisfy customers and key stakeholders. Thus, superior CSR will increase shareholder value and enhance the firm's competitive advantage (Miles & Covin, 2000). Ultimately, this will improve the firm's revenues and profitability, which leads to higher firm value emphasised by higher stock prices.

Many studies suggest how the CSR-dynamics of the good management theory lead to shared value between the company and stakeholders. Cheng et al. (2014) argue that good employee relations increase productivity and job satisfaction, and reduce sick leave. They further argue that high degrees of CSR lead to capital market benefits in terms of fewer capital constraints and lower cost of capital, as the firm gets better access to bank loans. Turban and Greening (1997) and Harter et al. (2002) suggest that highly qualified workers are more attracted to companies they perceive to be sustainable and, in many cases, even at the expense of higher wages. Furthermore, customers deem sustainable companies more trustworthy (Pedersen, 2013)(Zsolnai, 2004) and, under some circumstances, prefer and are more loyal to companies that promote sustainability and highlight CSR in their strategy (Sen & Bhattacharya, 2001)(Bollen, 2007).

Stakeholders' awareness and knowledge of CSR is a precondition for the good management theory (Fatma & Rahman, 2015), and a change in stakeholders' perception of CSR might directly lead to a change in the effect of CSR on financial performance (Malik, 2015).

2.2.2 Empirical findings

Empirical findings on the relationship between CSR and CFP have generally been ambiguous. Many scholars have found the impact to be negative or non-existent (Griffin & Mahon, 1997)(Waddock & Graves, 1997)(Harrison & Freeman, 1999)(McWilliams & Siegel, 2000), and some have even argued that investment strategies aimed at sin-stocks, rather than SRI, are likely to create abnormal positive returns (Hong & Kacperczyk, 2009). Nonetheless, the majority of prior research demonstrates a positive impact of CSR on financial performance (Roman et al., 1999)(Porter & Kramer, 2002)(Saiia et al., 2003)(Orlitzky et al., 2003)(Brammer & Millington, 2005)(Godfrey, 2005).

Morgan Stanley Institute for Sustainable Investing (2020) proposes findings from 2020 that support the perception of the mainstream literature. They found that sustainable equity funds outperformed their traditional peers by 3.9% in the first half of 2020, suggesting an outperformance by sustainable funds following the beginning of Covid-19. Folger-Laronde et al. (2020) argue that this was due to SRI holding up better in periods of high uncertainty and market turmoil, and is supported by Ducassy (2013) and Chiappini et al. (2018) who found similar results during the financial crisis of 2007-2008 and the Brexit referendum in

2016.

MSCI (2020) have compared company stock performance based on their industry-neutral MSCI ESG ratings over a sample period from 31 May 2013 to 30 November 2020. Over this period, the top third of companies sorted semi-annually by ESG rating outperformed the bottom third by 2.56% per year. Their findings suggest that the positive relationship between CSR and CFP has been apparent in the market for some time and that the outperformance is driven by consistent earnings growth and re-investment return, rather than a premium paid by investors.

To summarise, consensus as of today seems to be that investing in corporate social responsibility stimulates financial performance but the drivers behind the outperformance is still debated.

2.2.3 Measurement of CSR

Due to a missing consensus on the theoretical concept of CSR (Dahlsrud, 2008) and the concept being multidimensional with relatively heterogeneous dimensions (Carhart, 1997), different approaches have been used to measure the degree of social responsibility a company takes on (Galant & Cadez, 2017). Galant and Cadez (2017) summarise and order the approaches by frequency of use: Reputation indices, content analyses, questionnaire-based surveys and one-dimensional measures. In compliance with most modern research on CSR, we employ the reputation index approach, as the other three approaches have significant weaknesses. Content analyses suffer from researcher subjectivity and reporting bias, questionnaire-based surveys suffer from response bias, and one-dimensional measures do not capture the full effect of CSR as it is a multi-dimensional concept (Galant & Cadez, 2017).

In this thesis, we employ the reputation index, ESG rating. ESG is often used interchangeably with sustainability or CSR, and refers to three central factors when measuring a firm's degree of CSR: environmental, social and corporate governance. ESG metrics are considered a satisfactory proxy for CSR and are dominating the sustainability reporting landscape (Widyawati, 2020). ESG metrics have become the mainstream measurement tool, especially in relation to SRI (International Investment, 2020). However, there are several providers offering ESG metrics and we will justify our choice of provider in section 3.1.

3 Data

In the following section, we describe the data and the data collection process. We first describe our chosen way of measuring corporate social responsibility. Thereafter, we go through our data collection process. Lastly, we introduce the variables of interest.

3.1 Data source

In our thesis, we use ESG data collected from Refinitiv Eikon, a Thomson Reuters terminal. This is a financial software system that offers ESG ratings on more than 9000 companies world-wide and 2100 companies in Europe (Refinitiv, 2020). Refinitiv is one of the only provider not to base its ranking on questionnaires, avoiding the risk of companies, knowingly or otherwise, providing incorrect information regarding the ESG measures. Thus, Refinitiv's ESG ratings seem to be somewhat more robust than ratings from other agencies. Robustness is considered an important trait when researchers choose a rating provider and the Refinitiv ESG score has become a renowned tool for measuring ESG performance in the literature (Eccles et al., 2014)(Cheng et al., 2014). In this thesis, ESG performance is used interchangeably with environmental and socially sustainable efforts.

Considering the availability, comprehensiveness and robustness of the rating, in addition to its extensive use in the literature, we choose Refinitiv's ESG rating to study our research question. For convenience, we also retrieve the remaining data we need in order to implement our analysis from Refinitiv Eikon.

3.2 ESG

3.2.1 ESG score

Refinitiv calculates its ESG scores using the three main pillars: environmental, social and corporate governance, which are divided into subcategories as illustrated in Table 3.1. The subcategories are based on more than 450 different measures and within each industry group, a business classification provided by Refinitiv, the 186 most comparable measures are used in the process of calculating the score (Refinitiv, 2020). Examples of measures employed in calculation of subcategory scores are "Total recycled and reused waste", "Does the company have a policy to drive diversity and equal opportunity?" and "Percentage of females on the board" (Refinitiv, 2020).

Table 3.1: ESG pillars

Pillar	Subcategories
Environmental	Emmisions
	Innovative
	Resource use
Social	Community
	Human rights
	Product responsibility
	Workforce
Governance	CSR strategy
	Management
	Shareholder

Note: ESG pillars with respective subcategories.

Refinitiv calculates a score for the subcategories between 0 and 1, where 1 represents the best possible score. The score is calculated as a percentile rank, using Equation 3.1, which scores a company relative to its peers. The subcategory scores within the governance pillar are benchmarked against companies within the same country of exchange, while subcategories within the environmental and social pillars are benchmarked against companies within the same industry group (Refinitiv, 2020).

$$\text{score} = \frac{\#\text{ companies with a worse value} + \frac{\#\text{ companies with the same value included the current one}}{2}}{\#\text{ companies with a value}} \tag{3.1}$$

The final ESG score ranges between 0 and 1 and is a weighted average of the subcategory scores, where the weighting depends on the industry group to which a company belongs, due to variations in relevance, impact and availability of data between industries.

3.2.2 ESG Combined score

In addition to offering ratings based on publicly reported information, Refinitiv provides an ESG Combined (ESGC) score, an extension that combines the ESG score with a controversy score (Refinitiv, 2020). The objective of this score is to discount a company's ESG score if it receives negative publicity in the media. Refinitiv calculates the controversy score from 23 different controversy measures, capturing all new media coverage. See Table

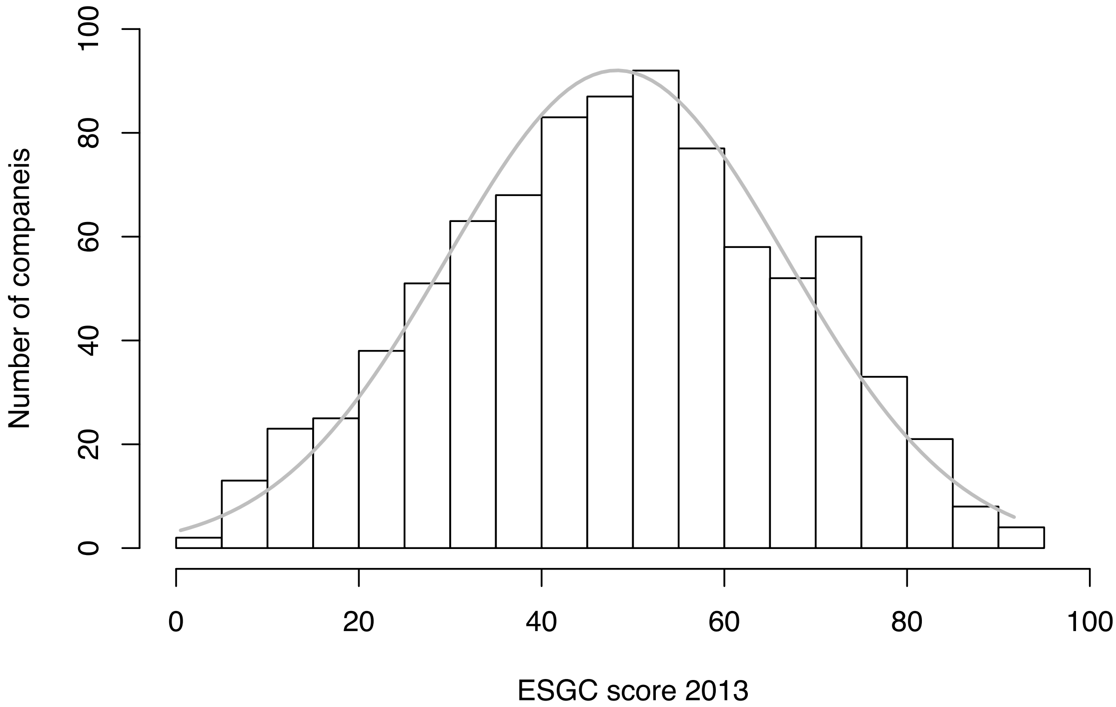
A4.1 in appendix for full disclosure of controversy measures. The controversy score is also calculated using Equation 3.1, and the scores are benchmarked against companies within the same industry group. For a company receiving a controversy score above its ESG score, the ESG Combined score will be equal to its ESG score. However, if a company receives a score below their ESG score, the controversy score will be weighted against the ESG score, giving it a lower ESG Combined score. The weighting between ESG score and the controversy score is based on market capitalisation in order to compensate for company size. Without this, larger cap companies would suffer, as they receive more attention by the media.

The ESGC score captures how investors perceive a company's ESG performance. As investors place considerable weight on subjective factors when investing (Guiso et al., 2008), we believe ESGC score is a better tool measuring market reactions, thus it better suits our analysis. Therefore, we use ESGC score as the measure of ESG performance in our study.

3.3 Sample selection process

We collect data for the time period 2010-2019 on all listed European companies available from Refinitiv Eikon. From the sample of listed European firms, we omit the companies which lack a provided ESGC score in 2013. This leaves us with 858 European companies. We use ESGC score in 2013 as a criterion because the ESGC scores are calculated annually on 31 December and the scores from 2013 will therefore be the last recorded measures of CSR before the oil price shock. These scores should therefore be a good reflection of how investors perceive the companies' ESG performance during and following the shock. Figure 3.1 shows the distribution of ESGC scores for the companies with an available score in 2013. The scores appear to be normally distributed.

Figure 3.1: Distribution of ESGC scores in the total sample



Note: Histogram illustrating the distribution of ESGC scores for the sample companies with available score in 2013. Each bar contains a 5-point interval.

We choose 2010 to 2017 as the relevant study period because this reflects the oil price shock +/- four years. We deem more than four years forward or backward to include too much noise to be included in our regressions. We omit 80 companies which lack data on stock returns from 2010 to 2017. A distribution of the omitted companies' ESGC scores can be found in the appendix. We sort the remaining companies by industry group and remove companies belonging to the groups (1) investment banks & investment services and (2) investment holding companies. We do this as many of the measures used to calculate ESGC score are not applicable to companies in these industries, as their performance is more likely to be affected by the environmental and social policies of the companies they are invested in (Eccles et al., 2014). This reduces our sample to 748 companies.

Industries are fundamentally different with regard to sustainability challenges, and the subcategory weightings when calculating the ESGC score depend on the industry (Refinitiv, 2020). At the same time, different industries will be asymmetrically impacted by a sudden fall in oil prices, some impacted positively and others negatively (Baffes et al., 2015)(Sadorsky, 1999). These factors pose a threat to our analysis and might heavily influence our results, unless we sort the sample by industry group. By sorting this way, we make sure the individual effects contributed by the underlying industries are equally distributed between the treatment and control groups.

Based on ESGC score, we label the upper quartile of the companies in each industry group as the high scoring sustainability group, and the lower quartile as the low scoring sustainability group. We add our high scoring sustainability groups together to create the treatment group, and the low scoring groups to create the control group. We will from here on refer to the treatment and control groups as the *high-ESGC group* and the *low-ESGC group*. In addition, we omit any industry group represented by less than five companies. An industry represented by few companies increases the probability that the sample is non-representative, e.g. that all the observed companies in one industry are low-ESGC relative to their omitted industry-peers. Thus, we have reduced our sample to 330 companies, 165 companies in each group. A descriptive summary of the sample follows in Table 3.2, Table 3.3 and Table 3.4.

Table 3.2: Descriptive statistics: ESGC scores

	n	**mean**	**median**	**sd**	**min**	**max**
Control	165	25.86	26.99	8.68	0.49	44.89
Treatment	165	71.84	71.41	8.43	52.77	91.71
Equality test		p=2.2e-16				

Note: Descriptive statistics of ESGC scores for the high- and low-ESGC group, showing number of observations, mean, median, standard deviation, minimum value and maximum value. The p-value is derived from a test of the equality of the means across the two groups.

Table 3.2 displays descriptive statistics of ESGC scores for both groups. The high- and low-ESGC groups have mean scores of 71.84 and 25.86, respectively and the scores do not overlap in spite of sorting within industry group. T-test of the means shows a statistical significant difference.

Table 3.3: Descriptive statistics: Industry Group

Industry group	% of sample	Industry group	% of sample
Banking Services	9.09	Real Estate Operations	2.42
Machinery, Tools, Heavy Vehicles, Trains & Ships	6.06	Software & IT Services	2.42
Metals & Mining	5.45	Aerospace & Defense	1.82
Professional & Commercial Services	5.45	Automobiles & Auto Parts	1.82
Chemicals	4.24	Healthcare Equipment & Supplies	1.82
Construction & Engineering	4.24	Beverages	1.21
Insurance	4.24	Containers & Packaging	1.21
Oil & Gas	4.24	Freight & Logistics Services	1.21
Telecommunications Services	4.24	Multiline Utilities	1.21
Media & Publishing	3.64	Passenger Transportation Services	1.21
Electric Utilities & IPPs	3.03	Personal & Household Products & Services	1.21
Food & Tobacco	3.03	Textiles & Apparel	1.21
Oil & Gas Related Equipment and Services	3.03	Transport Infrastructure	1.21
Pharmaceuticals	3.03	Biotechnology & Medical Research	0.61
Residential & Commercial REITs	3.03	Communications & Networking	0.61
Specialty Retailers	3.03	Construction Materials	0.61
Food & Drug Retailing	2.42	Electronic Equipment & Parts	0.61
Homebuilding & Construction Supplies	2.42	Paper & Forest Products	0.61
Hotels & Entertainment Services	2.42	Semiconductors & Semiconductor Equipment	0.61

Note: Distribution across industries for the final sample. The same distribution applies to the two groups because the high- and low-ESGC groups are sorted within industry.

Table 3.3 displays the industry groups and their respective share of the final sample. The sample represents 38 industry groups and many of them are represented by only a few companies. Banking services is the largest industry, with 30 companies and 9.09% of the sample. Six industries are represented with only two companies and 0.61% of the sample.

Table 3.4: Descriptive statistics: Country of exchange

Country of exchange	% of sample	
	Low-ESGC	High-ESGC
United Kingdom	31.52	19.39
Germany	10.91	9.70
Russia	7.88	
Switzerland	7.88	7.27
Italy	6.67	4.24
Poland	6.06	0.61
Norway	4.24	3.03
France	3.64	13.94
Belgium	3.03	1.82
Denmark	3.03	2.42
Sweden	3.03	13.33
Austria	2.42	1.21
Finland	2.42	4.24
Spain	2.42	10.30
Ireland	1.82	0.61
Netherlands	1.21	5.45
Hungary	0.61	1.21
Luxembourg	0.61	
Portugal	0.61	1.21

Note: A comparison of companies' country of exchange between the high- and low-ESGC groups. Russia and Luxembourg are not represented in the high-ESGC group.

Table 3.4 displays a distribution of country of exchange for the companies in the high- and low-ESGC groups. Companies listed in the United Kingdom and Poland are more frequently represented in the low-ESGC group, and companies listed in France, Sweden and Spain are more frequently represented in the high-ESGC group. Russia and Luxembourg are not represented by the high-ESGC group at all. These findings might indicate that companies in France, Sweden and Spain perform better in terms of ESGC than companies in United Kingdom, Russia and Poland. Remaining countries of exchange have companies relatively equally distributed between the two groups.

3.4 Variables

This section discusses and motivates the variables used in our analysis. The choice of variables is based on previous empirical research.

3.4.1 Dependent variable

In our main analysis, the dependent variable used is company performance, measured as simple average monthly stock returns. The returns are retrieved directly from Refinitiv Eikon as the Total Return Index (RI), where the returns are based on closing prices adjusted for reinvested dividends, thus facilitating examination of historical returns. We use returns instead of prices to avoid the many challenges arising with non-stationary data.

The Total Return Index is derived as follows, where P_t is the price in period t:

$$RI_t = RI_{t-1} \times \frac{P_t}{P_{t-1}} \tag{3.2}$$

On the day dividends are reinvested the Total Return Index is derived slightly different, where D_t is the dividend reinvested in period t:

$$RI_t = RI_{t-1} \times \frac{P_t + D_t}{P_{t-1}} \tag{3.3}$$

Refinitiv Eikon converts the Total Return Index into percentage return upon retrieval, using the following calculation:

$$r_t = \Delta RI_t = \frac{RI_t - RI_{t-1}}{RI_{t-1}} \times 100 \tag{3.4}$$

3.4.2 Independent and control variables

Dummy variables

In order to investigate and compare the relative development between two groups, we include a dummy variable informing whether the relevant company belongs to the high- or low-ESGC group.

As we are interested in the effect of the oil price shock, we add a time-dummy to divide the observations into time periods before and after the shock, to facilitate a comparison between the two time periods.

Four-factor variables and financial health variables

We want to control for unobservable characteristics correlated with ESGC score which differs between the two groups and might affect the returns. The asset-pricing model of Sharpe (1964), Lintner (1975) and Black (1972) states: under the assumption of an efficient market, (1) the expected return on securities is a positive linear function of their market risk and (2) the market risk is sufficient to describe the cross-section of expected returns. Fama and French (1993) adds to this by arguing that market risk, firm size and book-to-market are proxies for non-diversifiable factor risk. Carhart (1997) later adds momentum as a non-diversifiable risk factor, thus constructs what is today known as the Carhart four-factor asset pricing model. We control for the non-diversifiable risk factors stated by Carhart by adding proxies for market risk, size, market to book and momentum in our model. The calculations of the proxy variables are described in Appendix A1.

In addition, a company's financial health has been proven to affect stock prices in market turmoil. Profitable, cash-heavy firms with low debt-levels can continue investing in a down-period while others might be forced to cut back (Harford et al., 2014). Therefore, significant differences in financial health between the two groups might drive differences in returns in the event of an oil price shock. In order to control for this aspect, we add three well-known proxies for financial health: operating profitability, cash holdings and leverage. The calculations of the proxy variables are described in Appendix A1.

The variables are winsorised at the 99% level to limit extreme values and summarised in Table 3.5. The table represents a snapshot of the situation on the last trading day of 2013 when we divide companies into the high- and low-ESGC groups.

Table 3.5: Descriptive statistics: Control variables

	Group	**n**	**mean**	**median**	**sd**	**min**	**max**
Market Risk	**Total sample**	**327**	**0.65**	**0.62**	**0.36**	**-0.02**	**1.77**
	Low-ESGC group	163	0.65	0.60	0.38	-0.02	1.77
	High-ESGC group	164	0.66	0.62	0.33	-0.00	1.72
	Equality test		p=0.6926				
Market Cap (mill Euros)	**Total sample**	**327**	**10925**	**4021**	**16805**	**45**	**88590**
	Low-ESGC	163	4286	1820	8056	45	64115
	High-ESGC	164	17525	9543	20307	679	88590
	Equality test		p=3.534e-13				
Market-to-Book	**Total sample**	**327**	**2.69**	**1.75**	**2.99**	**-6.50**	**16.79**
	Low-ESGC	163	2.95	1.83	3.16	-4.44	16.79
	High-ESGC	164	2.43	1.73	2.79	-6.50	15.36
	Equality test		p=0.1123				
Momentum	**Total sample**	**326**	**0.03**	**0.02**	**0.12**	**-0.02**	**1.32**
	Low-ESGC group	163	0.04	0.02	0.12	-0.02	1.32
	High-ESGC group	163	0.03	0.01	0.12	-0.00	1.32
	Equality test		p=0.8535				
Profitability	**Total sample**	**298**	**0.08**	**0.07**	**0.08**	**-0.25**	**0.35**
	Low-ESGC group	150	0.08	0.07	0.09	-0.25	0.35
	High-ESGC group	148	0.08	0.06	0.07	-0.12	0.35
	Equality test		p=0.8202				
Debt-to-Value	**Total sample**	**322**	**0.34**	**0.24**	**0.33**	**0.00**	**1.69**
	Low-ESGC	161	0.31	0.19	0.34	0.00	1.69
	High-ESGC	161	0.37	0.29	0.32	0.00	1.52
	Equality test		p=0.09538				
Cash holdings	**Total sample**	**233**	**0.07**	**0.04**	**0.06**	**0.00**	**0.32**
	Low-ESGC group	109	0.07	0.05	0.07	0.00	0.32
	High-ESGCg group	124	0.06	0.04	0.05	0.00	0.26
	Equality test		p=0.1718				

Note: Control variables with their respective number of observations, mean, median, standard deviation, minimum and maximum value for the total sample, low- and high-ESGC group. All numbers are calculated using data from December 2013. Total number of observations for the sample is 330, while n varies if variables are unavailable for a company. All variables are winsorised at the 99% level. The p-value is derived from a test of the equality of the means across the two groups. Calculations of variables can be found in Appendix A1.

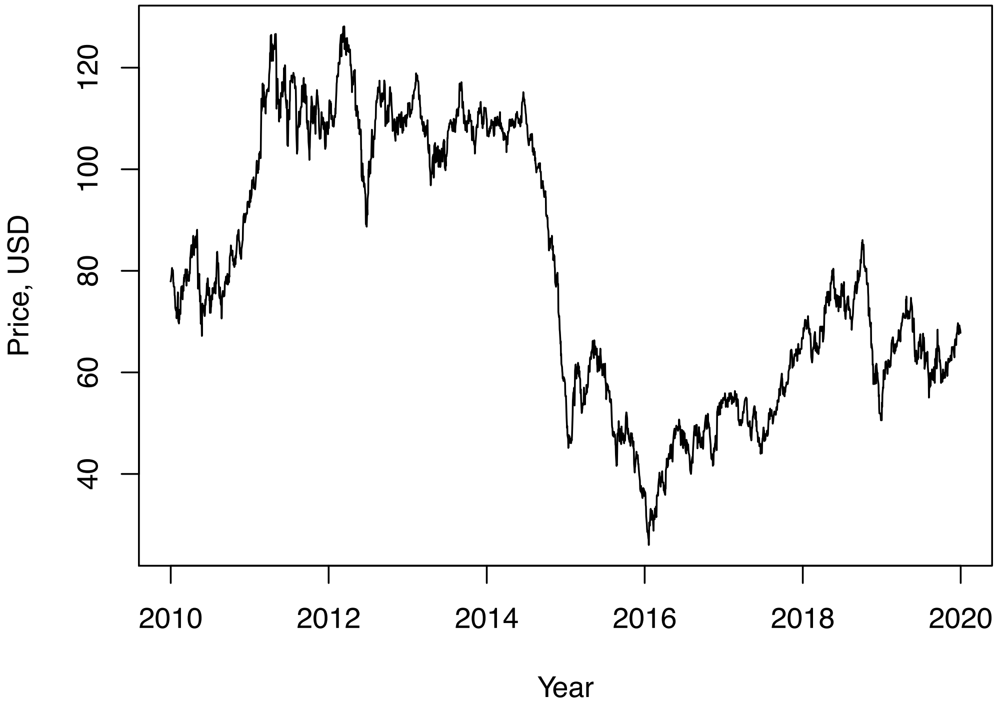
Table 3.5 shows descriptive statistics of the total sample, the high-ESGC sample and low-ESGC sample. The table further shows the average values of the company metrics across the two groups, number of observations, median, standard deviation, minimum value and maximum value. In order to conduct an equality test of means, we use the Welch Two Sample T-test and the corresponding p-value is reported in the table.

From the equality tests, one can conclude that the two groups are similar across the majority of descriptive metrics. Only for the market cap is the difference in means statistically different from zero on the 5% level. This means that the high-ESGC group on average consists of larger firms than the low-ESGC group and should be controlled for. Additionally, this suggests that large companies are more likely to embrace ESG efforts, thus more likely to receive a high ESGC-score. The number of observations for each metric is somewhat different due to missing values in our sample. When integrating the variables in our model, we control for them in a flexible way. The financial characteristics based on market data (size, market-to-book, leverage and momentum) are recalculated monthly. The characteristics based on accounting data (cash-holding and profitability) are recalculated at the end of every fiscal year.

Oil price variable

When investigating the direct effect of changes in oil price on the high- and low-ESGC groups, we collect the monthly spot price of a barrel of Brent crude oil. This is one of the two main benchmark prices for purchase of oil worldwide, the other being the West Texas Intermediate (WTI) (Fattouh, 2010). The Brent crude benchmark is a reference price for Atlantic basin crude oils and is widely used in Europe, and thus seems to be an appropriate measure of oil price in our analysis, considering we are investigating European companies. Figure 3.2 shows the development of the Brent crude oil price over a 10-year window spanning from the beginning of 2010 to the end of 2019.

Figure 3.2: Brent crude oil, 2010-2019



Note: The graph shows daily Brent crude oil prices for the period 2010-2020. Prices in USD.

In order to investigate the effect of oil price changes on stock returns, we convert the monthly oil price into monthly changes in oil price. In doing so, non-stationary data will be less of a problem, as we compare changes instead of levels (Angrist & Pischke, 2014). Changes in oil price is calculated using the following equation, where P_t is the price in period t:

$$r_t = \Delta P_t = \frac{P_t - P_{t-1}}{P_{t-1}} \times 100 \tag{3.5}$$

4 Methodology

In this section we start by defending our choice of method. Thereafter, we present the principles of the methodology and address the assumptions of the method. Lastly, we present an additional model for robustness testing.

4.1 Choice of method

In evaluating the effect of the oil price shock on our sample, we analyse and compare their performance prior to, and after, the shock. In an ideal world, we would compare performance between the high-ESGC group and the low-ESGC group in two scenarios: (1) in the event of the oil price shock and (2) in absence of the oil price shock. The difference in returns in the two scenarios would have been an estimate on the causal effect of the shock on performance, and we would have been able to determine with certainty whether the high- or low-ESGC group performed better or worse as a consequence of the shock. Unfortunately, the latter counterfactual scenario is purely hypothetical and cannot be observed.

A traditional difference-in-differences (DiD) method would solve this by estimating the latter scenario, using returns from a comparable control group (Lechner, 2011). In our case, there are arguably no comparable control groups as the effects of the sudden fall in oil prices are believed to reflect a change in the global economy as a whole (Baffes et al., 2015). In addition, theory of the market as efficient (at least semi-strong efficient) states that the past series of stock prices cannot be used to predict future stock price changes (Fama, 1995). Therefore, we argue we cannot satisfactorily predict returns in the absence of the oil price shock.

Instead, we choose the high-ESGC group as the treatment group and low-ESGC group as the control group. As long as the two groups have parallel pre-trends, the divergence of post-shock trends may signal a treatment effect (Angrist & Pischke, 2014). Consequently, our model will not be able to explain whether the two groups are performing better or worse than they would in the absence of the oil price shock. However, it can satisfactorily state whether one of the groups performs better than the other in response to the shock, which is satisfactory to study our research question. In consequence, the DiD-method seems suitable for our analysis.

4.2 Presentation of method

4.2.1 Difference-in-Differences base model

The DiD method is a research design for estimating causal relationships. The idea is to identify the effect of a specific intervention, called the event or treatment, on a group of entities affected by the event/treatment. In its traditional form, one compares the difference in outcomes before and after the treatment of a group, to the difference in outcomes of a similar group unaffected by the treatment (Lechner, 2011). The benefit of comparing changes instead of levels is that the model eliminates fixed differences between groups that might otherwise generate omitted variable bias (Angrist & Pischke, 2014). The group affected by the treatment and the group unaffected by the treatment are referred to as the treatment and control groups, respectively.

This gives us four different groups of objects:

1. Pre-treatment control group
2. Post-treatment control group
3. Pre-treatment treatment group
4. Post-treatment treatment group

As all the companies in our sample are observed in both time periods, we have a balanced panel data set. Optimally, the two groups are subject to the same pre-trends and one can exclude any treatment effects prior to the event-date. Then, the estimate of the non-existent treatment "effect" in the pre-treatment period can be used to eliminate any effects of confounding factors that might influence the comparison of the post-treatment outcomes between the two groups (Lechner, 2011). The idea is that one can compare the outcome that the treatment group would have experienced in the absence of treatment, indicated by the control group, with the outcome that the treatment group actually experienced post-treatment. The result is referred to as the DiD-estimator and is an estimator of the causal effect of the treatment. To estimate the DiD-estimator, we use the panel data regression DiD model (Angrist & Pischke, 2014):

$$Y_{it} = \alpha + \beta\, TREAT_i + \gamma\, POST_t + \delta_{rDD}\, (TREAT_i \times POST_t) + e_{it} \tag{4.1}$$

In our model, Y_{it} represents return for company i in period t, and is referred to as the dependent variable. $TREAT_i$ is a dummy variable taking on the value one if the relevant company belongs to the treatment group – the high-ESGC group – and zero otherwise. $POST_t$ is a dummy variable taking on the value one for periods after the event – the oil price shock – and zero otherwise. The interaction term $TREAT_i \times POST_t$ indicates observations of the treatment group in the period affected by the treatment. The δ_{rDD} coefficient is the DiD-estimator and captures the effect of treatment on the treatment group.

As both groups are affected by the shock, we use the DiD-method to state whether the treatment group performs significantly better (or worse) than the control group, in response to the event. Hence, the DiD-estimator discloses any difference in effects of the oil price shock between the high- and low-ESGC groups.

The treatment and control groups are not randomly assigned, and we believe there could be unobserved characteristics influencing a company's ESGC score and return, posing a threat to the validity of our results (Angrist & Pischke, 2014). In order to control for this, we use firm fixed effects that capture a vector of unobserved time-invariant confounders for each firm. This is equivalent to replacing the $TREAT_t$ dummy in 4.1 with dummy variables reflecting each firm. In addition, we add month-fixed effects, controlling for the average effect of being in a certain month, by replacing the $POST_t$ dummy with dummies reflecting each month. In doing so, we control for both company-specific trends in levels and certain month-specific phenomena. We will apply month- and firm-fixed effects in all regressions.

We simplify the new model by writing the regression compactly using sum expressions:

$$Y_{it} = \alpha + \sum_{n=1}^{N-1} \beta_n COMPANY_{ni} + \sum_{j=1}^{J-1} \gamma_n MONTH_{tj} + \delta_{rDD}(COMPANY_i \times MONTH_t) + e_{it} \tag{4.2}$$

A drawback with the fixed effects model is that it eliminates the independent variables that are either constant over time for all i or whose change across time is constant (Wooldridge, 2016). This means the regression output will only show the δ_{rDD} coefficient and omit the other coefficients. If the δ_{rDD} coefficient is statistically significant, we can conclude that one of the groups have outperformed the other following the shock. We use robust standard errors clustered around firms to account for heteroscedasticity in all regressions.

4.2.2 Parallel pre-trend assumption

The fundamental assumption behind the DiD model is the parallel pre-trends assumption: "In the absence of an event or treatment, the outcome of the two groups should move in parallel" (Angrist & Pischke, 2014). If performance prior to the event shows a parallel trend between the treatment and control groups, we assume the trend will continue to be parallel in the absence of the event. It is common to test the assumption both visually and by using a regression analysis (Pischke, 2005).

In order to formally control for parallel pre-trends, we use the same regression as in Equation 4.1 but replace the $POST$ dummy variable with a continuous indicator of time which we call $PERIOD$, taking on the value of one for the first period and increasing by one for each period thereafter.

$$Y_{it} = \alpha + \beta\, TREAT_i + \gamma\, PERIOD_t + \delta\,(TREAT_i \times PERIOD_t) + e_{it} \tag{4.3}$$

The coefficient δ states the difference in slope, thus whether significant the coefficient indicates that the two time series follow different trends.

4.2.3 Difference-in-Differences with period dummies

To shed further light on the development of returns in the two groups and a deeper understanding of the results, we extend the main DiD model with period dummies. The model includes the treatment dummy and a set of year dummies. By interacting our treatment dummy, which is constant over time, with the year dummies, we can track the development of differences in returns between the groups over the sample period. This will let us conclude whether the partial treatment effect changes over time (Wooldridge, 2016).

We also apply month- and firm-fixed effects in our model, which eliminates the year dummies, thus we cannot estimate the actual returns in these periods (Wooldridge, 2016). Instead, the coefficient of the interaction term shows how the difference in returns between the treatment and control groups differs year on year compared to the base period.

By choosing a base period with parallel trends, the interaction terms between the treatment variable and the year dummies can tell us whether the treatment and control groups deviate from the parallel trend in the years represented by dummies. In our analysis, we assume a parallel trend period in 2013 to be the base period.

$$\begin{aligned} Y_{it} = \alpha_0 &+ \beta_1 D10_t + \beta_2 D11_t + \beta_3 D12_t + \beta_4 D14_t + \beta_5 D15_t + \beta_6 D16_t \\ &+ \beta_7 D17_t + \alpha_1 TREAT_i + \gamma_1 (D10_t \times TREAT_i) + \gamma_2 (D11_t \times TREAT_i) \\ &+ \gamma_3 (D12_t \times TREAT_i) + \gamma_4 (D14_t \times TREAT_i) + \gamma_5 (D15_t \times TREAT_i) \\ &+ \gamma_6 (D16_t \times TREAT_i) + \gamma_7 (D17_t \times TREAT_i) + e_{it} \end{aligned} \tag{4.4}$$

The base period $D13$ is removed from the equation to avoid multicollinearity and the rest of the year dummies, $D10$ to $D17$, will take on the value of one when indicating their relevant year. Assuming the groups have a parallel development in the base period, a significant γ coefficient indicates a non-parallel trend in the year of interest, specified by the active year dummy. This would imply that in that period, either the treatment or the control group performed significantly better than the other.

4.2.4 Additional model

Lastly, we will employ an OLS model to analyse the direct effect of changes in oil price on both groups. We base our model on Equation 4.1. The model includes the same treatment dummy as before, taking on the value of one for the high-ESGC group and zero for the low-ESGC group. In addition, the new model replaces the variable $POST$ with an indicator of oil price change which we call *oil.price.change*.

$$Y_{it} = \alpha + \beta \, TREAT_i + \gamma \, oil.price.change + \delta \, (TREAT_i \times oil.price.change) + e_{it} \tag{4.5}$$

As previously, the interaction term provides the coefficient of interest. The direction and magnitude of δ explain the difference in how changes in oil price affects differences in returns between the high- and low-ESGC groups.

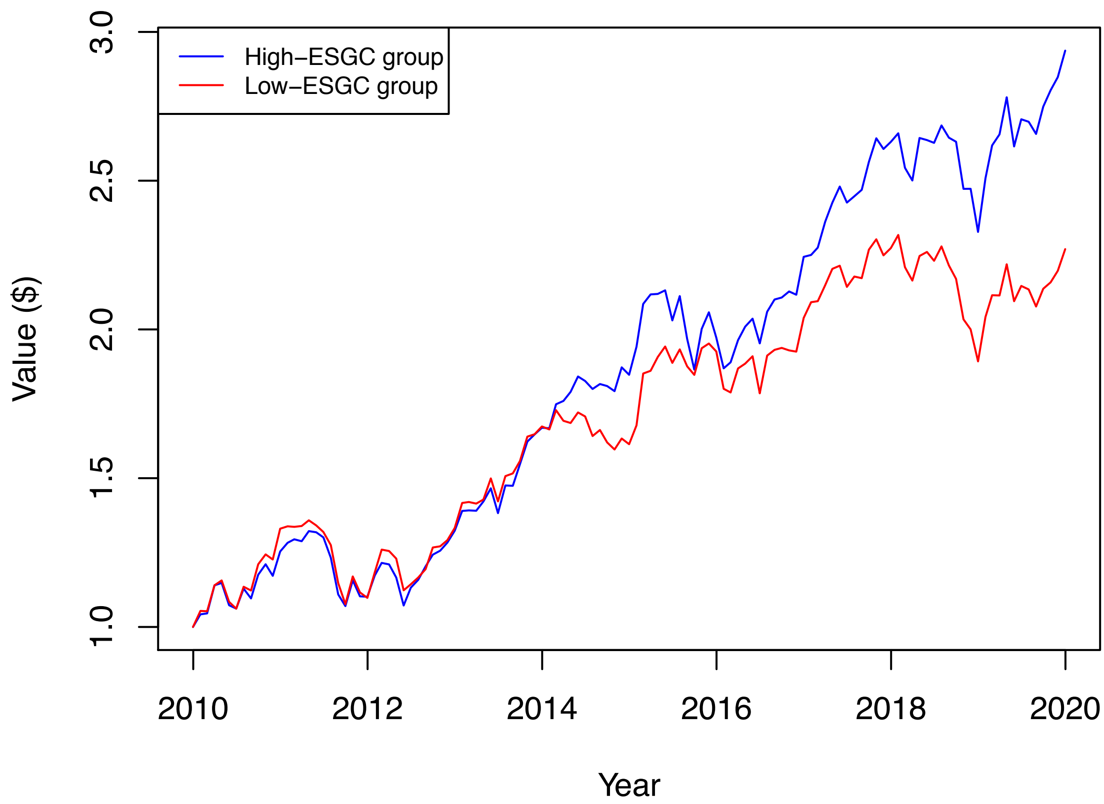
5 Results

In this chapter we cover the results of our analyses. We start by visually analysing the aggregate cumulative returns of the two groups. Thereafter, we investigate differences in simple average monthly returns between the groups, using the DiD model. Lastly, we implement additional models for robustness testing.

5.1 Aggregate cumulative returns

To set the stage for our analysis, we graphically inspect how the high- and low-ESGC groups have performed over the last decade. We do this by plotting the aggregate cumulative returns of $1 invested in an equally weighted portfolio of the companies in each group from 1 January 2010 to 31 December 2020. In this case, we use levels instead of returns because this makes it easier to visually address the trend. Figure 5.1 illustrates the value of the investment in the two portfolios, where the blue and red lines mark the development of the high- and low-ESGC investments, respectively. When referring to the indices in the plot, we will further on refer to the high- and low-ESGC indices.

Figure 5.1: Aggregate cumulative return of $1 invested in the high- and low-ESGC group



Note: The plot illustrates the aggregate cumulative returns of $1 invested in January 2010 to December 2019 in two equally weighted portfolios consisting of the high- and low-ESGC groups. The y-axis displays value ($) and the x-axis displays years.

Figure 5.1 illustrates the two indices following a similar trend from 2010 until the beginning of 2014, before the two indices show a clear change in trends. The low-ESGC index reacts negatively to the shock, proceeding to decline throughout 2014. The high-ESGC index performs better and remains relatively stable throughout 2014. In the beginning of 2015, both indices rise rapidly. This corresponds with a sudden pick-up in oil price and might indicate a more positive view on the future of the economy. While the two indices rise, the divergence in trends created in 2014 remains constant. In the second half of 2015, both indices fall; however, this time the high-ESGC index takes a bigger fall than the low-ESGC index, nearly neutralising the divergence created in 2014. From 2016 to 2020, there is a clear-cut trend of the high-ESGC index outperforming the low-ESGC index.

As there seems to be a parallel trend in the four years prior to the shock, the new trend after the shock leads us to believe the shock had a lasting impact on the market, changing the trend of each group. This corresponds well with our initial hypothesis.

5.2 Defining the event

In order to estimate the effect of the shock on the stock market using a DiD model, we need to define an event date. We will define our event date by combining a visual analysis of Figure 5.1 and a reflection surrounding the underlying drivers of the shock.

When analysing the two trends in Figure 5.1, we observe that the high- and low-ESGC indices diverge at the beginning of 2014. This is somewhat before the shock hits. We suggest this is because characteristics that eventually will lead to the plunge in oil prices are starting to be reflected in investor behaviour. Accordingly, we set the event date to 01.01.2014 in order to capture the full effect of changes in investor behaviour.

To supplement the analysis and increase its robustness we include a model analysing the direct effect of changes in oil price on returns. This does not require an event date and reduces the potential impact of an inaccurate event date in the main DiD model.

5.3 Parallel pre-trends

In order to run a robust DiD-model, the assumption of parallel pre-trends must hold. In addition to the analysis of Figure 5.1, we perform a formal test to conclude whether the trends are parallel. This is done using Equation 4.3 and a four-year pre-shock period. Unlike Figure 5.1, we regress the first difference of levels to avoid the problems arising from regressing index levels. We are interested in the interaction coefficient of the *ESG:period* variable, which, if not statistically significant, means that the parallel pre-trends assumption holds.

Table 5.1: Testing for parallel pre-trends

	Simple average monthly return			
	Time period			
	(1) 2013	(2) 2012-2013	(3) 2011-2013	(4) 2010-2013
ESG:period	0.001 (0.001)	0.0004 (0.0003)	−0.0001 (0.0002)	0.0002 (0.0001)
Firm FEs	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes
Robust SE clustered by	Firm	Firm	Firm	Firm
Observations	3,960	7,920	11,880	15,840
R^2	0.0004	0.0003	0.00004	0.0002
Adjusted R^2	−0.094	−0.046	−0.032	−0.024
F Statistic	1.548 (df = 1; 3618)	2.098 (df = 1; 7566)	0.466 (df = 1; 11514)	2.650 (df = 1; 15462)

Note: The dependent variable is simple average monthly return. The independent variables are *period*, taking on the value of one for the first period and increasing by one for each period thereafter, and an *ESG* dummy indicating whether a company belongs to the high-ESGC group. The coefficient of the interaction term *ESG:period* captures the difference in trends of monthly returns between the high- and low-ESGC groups. The study periods for regression (1), (2), (3) and (4) are 2013, 2012-2013, 2011-2013 and 2010-2013. The numbers in parenthesis are heteroscedasticity-robust standard errors, clustered at firm level. We apply firm- and month-fixed effects. *, ** and *** indicate that the associated coefficient is statistically significant at the 10%, 5% and 1% levels, respectively.

Table 5.1 includes four regressions considering data for different time periods. Regression (1) considers one year of data prior to the oil price shock, while regression (2), (3) and (4) expand this time period to include two, three and four years prior to the shock, respectively.

The interaction coefficient is not statistically different from zero in the four regressions. This means that the trend explained by *period* in Equation 4.3, is valid for both groups whether we use one, two, three or four years of data prior to the shock.

If one combines Figure 5.1 and the insignificant results from Table 5.1, this strongly suggests the assumption of parallel pre-trends hold for our sample data. Based on this conclusion, we can continue our analysis using the DiD-model to investigate whether the high-ESGC group performed differently than the low-ESGC group following the shock.

5.4 Difference-in-Differences models

5.4.1 Difference-in-Differences base model

We start by employing a regular DiD approach to investigate the relationship between ESGC score and return in the period following the the shock.

Table 5.2: Difference-in-Differences results

	Simple average monthly return			
	Event study time period			
	(1) 2010-2014	(2) 2010-2015	(3) 2010-2016	(4) 2010-2017
ESG:oil.shock	0.012***	0.002	0.003	0.004*
	(0.003)	(0.003)	(0.002)	(0.002)
Firm FEs	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes
Robust SE clustered by	Firm	Firm	Firm	Firm
Observations	19,800	23,760	27,720	31,680
R^2	0.001	0.00003	0.0001	0.0001
Adjusted R^2	−0.019	−0.017	−0.015	−0.013
F Statistic	17.280***	0.692	2.734*	3.931**
	(df = 1; 19410)	(df = 1; 23358)	(df = 1; 27306)	(df = 1; 31254)

Note: The dependent variable is simple average monthly return. The independent variables are an *oil.shock* dummy, indicating whether an observation takes place after the oil price shock, and an *ESG* dummy, indicating whether a company belongs to the high-ESGC group. The coefficient of the interaction term *ESG:oil.shock* captures the differences in returns between the high- and low- ESGC groups. The study periods for regression (1), (2), (3) and (4) are 2010-2014, 2010-2015, 2010-2016 and 2010-2017, respectively. The numbers in parenthesis are heteroscedasticity-robust standard errors, clustered at firm level. We apply firm- and month-fixed effects. *, ** and *** indicate that the associated coefficient is statistically significant at the 10%, 5% and 1% levels, respectively.

Table 5.2 presents the results from four different regressions. They all include the pre-shock period, from the beginning of 2010 until the end of 2013. Regression (1) adds one year (2014) of the post-shock period to capture the differences in returns between the two groups in 2014 compared to the pre-shock period. Regression (2), (3) and (4) expands the post-shock period with two, three and four years, respectively. As we have established a parallel pre-trend, the interaction term *ESG:oil.shock* explains how much better (or worse) the high-ESGC group performs relative to the low-ESGC group following the shock.

Regression (1) in Table 5.2 shows that in 2014, the high-ESGC group significantly outperforms the low-ESGC group, generating a simple average monthly return 1.2 pp above that of the low-ESGC group. The result is significant at the 1% level. In regressions (2) and (3), the high-ESGC group only performs 0.2 and 0.3 pp better. However, the significance of the *ESG:oil.shock* coefficient disappears. The *ESG:oil.shock* coefficient in regression (4), however, is significant at the 10% level and indicates that over a four-year period following the shock, the high-ESGC group has on average outperformed the low-ESGC group by 0.4 pp per month.

The result in regression (4) corresponds with the trends in Figure 5.1. Despite a smaller coefficient than in regression (1), a monthly outperformance by 0.4 pp accumulated adds up to an annual outperformance by 4.81 pp. This accumulates to a considerable difference in value between the two groups and indicates that rather than just performing better in the short term, the high-ESGC group outperforms the low-ESGC group on a more general level. This result corresponds with the mainstream literature and consensus that environmental and socially sustainable assets outperform non-sustainable assets (Friede et al., 2015) and add further confidence in our hypothesis.

5.4.2 Difference-in-Differences model with period dummies

In order to understand the dynamics of the pre- and post-shock period, we analyse the year on year changes in trends.

The regression in Table 5.3 is based on a sample containing observations from four years prior to four years after the shock. What sets it apart from regression (4) in Table 5.2 is that it replaces the *oil.shock* dummy with a set of dummies for 2010, 2011, 2012, 2014, 2015, 2016 and 2017 and interacts them with the treatment dummy, *ESG*. We use 2013 as base period, and since we concluded with parallel pre-trends for this period in Section 5.3, the coefficients indicate by how many percentage points the average monthly returns of the high- and low-ESGC groups diverge from one another.

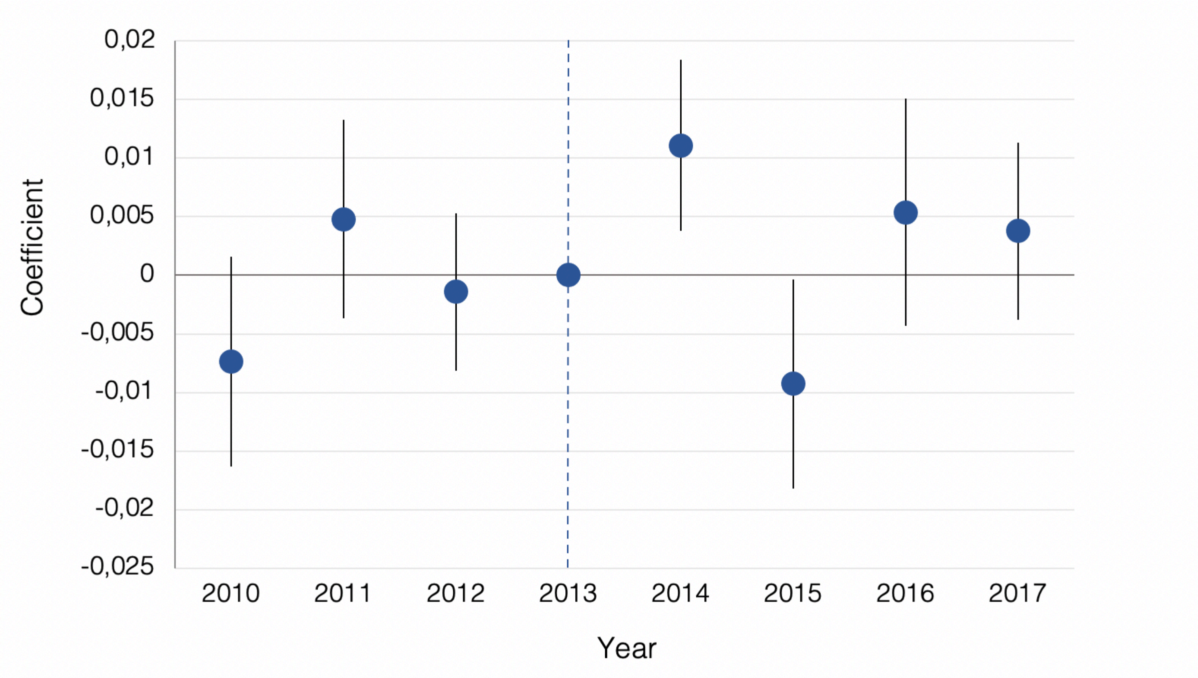
Table 5.3: Difference-in-Differences model with period dummies

	Simple average monthly return
	Period 2010-2017
	(1)
ESG:Y2010	−0.007
	(0.005)
ESG:Y2011	0.005
	(0.004)
ESG:Y2012	−0.001
	(0.003)
ESG:Y2014	0.011***
	(0.004)
ESG:Y2015	−0.009**
	(0.005)
ESG:Y2016	0.005
	(0.005)
ESG:Y2017	0.004
	(0.004)
Firm FEs	Yes
Month FEs	Yes
Robust SE clustered by	Firm
Observations	31,680
R^2	0.001
Adjusted R^2	−0.012
F Statistic	6.530*** (df = 7; 31248)

Note: The dependent variable is simple average monthly return. The independent variables are seven dummies indicating which year an observation belongs to and an *ESG* dummy indicating whether a company belongs to the high-ESGC group. The coefficients of the interaction terms between *ESG* and the year dummies captures the difference in returns between the high- and low-ESGC group compared to the base period 2013. The study period for the regression is 2010-2017. The numbers in parenthesis are heteroscedasticity-robust standard errors, clustered at firm level. We apply firm- and month-fixed effects. *, ** and *** indicate that the associated coefficient is statistically significant at the 10%, 5% and 1% levels, respectively.

In addition to Table 5.3, we plot the coefficients with their respective 95% confidence intervals in Figure 5.2. From the plot, one can visually analyse how the returns of the high-ESGC group diverge from the parallel trends found in 2013 and whether this divergence is statistically different from zero.

Figure 5.2: Estimated impact of the oil shock



Note: The graph shows the coefficients of the year dummies, taking the value of one for the high-ESGC group and zero for the low. The coefficients are the same as those calculated in Table 5.3. The confidence intervals are 95% and calculated using heteroscedasticity-robust standard errors clustered at company level. The time period is 2010-2017 and the vertical line is indicating the base period, 2013.

Table 5.3 shows that neither of the interaction coefficients for 2010, 2011 or 2012 indicates a significant difference in returns between the high- and low-ESGC groups. This reinforces the assumption of parallel pre-trends.

The coefficient of *ESG:Y2014* is significant at the 1% level, which corresponds with the findings from regression (1) in Table 5.2. However, as regression (1) in Table 5.2 compares returns in 2014 with the entire pre-shock period, the result generated in regression (1) in Table 5.3 is somewhat different as it uses 2013 as base period. The results can, however, be interpreted in a similar way.

In 2015, the direction of the interaction coefficient somewhat surprisingly changes from positive to negative. The significance level falls and from Figure 5.2, one can see that it is barely significant at the 5% level. The result shows that the low-ESGC group outperforms the high-ESGC group by an average of 0.9 pp each month, in what seems to be a price correction. This provides an explanation as to why regression (2) in Table 5.2 is insignificant.

In both 2016 and 2017, the coefficients are positive, indicating an outperformance by the high-ESGC group compared to 2013. Seen in relation to Figure 5.1 which shows a lasting gap between the high- and low-ESGC indices, this adds confidence in a lasting trend. However, as the coefficients lack significance, we cannot reject them being equal to zero.

5.4.3 Difference-in-Differences model with control variables

In this section, we will examine whether our results from Table 5.2 can in fact be attributed to ESGC score or if there are unobserved characteristics correlated with ESGC score and returns that are driving the results.

The number of observations decreases as we add new variables because some firms do not publicly provide the necessary information to calculate these measures. In addition, the market risk in our sample does not vary over time, thus it is differenced away due to fixed effects.

Table 5.4: Difference-in-Differences model with control variables

	Simple average monthly return			
	Event study time period: 2010-2014			
	(1) Base	(2) FF-model control	(3) Fin.health control	(4) Control w/ interactions
log(lagMC)		-0.020^{***}	-0.020^{***}	-0.022^{***}
		(0.006)	(0.006)	(0.005)
lagM2B		-0.0001	-0.0001	-0.001^{*}
		(0.0001)	(0.0001)	(0.001)
mom		-0.002	-0.002	-0.0003
		(0.007)	(0.007)	(0.008)
prof			0.011	0.021
			(0.012)	(0.014)
cash			-0.008	-0.010
			(0.015)	(0.015)
lagD_EV			-0.00001	0.00002
			(0.0001)	(0.0001)
oil.shock:beta				0.0002
				(0.005)
oil.shock:log(lagMC)				0.001
				(0.002)
oil.shock:lagM2B				0.001^{*}
				(0.001)
oil.shock:mom				0.001
				(0.010)
oil.shock:prof				-0.014
				(0.010)
oil.shock:cash				0.019^{*}
				(0.010)
oil.shock:lagD_EV				0.006
				(0.005)
ESG:oil.shock	0.012^{***}	0.012^{***}	0.012^{***}	0.011^{***}
	(0.003)	(0.003)	(0.003)	(0.004)
Firm FEs	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes
Four-factor characteristics	No	Yes	Yes	Yes
Financial health characteristics	No	No	Yes	Yes
Variable:oil.shock interactions	No	No	No	Yes
Robust SE clustered by	Firm	Firm	Firm	Firm
Observations	19,800	19,227	18,883	18,883
R^2	0.001	0.008	0.008	0.010
Adjusted R^2	-0.019	-0.012	-0.013	-0.011
F Statistic	17.280^{***} (df = 1; 19410)	39.519^{***} (df = 4; 18839)	21.150^{***} (df = 7; 18492)	13.752^{***} (df = 14; 18485)

Note: The dependent variable is simple average monthly return, and the *ESG:oil.shock* interaction term captures the difference in return between the high- and low-ESGC groups in 2014 compared to the four-year pre-shock period. The control variables are the same as illustrated in table 3.5 and are added to the model both individually and interacted with the oil:shock dummy. The financial characteristics based on market data (size, market-to-book, leverage and momentum) are recalculated monthly. The characteristics based on accounting data (cash-holding and profitability) are recalculated at the end of every fiscal year. We lag the variables based on price calculations (size, market-to-book and leverage) by one month to reduce the risk of including endogenous controls. The control variables are winsorised at the 99 % level to limit extreme values. The numbers in parenthesis are heteroscedasticity-robust standard errors, clustered at firm level. We apply firm- and month-fixed effects. *, ** and *** indicate that the associated coefficient is statistically significant at the 10%, 5% and 1% levels, respectively.

Regression (1) in Table 5.4 is equal to regression (1) in Table 5.2 and adds a foundation to control for alternative variables. In regression (2), we control for non-diversifiable risk factors known to be correlated with expected returns (Carhart, 1997). Despite adding three variables, one of which is significant on the 1 % level, the coefficient of the interaction term remains at 1.2 pp and is statistically significant.

In regression (3), we add three proxy variables measuring financial health. We have already stated in Table 3.5 that these variables' differences in means are insignificant between the two groups at the end of 2013. Hence, their insignificance in Table 5.4 is in accordance with our expectations. In addition, the *ESG:oil.shock* variable still remains at 1.2 pp and is significant at the 1% level, suggesting that differences in returns cannot be attributed to differences in financial health.

In regression (4), we interact the three four-factor variables and the three financial health variables with the oil shock dummy. This is in order to capture effects in the control variables triggered by the oil shock. The interactions lead to a slight reduction in the *ESG:oil.shock* variable; however, the variable is still significant at the 1% level, implying that the control variables account for little of the outperformance.

The results outlined in Table 5.4 show that the *ESG:oil.shock* coefficient remains positive and significant at the 1 % level and is barely affected throughout all the specifications. This implies that the estimate is robust and increases confidence in the result. We conclude that the outperformance cannot be contributed to either differences in non-diversifiable factor risk or differences in financial health between the two groups. Instead, the outperformance is likely to be due to the differences in ESGC score.

5.5 Additional model

To account for the weaknesses arising from the DiD model with an explicit event date, we also run an analysis with change in oil prices, directly. We use the same regression as in Table 5.2 but replace the oil shock dummy with a variable for monthly change in oil price. In Table 5.5, we use five different periods; regression (1) consists of the four year pre-shock period, while regressions (2), (3), (4) and (5) expands the study period by one, two, three and four years of the post-shock period, respectively.

Table 5.5: Linear model with oil price changes

	Simple average monthly return				
	Time period				
	(1) 2010-2013	(2) 2010-2014	(3) 2010-2015	(4) 2010-2016	(5) 2010-2017
ESG:oil.price.change	-0.037	-0.045^{*}	-0.045^{**}	-0.024	-0.025
	(0.025)	(0.023)	(0.022)	(0.021)	(0.021)
Firm FEs	Yes	Yes	Yes	Yes	Yes
Month FEs	Yes	Yes	Yes	Yes	Yes
Robust SE clustered by	Firm	Firm	Firm	Firm	Firm
Observations	15,840	19,800	23,760	27,720	31,680
R^2	0.0002	0.0004	0.001	0.0002	0.0002
Adjusted R^2	-0.024	-0.020	-0.017	-0.015	-0.013
F Statistic	3.170^{*}	7.144^{***}	12.600^{***}	4.658^{**}	5.227^{**}
	(df = 1; 15462)	(df = 1; 19410)	(df = 1; 23358)	(df = 1; 27306)	(df = 1; 31254)

Note: The dependent variable is simple average monthly return. The independent variables are *oil.price.change* and an *ESG* dummy indicating whether a company belongs to the high-ESGC group. The coefficients of the interaction term *ESG:oil.price.change* captures the difference in returns between the high- and low- ESGC groups following a change in oil price. The study periods for regressions (1), (2), (3), (4) and (5) are 2010-2013, 2010-2014, 2010-2015, 2010-2016 and 2010-2017, respectively. The numbers in parenthesis are heteroscedasticity-robust standard errors, clustered at firm level. We apply firm- and month-fixed effects. *, ** and *** indicate that the associated coefficient is statistically significant at the 10%, 5% and 1% levels, respectively.

Regression (1) in Table 5.5 indicates that the correlation between oil price and simple average monthly return is equal for the high- and low-ESGC group in the four year pre-shock period. For regression (2) and (3) the interaction coefficient is negative and significant at 10% and 5% levels, respectively. This indicates that when oil price is increasing, the high-ESGC group is affected worse than the low-ESGC group in the given period. For both regressions (2) and (3), a doubling in oil price will result in a change in monthly return 4.5 pp lower for the high ESGC group than the low-ESGC group.

Another interpretation of this result is that when the oil price is falling, like in the event of the oil price shock in 2014, the returns of the high-ESGC group are affected less negative than the returns of the low-ESGC group. This result is in line with Figure 5.1 and our earlier results which imply that the high-ESGC group outperformed the low-ESGC group in 2014. However, when including the years after 2015 for regressions (4) and (5), the interaction terms are no longer significant, meaning we cannot state that the high-ESGC group is differently affected by oil price changes when taking a longer perspective into account.

The results suggest that the shock itself, or the underlying effects reflected by the shock, is what drives the difference in returns and that smaller fluctuations in oil prices do not affect the returns of the high- and low-ESGC groups differently.

6 Discussion

This thesis attempts to answer whether European companies with superior environmental and social responsibility efforts perform differently compared to those with low degrees of such efforts, following the oil price shock in 2014. In this section, we discuss our most prominent findings and their implications. In addition, we address limitations of our study and suggest future research subjects.

6.1 Long term findings

We find that over the four-year period prior to the shock, the two groups have parallel trends both during the whole period and in each year individually. When looking at the four-year period after the shock, the high-ESGC group has on average outperformed the low-ESGC group by 0.4 pp per month. This results is significant at the 10% level. The visual analysis supports the results by illustrating a lasting shift in performance created in 2014.

Consensus as of today is that superior environmental and social efforts stimulate financial performance, thus our findings from 2014 and onwards correspond with the literature. However, in contrast to this, we cannot find such a relationship prior to 2014. This may indicate that the relationship between CSR and CFP was stronger in the post-shock period than in the pre-shock period. An explanation of this may be a positive shift of stakeholders' perception of CSR in 2014 and should, in accordance with the good management theory, directly lead to an increased positive effect of CSR on financial performance (Waddock & Graves, 1997). Depending on a firm's business model, such effects could be product market benefits, capital market benefits, employee benefits and/or regulatory benefits (Malik, 2015). As the firms of interest are publicly listed, increased financial performance should be visible in stock prices, thus picked up by our model.

We suggest the lasting impact can be attributed to underlying drivers reflected by an expectation of a green shift. As mentioned in the literature review, such drivers might be long-term expectations of decarbonisation and hence low carbon prices, a tendency of companies moving towards less oil-intensive production technologies and increased investments in alternative energy sources. These drivers represent increased stakeholder awareness of ESG factors, and should, according to Waddock and Graves (1997), lead to increased financial performance for companies with superior environmental and social performance, which in our study is captured by ESGC score.

MSCI (2020) has conducted a similar study to ours, further described in the literature review, over a sample period from April 2013 to November 2020. The sample period starts at approximately the same time as our post-shock period, and thus captures many of the same market effects we capture in our post-shock analysis. The study finds that the top third of companies in terms of ESG rating outperform the bottom third by 2.56% per year, over the seven-year study period. This corresponds well with our visual analysis, illustrating a lasting outperformance in the same seven-year period. Our findings of a monthly outperformance of 0.4 pp translates to approximately 4.8 pp annually over the four-year period after the shock. Our result is somewhat larger, which might be driven by our choice of sorting our high sustainability group by the top quartile in terms of ESGC score instead of top third, or that we are using a different ESG rating provider. While our result is somewhat larger than that found in the study by MSCI, we conclude that they both suggest a lasting outperformance in the post-shock period by the top rated companies.

In 2020, the discussion regarding drivers of ESG performance has become ever more apparent. Some argue the outperformance is due to a higher premium paid by investors for companies with superior environmental and social performance (Dillan, 2020). However, MSCI (2020) found the primary reason of outperformance to be earnings growth for the higher-rated companies. This is in line with our hypothesis as we explain the increased earnings by a shift in stakeholders' perception of CSR. This would benefit companies with superior CSR through various stakeholder channels, such as, better employee relations, better access to capital and increased customer loyalty. (Waddock & Graves, 1997)(Malik, 2015). This would increase earnings and profitability and lead to improved stock performance. However, it is still debated whether the increased stock performance commes with greater risk

The investments in ESG related assets continue to increase (Elliot, 2020) and we can trace a positive relationship between CSR and CSP back to the oil price shock. As Morgan Stanley Institute for Sustainable Investing (2020) has found sustainable assets to outperform non-sustainable assets in 2020 as an isolated year, we argue that the effect following the 2014 oil price shock is still apparent in the market today and driving outperformance.

6.2 Short term findings

In the stock market, there are plenty of effects working together and we can hardly state that an expectation of a green shift is the only effect driving differences in returns between the two groups. Despite the more general long-term trend of outperformance, we find contradicting results when considering 2014 and 2015 individually. In 2014, the high-ESGC group starts to outperform the low-ESGC group by 1.2 pp each month. In 2015, the roles are reversed and the low-ESGC group outperforms the high, which neutralises the majority of the effect generated in 2014.

The 2014 result corresponds with research stating that companies focusing on environmental and social responsibility outperform during times of market stress (Nofsinger & Varma, 2014). This is in line with the theory of Alexander and Buchholz (1978), arguing that CSR works as a proxy for superior management. Nofsinger and Varma (2014) argue that the high sustainability companies outperform because companies with good governance standards are better suited to manage in periods of market turmoil . This might explain the higher outperformance in 2014 relative to the other years. Previous literature have found similar results during the financial crisis of 2007-2008 (Ducassy, 2013), Brexit in 2016 (Chiappini et al., 2018) and Covid-19 in the beginning of 2020 (Folger-Laronde et al., 2020). We argue that the effect of superior management might work together with the effect of a shift in stakeholders' perception of CSR, to generate the high outperformance in 2014.

The counter-effect seen in 2015 might be explained as a price correction of the effect found in 2014. This corresponds with Ducassy's (2013) analysis of the financial crisis in 2007-2008, which finds a temporary significant positive link between sustainability efforts and financial performance in the beginning of the crisis due to high levels of market uncertainty, which later is neutralised (Ducassy, 2013). Thus, the effect of superior management might be temporary and, in contrast to stakeholders' perception of CSR, does not affect the long-term performance of high sustainability companies.

6.3 Oil price correlation

When investigating the relationship between differences in returns of the high- and low-ESGC groups and changes in oil price, we find a significant difference only for the periods 2010-2014 and 2010-2015. When only considering the pre-shock period or when expanding the sample to include three or four years of post-shock data, the results are insignificant.

The results suggest there only exists a relationship between differences in returns and oil price in periods with big fluctuations, such as in 2014 and 2015. The explanation for this may be seen in relation to the short-term findings and the theory of Alexander and Buchholz (1978) arguing for CSR as a proxy for superior management. A sudden negative shock in oil prices creates market stress and facilitates an environment where the high-ESGC group is less reactive to turmoil than the low-ESGC group (Folger-Laronde et al., 2020), thus the groups react differently to the two big plunges in price happening in 2014 and 2015, to how they do in 2016 and 2017. As only smaller fluctuations are present in 2016 and 2017, they are not able to create the same environment as during the shock and the effect of oil price changes in these periods are the same for both groups.

Another explanation might be that the shock reflects other underlying characteristics that smaller oil price fluctuations do not. Therefore, the significant difference in effects on the high- and low-ESGC groups is only apparent during 2014 and 2015.

6.4 Limitations

In our work we have adjusted for inaccuracies to the best of our ability, however there are still limitations and possibilities of inaccuracy in our data sample. In this section we address the most relevant limitations; selection bias and measurement error.

6.4.1 Selection bias

Our first concern is raised as a consequence of requiring the companies to have an available stock price every month in the sample period. Although this is necessary for testing our research question, it could result in exclusion of companies that went bankrupt between 2010 and 2017. If a significant share of the companies excluded were the best or worst scoring companies in regards to ESGC, we would have reason to suspect a survival bias

(Brown et al., 1992). To address this concern, we study the distribution of ESGC scores available in 2013 for the companies omitted due to lacking stock price data. As shown in Appendix A2, the companies are evenly distributed across different ESGC scores, thus survival bias is not likely to be an issue.

Another concern is raised as a consequence of requiring each company to have an available ESGC score in 2013. There are more than 12,000 listed European companies available from the Eikon terminal; however, when requiring ESGC score in 2013, the sample is reduced to 858 companies. Firms with certain characteristics might be more likely to be given an ESGC score than others, thus our final sample might be subject to a selection bias (Phillips et al., 2009).

Selection bias raises a concern of external validity in our study. However, our study provides internal validity for European companies with an ESGC score in 2013 and monthly returns in 2010-2017 provided by Refinitiv Eikon.

6.4.2 Measurement error in ESGC score

When ranking the companies from high to low based on ESGC score, we define good performance as the upper quartile and bad performance as the bottom quartile. However, some studies have found that ESG rating agencies, e.g. Sustainalytics, RobeccoSam and Vigeo Eiris, to some extent differ in their ratings of a company's ESG performance (Rigobon et al., 2020). We cannot know if this is the case for our sample, as we only have access to Refinitiv's ESG rating. This implies that a company receiving a high score from Refinitiv and thus included in our high-ESGC group, might not have been in this group using another rating agency. Due to this, the choice of using Refinitiv over another rating agency may have altered the results in our empirical study.

In addition, our choice of employing ESGC score from 2013 might imply a weakness to our model, as the high- and low-ESGC groups reflect sustainability efforts in 2013. A solution to this could be to re-balance the two groups yearly based on updated scores. However, in doing so we believe the issues in terms of reverse causality and omitted variable bias would inflict a greater weakness to our model. By re-balancing the groups it will be difficult to isolate the effect of the shock on companies, as ESGC scores might be affected by both returns and the oil shock. Therefore, we choose the predetermined value and answer whether the effect of the oil price shock on returns is different for companies with a high or low ESGC score in 2013.

6.5 Future research suggestions

The scope of this study entails some limitations due to time constraints, indicating room for extensions in future research. As we limit our data sample to European listed companies with a Refinitiv ESGC score from 2013, this makes room for robustness testing using different markets, ESG providers and definitions of treatment and control group. Additionally, future research could exploit the ESG score directly instead of creating two groups for comparison.

7 Conclusion

The main purpose of this thesis is to study whether high sustainability companies outperform low sustainability companies in terms of stock performance following the oil price shock in 2014. Our results provide evidence of a parallel trend prior to the shock followed by an outperformance by the high sustainability companies following the shock. This implies that a lasting effect has impacted the dynamics between the high and low sustainability companies as a result of the shock. We argue this is due to characteristics of a shift towards a greener and more sustainable society. Moreover, we find a substantial outperformance in 2014 compared to the more general trend. This corresponds with findings stating that sustainable companies outperform in times of uncertainty. However, this effect is temporary and nearly neutralised in 2015.

The general consensus in the existing literature is that corporate social sustainability increases corporate financial performance. We find this to be true as a consequence of the shock. Therefore, we argue our results contribute to the existing literature by adding insight to the discussion of drivers of outperformance, and shed light on reasons for companies to invest in CSR.

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Appendix

A1 Control variable calculations

Market risk

The market risk, illustrated by β, is calculated using R-Studio. As we lack return data for many stocks prior to 2010 we calculate a fixed beta for the relevant sample size rather than a rolling window. Beta is calculated using Equation A.1 via OLS (Sharpe, 1964).

$$R_{it} = \alpha + \beta\, R_{Mt} + e_{it} \tag{A.1}$$

R_{it} is the vector of excess return of the company for every month in the sample period. R_{Mt} is the vector of monthly market excess return over the same period and the company's market risk is defined as the β coefficient.

Size

The market capitalization (MC) works as a proxy for size and represents the market value for all issue level share types. The issue level market value is calculated multiplying the requested share types by latest closing price. As it is necessary that the MC is comparable across firms, we retrieve the monthly MC using Euros as a common currency.

Market to book

The market-to-book equity (M2B) is a ratio explaining the book value of common equity to the market value. The M2B ratio is calculated by dividing the company's latest closing price by its book value per share. Book value per share is calculated by dividing total equity from latest fiscal period by current total shares outstanding. The ratios are retrieved on a monthly basis.

Momentum

Momentum refers to the tendency that high-performing stocks continue to perform well and vice versa for low-performing stocks (MSCI, 2020). Momentum is calculated as the rolling average monthly return over the last 52 weeks. This factor is retrieved directly from Refinitiv and recalculated monthly.

Profitability

We use operating profitability relative to book value of equity as a proxy for profitability. Companies with high ratios are considered robust and less reactive to market downturns. The ratio is calculated by taking operating profit less interest expenses and dividing it by the book value of equity. As the ratio is based on accounting data, the ratio is recalculated in the end of the fiscal year when the companies publish updated information.

Cash holding

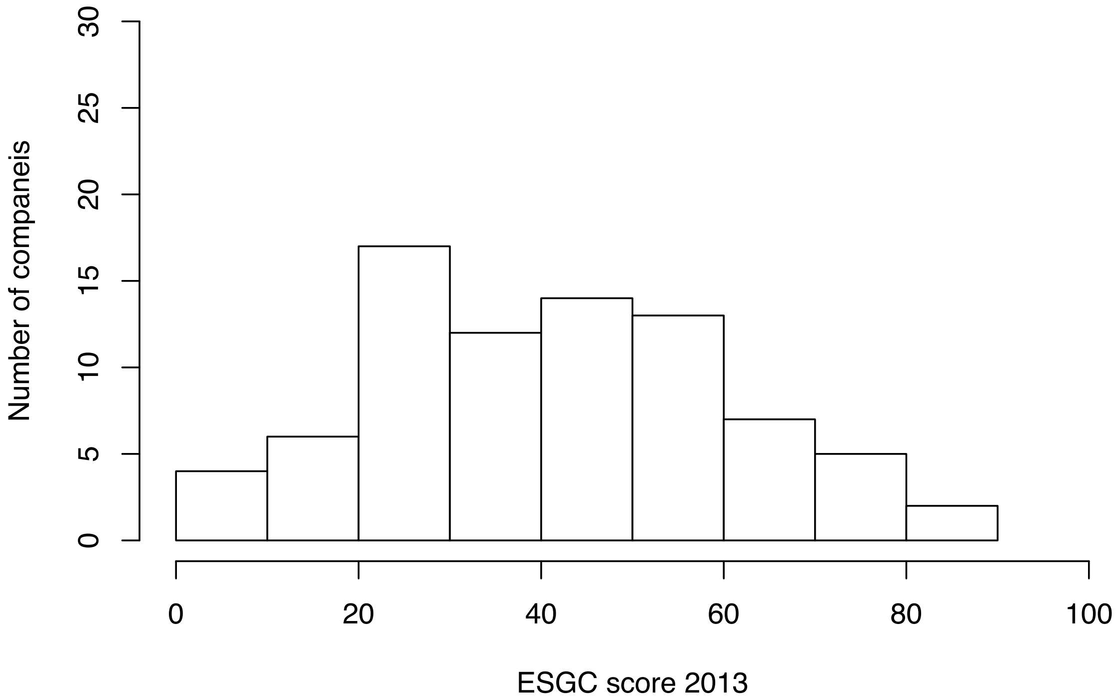
Cash holding is calculated by adding cash and marketable securities together and then dividing by total assets.

Leverage

The debt-to-enterprise value (D/EV), which divides total debt (D) by the enterprise value (EV), works as a proxy for leverage. Total debt includes short and long term debt for the most recent fiscal period. EV represents the sum of market capitalization, total debt, preferred stock and monthly interest minus cash and short term investments for the most recent fiscal period and are retrieved on a monthly basis.

A2 Control for survival bias

Figure A2.1: Distribution of ESGC score of the omitted companies



Note: Histogram illustrating the distribution of ESGC scores available in 2013 for the companies omitted due to lacking stock price data in the study period 2010-2017.

A3 Robustness checks

We present the following robustness checks using different definitions for the high- and low-ESGC group based on choice of top and bottom percentiles:

- Table A3.1 presents a difference-in-differences estimation using the top and bottom 50 percentile of companies based on ESGC score. Results for all time periods are positive and significant on at least a 10% level, indicating the top 50 percentile outperformed the bottom 50 percentile both in the short term and long term following the shock.

Table A3.1: Difference-in-differences with 50 percentiles

	Simple average monthly return			
	Event study time period			
	(1) 2010-2014	(2) 2010-2015	(3) 2010-2016	(4) 2010-2017
ESG:oil.shock	0.007***	0.003*	0.003**	0.003**
	(0.002)	(0.002)	(0.001)	(0.001)
Time FEs	Yes	Yes	Yes	Yes
Entity FEs	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes
Observations	42,000	50,400	58,800	67,200
R^2	0.0003	0.0001	0.0001	0.0001
Adjusted R^2	−0.018	−0.015	−0.013	−0.012
F Statistic	13.371***	3.580*	5.814**	5.699**
	(df = 1; 41240)	(df = 1; 49628)	(df = 1; 58016)	(df = 1; 66404)

Note: The dependent variable is simple average monthly return. The independent variables are an *oil:shock* dummy, indicating whether an observation takes place after the oil price shock, and an *ESG* dummy, indicating whether a company belongs to the high-ESGC group. The coefficient of the interaction term *ESG:oil.shock* captures the differences in returns between the high- and low- ESGC groups. The study periods for regression (1), (2), (3) and (4) are 2010-2014, 2010-2015, 2010-2016 and 2010-2017, respectively. The numbers in parenthesis are heteroscedasticity-robust standard errors, clustered at firm level. We apply firm- and month-fixed effects. *, ** and *** indicate that the associated coefficient is statistically significant at the 10%, 5% and 1% levels, respectively.

- Table A3.2 presents a difference-in-differences estimation using the top and bottom 40 percentile of companies based on ESGC score. Results for regression (1), (3) and (4) are positive and significant on at least a 10% level, indicating the top 40 percentile outperformed the bottom 40 percentile both in the short and long term following the shock.

Table A3.2: Difference-in-differences with 40 percentiles

	Simple average monthly return			
	Event study time period			
	(1) 2010-2014	(2) 2010-2015	(3) 2010-2016	(4) 2010-2017
ESG:oil.shock	0.008^{***}	0.002	0.003^{*}	0.003^{*}
	(0.002)	(0.002)	(0.002)	(0.001)
Time FEs	Yes	Yes	Yes	Yes
Entity FEs	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes
Observations	32,760	39,312	45,864	52,416
R^2	0.0004	0.00003	0.0001	0.0001
Adjusted R^2	−0.018	−0.016	−0.014	−0.012
F Statistic	11.607^{***}	1.252	3.633^{*}	4.028^{**}
	(df = 1; 32154)	(df = 1; 38694)	(df = 1; 45234)	(df = 1; 51774)

Note: The dependent variable is simple average monthly return. The independent variables are an *oil:shock* dummy, indicating whether an observation takes place after the oil price shock, and an *ESG* dummy, indicating whether a company belongs to the high-ESGC group. The coefficient of the interaction term *ESG:oil.shock* captures the differences in returns between the high- and low- ESGC groups. The study periods for regression (1), (2), (3) and (4) are 2010-2014, 2010-2015, 2010-2016 and 2010-2017, respectively. The numbers in parenthesis are heteroscedasticity-robust standard errors, clustered at firm level. We apply firm- and month-fixed effects. *, ** and *** indicate that the associated coefficient is statistically significant at the 10%, 5% and 1% levels, respectively.

- Table A3.3 presents a difference-in-differences estimation using the top and bottom 30 percentile of companies based on ESGC score. The coefficient is statistical significant for regression (1) and (4) on at least a 10% level, indicating the top percentile outperformed the bottom percentile during the first year and the four-year period following the shock.

Table A3.3: Difference-in-differences with 30 percentiles

	Simple average monthly return			
	Event study time period			
	(1) 2010-2014	(2) 2010-2015	(3) 2010-2016	(4) 2010-2017
ESG:oil.shock	0.010***	0.002	0.003	0.003*
	(0.003)	(0.002)	(0.002)	(0.002)
Time FEs	Yes	Yes	Yes	Yes
Entity FEs	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes
Observations	23,760	28,512	33,264	38,016
R^2	0.001	0.00002	0.0001	0.0001
Adjusted R^2	−0.019	−0.017	−0.015	−0.013
F Statistic	13.682***	0.525	2.223	3.498*
	(df = 1; 23304)	(df = 1; 28044)	(df = 1; 32784)	(df = 1; 37524)

Note: The dependent variable is simple average monthly return. The independent variables are an *oil:shock* dummy, indicating whether an observation takes place after the oil price shock, and an *ESG* dummy, indicating whether a company belongs to the high-ESGC group. The coefficient of the interaction term *ESG:oil.shock* captures the differences in returns between the high- and low- ESGC groups. The study periods for regression (1), (2), (3) and (4) are 2010-2014, 2010-2015, 2010-2016 and 2010-2017, respectively. The numbers in parenthesis are heteroscedasticity-robust standard errors, clustered at firm level. We apply firm- and month-fixed effects. *, ** and *** indicate that the associated coefficient is statistically significant at the 10%, 5% and 1% levels, respectively.

- Table A3.4 presents a difference-in-differences estimation using the top and bottom 20 percentile of companies based on ESGC score. The coefficient is only statistical significant for regression (1), indicating the top 20 percentile only outperformed the bottom percentile the first year following the shock.

Table A3.4: Difference-in-differences with 20 percentiles

	Simple average monthly return			
	Event study time period			
	(1) 2010-2014	(2) 2010-2015	(3) 2010-2016	(4) 2010-2017
ESG:oil.shock	0.009***	−0.001	0.002	0.003
	(0.003)	(0.003)	(0.003)	(0.002)
Time FEs	Yes	Yes	Yes	Yes
Entity FEs	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes
Observations	15,600	18,720	21,840	24,960
R^2	0.0005	0.00000	0.0001	0.0001
Adjusted R^2	−0.020	−0.018	−0.016	−0.014
F Statistic	7.367***	0.070	1.145	1.730
	(df = 1; 15280)	(df = 1; 18388)	(df = 1; 21496)	(df = 1; 24604)

Note: The dependent variable is simple average monthly return. The independent variables are an *oil:shock* dummy, indicating whether an observation takes place after the oil price shock, and an *ESG* dummy, indicating whether a company belongs to the high-ESGC group. The coefficient of the interaction term *ESG:oil.shock* captures the differences in returns between the high- and low- ESGC groups. The study periods for regression (1), (2), (3) and (4) are 2010-2014, 2010-2015, 2010-2016 and 2010-2017, respectively. The numbers in parenthesis are heteroscedasticity-robust standard errors, clustered at firm level. We apply firm- and month-fixed effects. *, ** and *** indicate that the associated coefficient is statistically significant at the 10%, 5% and 1% levels, respectively.

A4 Refinitiv ESG controversy measures

Table A4.1: ESG controversy measures

Category	Label	Description
Community	Anti-Competition Controversy	Number of controversies published in the media linked to anti-competitive behavior (e.g., antitrust and monopoly), price-fixing or kickbacks.
Community	Business Ethics Controversies	Number of controversies published in the media linked to business ethics in general, political contributions or bribery and corruption.
Community	Intellectual Property Controversies	Number of controversies published in the media linked to patents and intellectual property infringements.
Community	Critical Countries Controversies	Number of controversies published in the media linked to activities in critical, undemocratic countries that do not respect fundamental human rights principles.
Community	Public Health Controversies	Number of controversies published in the media linked to public health or industrial accidents harming the health and safety of third parties (non-employees and non-customers).
Community	Tax Fraud Controversies	Number of controversies published in the media linked to tax fraud, parallel imports or money laundering.
Human Rights	Child Labor Controversies	Number of controversies published in the media linked to use of child labor issues.
Human Rights	Human Rights Controversies	Number of controversies published in the media linked to human rights issues.
Management	Management Compensation Controversies Count	Number of controversies published in the media linked to high executive or board compensation.
Product Responsibility	Consumer Controversies	Number of controversies published in the media linked to consumer complaints or dissatisfaction directly linked to the company's products or services.
Product Responsibility	Controversies Customer Health & Safety	Number of controversies published in the media linked to customer health & safety.
Product Responsibility	Controversies Privacy	Number of controversies published in the media linked to employee or customer privacy and integrity.
Product Responsibility	Controversies Product Access	Number of controversies published in the media linked to product access.
Product Responsibility	Controversies Responsible Marketing	Number of controversies published in the media linked to the company's marketing practices, such as over-marketing of unhealthy food to vulnerable consumers.
Product Responsibility	Controversies Responsible R&D	Number of controversies published in the media linked to responsible R&D.
Resource Use	Environmental Controversies	Number of controversies related to the environmental impact of the company's operations on natural resources or local communities.
Shareholders	Accounting Controversies Count	Number of controversies published in the media linked to aggressive or non-transparent accounting issues.
Shareholders	Insider Dealings Controversies Count	Number of controversies published in the media linked to insider dealings and other share price manipulations.
Shareholders	Shareholder Rights Controversies Count	Number of controversies linked to shareholder rights infringements published in the media
Workforce	Diversity and Opportunity Controversies	Number of controversies published in the media linked to workforce diversity and opportunity (e.g., wages, promotion, discrimination and harassment).
Workforce	Employee Health & Safety Controversies	Number of controversies published in the media linked to workforce health and safety.
Workforce	Condition Wages or Working Condition Controversies Count	Number of controversies published in the media linked to the company's relations with employees or relating to wages or wage disputes.
Workforce	Management Departures	Has an important executive management team member or a key team member announced a voluntary departure (other than for retirement) or been ousted?

Note: List of all controversy measures that make up the ESG Controversy Category Score