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No News is Good News?

An empirical analysis of the Scandinavian stock market reaction to negative environmental news

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NORWEGIAN SCHOOL OF ECONOMICS

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This master thesis is written as a part of our Master of Science in Economics and Business Administration at the Norwegian School of Economics.

The goal of this thesis is to analyze the market maturity and consideration of ESG news in the Scandinavian markets, thereby contribute to the research field of sustainable finance.

In the process of writing this thesis, we have gained valuable knowledge about the market consideration to ESG news and the drivers behind movements in security prices. In addition, we have gained insight into the potential of big data, and advanced our knowledge within statistical programming. Hence, working on this thesis has been rewarding both from an analytical and educational point of view.

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Abstract

This thesis examines the market reaction to negative environmental news in the Scandinavian stock market. As leading markets within ESG practices, these countries provide an interesting insight into the incorporations of ESG actions into investors' decisions. Accordingly, we investigate whether the degree of carbon exposure or the firm's environmental incident history affects investors' expectations and, consequently, reactions.

In contrast to previous research, we find no reaction to environmental news when examining the sample as a whole. While we hypothesize a different stock price reaction for carbon-intensive sectors, followed by a higher increase in abnormal trading volume than non-carbon intensive ones, we find no support for these two hypotheses. We argued that investors alter their anticipations due to carbon-intensive sector characteristics and environmental regulatory risk. However, we find no difference in market reaction based on carbon exposure. Secondly, we examine whether the firms' history of environmental offenses affects investors' expectations, hypothesizing lower stock price reaction and a smaller increase in abnormal trading volume for high- compared to low-frequency offenders. We argued that a higher incident rate should reduce asymmetric information related to the firms' ESG business conduct, causing a convergence in investors' opinions. This convergence is additionally explained by the high-frequency offenders contains larger firms on average. These firms often experience higher media coverage, reducing the asymmetric information. However, we find no difference between the two groups.

Nevertheless, the proposed firm size effect seems to hold. We detect an interesting relationship between market reaction and firm size, and time, respectively. Larger companies experience a less negative stock price and trading volume reaction, in line with the reduced asymmetric information argument. Concerning the time trend, we find a less negative market reaction over the decade. We argue that this reflects an increase in ESG awareness in the Scandinavian markets.

Accordingly, we conclude that no news for investors, is good news for ESG awareness and the transition towards a sustainable future.

Keywords: *ESG, Sustainable Investments, Carbon-Intensive Companies, High-frequency Offenders*

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1 Introduction

Over the past decade, the focus on environmental, social, and governance (ESG) issues has increased massively as sustainability has become an important aspect of business conduct. As a result, sustainable initiatives, ESG rating agencies, and ESG-linked databases have flourished. A change towards a sustainable path is dependent on the stock market, however, the value maximization of investors is often contradictory to the Paris Agreement, where recent research reveals that the total amount of greenhouse emissions is not declining (Broadstock et al., 2021). It is therefore appropriate to ask if companies embracing a more sustainable path are rewarded by investors or if investors, on the contrary, continue to invest in business as usual?

> "*Climate change cannot be denied, and in the future, capital will be significantly reallocated*" - *Larry Fink* (BlackRock, 2020)

Globally, The United Nations Global Compact (UNGC) and the Principles for Responsible Investment (PRI) put sustainable investments on the agenda in 2007. Since then, more than 4000 institutional investors and service providers from 60 countries have signed onto the PRI, and combined Assets under management (AuM) have increased from $6.5 trillion in 2006 to over $120 trillion in 2021 (PRI, 2022). While few companies published ESG reports back in 1990, this number has increased rapidly over the last few years. Initiatives like this have paved the way for sustainable investment strategies, where the capitalization of ESG-focused portfolios in major markets exceeded 300 billion US dollars in 2021(Broadstock et al., 2021). As an increasing number of investors integrate ESG information into their investment strategies (Serafeim & Yoon, 2021), this motivates for conducting our study.

In the transition towards a more sustainable future, players in the Scandinavian markets are often pointed out as leading markets (Gjølberg, 2009; SRI, 2018). For instance, the Norwegian financial industry has historically been considered to be at the forefront of socially responsible investing (SRI, 2018). In Denmark, there has been a further formalization of responsible investment principles, and the Swedish SRI market, where several institutional players that have been active for more than ten years, is considered mature (SRI, 2018). Although they are considered to be at the forefront of addressing the challenge of mitigating global climate change (Rootzén & Johnsson, 2015), their overall emissions continue to increase (Davis & Caldeira, 2010). Hence, while the Nordic economies have undergone a structural transformation, they are still dominated by carbon-intensive firms (Rootzén & Johnsson, 2015). Consequently, as the stock exchanges are closely related to several important global climate challenges, it is particularly interesting to examine whether the valuation of ESG is reflected in the Scandinavian equity markets by analyzing the market reaction to negative environmental news. Consequently, the analysis can serve as a thermometer for investors' ESG consideration of sustainable business conduct within the Scandinavian markets.

Furthermore, the media has become increasingly important in the transition toward a more sustainable global economy, by communicating aggregated ESG information. This has lead to an origin of new extensive databases which track ESG news for individual companies, which enables new research on the stock market reaction to ESG news on larger samples, to gain insights into investors' ESG considerations (Serafeim & Yoon, 2021). To further elaborate on this relationship and expand upon existing literature, we want to examine the relationship between ESG performance and firm value by analyzing how, and whether, investors react to environmental news.

Hypotheses

Formally, the thesis examines the impact of ESG news incidents on firm value and trading volume for Scandinavian companies from 2010 to 2020, by applying the RepRisk database which tracks daily ESG news across thousands of companies globally. We provide novelty to the literature by expanding our analysis by examining both price and volume reactions to gain more profound insight into investors' consideration of ESG news.

The analysis is divided into two parts. Firstly, we compare the market reaction to environmental news for carbon-intensive and non-carbon-intensive sectors, to gain insight into potential differences in investors' anticipations due to sector characteristics. Secondly, we separate the sample firms into either high- or low-frequency offenders to examine if there are differences in investor reactions due to firms' recent incident history. Consequently, we provide an in-depth insight into investors' ESG considerations, examining both firm and sector characteristics. We have formulated two research questions based on a review of previous research. Each research question has two subsequent hypotheses, to account for both stock price and trading volume reactions.

Research question 1: Is there a significant difference in the stock market reaction for firms in carbon-intensive sectors compared to non-carbon-intensive sectors, to negative environmental news?

> **H1.1:** *Carbon-intensive sectors will experience a different stock price reaction to negative environmental news than non-carbon-intensive sectors*

> **H1.2:** *Carbon-intensive sectors will experience a higher increase in trading volume in the days surrounding negative environmental news than non-carbon-intensive sectors*

Research question 2: Is there a significant difference in the stock market reaction for high-frequency offenders compared to low-frequency offenders, to negative environmental news?

> **H2.1:** *High-frequency offenders will experience a less negative stock market reaction to negative environmental news than low-frequency offenders*

> **H2.2:** *High-frequency offenders will experience a smaller increase in trading volume in the days surrounding negative environmental news than low-frequency offenders*

An implication of the analysis, relevant in this context, is that a common practice among investors, especially among Swedish investors, is to combine several strategies when responding to ESG incidents. These investors include both Exclusions, Engagement, and Voting, as part of a holistic approach to integrating ESG factors into the investment policy, process, and decision-making (SRI, 2018). Thus, when analyzing investor reactions, it is important to recognize that there are two main approaches an ESG-aware investor can apply; divestment or active engagement. Divestment is the removal of capital from funds, stocks, and other investment vehicles for moral and financial reasons (UNFCCC, 2021). Active engagement, on the other hand, is to actively engage with the company to tackle the ESG issue. Both approaches are important for the transition to a more sustainable future.

Findings

With respect to the first hypothesis H1.1 we argue that while environmental news incidents may be more expected within the carbon-intensive sectors, large cost uncertainties related to environmental regulatory risk and future growth opportunities complicate this picture leading to a significantly different abnormal stock price reaction. However, we find no support for this hypothesis. In the second hypothesis, H1.2, we argue that carbon-intensive firms experience larger abnormal trading volume at the occurrence of environmental news due to differences of opinion about the outlined cost uncertainties, thereby leading to higher abnormal trading volume. However, we neither find support for this hypothesis.

In the third hypothesis, we expand our analysis by examining whether the firms' recent incident history affects investors' anticipation and expectations of environmental news by dividing the sample into high-frequency and low-frequency offenders. Thus, hypothesis H2.1 tests whether high-frequency offenders experience a lower abnormal price reaction than low-frequency offenders. We argue that as the firms' incident rate increases, the investor will to a larger extent have anticipated and adjusted for such incidents, leading to a lower abnormal stock price reaction. However, we find no evidence of the proposed anticipation effect. With respect to the last hypothesis, H2.2, we test if the outlined anticipation effect is reflected in a smaller increase in abnormal trading volume. We neither find no support for this hypothesis, thereby concluding there is no evidence that the news is less unexpected for high-frequency offenders. Summarized, we argue that investors do not change their expectations and subsequently market reaction towards the Scandinavian firms, based on carbon exposure or their incident rate.

Structure

The thesis is divided into ten sections. The first section introduces the topic and relevance of the market reactions to ESG news. The second section accounts for existing literature, while the theoretical framework is presented in the third section. In section four, the research questions and hypotheses are developed. Further, the data sources are presented with the data selection criteria in section five. We present the research methodology in section six. In section seven, the results from the regression analysis are presented and discussed. Finally, in sections eight and nine, robustness analyses are conducted together with a critical assessment of the analysis before we provide our conclusion in section ten.

2 Literature review

2.1 ESG and Firm Value

The link between firms' choices around corporate responsibility and firm value has been studied for decades. One of the first views within neoclassical economics was Milton Friedman, who stated that "The social responsibility of business is to increase its profits" (Friedman, 1970). Later research emphasizes a trade-off between environmental initiatives and increasing profits, which all else equal, will lead to a point where the benefits of corporate social responsibility (CSR) and the marginal costs offset each other (Martin Curran & Moran, 2007). Furthermore, Benabou and Tirole (2010) and Kitzmueller and Shimshack (2012) argue that CSR activities do not enhance shareholder value from an agency perspective. Cheng, Hong & Shue (2013) find that ESG investments are associated with agency costs, as the managers conducting ESG initiatives are driven mainly by altruism, being more concerned about their own reputation than maximizing shareholder value, which according to Friedman (1970) is a disadvantage in a competitive market. This view aligns with Krüeger (2015), who finds that even positive ESG news results in a negative market reaction, though only for social and environmental related news.

Ferrell, Hao and Renneboog (2016) conclude oppositely, finding that well-governed firms experience fewer agency concerns while performing better on ESG management. They argue that, although it may be possible to increase profits in the short-term while disregarding ESG, it may lead to a higher probability of ESG incidents, negatively affecting firm value in the long run (Bénabou & Tirole, 2010). In addition, disregarding ESG could lead to a higher cost of capital (El Ghoul, Guedhami, Kwok & Mishra, 2011), reduced trust, and severe reputational damage to the firm (Fombrun, 1996; Fombrun & Shanley, 1990). From this point of view, ESG information and shareholder value may be related. It is suggested that improved ESG performance could lead to higher firm value due to stronger brand and customer loyalty, improved operating efficiency and employee engagement, as well as a higher credit rating, improved accounting and financial performance (Flammer, 2013; Fombrun & Shanley 1990; Turban & Greening 1997; Freeman, Harrison, and Wicks 2007; Edmans, 2011; Eccles, Ioannou, & Serafeim 2014; Lins, Servaes & Tamayo 2017).

2.2 Sustainability Within Sectors

Sustainability issues vary across industries and companies (Eccles & Serafeim, 2013). When considering financial materiality for the company, Eccles and Serafeim (2013) emphasize that ESG information is value relevant as it contains information about the firms' future growth, competitiveness and risk position. This view is supported by Khan et al. (2016), who show that investment in material sustainability issues can be value-enhancing for shareholders. However, the variation in the valuation impact of CSR issues across industries should be considered when conducting a multi-industry study (Griffin & Mahon, 1997). Overall, the extant literature points to considering the firm and industry-specific ESG materiality in determining value-creating and destroying dimensions of business conduct.

2.3 ESG Events

Several papers have investigated the stock market's reaction to ESG events. Flammer (2013) finds that the market reacts positively to the announcement of eco-friendly initiatives and negatively to eco-harmful events over the period from 1980 to 2009. Grewal, Riedl, and Serafeim (2019) examine the impact of ESG disclosure mandates in the European Union and document less negative market reaction to negative ESG events for firms with high ESG disclosure. This is consistent with Qureshi, Kirkerud, Theresa & Ahsan (2020), who find that ESG disclosure is positively correlated with firm value for European firms. Moreover, Minor and Morgan (2011) find that enhanced CSR reputation protects firms from negative news about the firm, thereby maintaining organizational legitimacy. In addition, Karakas, Dimson and Li (2015) examine ESG engagements by investors and find positive abnormal returns for engagements that were considered successful. Another stream of the literature considers various negative events such as corporate fraud (e.g., Karpoff & Lott, 1993; Chaney & Philipich, 2002), "unethical behavior" (Gunthorpe, 1997), product recalls (e.g., Jarrell & Peltzman, 1985), showing that these events have a significant negative impact on firm value.

2.3.1 ESG, Media Coverage, and Big Data

The great evolution of social media enables ordinary news events to be potential market movers (Capelle-Blancard & Petit, 2019). Accordingly, the media plays an essential role in disseminating information to a broad audience, especially individual investors (Fang & Peress, 2009). Hence, recent research considers a wider range of news. Within the Scandinavian markets, Larsen and Thorsrud (2018) examine the market response to economic news gathered from the Norwegian business newspaper Dagens Næringsliv. They find that news can effectively predict daily returns, confirming the media's crucial informational role. Furthermore, Serafeim and Yoon (2021) examine stock price reactions to different types of ESG news from the period 2010 to 2018, gathered from an artificial intelligence ESG database. They find a significant positive reaction to positive news considered material for the industry and a negative stock price reaction to material news, that are widely covered. Capelle-Blancard and Petit (2019) use the same type of database and find a significant negative price reaction of 0.137 percent for US firms to negative ESG news in their analysis of the period 2002 to 2010. However, they do not find a significant effect on the stock price to positive news (Capelle-Blancard & Petit, 2019).

While the literature often finds an immediate price reaction to negative ESG news, analysis of long-term stock performance yield inconclusive results. Cui and Docherty (2020) investigate the period 2014 to 2018 and find a significant drop in the stock price following negative ESG news, however, which recovers within the next 90 days. This may imply an overreaction to ESG controversies or firms reacting by undertaking actions to mitigate any negative effects of these news. On the other hand, findings by Glossner (2021) suggest that firms with poor ESG practices subsequently underperform their peers in terms of operational and stock performance. He suggests that investors underreact as understanding the value implications is difficult due to ESG rating disagreement, the need to separate material from immaterial ESG information, lack of standardized ESG reporting, and potential "greenwashing" activities by corporations (Glossner, 2021; Christensen, Hail, & Leuz, 2021).

2.4 Trading Volume and Market Reaction

Lastly, while several papers examine the market evaluation of new information through stock price changes, less research has been conducted on the trading volume effects of ESG news. Trading volume studies are more prominent within financial incidents such as earnings, dividends, and acquisition payments used to observe capital market reactions through trading volume movements (Mahendra & Rasmini, 2019). However, closely related to our paper, Cui & Docherty (2020) examine American listed stocks and find a significant increase in abnormal trading volume around negative ESG news incidents and a small increase in positive ESG news. Guo et al. (2020) examine the predictive power of ESG news on trading volume in the United States and European equity markets. They show that ESG news incidents are relevant for investors to consider as they may impact company risk and future returns. These papers demonstrate the value of examining the relationship between ESG and trading volume to gain further insight into the investors' perception of ESG and how these risk dimensions can affect the firms' performance.

3 Theory

3.1 Stakeholder Theory

The stakeholder theory discusses the relationship between corporate social responsibility in business and value creation. In stakeholder theory, a company is characterized as a set of relationships crucial to its functioning among individuals or groups who affect or are affected by its business operations (Freeman, 1984; Freeman et al., 2010). As opposed to the shareholder theory, where Friedman (1970) argues that business should focus on profits rather than social welfare, the stakeholders provide resources, benefit from the company, influence the business environment and influence its efficiency and impact (Donaldson & Preston, 1995). Therefore, value creation stems from the collective efforts of the stakeholder network and the withdrawal of support from stakeholders, which can threaten the company's viability (Freeman, 2010). According to stakeholder theory, effective management of stakeholder relationships may mitigate the possibility of negative legislative, fiscal action, or regulatory action (Freeman, 1984; Hillman & Keim, 2001). Thus, through positive relationships with stakeholders, CSR can increase firm value (Donaldson & Preston, 1995; Kacperczyk, 2009) and enhance corporate reputation (Fombrun, 2005), which connects CSR and thereby ESG directly to firm value and competitive advantage for firms (Jiao, 2010).

3.2 Market Efficiency and Informational Asymmetry

The efficient market hypothesis was introduced by Eugene F. Fama in 1970 and states that "security prices fully reflect all information" (Fama, 1970). Market efficiency can be divided into three different forms; weak, semi-strong, and strong efficiency. In the weak form of market efficiency, the security prices reflect all past stock prices. In the semi-strong form of market efficiency, all past stock prices and all publicly available information are reflected in the security prices. Lastly, in strong form efficiency, all information is reflected; past stock prices, as well as public and private information.

Fama (1991) acknowledges that it is generally accepted to classify the market as roughly semi-strong. As a result, there is an informational asymmetry between the owners of the firm and the investors. Under this assumption, if investors value the information embedded in the news incident, it should immediately be incorporated into the stock prices. Consequently, material negative news incidents will reduce the asymmetric information, and change the future expectations towards the firm based on the economic materiality of the incident.

4 Hypothesis

The thesis aims to quantify the stock market reaction for carbon-intensive companies exposed to environmental news, by examining investors' ESG considerations and, consequently, the market driver incentives for these companies to become sustainable. As presented in the literature review, previous research is somewhat divergent in how poor ESG practices affect firm value. In addition, to our knowledge, limited research has been conducted on the relationship between a sector's carbon intensity and the market reaction to negative environmental news incidents, especially in Scandinavia. Consequently, we have developed two research questions with subsequent hypotheses to gain deeper insights into this market while building upon previous literature.

According to stakeholder theory and theory of asymmetric information, a negative market reaction is expected following a negative material ESG news incident regardless of the firm's industry belonging and type of news. Stakeholders are agents of social control, and corporate controversies trigger higher stakeholder skepticism and perceptions of predominantly extrinsic motives, leading to less favorable stakeholder attitudes and behaviors toward the company (Du et al., 2010), leading to lower credibility (Yoon et al., 2006). Over the past decade, addressing environmental issues has become increasingly important to reach urgent climate goals. While there has been a structural transformation of the Scandinavian economies, they mainly consist of energy and carbon-intensive sectors (Rootzén & Johnsson, 2015). This leaves open the question of whether the reaction to environmental news is more or less negative for carbon-intensive sectors than for the rest of the market?

4.1 Research Question 1: Carbon-intensive Companies

4.1.1 Carbon-intensive Companies and Stock Price Reaction

Based on previous literature and discussion, we have developed the first research question: *Is there a significant difference in the stock market reaction for firms in carbon-intensive sectors compared to non-carbon-intensive sectors, to negative environmental news?*

Market reactions occur due to the news incident changing the firm's expected future cash flows through prospects of risk, competitive positioning, or future growth (Khan, Serafeim, & Yoon, 2016; Grewal, Riedl & Serafeim, 2019). According to perceived probability and cost expectation, rational investors price future anticipated environmental crises. Consequently, investors' anticipation of future environmental incidents for the firm determines the stock price reaction.

Carbon-intensive companies create value by exploiting and processing natural resources. Consequently, they are more heavily exposed to the environmental pillar than non-carbon-intensive firms due to the embedded operational risk. This makes their future earnings, risk, and positioning largely impacted by environmental incidents and subsequent penalties. As the high carbon emitters are associated with higher carbon risk, forward-looking investors should, consistent with Bolton and Kacperczykab (2021), seek compensation for holding these stocks. Likewise, we argue that environmental incidents, to a larger extent, should be anticipated by the investors, thereby reflected in the firm value. Following this argument, we expect the marginal impact of an environmental news incident to be smaller for carbon-intensive companies, as the incident is less likely to alter the anticipated growth prospects of the firm. Hence, one could expect a less negative reaction for carbon-intensive sectors than non-carbon-intensive ones.

However, investors face challenges when determining the financial consequences of future environmental incidents. Carbon-intensive companies have strong elements of complexity as these sectors face several uncertainties concerning the energy transition, such as being susceptible to more stringent regulations concerning the timing and commitment requirements of policies, i.e., carbon risk and application of new green technologies (Hsu et al. 2021; De Haas et al., 2021). Several environmental metrics such as CO2 emissions, total energy use and waste production are not necessarily considered financial material today, though they are core in assessing any company's environmental impact (OECD, 2021), especially for the carbon-intensive companies. Thus, while we argue that environmental incidents are likely more expected within these sectors, assessing their exact probability and economic magnitude may be difficult for investors. Furthermore, they are prone to more public scrutiny than other industries, as they face more stakeholder demand and pressure for increased transparency and compliance (Banerjee, 2019).[1] Consequently, the marginal effect can still be more prominent in these sectors.

Thus, while we argue that the sector characteristics of carbon-intensive companies may increase investors' anticipation of an environmental incident occurring, the complexity in estimating its financial impact makes it challenging to determine which of the marginal effects will dominate relative to the non-carbon-intensive. Consequently, we hypothesize the following:

H1.1: *Carbon-intensive sectors will experience a different stock price reaction to negative environmental news than non-carbon-intensive sectors*

[1] An example is oil majors who gave into investor pressure recently where for example Royal Dutch Shell had to set carbon emissions targets, and ExxonMobil had to disclose the impact on future activities (Financial Times, 2017; The Economist, 2018; Wall Street Journal, 2019)

4.1.2 Carbon-Intensive Companies and Trading Volume

We expand the analysis by examining trading volume reactions. As pointed out in the literature review, one should be cautious with inference based only on volume (Lamoureux & Lastrapes, 1990), however, the price-volume relationship can be exploited for fine-tuning the inference (Richardson et al., 1986). Karpoff (1987) states that testing for abnormal returns in combination with abnormal trading volume could increase the power of the tests. Thereby, combining the stock price reaction with trading volume could provide a deeper insight into investors' reactions to the environmental news.

A relevant theory in the literature of why investors trade is heterogeneity in investors' beliefs regarding the financial impact of new information (Beaver, 1968; Harris & Raviv, 1993; Kim & Verrecchia, 1997).[2] Harris and Raviv (1993) explain that while investors receive the same information, "differences of opinion" may occur where each investor assumes their interpretation is the most valid. In addition, according to Kim and Verrecchia (1991a, 1991b), it is the combination of the financial importance of the news and the amount of unexpectedness among the investors which generates abnormal trading volume following a news incident.

As previously argued, investors should expect environmental incidents for carbon-intensive companies to a larger extent due to their inherent link to natural resources. Thus, the unexpectedness of an environmental news incident is likely lower for carbon-intensive companies. All else equal, this should lead to a smaller increase in abnormal trading volume for these companies. Nevertheless, we argue that carbon-intensive companies could experience differences in opinion regarding the extent to which the financial consequences of the environmental incidents occur. While there has been an increasing scientific consensus on the cause of climate change, Barosso del Toro et al. (2022) argue that the factuality of climate change proven by the scientific community is not evident to all market participants. Consequently, within the carbon-intensive sectors, investors are divided

[2] Beaver (1968) provides two definitions of informational content. Firstly, the environmental news has information content if it leads to a change in investors' assessment of the probability distribution of future returns (Beaver, 1968), meaning there is a change in the equilibrium value of the current market price, which we test by the former hypothesis. However, the second definition emphasizes that the former change in expectations must also be sufficiently large to induce a change in the decision-maker's behavior (Beaver, 1986), meaning that the environmental news have informational content if it leads to reallocation of the holding of that firm's stock in the portfolios of individual investors, which would be reflected in the volume (Beaver , 1986).

between this narrative versus the search for high returns (Barosso del Toro et al., 2022) when environmental news incidents occur. This can give rise to different opinions among investors. Those who emphasize sustainability and its consequences in their investment decision may react negatively to ESG news, while investors chasing higher returns will trade on this opportunity as long as there are no financial consequences. Hence, we argue this will generate higher abnormal trading volume when environmental news incidents occur.

In addition, we argue that the expected regulation risks carbon-intensive firms are facing further generate differences in opinion. The regulation risks are likely to impose larger financial consequences through regulatory interventions for these sectors, as they impact their core operations and business conduct. Hence, when an environmental incident occurs, the investors may be more divided in opinion regarding the time horizon for when and to what extent potential financial consequences for the firm will occur. This could induce higher abnormal trading volume for carbon-intensive firms than for non-carbon-intensive firms. Based on these arguments, we argue that the sum of differences in the investors' opinions will be reflected in significantly higher abnormal trading volume. Accordingly, we hypothesize:

H1.2: *Carbon-intensive sectors will experience a higher increase in trading volume in the days surrounding negative environmental news than non-carbon-intensive sectors*

4.2 Research Question 2: High-frequency Offenders

4.2.1 High-frequency Offenders and Stock Price Reaction

Our next research question elaborates on how companies' incident history affects investors' anticipation and expectation towards the firm and subsequently the stock market reaction when a news incident occurs. By separating the sample into high-frequency and low-frequency offenders, we examine whether investors react systematically differently towards the two groups when an environmental news incident occurs.[3] This separation allows us to examine whether investors change their firm expectations based on historical incident

[3] The two groups are divided based on the median of all the 316 events incident rate, calculated as the number of incidents preceding 12 (1-year lookback period) or 24 months (2-year lookback period) from the event date, respectively. A thorough explanation of the construction of the measure is provided in section 5.3.

rates. Thus our second research question is developed: *Is there a significant difference in the stock market reaction for high-frequency offenders compared to low-frequency offenders, to negative environmental news?*

While a single news incident does not necessarily reflect the firms' ESG practices, an extensive history of environmental violations is more likely to do so. Accordingly, a firm with repeat involvement in negative environmental incidents should lead investors to alter their anticipation of future potentially costly incidents. Hence, consistent with the efficient market hypothesis, investors will to a larger extent anticipate subsequent news incident, thereby adjusting their expectations. This will, all else equal, lead to a lower relative marginal impact of the incident when it occurs. An adjustment of expectation seems plausible and is consistent with Glossner (2021), who finds that the historical ESG incident rates predict additional future incidents.

Furthermore, there are potential differences in the two groups' sample composition, which should further impact the relative stock price reactions. Fang and Peress (2009) find that firm size has an overwhelming effect on media coverage. Hence, we argue that there should be a disproportional amount of large companies within the high-frequency offender group. As larger firms often consist of several divisions, due to their widespread operations, they should be more prone to such incidents. Thus, while being more exposed to environmental news incidents, the marginal relative effect of the news incident is likely lower for larger companies as the incidents only affect parts of the company. Hence, all else equal, this should lead to a lower stock price reaction for high-frequency offenders.

Summarized, due to an expected convergence regarding the anticipation of future news incidents and probable firm characteristics of high-frequency offenders, we have developed the following hypothesis:

H2.1: *High-frequency offenders will experience a less negative stock market reaction to negative environmental news than low-frequency offenders*

4.2.2 High-frequency Offenders and Trading Volume

As discussed, the high-frequency offenders have distinct characteristics, which may further result in a different volume reaction. Therefore, similarly to the price-volume discussion leading up to hypothesis 1.2 in section 4.1, examining the volume effects of being at high-frequency offenders can give valuable insight into investors' expectations of these companies.

Based on the proposed difference in expectation between high-frequency and low-frequency offenders, it is reasonable to believe that investors' should converge in opinion regarding their anticipation of future incidents based on the historic incident rate of the firm. This implies that the high incident rate should reduce information asymmetry and subsequently reduce the element of unexpectedness in the news, leading to a smaller increase in relative abnormal trading volume. Furthermore, the proposed extensive amount of larger firms among the high-frequency offenders will further reduce the asymmetrical information due to higher media coverage. As the informational asymmetry regarding the firm's ESG practice decreases, the subsequent news conveys less novel information that does not alter the subjective anticipated growth prospects, thereby further prompting convergence in opinion. Consequently, the high-frequency offenders should experience a smaller increase in abnormal trading volume than the low-frequency offenders to an environmental news incident. With this last hypothesis we conclude the hypothesis development section:

H2.2: *High-frequency offenders will experience a smaller increase in trading volume in the days surrounding negative environmental news than low-frequency offenders*

5 Data

5.1 Event Data

5.1.1 The RepRisk Database

The environmental news incident data is collected from the RepRisk News Data database. The database uses a combination of artificial intelligence (AI), machine learning, and human intelligence to identify material ESG news using the SASB Materiality Map Classification System (Reprisk, 2022). This ensures that the incidents are likely financially material for the firms, which is crucial as only material news are expected to change the firm value (Serafeim & Yoon, 2021).

RepRisk identifies, categorizes, and links ESG incidents to companies and projects worldwide from more than 100,000 third-party sources and stakeholders in 23 languages. The process consists of four steps. The first step is the screening and identifying ESG incidents using AI and machine learning. Each ESG incident is categorized into one or more of Reprisks 28 defined topics and linked to the relevant company. The second step consists of an internal analyst reviewing and approving the screening results to ensure that the news about the incident and the incident itself has been correctly logged. Thirdly, before a risk is published, the analysis undergoes quality control by a senior RepRisk analyst to ensure that the overall process aligns with RepRisk's strict, rule-based methodology. As a final step, the incident is quantified by the proprietary RepRisk Index, which is a weighted moving average of a firm's incidents done using data science (Reprisk, 2022).

Using Reprisk to gather ESG news data results in a cross-national sample over multiple years, eliminating initial selection bias.[4] We have downloaded data from the 1st of January 2010 to the 31 st of December 2020 for companies listed on the Oslo Stock Exchange, Nasdaq Stockholm and Nasdaq Copenhagen. The data was downloaded on 20.02.2022.

The relevant information gathered from the database is *the ID of the news incident, the date of the news incident, the company linked to the news incident, the SDG topics linked*

[4]Conditional on the initial RepRisk data collection process not being biased

to the incident, country of news origin, the severity of the incident, and the source reach of the incident.

In total, the sample consist of 316 environmental news incidents, distributed over 95 firms. The environmental news incidents are categorized by the RepRisk methodology to be linked to one or more of the following six topics, presented in the table 5.1 below.

Table 5.1 List of Environmental News in the RepRisk Database

Issue	**Definition**
Animal mistreatment	This issue refers to the torture, mistreatment or abuse of animals, through experiments, husbandry, trophy hunting, etc.
Climate change, GHG emissions, and global pollution	This issue covers impacts of company activities on ecosystems or landscapes such as forests, rivers, seas, etc., contamination of groundwater and water systems, deforestation, impacts on wildlife, etc.
Impacts on landscapes, ecosystems, biodiversity	This issue includes pollution, mainly atmospheric, that has negative impacts beyond the surroundings in which the emissions occur.
Local pollution	This issue covers pollution into air, water, and soil that has a primarily local effect, including oil spills, etc.
Overuse and wasting of resources	This issue relates to inappropriate disposal or handling of waste from the company's production processes or projects, as well as waste trafficking.
Waste issues	This issue refers to a company's overuse, inefficient use of waste of renewable and nonrenewable resources, such as energy, water, commodities, etc.

Source: RepRisk

5.1.2 Confounding Events

As for all event studies, there is a risk of confounding events. McWilliams and Siegel (1997) point out that it is difficult to isolate the studied event's impact if other financially relevant events occur during the event window, which will lead to an unreliable inference. Nevertheless, they argue that a short event window to some extent can limit the potential for confounding effects.

We have taken several precautions to adjust for confounding events that may affect the stock price. First, as Reprisk provides a "News-ID" for each news item, we delete the subsequent news with the same ID to ensure that only novel news is present in the sample. Second, we have excluded news incidents within five days of a previous news incident for the same firm, to ensure no overlapping event days for the same firm. This rule-based method is used to avoid selection bias in the data sample. Third, to ensure that the effects captured in the event window are not related to other apparent confounding events, we have manually examined the most extreme abnormal returns and trading volumes, thereby deleted events where we find confounding events.

Consequently, while we have removed the most prominent confounding events, there may still be confounding events within the sample. However, as these are likely to be random, implying that they are not systematically correlated with the news incidents, it is unlikely that they will affect the validity and robustness of the study.

5.2 Data Sources

5.2.1 Stock Prices and Trading Volume

Share price and trading volume data has been collected from Datastream Refinitiv for each event to calculate returns. In addition, to control variables used in the cross-sectional regressions have been retrieved from the same database.[5] All price data is downloaded in dollars to ensure that currency fluctuations has been taken into account. The estimation data used for the market model has been downloaded with an estimation window of 120 trading days preceding the news incident date, in line with MacKinlay (1997). The length

[5]We have supplemented the control variable data on debt from Datastream Refinitiv using Bloomberg when needed.

of the estimation window is chosen to have sufficient data points for each event, while at the same time ensuring event proximity for data comparability. The last 20 days before the event date has been left out to avoid possible news leakage effects in the estimation period (MacKinlay, 1997).

5.2.2 The Stock Market Index

In applying the Market Model, we select the MSCI World Value Weighted Index to represent the market portfolio under the assumption that the marginal investors are global investors. The MSCI World Value Weighted Index comprises 1,542 companies across 23 developed markets, covering about 85% of the free-float adjusted market capitalization (MSCI, 2022). We downloaded the MSCI World Value Weighted Index for the sample period, spanning from the 1st of January 2009 to the 31 st of December 2020.

5.2.3 Data Corrections

To ensure that the event data is sufficiently comprehensive and accurate, we have made additional corrections. Firstly, the news incidents in the RepRisk datbase are logged in accordance to publication date of the news incident. Thus, we have corrected for news incident occurring during weekends or bank holiday over the whole sample period.[6] Second, some news incidents occur on days in which are bank holidays in the United States. Thus, we have estimated these days' returns by averaging the days' returns in the event window for the MSCI World Value Weighted Index. Third, we have filtered out all events between the 1st of March to the 21 st of November 2020 to adjust for probable confounding events and extreme return effects from the Covid-19 pandemic. Therefore, we have assumed that stock markets returns between 1st of March and 1st of June are largely affected by the pandemic. Subsequently, all events which occur during this period, or have an estimation period including these dates, are excluded from the sample. The remaining events are selected based on the following criteria:

- The entity must be publicly listed on one of the three stock exchanges, for the whole event estimation period. However, we allow for firms to be de-listed or dissolved over the time period of the analysis (2010-2020).

[6] The incidents have been re-dated to the first subsequent trading day of the respective stock exchange.

- Only companies with available data in Refinitiv Datastream, alternatively Bloomberg, are included in the sample.
- We have filtered out the least severe news according to RepRisk's own classification, keeping only medium and high severe news. For simplicity reasons, we combine these two levels under the definition "severe news".[7] This ensures that the news has sufficient influence and consequences, consistent with Serafeim and Yoon (2021).
- Lastly, as we focus on environmental incidents, news related solely to governance and social issues are excluded from the sample.

5.3 Variables

In this section, we describe and define the explanatory variables used in the analysis.

5.3.1 Key Explanatory Variables of Interest

Carbon-intensive sectors

In this analysis, carbon-intensive sectors are defined as all companies directly responsible for Scope 1 emissions, classified by SASB's Sustainable Industry Classification System (SICS)(SASB, 2022).

High-frequency Offenders

We separate the data sample into low-frequency offenders and high-frequency offenders, thus creating two sub-sample groups. Through this division, we aim to examine if there is a difference in investor expectations and subsequently market reaction, between being a high-frequency or low-frequency offender. The division is based on whether the company's incident rate preceding the event has been below or above the sample median of the total sample' incident rates.

We calculate each event's incident rate using a look-back window preceding 12 months of each event.[8] This allows for a rolling annual look-back period. Thus, the preceding events

[7] "The severity is determined as a function of three dimensions: firstly, what are the consequences of the risk incident (e.g., concerning health and safety: no further consequences, injury, death); secondly, what is the extent of the impact (e.g., one person, a group of people, a large number of people); and thirdly, was the risk incident caused by an accident, by negligence, or intent, or even in a systematic way. There are three levels of severity: low severity, medium severity, and high severity." (Reprisk, 2022)

[8] For incidents occurring in 2010, we have used 2009 event data to give each event an accurate incident rate. Ensuring that all events have equally long lookback-period.

determine whether a firm is categorized as a high-or low-frequency offender at the event date. This allows companies to change between being high-or low-frequency offenders over the sample period, making it a dynamic relationship which takes into account changes in firms ESG business conduct over time.

The sample median is the median of all events' incident rates. Thus, the sample median reflects the most frequent incident rate in the sample. Hence, we split the data sample using an incident rate of 3 incidents employing the one-year lookback period and 5 incidents within a two-year lookback period.

The one-year calendar look-back window is based on the assumption that the marginal global investor has a one-year investment horizon. To ensure robustness in our results, we further consider a longer investment horizon using a two-year calendar lookback period.

5.3.2 Additional Explanatory Variables

5.3.2.1 Company Characteristics

Market Capitalization

In order to control for size, we compute company market capitalization by multiplying the closing price and the total number of shares outstanding the day prior to the news event date. This methodology is in line with the method used by Serafeim and Yoon (2021) on the American stock market. As the variable may include large outliers that could influence the results, we use the natural logarithm of market capitalization. Formally, the equation can be derived as:

$$Equity_{MV,t-d} = Outstanding\_Shares_{t-d} * PPS_{t-d} \tag{5.1}$$

Debt Ratio

Fama and French (1992) found a negative relationship between the book value of leverage and stock returns. Thus, as a proxy for financial risk and capital structure, we control for the company's debt ratio (Chen et al., 2021). The debt ratio is calculated by dividing the book value of equity over the book value of debt using the last reported debt value. Debt is reported quarterly. Formally derived as:

$$D/E\_Ratio_{t-y} = \frac{Debt_{BV,t-y}}{Equity_{BV,t-y}} \tag{5.2}$$

5.3.2.2 Market Conditions

Time

As illustrated by the descriptive statistics in the next section 5.4, there has been a substantial increase in environmental news during the decade. Thus, we have created a time indicator to control for variations over time that may occur due to the increasing focus on ESG. We control for four periods: 2010 to 2012, 2013 to 2015, 2016 to 2017, and 2018 to 2020, where 2010 to 2012 is treated as the reference category in the cross-sectional regressions.

Furthermore, we have created an interaction variable between being in a carbon-intensive sector and the time indicator. Thereby, we can examine whether the market perception and reaction to environmental news for carbon-intensive sectors have changed between the different time periods.

5.3.2.3 News Characteristics

Reach

Reach can indicate the extent to which the news incident is broadcasted to the market. Reach is a variable provided by RepRisk in relation to a news incident and is "classified in accordance to influence based on readership/circulation as well as by its importance in a specific country" (Reprisk, 2022). The database classifies the news incident as either limited, medium, or high reach. Limited reach sources are for instance local media, smaller NGOs, and social media. Medium reach is most national and regional media, international NGOs, and international governmental bodies. Lastly, high reach is truly global media outlets such as BBC, China Morning Post, and NY Times (Reprisk, 2022).

Due to a limited amount of high reach media coverage within our data sample, we choose to pool the medium reach and high reach media sources. This is to avoid a small sample bias which would invalidate inference. Hence, we end up with two groups, High Reach and Low Reach, and create an indicator variable "High Reach" which takes takes the value one or zero.

5.4 Descriptive Statistics

The following subsection provides descriptive statistics of the data sample. The first section describes the full sample, while the second section shows the sample divided into carbon-intensive and non-carbon-intensive sectors. The third section describes the sample divided into high- and low-frequency offenders separately, allowing for a comparison of the two groups. Finally, we will provide an overview of the most frequent offenders, as well as an illustration of the environmental news incident in the sample throughout the decade. The final data set consists of 316 news incidents distributed over 95 firms.

Table 5.2 Full Sample

Full Sample N=316

Statistic	Mean	Median	St. Dev.	Pctl(25)	Pctl(75)	Max
News Incident Rate	6.585	3	8.378	1	8	39
Market Capitalization	18,348	6,638	25,058	1,823	23,286	113,771
Debt Ratio	0.370	0.187	0.503	0.077	0.431	3.211
Reach	1.535	2	0.548	1	2	2

The news incident rate is provided using a 12 month lookback period.
Market Capitalization is reported in thousands. Source: RepRisk, Datastream Refinitiv, Bloomberg

Table 5.2 presents the total number of events, mean, median, and the first and third percentile of all the explanatory variables applied in the analysis. The news incident rate represents the number of environmental news for a firm over a 12-month period. This news incident rate conveys that a few companies have a substantially high number of news incident, as the 75^{th} percentile is the number of 8 while the maximum is 39. This must be considered as it conveys that the data most likely contains substantial individual effects, which can limit the applicability of the cross-sectional regression results outside the sample, and affect the validity of our sample.

Table 5.3 Carbon-Intensive vs. Non-Carbon-Intensive Sectors

	Carbon-Intensives *N=198*		Non-Carbon-Intensives *N=118*		*Difference in*	
Statistics	Mean	Median	Mean	Median	*Mean*	*Median*
News Incident Rate	8.2	4	3.6	2	4.2***	2*
Market Capitalization	15.625	15.847	15.188	15.221	0.437	0.626
Debt Ratio	0.319	0.141	0.475	0.374	-0.156***	-0.233***
Reach	0.495	0	0.534	1	-	-
	Pctl(25)	Pctl(75)	Pctl(25)	Pctl(75)	*Pctl(25)*	*Pctl(75)*
News Incident Rate	1	10	1	4	0	6***
Market Capitalization	14.763	16.423	13.688	17.121	1.075	-0.698
Debt Ratio	0.067	0.336	0.128	0.754	-0.061*	-0.418***
Reach	1	2	1	2	-	-

Test for difference in means: t-test (we control for diff. in variances using F-tests for variances)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The news incident rate is provided using a 12 month lookback period.
Source: RepRisk, Datastream Refinitiv, Bloomberg

Table 5.3 compare carbon-intensive companies with non-carbon-intensive companies. As expected, the highest number of offenses is found within the carbon-intensive sectors, with a significant higher incident rate concerning the mean and median. Comparing the market capitalization, we find no significant difference between the two groups. However, the non-carbon-intensive firms have significantly higher debt ratio, implying they are more leveraged. Thus, the two groups somewhat differ in company characteristics. Thereby, these descriptive further emphasizes the motivation for comparing the two groups.

While there seems to be a slight difference in the average media reach of news incident ("Reach") between the two groups, it is not significantly different. Thereby, it does not appear to be difference in reach of environmental news incident based on carbon exposure. This could be reasonable as the news examined are classified as severe through RepRisk's classification system. Consequently, due to lack of difference in reach, there is limited possibility of a sample bias concerning media coverage between the two groups.

Table 5.4 High-frequency vs. Low-frequency Offenders

	1-Y Incident Rate		*Diff.*	2-Y Incident Rate		*Diff.*
	High Firms=26 *N=145*	Low Firms=90 *N=171*	*H-L*	High Firms=22 *N=100*	Low Firms=94 *N=216*	*H-L*
Mean	12	2	10***	28	3	25***
Median	8	1	7***	24	3	21***
Market Capitalization	16.410	14.658	1.752***	16.843	14.822	2.021***
Debt Ratio	0.263	0.471	-0.208***	0.207	0.454	-0.247***

Test for difference in means: t-test (we control for diff. in variances using F-tests for variances)
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
This table presents summary statistics for high-frequency offenders (*High*) versus low-frequency offenders (*Low*) for each level of over 4 incidents over a 12 month period (1-Y Incident Rate), and 6 incidents over a 24 month period (2-Y Incident Rate), respectively.
Source: RepRisk, Datastream Refinitiv, Bloomberg

Table 5.4 presents the same statistics as above, however, divided into being a low- or high-frequency offender. As expected, due to the wide range in incident rates, there is a significant difference in the mean and the median between the two groups. Furthermore, high-frequency offenders have a significantly lower debt ratio and higher market capitalization. This is consistent across the two look-back windows. As expected, high-frequency offenders are in our data sample larger. This seems reasonable as larger firms often have a higher analyst and media coverage (Eleswarapu et al., 2004), which implies that more environmental incidents may be captured by the media. The significant difference confirms the argument upon hypothesis H2.1 in section 4.2, where we argued that high-frequency offenders where more likely to be larger firms.

To further examine the characteristics of the high-frequency offenders we isolate the top 15 firms with the highest incident rates over the examination period 2010 to 2020, illustrated in table 5.5

Table 5.5 The fifteen companies with the highest # of environmental news incidents

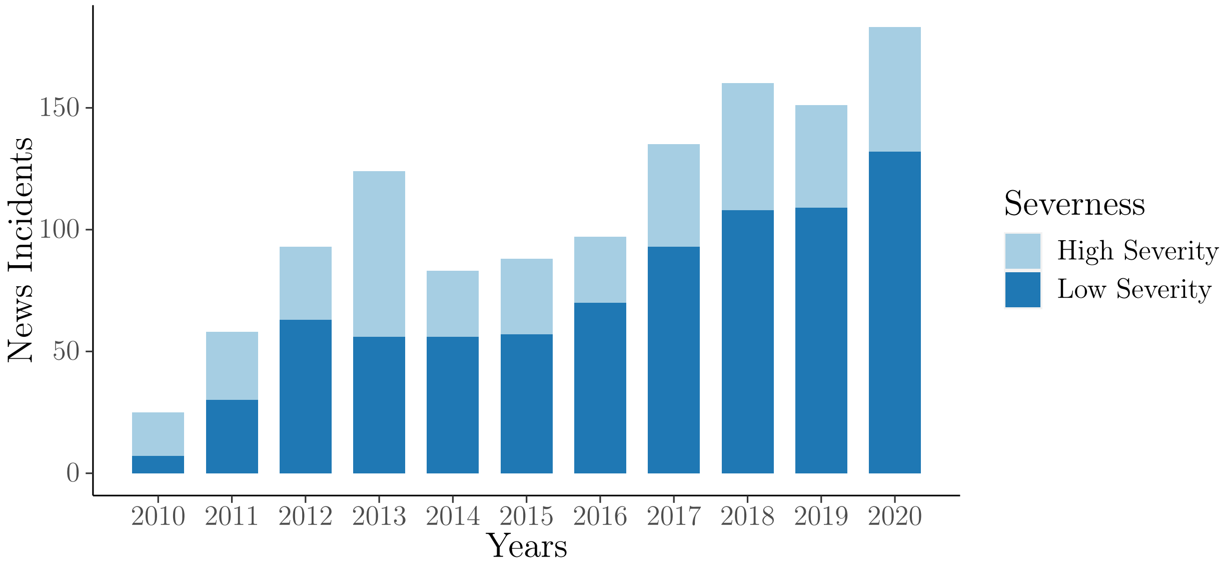
	Firm	News	Market Capitalization	Carbon-Intensive?
1	Equinor ASA	40	70,916	Yes
2	Norsk Hydro ASA	24	10,597	Yes
3	Yara International ASA	14	11,836	Yes
4	Mowi ASA	12	8,842	Yes
5	AAK AB	10	3,637	Yes
6	Boliden AB	9	4,916	Yes
7	Hennes & Mauritz AB	9	41,649	No
8	Nordea Bank Abp	9	40,499	No
9	Afry Services AB	8	998	No
10	Lundin Energy AB	8	7,455	Yes
11	Danske Bank A/S	7	27,211	No
12	Skandinaviske Enskilda Banken	7	21,657	No
13	Swedbank AB	7	23,610	No
14	DLT ASA	6	94	No
15	Odfjell SE	6	268	Yes

Table 5.4 illustrates the fifteen companies with the highest number of environmental news incidents. News are maximum environmental news within the period, and the market capitalization is shown in thousands. Source: Reprisk and Datastream Refinitiv

As illustrated in table 5.5 it is evident that the high-frequency offenders are from several sectors, both carbon-intensive and not. This is interesting and motivate for further examination of the differences based on frequency of news incident across the sectors. Furthermore, the table shows that there are some firms which represent a large part of the sample, Especially Equinor and Hydro. Consequently, when we separate the sample between high- and low-frequency offenders, these companies may influence the results and affect the validity of our study as they together constitutes 44 percent of the high-frequency offenders. Nevertheless, we have chosen to include them in the data sample and provide the results without Equinor and Hydro in Appendix A.2.1.[9]

[9]An alternative approach for handling this problem could be to increase the sample size by including additional stock exchanges. However, as the motivation of this analysis was to gain insight into the Scandinavian market, we have rather chosen to conduct the analysis with and without the two firms, addressing potential differences in the robustness section.

Figure 5.1 Environmental News Incidents per Year



Source: Reprisk

Figure 5.1 illustrates the distribution of environmental news incidents in our data sample over the the last decade. In this figure we have included all news incidents, both the severe and non severe to gain full insight into the development of media coverage on environmental news. The figure reveals a growth in news incidents, which is expected due to the rapidly increasing focus on ESG and ESG disclosure in the last few years. However, by isolating the severe news into high and low there is no apparent time trend. Hence, in the cross-sectional analysis we control for time in order to investigate whether the overall increase in all levels of environmental news has altered the investors anticipation towards carbon-intensive companies and frequent-offenders, thereby examining if they have become more sophisticated in interpreting the possible financial consequences.

6 Methodology

6.1 A Two-Step Hypothesis Testing Procedure

To test the hypotheses, presented i section 4, we apply a two-step hypothesis testing procedure. First, we apply a t-test on the event study returns and trading volume, and secondly, a cross-sectional analysis as described by MacKinlay (1997). An event study allows for estimating the effect of an economic event on the firm's value, giving more profound insights into how investors value negative Environmental news incidents and thereby one can approximate the valuation impact. To further investigate whether there is an association between the magnitude of abnormal returns and trading volume and certain determinants of the event observation, we use a cross-sectional analysis.

This section will explain the econometric methodology of event studies for investigating both the stock price and the trading volume. Firstly we will explain the structure of the event study, then we will elaborate on models to estimate normal performance. Furthermore we derive the equation for computation and aggregation of abnormal returns and trading volume. Lastly, we explain the cross-sectional tests and the methodology for the multivariate cross-sectional analysis.

6.1.1 Event Study Methodology

Event studies can be used to estimate the stock price reactions around corporate events. Stock price changes reflect how rational investors adjusted expectations of the discounted value of all future and current cash flow. The four underlying assumptions of event studies are that (1) markets are efficient (Fama et al., 1969) as discussed in section 3, (2) the market participants are fully rational, (3) the event must be unanticipated, meaning no related information has been leaked in advance of the event, and (4) finally, there are no confounding events to ensure the stock market reaction is related to the specific event (McWilliams & Siegel, 1997).

An advantage of using the event study methodology is that one can precisely calculate abnormal returns due to a firm-specific, yet time-independent, event, as one aggregates results across many firms experiencing a similar event at different times (Ahern, 2009).

This is beneficial for our study, which consists of several firm-specific Environmental events which are independent over time. Though many have criticized statistical issues with the event-study methodology, simple solutions have been developed leading to unbiased and powerful tests the average effect of the event on the sample firms (Binder, 1998).

6.1.2 The Structure of The Event Study

This section will provide a brief explanation of the event study framework. There are several structures of an event study, where we choose to use the framework of MacKinlay (1997). Figure 6.1 illustrates the time line for our event study. The initial task of an event study is to select the event that will be analyzed based on the purpose of the study, which in our study is the environmental news retrieved from the Reprisk database. To examine the stock price during the days surrounding the publication of the Environmental news incidents one must define the "event window" which is defined from [t_2, t_3]. The event window can expand from one to several days depending on the certainty which one can identify the event date and whether the event may already be known to the market. In our study, Reprisk relies on AI to identify the date of interest. While this is reasonably satisfactory, one should according to MacKinlay (1997) expand the event window to avoid omission of the event. Albeit, a too long window may increase the the risk of confounding events. This is widely supported in the literature, where McWilliams & Siegel (2001) argue that a narrow event window gives more precise tests and results. Accordingly, we examine three event windows which are [0], [-1, 1] and [-2, 2] days.

Furthermore, the event study is conducted by subtracting the estimated expected return from the actual return during the event window. Thus, it is necessary to estimate the normal performance of the stock which will be elaborated on in the next section 6.2. For the estimation of the normal performance one must use a estimation window pre of the event (Henderson, 1990). According to MacKinlay (1997), a period prior to the event is most commonly used for the estimation window, and it should not overlap with the event window. Thus we include a "hold-out window" which are not included in the estimation of normal performance to prevent of 20 days to exclude potential drift and co-founding events, preventing this from impacting the estimation window. This is illustrated in the figure as the period (t_1, t_2).

However, when choosing the length of the estimation window there are no set rules in the literature. It should be sufficiently long to obtain a precise estimate, meaning that the variance of the daily returns should be minimized, and short enough to not have structural breaks, meaning only including most recent price movements and thereby preventing changes in systemic risk (Strong, 1992). Nevertheless, a minimum of 100 days is adequate to obtain a precise estimate according to Armitage (1995). Nevertheless, consistent with MacKinlay (1997) we use 120 trading days for our estimation window, illustrated in figure 6.1 by (t_0, t_1).

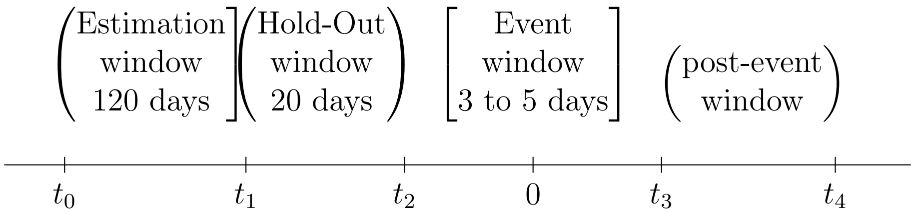


Figure 6.1 Time Line for an Event Study

We use daily stock returns and trading volume in this thesis. As we have several events for the same company, one should avoid past events influencing the estimation window upon the new event as it could increase variance. Consequently, these events are excluded from the estimation window for the respective company. Furthermore, the holdout window consists of 20 days. The event window varies from 3 to 5 trading days because of a possible imprecise event date as elaborated on in subsection 5.1.

6.2 Normal Performance Models

In order to calculate abnormal returns during the event window, it is necessary to estimate the normal performance of the securities. According to MacKinlay (1997), there are several approaches for calculating the normal returns. The approaches can be grouped into two categories: statistical and economical. An example of the first category is *the Market Model* which is based on statistical assumptions for the asset returns, and it assumes that it is only one factor, the market, which cause systematic risk. The economic models such as the *Fama French's three-factor model* add other explanatory macro factors that may affect the stock price. However, there are small gains in using the economic models compared to the statistical models such as the Market Model, which is reflected by the statistical models used more frequently in event studies (MacKinlay, 1997). The Market Model is often the preferred model (MacKinlay, 1997), where Armitage (1995) has tested it against several models and found the Market Model to perform equivalently to the best alternative. Thus, we will apply the Market Model in line with previous literature. However, The Market Adjusted Model serves as an alternative model when it is not feasible to have a pre-event estimation period for the normal model parameters (MacKinlay, 1997). This model may be beneficial as Environmental news incidents may occur within the estimation period for the same firm, thus potentially increasing variance during the estimation period. We will apply this model as an alternative to the Market model to test the robustness of our results. The two following subsections will elaborate on the chosen normal performance models.

6.2.1 The Market Model

The market model is a one-factor model which assumes a stable linear relationship between the return of a market portfolio and the security return. This linear specification is based on an assumption of joint normality of asset returns (MacKinlay, 1997). Equitation 6.1 derives the market model for each security i,

$$\begin{gathered} R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it} \\ E(\epsilon_{it} = 0), \quad var(\epsilon_{it}) = \sigma^2_{(\epsilon_i)} \end{gathered} \tag{6.1}$$

where R_{it} and R_{mt} represent the returns on security i and the market portfolio, respectively, at time t, and the e_{it} is the disturbance term with an expected mean value equal to zero and a variance of σ_{ei}. The parameters alpha and beta are estimated using OLS by the observations during the event window. For the market portfolio, we use the MSCI World Value Weighted Index as a proxy for the market returns, as we assume all investors to hold a global portfolio of stocks based on the assumption of no restrictions in investing abroad. As the model captures some of the return of the security which is associated with the market return, it is possible to reduce the variance of the abnormal return and in turn increase the ability to detect event effects (MacKinlay, 1997).

6.2.2 The Market Adjusted Model

With limited data available on the securities stock prices it can be beneficial to use the Market Adjusted Model. The model can be viewed as a restricted market model (jf. equation 6.1 above) with $_i$ constrained to be zero and β_i constrained to be one (MacKinlay, 1997), thus expected returns are constant across securities but not across time (Dyckman et a., 1984). The pre-event estimation window is unnecessary as the model coefficients are pre-specified, and the market-adjusted abnormal return is calculated directly. Similar to the market model we use the MSCI World Value Weighted Index as a proxy for the market returns.

6.3 Abnormal Returns

To determine the effect of the Environmental news incident on the stock price one has to calculate the abnormal returns during the event window. According to MacKinlay (1997), abnormal returns can be defined as "the actual ex-post returns of the security over the event window minus the normal return of the firm over the event window" (MacKinlay, 1997). Consequently, the abnormal returns can be calculated by first estimating the security's expected return during the event window, assuming no event has occurred, where section 6.1.2 discusses the use of normal performance models to calculate the normal returns. Thus, after estimating the normal expected returns, the abnormal returns of the security can be obtained by subtracting the actual ex-post returns. The abnormal returns for each security i at time t are derived in equation 6.2:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}|X_t) \tag{6.2}$$

Where AR_{it} represents the abnormal return for the firm i at time t during the event window. R_i is the observed return and $E(R_{i,t}|X_t)$ is the estimated expected return for time period t where the X_t expresses the conditioning of no event taking place. By estimating the parameters alpha and beta in the market model, the abnormal returns using the market model can be derived by the model, as expressed by equitation 6.3.

$$AR_{i,t} = R_{i,t} - \hat{\alpha_1} + \hat{\beta}_i R_{mt} \tag{6.3}$$

Given the market model and under the null hypothesis, conditional on the market returns of the event window the abnormal return will be jointly normally distributed with a zero conditional mean and conditional variance $\sigma^2(AR_i)$ (MacKinlay, 1997), where the same notation is used in equitation 6.4 as when explaining the market model in subsection 6.1.2.

$$\sigma^2(AR_i) = \sigma^2_{\epsilon i} + \frac{1}{L_1}\Big[1 + \frac{(R_{mt} - \hat{\mu}_m)^2}{\hat{\sigma}^2_m}\Big] \tag{6.4}$$

The first component in equation 6.4 is the variance of the disturbance term from equation 6.1. The second component represents the additional variance that occurs from sampling error in alpha and beta. $\hat{\mu}_m$ represents the estimated average return of the market portfolio during the estimation window. L_1 represents the estimation window, and as it becomes large the second component of the equation will converge to zero since the sampling error of the parameters alpha and beta disappears (MacKinlay, 1997). Thus the variance of the abnormal returns may be approximated as

$$\sigma^2(AR_i) = \sigma^2_{\epsilon i} \tag{6.5}$$

Using the market-adjusted model the abnormal returns can be derived, as expressed by equitation 6.6

$$MAR_{i,t} = R_{i,t} - R_m \tag{6.6}$$

6.3.1 Aggregating Abnormal Returns

In order to draw overall inferences for the event of interest, it is necessary to aggregate the abnormal return observations (MacKinlay, 1997). These must be aggregated across time and securities. Aggregation across securities is necessary as only one security's return data will generate disturbing noise. Due to uncertainty of when the event information reaches the market, aggregation across time is necessary to fully measure the event's effect (Strong, 1992).

First, the abnormal return for a security must be aggregated across time, which yields the cumulative abnormal return (CAR) for each event. Equation 6.7 derives the computation of the CAR:

$$CAR_i(t_2, t_3) = \sum_{t=t_2}^{t_3} AR_{i,t} \tag{6.7}$$

The CAR is the cumulative sum of abnormal returns for each security i from the beginning, t_2, to the end, t_3, of the event window.

Secondly, it is necessary to aggregate the abnormal returns across securities to conduct statistical tests on the sample. This yields the cumulative average abnormal return ($\overline{CAR}$). The $\overline{CAR}$ is calculated by summarizing the CAR for each firm which is divided by the number of events in the sample. It is assumed normal distribution and no clustering of events, meaning there is no overlap for each event window, implying that abnormal returns will be independent across securities (MacKinlay, 1997). Within the event window t_2 to t_3, the $\overline{CAR}$ can be expressed formally as:

$$\overline{CAR}_i(t_2, t_3) = \frac{1}{N} \sum_{i=1}^{N} CAR_i(t_2, t_3) \tag{6.8}$$

Finally, in order to test the null hypothesis and draw inferences one needs the variance of the $\overline{CAR}$, derived formally as:

$$var\big(\overline{CAR}_i(t_2, t_3)\big) = \frac{1}{N^2} \sum_{i=1}^{N} \sigma_1^2(t_2, t_3) \tag{6.9}$$

6.4 Cross-sectional Test

6.4.1 Testing the Significance of Abnormal Returns

To determine whether negative environmental news incidents have a significant impact on the stock market we employ a cross-sectional test to test the null hypothesis, i.e. the $\overline{CAR}$ being zero. Significance testing and the power of tests for event studies are widely covered in the literature, however when using daily returns data, standard parametric tests are well specified under various conditions (Brown & Warner, 1985). Thus, as we test for a negative reaction to the news incidents, we conduct a two-sided t-test. According to MacKinlay (1997), it is assumed that cumulative abnormal returns are normally distributed. Thus, using the test statistic proposed by MacKinlay (1997), the null hypothesis is derived as:

$$t_{\overline{CAR}(t_2,t_3)} = \frac{\overline{CAR}(t_2,t_3)}{var\big(\overline{CAR}(t_2,t_3)\big)^{\frac{1}{2}}} \sim N(0,1) \tag{6.10}$$

, where t is normally distributed. Furthermore, as the variance of the abnormal returns $\sigma^2_{\epsilon}t$ is unknown it must be estimated as derived in equation 6. It is appropriate to use the sample variance measure of $\sigma^2_{\epsilon}t$ from the market model regression in the estimation window (MacKinlay, 1997).

Furthermore, the abnormal returns need to be uncorrelated in the cross-section to ensure the estimator of the variance is consistent (MacKinlay, 1997). This means there must be an absence of clustering for this to hold. Thus one can use the cross-sectional approach to estimate the variance of the average cumulative abnormal return, formally derived in equation 6.11 as:

$$var(\overline{CAR}(t_2,t_3)) = \frac{1}{N^2}\sum_{i=1}^{N}(CAR(t_2,t_3) - \overline{CAR}(t_2,t_3))^2 \tag{6.11}$$

However, when using daily returns, event-induced variance may be applicable (Brown & Warner, 1985), meaning the comparison of the estimated and actual returns may be biased. This can lead to type 1 error as the variance is understated and thus, the abnormal returns are overstated, thereby finding significance where it is not. As the variance may increase in the event window this causes heteroskedasticity in cross-sectional regressions and thus the estimators from the OLS estimation will be biased. Thus we apply robust standard errors to correct for heteroskedasticity in the error terms.

6.5 Trading Volume-based Event Studies

In addition to studying the price reaction, this study will investigate if the stock experiencing an Environmental news incident experiences abnormal trading.

In line with Beaver (1968) and Morse (1981) we will measure volume as the number of shares traded for the given company, on a given date divided by the number of shares outstanding. This will capture the fraction of shares of a firm i traded in period t.

$$V_{it} = \frac{Number\,of\,shares\,of\,firm\,i\,traded\,in\,period\,t}{Total\,number\,of\,shares\,of\,firm\,i\,in\,period\,t} \tag{6.12}$$

As pointed out by Yadav(1992), this measure is a natural measure for inter-temporal comparison since the number of shares traded depends on the number of shares outstanding. Furthermore, it prevents potential cross-sectional heteroskedasticity problems associated with raw volume measures.

Furthermore, as volume data is decidedly not normally distributed (Yadav, 1992), the analysis will be conducted using a log transformation of volume, in line with Yadav (1992) and Chae (2005). While log transformation has proven effective in approximating the normal distribution there is the occasional problem of zero volume. This will be solved by adding a small constant equal to 0.0025 to the entire volume data set, as suggested by Yadav (1992). The normalized volume metric will therefore be written as:

$$V_{it} = ln\Big(\frac{n_{i,t}}{S_{i,t}} * 100\Big) \tag{6.13}$$

Where $n_{i,t}$ and $S_{i,t}$ represent the number of shares traded and the number of shares outstanding for each firm i at time t.

There is no widespread economic model for calculating ex-ante volume expectation, as there is with market returns. Thus, the mean adjusted approach calculates the difference between the abnormal trading volume and the expected trading volume to estimate the abnormal trading volume. This gives the following formula:

$$AV = V_{it} - \overline{V}_{it} \tag{6.14}$$

Where V represents the observed trading volume metric for stock i at time t, and $V_{i,t}$ represents expected trading volume for stock i at time t. Further, expected trading volume is defined as the average daily trading volume over the estimation period:

$$\overline{V}_{it} = \frac{1}{T}\sum_{T=t_0}^{T_1} V_{i,t} \tag{6.15}$$

T denotes the number of days included in the estimation window. Further, to calculate the cumulative abnormal trading volume it is necessary to aggregate the results across time. This is done using the following formula:

$$AAV_t = \frac{1}{N} \sum_{i=1}^{N} AV_{i,t} \tag{6.16}$$

The AAV is the cumulative sum of abnormal trading volume for security i during the event window. Further, it is necessary to aggregate the abnormal returns across securities to conduct statistical tests on the sample. This gives the final term of cumulative average abnormal volume ($\overline{CAV}$). The term is calculated by summarizing the CAV for each security and dividing it by the total number of securities in the sample. As with the abnormal returns, it is assumed normal distribution and no clustering. With defined event window t_2 to t_3 the $\overline{CAV}$ can be formally expressed as:

$$\overline{CAV} = \sum_{t=t_2}^{t_3} AAV_t \tag{6.17}$$

Lastly, we have to calculate the variance to conduct the statistical test. We use a parametric test in line with Ajinkya and Jain (1989), Cready and Ramanan (1991) and Campbell and Wasley (1996). While we apply the estimation window variance for testing abnormal returns, we follow the methodology of Campbell and Wasley (1996) and Chae (2005) and apply the event window variance in our test statistic to ensure robustness. Furthermore, it is assumed that the abnormal trading volume is independent and identically distributed random variables, for each firm i at time t, where the following test statistic is thereby according to Campbell Wasley (1996) distributed student t under the null hypothesis, and hence the test statistic is formally derived as:

$$t_{\overline{CAV}} = \frac{\overline{CAV}(t_2, t_3)}{\sqrt{var(\overline{CAV}(t_2, t_3)}} \sim N(0, 1) \tag{6.18}$$

6.6 Cross-sectional Regression Analysis

In addition to examining the effect of the environmental news on the stock price market, we use cross-sectional regression analysis for the second step of the hypothesis testing. Cross-sectional regression analysis can be used to examine whether certain firm-specific characteristics affect the abnormal returns specific to the event observation (Macinley, 1997). Given the sample of N observations and M characteristics, the regression testing for abnormal returns (CAR) is estimated using ordinary least square (OLS), formally derived in equation 6.19 as:

$$\begin{aligned} CAR_j = \gamma_0 + \gamma_1 x_{1j} + ... + \gamma_M x_{Mj} + n_j \\ E(n_j = 0), \quad var(n_j) = \sigma^2_{nj} \end{aligned} \tag{6.19}$$

The CAR represents the j^{th} cumulative abnormal return observation and $x_m j$,m=1,...,M, represent M firm characteristics for the j^{th} event observation, while n_j is the disturbance term with an expected mean value equal to zero and a variance of σ_{ei}, which is assumed to be uncorrelated with the x´s. S_m, m=0,...,M represent the regression coefficients.

Similarly, testing for abnormal trading volume the regression is estimated using ordinary least square (OLS), formally derived in equation 6.20 as

$$\begin{aligned} CAV_j = \gamma_0 + \gamma_1 x_{1j} + ... + \gamma_M x_{Mj} + n_j \\ E(n_j = 0), \quad var(n_j) = \sigma^2_{nj} \end{aligned} \tag{6.20}$$

The same notation is used in equitation 6.19 as 6.20. However, the CAV represents the j^{th} cumulative abnormal volume. Finally, inference can be conducted using the OLS standard errors assuming the n^s_j are cross-sectionally uncorrelated and homoscedastic (MacKinlay, 1997). However, as MacKinlay (1997) argues, there is no reason to expect the residuals of the model to be homoscedastic. Thus it is appropriate to use heteroskedasticity robust standard errors clustered at firm level.

7 Results

In this section, we present the most interesting findings from the research questions presented in section 4 using the event study methodology and OLS regressions. The analysis is based on estimated cumulative abnormal returns (CAR), cumulative average abnormal returns ($\overline{CAR}$), cumulative abnormal volume (CAV) and cumulative average abnormal volume ($\overline{CAV}$), using the equations presented in section 6. In addition, different event windows are employed to incorporate possible market leakage effects. We apply heteroskedastic robust standard errors clustered by firm throughout the analysis.

The analysis consists of several parts. First, we examine the market reaction to environmental news incidents for firms in carbon-intensive and non-carbon-intensive sectors by conducting an event study of the abnormal stock price reaction $\overline{CAR}$. Furthermore, we analyze the difference in CAR, applying cross-sectional regression analysis. To further gain insight into investors' expectations, we analyze the abnormal trading volume by conducting an event study of $\overline{CAV}$ and a subsequent cross-sectional analysis of CAV. Second, we examine the relevance of incident history on investors' expectations by splitting the sample into high-frequency and low-frequency offenders. Applying the above-mentioned procedure, we conduct an event study and cross-sectional analysis of the abnormal stock price and trading volume reaction, respectively. The analysis aims to examine whether the investors react differently based on firms' carbon exposure or their recent environmental incident history.

7.1 Research Question 1: Analysis of Carbon-Intensive Companies

7.1.1 Hypothesis 1.1: Stock Price Reaction

To capture the effect of being in a carbon-intensive industry we have conducted a t-test of the $\overline{CAR}$ and a cross-sectional regression analysis of the CAR. We test H1.1 by the following null and alternative hypotheses:

$H1.1_0$: *Carbon-intensive sectors* ***will not*** *experience a different stock price reaction to negative environmental news than non-carbon-intensive sectors*

$H1.1_A$: *Carbon-intensive sectors* ***will*** *experience a different stock price reaction to negative environmental news than non-carbon-intensive sectors*

Table 7.1 Event Study of $\overline{CAR}$

Window	Sample	$\overline{CAR}$	t.stat	N
[0]	Full Sample	-0.0012	-0.1371	316
[-1, 1]	Full Sample	-0.0047	-0.5302	316
[-2, 2]	Full Sample	-0.0062	-0.7088	316
[0]	Non-Carbon-Intensives	-0.0016	-0.1185	118
[-1, 1]	Non-Carbon-Intensives	-0.0034	-0.2561	118
[-2, 2]	Non-Carbon-Intensives	-0.0042	-0.3218	118
[0]	Carbon-Intensives	-0.0010	-0.0854	198
[-1, 1]	Carbon-Intensives	-0.0054	-0.4668	198
[-2, 2]	Carbon-Intensives	-0.0074	-0.6378	198

Note: Two-tailed t-test. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 7.1 presents the $\overline{CAR}$, using three different event windows, to determine if the average abnormal price reaction is significantly different from zero. When testing the two groups separately and the sample as a whole, we find no significant abnormal stock price reaction. Based on these results, the interpretation is that negative environmental news incidents, on average, do not affect companies' market value in the Scandinavian markets.

This finding is interesting as it contradicts recent analyses of the American and European stock markets.[10] However, these analyses are conducted by examining the full spectrum of ESG news, where Serafeim & Yoon (2021) find the strongest reaction to social and governance news incidents. Consequently, the type of incidence could explain the lack of significance in our results. An alternative explanation could be that many of the incidents are not found financially material by investors, as discussed in the hypothesis, section 4. While we know that RepRisk reports only material incidents based on the SASB classification, the investors may still find limited novelty in many of the news. A possible explanation for this proposed lack of novelty is higher ESG transparency in Scandinavian markets, leading to lower asymmetric information and less unexpectedness in the news.

[10] Serafeim & Yoon (2021), Krüeger (2015), Capelle-Blancard & Petit (2019)

Analyzing the differences between the two groups can further reveal information about potential differences in investors' treatment of the two groups as a result of differences in expectation.

Table 7.2 T-test H1.1: Comparison of Carbon-Intensive vs. Non-Carbon-Intensives Sectors

Window	Carbon-Intensives	Non-Carbon-Intensives	Difference	t.stat
[0]	-0.001	-0.002	0.001	0.385
[-1, 1]	-0.005	-0.003	-0.002	-1.406
[-2, 2]	-0.007	-0.004	-0.003	-2.175**

Note: Two-tailed t-test. *$p<0.1$; **$p<0.05$; ***$p<0.01$

Table 7.2 presents a t-test of the difference between the $\overline{CAR}$ for carbon-intensive and non-carbon-intensive sectors. The t-test shows significantly different abnormal returns in the five-day window [-2, 2], where carbon-intensive sectors experience significantly more negative returns, as hypothesized in H1.1. However, the result is not consistent when narrowing the event window, challenging the robustness of the result. Thus, we will not further discuss this finding before conducting the cross-sectional regression analysis.

To test if the variations of the $\overline{CAR}$ over the different firms and incidents could be explained by some causal variable(s) we regress the CAR. In the cross-sectional regression analysis, CAR is the dependent variable, and the indicator "carbon-intensive sectors" is the key explanatory variable. The non-carbon-intensive sectors are used as the base variable together with the time period 2010 to 2012 and low reach, which, together with all unexplained variation in y, form the constant term. In addition, we control for market capitalization and debt ratio.

Table 7.3 H1.1: OLS Regressions of CAR Carbon-Intensive vs. Non-Carbon-Intensive Sectors

	Dependent variable:				
	CAR				
	(1)	(2)	(3)	(4)	(5)
Carbon-Intensive	−0.003	−0.004	−0.005	−0.005	−0.012
	t = −0.685	t = −1.295	t = −1.449	t = −1.462	t = −1.357
ln(Market Capitalization)		0.004***	0.004***	0.004***	0.004***
		t = 4.177	t = 4.478	t = 4.414	t = 4.344
2013-2015			0.009*	0.009*	0.008
			t = 1.667	t = 1.684	t = 1.102
2016-2017			0.013**	0.013**	0.008
			t = 2.470	t = 2.481	t = 1.217
2018-2020			0.016***	0.015***	0.006
			t = 3.276	t = 3.239	t = 0.872
Debt Ratio		−0.004*	−0.007*	−0.007*	−0.006*
		t = −1.701	t = −1.711	t = −1.706	t = −1.695
High Reach				−0.002	−0.002
				t = −0.589	t = −0.657
Carbon-Intensive*(2013-2015)					0.002
					t = 0.243
Carbon-Intensive*(2016-2017)					0.006
					t = 0.587
Carbon-Intensive*(2018-2020)					0.014
					t = 1.444
Constant	−0.003	−0.063***	−0.068***	−0.066***	−0.065***
	t = −1.172	t = −4.218	t = −4.736	t = −4.638	t = −5.066
Time FE	No	No	No	No	No
Entity FE	No	No	No	No	No
Clustered SE	Yes	Yes	Yes	Yes	Yes
Observations	316	316	316	316	316

Note: *$p<0.1$; **$p<0.05$; ***$p<0.01$
We apply Robust standard errors, and report the associated t-statistics.

Table 7.3 presents the results from the cross-sectional analysis of CAR in carbon-intensive compared to non-carbon-intensive sectors, with five different model specifications. In model 1, we compare the CAR of the two groups and find that the two means are not statistically different from each other. In model 2, we control for market capitalization and debt ratio to consider size and risk, respectively, and find the market capitalization to be highly significant. In model 3, we control for the different time periods, keeping 2010 to 2012 as the base period, revealing a significant increasing time trend. In model 4, we include the indicator variable for high reach to control for news incident characteristics.

In model 5, we create an interaction variable between the time periods and the carbon-intensive sector indicator variable to investigate differences in market reaction over time. We do not encounter significant time differences.

7.1.2 Key Explanatory Variable

Carbon-Intensive Sectors

There is no significant difference between the carbon-intensive and non-carbon-intensive sectors when regressing CAR, considering firm and incident characteristics. Consequently, in line with the overall t-test results, we fail to reject the null hypothesis. Nevertheless, both debt ratio and market capitalization have significant coefficients and can potentially explain some variation in the cumulative abnormal returns. This will be further elaborated on in the next sub-section.

In the hypothesis development, we argued that two conflicting forces could affect investors' reactions to environmental news incidents. Firstly, we argued that due to the carbon-intensive industries having core operations directly linked to natural resources, anticipated environmental incidents are important factors in determining future cash flow and risk. Consequently, to a larger extent, investors anticipate and adjust for these types of incidents, leading to a lower relative reaction. However, we further argued that due to the uncertainty regarding the cost aspects of the incidents on their core operations, the marginal effect can still be larger due to the substantial cost uncertainty. As we find no significant difference between the two groups, these effects may cancel each other out, on average.

Subsequently, to determine if there is high disagreement among investors that explains the lack of difference in the stock price reaction between the two groups, the following analysis of the abnormal trading volume is necessary.

7.1.3 Explanatory Variables

Market Capitalization

There is a significant positive relationship between market capitalization and CAR, which implies that smaller companies experience larger negative market reactions, on average. A possible explanation is that these companies often have higher coverage and consequently monitoring, both from analysts and media, leading to lower information asymmetry

(Eleswarapu et al., 2004), as alluded to in hypothesis H2.1 in section 4.2. According to Wong (2021), as the ESG issues already may be anticipated for the larger firms, they are less likely to experience significant negative price movements from adverse media coverage of ESG activities. Likewise, the associated cost of acquiring information is higher for the smaller firms (McWilliams & Siegel, 2001). As a result, for smaller companies, higher informational asymmetry could lead the financial relevant informational content of the environmental news to be less anticipated by investors, which, all else equal, should generate a larger abnormal stock price reaction.

Debt Ratio

The debt ratio is significantly negative at 10% level when controlling for time and reach. This indicates that the higher the debt ratio, the more negative the abnormal stock price reaction to negative environmental news. We included the debt ratio as a proxy for firm uncertainty, in line with Chen et al. (2021). The measure captures the "leverage effect", a well-established relationship in the literature, where increased leverage should increase the volatility of the stock. Thus, this finding is in line with the literature. However, as this relationship is only significant at 10% level, we will not emphasize this finding further.

Time

With respect to time, the coefficients are significant and increasingly positive throughout the time periods, thus implying that the abnormal stock price reaction was more negative in the early years. Consistent with Blancard and Petit (2019), we do not find that the market reaction becomes more negative over time. They argue this can raise doubt towards the conventional idea of growing awareness in societies on ESG issues. Contrary, given our Scandinavian focus, we propose that our finding could reflect an increase in investor ESG awareness. This is explained by the fact that the news incidents, to a lower degree than in the earlier years, change investors' expectations towards the firms, on average.

Alternatively, in line with the argumentation for market capitalization, a smaller abnormal price reaction can also be explained, all else equal, by a smaller cost impact on the firms in recent years. Such an argument could be made if the reported news incidents systematically contain less valuable information. With the increase in environmental news over the decade, such an argument may seem plausible. However, when isolating the more severe news incident within our data sample, there is no apparent increase in news frequency over time, as demonstrated in figure 5.1 in section 5.4. As these are the foundation for our analysis, we conclude that the proposed increase in ESG awareness seems like the most likely explanation.

Furthermore, in model 5 we add an interaction between time and the carbon-intensive indicator variable. This allows for an examination of whether this effect is prominent when considering the carbon-intensive companies. The coefficients of all these variables are insignificant, hence we find no difference in reactions related to carbon exposure when isolating the time periods. Consequently, the proposed increase in ESG consideration and awareness is not found to be different between the two groups. As a final remark, the general increasing time trend is opposite to Flammer (2013), who found a significant negative time trend, though comparing three decades from 1980 to 2009. Thus, examining a longer time period may convey opposite results

7.1.4 Hypothesis 1.2: Trading Volume

To further examine the importance of being in a carbon-intensive sector, we have conducted an event study of the $(\overline{CAV})$, and a cross-sectional regression analysis with the same model specifications of (CAV). We test H1.1 by the following null and alternative hypotheses:

> $H2.1_0$**:** *Carbon-intensive sectors* ***will not*** *experience a higher increase in trading volume in the days surrounding negative environmental news than non-carbon-intensive sectors*
>
> $H2.1_A$**:** *Carbon-intensive sectors* ***will*** *experience a higher increase in trading volume in the days surrounding negative environmental news than non-carbon-intensive sectors*

Table 7.4 Event Study of $\overline{CAV}$

Window	Sample	$\overline{CAV}$	t.stat	N
[0]	Full Sample	0.0287	0.7704	316
[-1, 1]	Full Sample	0.1607	1.7160*	316
[-2, 2]	Full Sample	0.2261	1.711*	316
[0]	Non-Carbon-Intensives	0.0425	0.6629	118
[-1, 1]	Non-Carbon-Intensives	0.1750	1.0707	118
[-2, 2]	Non-Carbon-Intensives	0.2534	1.0177	118
[0]	Carbon-Intensives	0.0205	0.4482	198
[-1, 1]	Carbon-Intensives	0.1522	1.3387	198
[-2, 2]	Carbon-Intensives	0.2098	1.2665	198

Note: Two-tailed t-test. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 7.4 presents the $\overline{CAV}$, using three different event windows, to determine if the average abnormal trading volume is significantly different from zero. Neither the carbon-intensive nor the non-carbon-intensive companies experience significantly increased abnormal trading volume at any reasonable level of significance. Considering the full sample, there is a positive abnormal trading volume for the extended event windows, however only significant at 10% level. Combining these results with the event study of $\overline{CAR}$ in section 7.1.1, we find an insignificant abnormal stock price reaction that does not seem to be explained by heterogeneity in investors' beliefs, at least not when examining the sample period as a whole.

Table 7.5 T-test H1.2: Comparison of $\overline{CAV}$ for Carbon-Intensive vs. Non-Carbon-Intensive Sectors

Window	Carbon-Intensives	Non-Carbon-Intensives	Difference	t.stat
[0]	0.020	0.043	−0.022	0.2803
[-1, 1]	0.152	0.175	−0.023	0.1158
[-2, 2]	0.210	0.253	−0.044	0.1469

Note: Two-tailed t-test. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 7.5 presents a t-test of the difference between the $\overline{CAV}$ for carbon-intensive and non-carbon-intensive sectors. We find no significant difference between the carbon-intensive and non-carbon-intensive sectors. Thus, solely based on the t-test, we fail to reject the null hypothesis of no difference.

In order to test if the variations of the $\overline{CAV}$ over the different firms and incidents could be explained by some causal variable(s) we regress the CAV. In the cross-sectional regression, CAV is the dependent variable, and the indicator "Carbon-intensive" sectors is the key explanatory variable. The non-carbon-intensive is the base variable together with the time variable "2010-2013", and low media reach, which, together with all unexplained variation in the dependent variable, form the constant term. In addition, we control for market capitalization and debt ratio.

Table 7.6 H1.2: OLS Regressions of CAV Carbon-Intensive vs. Non-Carbon-Intensive Sectors

	Dependent variable:				
	CAV				
	(1)	(2)	(3)	(4)	(5)
Carbon-Intensive	−0.031	−0.026	−0.033	−0.029	0.661
	t = −0.156	t = −0.124	t = −0.162	t = −0.144	t = 1.398
ln(Market Capitalization)		−0.141**	−0.135**	−0.130**	−0.144***
		t = −2.538	t = −2.433	t = −2.400	t = −2.635
2013-2015			0.723***	0.703***	1.130**
			t = 2.750	t = 2.747	t = 2.361
2016-2017			0.558	0.581	1.013*
			t = 1.520	t = 1.508	t = 1.795
2018-2020			0.485*	0.500*	1.171**
			t = 1.830	t = 1.799	t = 2.517
Debt Ratio		−0.385*	−0.423*	−0.426*	−0.452**
		t = −1.787	t = −1.908	t = −1.922	t = −2.019
High Reach				0.150	0.153
				t = 0.733	t = 0.758
Carbon-Intensive*(2013-2015)					−0.689
					t = −1.256
Carbon-Intensive*(2016-2017)					−0.666
					t = −0.980
Carbon-Intensive*(2018-2020)					−1.034**
					t = −2.022
Constant	0.173***	2.500***	1.924**	1.767*	1.552
	t = 1.066	t = 2.665	t = 2.087	t = 1.933	t = 1.637
Time FE	No	No	No	No	No
Entity FE	No	No	No	No	No
Clustered SE	Yes	Yes	Yes	Yes	Yes
Observations	316	316	316	316	316

Note: *$p<0.1$; **$p<0.05$; ***$p<0.01$
We apply Robust standard errors, and report the associated t-statistics.

Table 7.6 presents the results from the cross-sectional regressions of the CAV for the carbon-intensive sectors in comparison to the non-carbon-intensive sectors, with identical model specifications as for the CAR regressions. In model 1, we compare the CAR of carbon-intensive and non-carbon-intensive sectors and find that the two means are statistically different from each other. In model 2, we control for market capitalization and debt ratio to consider size and risk, respectively, and find these company characteristics to be significantly negative. In model 3, we control for the different time periods, keeping 2010 to 2012 as the base period, revealing a significant difference across time. In model 4, to control for news characteristics, we include the indicator variable for high reach keeping low reach as the base variable, which does not change the results. Lastly, in model 5, we implement an interaction variable between the time periods and the carbon-intensive sector indicator variable to investigate differences in market reaction over time. We find a significantly smaller increase in abnormal trading volume for carbon-intensive companies for events occurring from 2018 to 2020 than non-carbon-intensive companies in the same period.

7.1.5 Key Explanatory Variable

Carbon-Intensive Sectors

There is no significant difference in CAV between carbon-intensive and non-carbon-intensive sectors when allowing for firm and news characteristics. Consequently, we cannot reject the null hypothesis of no difference and conclude that there is no evidence in favor of a difference in abnormal trading volume related to sector exposure to Scope 1 emissions.

We hypothesized a higher abnormal trading volume for carbon-intensive companies, where we argued for a higher difference in opinion regarding the cost aspect of the news incident and the regulatory risks. Nevertheless, the insignificance of the carbon-intensive variable yields no support for such a notion. Alternatively, the proposed cost and regulation effects might be higher for carbon-intensive companies, however the lack of unexpectedness in the news incident itself might sufficiently moderate this effect. Thus, the lack of support might be explained by competing forces inducing differences in abnormal trading.

In order to examine this effect, it would be interesting to create a regulation-risk proxy variable including in the regression analysis, through an interaction variable with carbon-intensive sectors. However, a detailed examination of this specific market trait is outside the scope of this analysis, and thereby we leave this for future research.

Albeit, it is not evident that these effects are not present in the market as the hypothesized relationship between the effects and carbon exposure may not hold. Rather, they may be related to the firm characteristics, market capitalization or debt ratio, which will be discussed in the next sub-section.

7.1.6 Explanatory Variables

Market Capitalization

There is a significant negative relationship between market capitalization and CAV. This indicates a possible size effect where larger companies experience a smaller increase in abnormal trading volume to a negative news incident, indicating that the reaction is accentuated within smaller firms. This further strengthens the argumentation presented for market capitalization in the OLS regression analysis for CAR of larger firms having higher coverage, both from analysts and the media, which can reduce asymmetric information. Accordingly, less novel information is released through the news, resulting in less abnormal trading volume for larger companies.

Debt Ratio

Contradictory to the leverage effect presented in section 4.1 for CAR, we find the debt ratio to be negatively correlated with CAV. Thus, the higher debt ratio, the smaller increase in abnormal trading volume. This is contra intuitive and contradicts the logic and results from the analysis of CAR. A possible explanation could be that debt ratio, and market capitalization correlates, as larger firms have significantly lower abnormal trading volume. However, from the correlation matrix in Appendix A2.3, we find a negative relationship between these variables. Thus, we find no support for this argument. However, as this finding is solely significant at 10% level, we put limited emphasis on the result.

Time

In model 5, all the indicator variables for time are significantly positive, with the time periods 2013 to 2015 and 2018 to 2020 being positive for all three models controlling for time. This is interesting as it reveals an increase in heterogeneity in investors' opinions towards environmental news over the time period for the market as a whole. This could result from increased interest in these news types, prompting investors to trade. Combining these findings with the reduction in abnormal stock price reactions over time, the proposed increase in ESG awareness is further strengthened.

Nevertheless, the increase in abnormal trading volume is significantly smaller for carbon-intensive firms in the last period, 2018 to 2020, compared to non-carbon-intensive firms. Thus, while the increased focus and reporting on ESG issues could explain the overall increase in abnormal trading volume, we find a relative convergence in investors' opinions regarding carbon-intensive firms in the later years, in line with the argumentation for H1.2.

7.2 Research Question 2: High-frequency Offenders

As presented in the descriptive statistics, some firms represent a large part of the sample, which may influence the validity of our results when constructing sub-samples through the separation between high- and low-frequency offenders. However, as addressed in the robustness section following the analysis, excluding these firms does not alter our results. Thus we have chosen to include all firms for the following analysis for consistency.[11]

7.2.1 H2.1: High-frequency Offenders and Abnormal Returns

Further, to examine the importance of being a high-frequency offender, we have conducted an event study of $\overline{CAR}$ and a cross-sectional regression analysis of CAR. We test H2.1 by the following null and alternative hypotheses:

> $H2.1_0$**:** *High-frequency offenders **will not** experience a less negative stock market reaction to negative environmental news than low-frequency offenders*
>
> $H2.1_A$ *High-frequency offenders **will** experience a less negative stock market reaction to negative environmental news than low-frequency offenders*

[11] These results can be found in Appendix A.2.1

Table 7.7 Event Study $\overline{CAR}$

Window	Sample	$\overline{CAR}$	t.stat	N
[0]	High-frequency Offenders	0.0006	0.0657	145
[-1, 1]	High-frequency Offenders	0.0007	0.0516	145
[-2, 2]	High-frequency Offenders	0.0004	0.0322	145
[0]	Low-frequency Offenders	-0.0019	-0.1405	171
[-1, 1]	Low-frequency Offenders	-0.0063	-0.6545	171
[-2, 2]	Low-frequency Offenders	-0.0098	-0.8300	171

Note: Two-tailed t-test. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 7.7 presents the results from the event study, employing three different event windows, to determine if the ($\overline{CAR}$) is significantly different from zero. When testing the two groups in isolation, neither of the two groups experience significant abnormal stock price reactions on average across the sample period. This is consistent when employing a two-year lookback period, in which results are provided in Appendix A1. Thus, by solely considering these results, the interpretation is that negative environmental incidents do not significantly lead to abnormal stock price reactions for high-frequency offenders, nor for low-frequency offenders, compared to days without a news incident. To examine potential differences in $\overline{CAR}$ between the high-frequency and the low-frequency offenders, we conduct a t-test, presented below, in table 7.8.

Table 7.8 T-test H2.1 of $\overline{CAR}$ of High-Frequency- vs. Low-Frequency Offenders

Window	High-frequency Offenders	Low-frequency Offenders	Difference	t.stat
[0]	0.0006	-0.0019	-0.0069	-1.7691**
[-1, 1]	0.0007	-0.0063	-0.0102	-4.9341***
[-2, 2]	0.0004	-0.0098	-0.0025	-5.1895***

Note: Two-tailed t-test. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

In line with our hypothesis, the t-test reveals significant differences between the two groups, where high-frequency offenders experience a significantly smaller increase in market reaction across all windows. Hence, based on the t-test, we reject the null hypothesis, H2.1.0, implying that high-frequency offenders experience a less negative stock market reaction to an environmental news incident than low-frequency offenders, on average.

To test if the variations of the CAR over the different firms and incidents could be explained by some causal variable(s) we regress the CAR. In the cross-sectional regression analysis, CAR is the dependent variable, and the indicator "high-frequency offenders" is the key explanatory variable. The non-carbon-intensive sectors are used as the base variable together with the time period from 2010 to 2013, and low reach, which, together with all unexplained variation in y, form the constant term. In addition, we control for market capitalization and debt ratio.

Table 7.9 H2.1: OLS Regressions of CAR of High-frequency vs. Low-frequency Offenders

	Dependent variable:				
	CAR				
	(1)	(2)	(3)	(4)	(5)
High Offender	0.011***	0.003	0.001	0.001	−0.004
	t = 3.179	t = 0.822	t = 0.385	t = 0.370	t = −0.593
ln(Market Capitalization)		0.004***	0.004***	0.003***	0.003***
		t = 3.387	t = 3.691	t = 3.617	t = 3.370
2013-2015			0.008	0.009	0.004
			t = 1.598	t = 1.613	t = 0.512
2016-2017			0.013**	0.013**	0.008
			t = 2.551	t = 2.550	t = 1.105
2018-2020			0.015***	0.015***	0.017**
			t = 3.171	t = 3.118	t = 2.141
Debt Ratio		−0.003	−0.006	−0.006	−0.006*
		t = −0.794	t = −1.508	t = −1.501	t = −1.719
High Reach				−0.002	−0.002
				t = −0.551	t = −0.499
High Offender*(2013-2015)					0.011
					t = 1.208
High Offender*(2016-2017)					0.013
					t = 1.568
High Offender*(2018-2020)					−0.002
					t = −0.170
Constant	−0.010***	−0.061***	−0.068***	−0.066***	−0.063***
	t = −3.593	t = −3.716	t = −4.256	t = −4.125	t = −3.565
Time FE	No	No	No	No	No
Entity FE	No	No	No	No	No
Clustered SE	Yes	Yes	Yes	Yes	Yes
Observations	316	316	316	316	316

Note: **p<0.1*; ***p<0.05*; ****p<0.01*
We apply Robust standard errors, and report the associated t-statistics.

Table 7.9 presents the results from the cross-sectional regressions of the CAR for high-frequency offenders compared to low-frequency offenders, with identical model specifications used in research question 1. In model 1, we compare the CAR of high-frequency and non-frequency-offenders and find that the two means are statistically different from each other. In model 2, we control for market capitalization and debt ratio to consider size and risk, respectively, and find market capitalization to be significantly positive. In model 3, we control for the different time periods, keeping 2010 to 2012 as the base period, revealing a significant increasing time trend in the second half of the decade. In model 4, to control for news characteristics, we include the indicator variable for high reach keeping low reach as the base variable. Adding this control does not alter the results. Lastly, in model 5, we implement an interaction variable between the time periods and the High-Offender indicator variable to investigate differences in market reaction over time. We do not find a significant difference in abnormal trading volume for high-frequency offenders than low-frequency offenders.

7.2.2 Key Explanatory Variable

High-frequency Offenders

In model 1, there is a significant positive difference in CAR between high-frequency offenders and low-frequency offenders. However, when adding controls, this difference turns insignificant for all models from 2-5.[12] We, therefore, fail to reject our null hypothesis of differences between the two groups, H2.1.0, when allowing for company and incident characteristics. In the hypothesis development, we argued that there should be less unexpectedness in the news incident for high-frequency offenders, which, all else equal should lead to a less negative market reaction. However, this effect is not apparent within our sample data. Thus we find no support for systematic differences in investors' reactions based on the firms' recent incident rate.

However, while the reduction in asymmetric information should lead to a less negative stock market reaction for high-frequency offenders, it is not apparent that this will be the case. If investors disagree substantially about the anticipation of a news incident occurring regarding the low-frequency offenders, the market reaction to a news incident

[12]These results are consistent when employing a two-year lookback period, and can be found in Appendix A1

will, all else equal, be very limited. Concerning this scenario, it may be unlikely that high-frequency offenders will experience significantly less negative returns than the low-frequency ones.However, it is theoretically possible if the standard errors are sufficiently small Hence, our hypothesis should only hold if low-frequency offenders experience a sufficiently low market reaction. Consequently, the proposed anticipation effect may still be valid within the data set. However, due to sufficiently large heterogeneity in investors' expectations of low-frequency offenders, the effect is canceled out.

Nevertheless, the lack of support for the hypothesis may be in line with Karpoff et al. (2005), who find that there are no reputational penalties connected to environmental incidents, while other incidents such as false advertising, product recalls, and lack of safety generate large reputational losses (Karpoff et al.,2005). On the contrary, as ESG incidents are not necessarily imposed directly on the firm, but can rather create implications for society at large, Karpoff et al. (2005) argued that the firm does not internalize the costs of ESG violations. Accordingly, the reputational penalties are negligible on the stock price beyond any fines.

Summarized, as we have not yet analyzed the trading volume reaction, it is unclear whether investors unalter their expectations or if there is a significant difference between these groups, where heterogeneity in beliefs may lead to a lack of abnormal stock price reaction.

7.2.3 Explanatory Variables

Market Capitalization

In line with the finding in section 7.1 we find that size is positively correlated with CAR. We will not further elaborate on this intuition as this has already been discussed. Thus, we will focus this section on the seemingly positive correlation between the high-frequency variable and size.

In model 1, there is a significant positive difference in CAR between high-frequency offenders and low-frequency offenders. However, this effect diminishes when controlling for market capitalization, where we find a significant positive relationship between market capitalization and CAR at 1% level. The results imply that it is not being a high-frequency offender which can explain the significant difference in $\overline{CAR}$ of the event study, but rather that this group is dominated by the larger companies. Due to the former variable being a categorical variable, we cannot formally test the correlation between the frequency variable and market capitalization. However, from the descriptive statistics in section 5.4, we see that high-frequency offenders are statistically larger in size.

A plausible explanation for this relationship is that larger firms tend to have larger analyst and media coverage due to their large impact on the economy relative to smaller companies (Elswarapu et al, 2004). This will likely increase their incident rate, as their operations may be of wider interest and thereby more closely monitored. Another reasonable explanation is that larger companies tend to have a higher number of divisions and business areas. This should, all else equal, make them more likely to get a news incident as their operations are more widespread, which is consistent with Fang and Peress (2009), who find that firm size has an overwhelming effect on media coverage.

Debt Ratio

In line with the finding in section 7.1, we find debt to be negatively correlated with CAR. This has been explained by the leverage effect, which leads companies with more debt to have higher volatility and consequently experience more negative abnormal returns. However, the debt ratio is only significant at 10% level in model 5. Furthermore, when excluding Equinor and Hydro from the sample to control for robustness, the relationship is insignificant.[13] Consequently, we do not emphasize this finding further.

Time

The general increase in CAR during the last part of the decade has been explained in our analysis as a result of increased ESG awareness and news interest, prompting investors to trade. Furthermore, we find no significant time trend for the interaction between time and high-frequency offenders. Thus, we do not find any systematic difference in investors' reactions based on the firm's recent ESG history across the different time periods. Hence, the proposed general increase in ESG awareness for the last decade does not seem to have caused investors to react differently towards companies with a more extensive incident history when controlling for size and debt.

[13] These results are discussed in section 8, and presented in Appendix A2.1

7.2.4 H2.2: High-frequency Offenders and Abnormal Trading Volume

Finally, we analyze the trading volume reaction to environmental news concerning the high-frequency offenders, through an event study $\overline{CAV}$ and a cross-sectional regression analysis of CAV. We test H2.2 by the following null and alternative hypotheses:

> $H2.2_0$**:** *High-frequency offenders* ***will not*** *experience a smaller increase in trading volume in the days surrounding negative environmental news than low-frequency offenders*
>
> $H2.2_A$ *High-frequency offenders* ***will*** *experience a smaller increase in trading volume in the days surrounding negative environmental news than low-frequency offenders*

Table 7.10 Event Study of $\overline{CAV}$

Window	Sample	$\overline{CAV}$	t.stat	N
[0]	High-frequency Offenders	0.0348	0.4716	145
[-1, 1]	High-frequency Offenders	0.0653	0.4047	145
[-2, 2]	High-frequency Offenders	0.0812	0.8855	145
[0]	Low-frequency Offenders	0.0269	0.3188	171
[-1, 1]	Low-frequency Offenders	0.2982	1.4441	171
[-2, 2]	Low-frequency Offenders	0.3770*	1.7245	171

Note: Two-tailed t-test. *$p<0.1$; **$p<0.05$; ***$p<0.01$

Table 7.10 presents the results from the t-test, employing three different event windows, to determine if the $\overline{CAV}$ is significantly different from zero. When testing the two groups isolated, high-frequency offenders do not experience a significantly abnormal trading volume. Table 7.10 provide the results using a one-year lookback period, whereas the results using a two-year lookback period can be found in Appendix A1. This does not change the results, providing robustness to the findings. Nevertheless, it is interesting to test if there is a systematic difference between the two groups. To examine the difference in $\overline{CAV}$ between the high-frequency offenders and the low-frequency offenders, we conduct a t-test, presented in table 7.11.

Table 7.11 T-test of H2.2 $\overline{CAV}$ for High-frequency- vs. Low-frequency Offenders

Window	High-frequency Offenders	Low-frequency Offenders	Difference	t.stat
[0]	0.0348	0.0269	0.0078	0.0701
[-1, 1]	0.0653	0.2982	-0.2329	0.8652
[-2, 2]	0.0812	0.5263	-0.2967	1.4941

Note: Two-tailed t-test. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

The t-test reveals there is no significant difference between the two groups at any reasonable level of significance. Consequently, we cannot reject the null hypothesis of no difference.

Combining these results with the t-test of $\overline{CAR}$ in section 7.3 above, the abnormal stock price reaction nor the abnormal trading volume is significantly different from zero. Thus, there does not seem to be heterogeneity in investors' beliefs that causes the lack of price difference between the two groups as previously proposed. Hence, the proposed convergence in investors' opinions based on a reduction of asymmetric information does not seem to hold when pooling the results across firms and time. Consequently, investors do not seem to find financially relevant informational content in a firm's recent incident history, on average, over the time period.

We turn to the cross-sectional regression analysis of CAV to examine to test if the variations of the $\overline{CAV}$ over the different firms and incidents could be explained by some causal variable(s). Thereby, CAV is the dependent variable, and the level of high-frequency offender is the explanatory variable, coded as an indicator variable. The low-frequency offenders are used as the base variable together with the time period 2010 to 2013 and low media reach, which, together with all unexplained variation in y, form the constant term. Furthermore, we control time, market capitalization and debt ratio.

Table 7.12 H2.2: OLS Regressions of CAV: High-frequency- vs. Low-frequency Offenders

	Dependent variable:				
	CAV				
	(1)	(2)	(3)	(4)	(5)
High Offender	−0.133	0.037	0.008	0.014	0.655*
	t = −0.739	t = 0.221	t = 0.049	t = 0.083	t = 1.706
ln(Market Capitalization)		−0.146***	−0.137**	−0.132**	−0.136**
		t = −2.611	t = −2.462	t = −2.443	t = −2.478
2013-2015			0.721***	0.700***	0.996***
			t = 2.728	t = 2.726	t = 2.778
2016-2017			0.558	0.581	0.648
			t = 1.530	t = 1.518	t = 1.453
2018-2020			0.480*	0.494*	0.983***
			t = 1.780	t = 1.758	t = 3.065
Debt Ratio		−0.376*	−0.416*	−0.420*	−0.463**
		t = −1.789	t = −1.907	t = −1.923	t = −2.047
High Reach				0.151	0.158
				t = 0.737	t = 0.773
High Offender*(2013-2015)					−0.769*
					t = −1.712
High Offender*(2016-2017)					−0.201
					t = −0.333
High Offender*(2018-2020)					−1.051**
					t = −2.530
Constant	0.214	2.532***	1.924**	1.774**	1.588*
	t = 1.311	t = 2.784	t = 2.144	t = 1.978	t = 1.789
Time FE	No	No	No	No	No
Entity FE	No	No	No	No	No
Clustered SE	Yes	Yes	Yes	Yes	Yes
Observations	316	316	316	316	316

Note: *$p<0.1$; **$p<0.05$; ***$p<0.01$
We apply Robust standard errors, and report the associated t-statistics.

Table 7.9 presents the results from the cross-sectional regressions of the CAV for the high-frequency offenders in comparison to the low-frequency offenders, with identical model specifications as for the regression models in section 7.3 for hypothesis H2.1. In model 1, we compare the high-frequency offender against non-frequency-offenders before we add controls in models 2 to 5.

7.2.5 Explanatory Variables

Carbon-Intensive Sectors

In models 1-3 there is no significant difference in CAV between high-frequency offenders and low-frequency offenders. However, when we include an interaction term with high-frequency offenders and time, the difference becomes significantly positive, while the interaction between High-Offender*(2013-2015) and High-Offender*(2018-2020) is negative. As the results lack consistency, as well as no systematic increasing or decreasing trend from the interaction term, we fail to reject the null hypothesis of no difference. Hence, we find no systematic difference in treatment between high and low-frequency offenders. Leading back to the hypotheses developed in section 4.2, the proposed convergence in anticipation of future news incidents is not evident from our analysis. Thus, we find no notion for the proposed difference in anticipation effect, which formed the basis for research question two.

An important implication of our findings is that our analysis is based on a self-constructed sample division of high- and low-frequency offenders. We have chosen to divide high- and low-frequency offenders based on the median to ensure sufficiently large samples in both groups. However, the two groups being compared may not be sufficiently different. Thus, we argue that analysis using a higher threshold for high-frequency should be employed before drawing final conclusions. Hence, increasing this threshold using our sample data will lead to severe small sample bias. Consequently, we propose such an analysis to be conducted on a larger data sample, either by including additional stock exchanges, such as Finland and Iceland, to maintain a Nordic analysis or by examining the full range of ESG news.

We reiterate our explanation from section 7.1, as we find the firm's size to mainly explain the abnormal variation in CAV, in combination with the capital structure and time effect. This will be further discussed in the next section.

7.2.6 Control Variables

Market Capitalization

As presented in the descriptive statistics, the high-frequency offenders in our sample consist mainly of the largest companies in the Scandinavian stock market, where their market capitalization was significantly higher than the low-frequency offenders. However, a substantial amount of the observations of the high-frequency offenders consist of two firms with high market capitalization, thereby driving the results. We provide the same analysis when excluding these companies in the robustness analysis. Albeit, this does not alter the results. Nevertheless, these findings support that size seems to explain most of the variation in CAR in section 7.3. Larger companies experience a less negative stock price reaction, implying that smaller companies experience a relatively more negative stock price reactions, on average. Similarly, this is thereby confirmed by the increase in abnormal trading volume around bad ESG news events being negatively correlated with firm size. Accordingly, the abnormal trading volume is accentuated to the smaller firms.

Debt Ratio

In line with the finding in section 7.2, however contradictory to the leverage effect presented in section 4.1 for CAR, we find the debt ratio to be negatively correlated with CAV. Thus, the higher debt ratio, the smaller increase in abnormal trading volume.This is contra intuitive and contradicts the logic and results from the analysis of CAR. As this finding is solely significant at 10% level, we put limited emphasis on the result.

Time

There is a positive increase in abnormal trading volume for 2013 to 2015, at 5% level, and for 2018 to 2020, at 10% level. Furthermore, the abnormal returns are smaller for the latter period. However, as this only holds at 10% level, the effect will not be further emphasized. In addition, we find a significantly different effect when adding an interaction variable between the time periods and the variable "High Offender". Thus, while the overall abnormal trading volume is higher in the above-mentioned time periods, high-frequency offenders have a significantly smaller increase in abnormal trading volume than low-frequency offenders. This reveals a convergence in opinion for high-frequency offenders in these periods, compared to the low-frequency offenders, in line with what we hypothesized in H2.2.

8 Robustness

8.1 Research Design Choices

In this section, we test the robustness of the analysis performed and the implications concerning the choices of research design. First, we test the effect of excluding Equinor and Hydro, as the firms have a disproportional large amount of events within the data sample. Second, we test how the choice of normal performance models affects the results and investigate the difference between the Market Model and the Market-Adjusted Model. Lastly, we summarize the section with some concluding remarks.

8.1.1 Exclusion of Substantially Influential Companies

To test the robustness of our results, we conduct the analysis without Equinor and Hydro, as these companies together represent 40% of the incidents within the high-frequency offenders. All the results can be seen in Appendix A2.2, where we provide the OLS regressions excluding the two firms. Albeit, excluding Equinor and Hydro, does not alter our results of the hypothesis, as we do not find a significant difference.

However, we note that the carbon-intensive indicator variable in the regression of CAV in H1.2 (Table A2.2) becomes significant. However, this is solely concerning model 1 before adding controls. Consequently, we do not further emphasize this finding.

8.1.2 Alternative Estimation Models

The results of the analysis depend on the choice of normal performance models to estimate abnormal trading volume and price. While there is a wider consensus for using the Mean-Adjusted Model to estimate abnormal trading volume, there is a lack of consensus regarding normal performance models to estimate abnormal returns.

To estimate abnormal returns, we have chosen the Market Model. This is both because of its favorable results in previous research and its isolation of company-specific returns, as presented in section 6.2. However, other models have also proven effective in the literature, and there is no universal agreement on estimation models for CAR. Thereby, an alternative model, proven effective in event studies with a high frequency of events per company, is the Market Adjusted Model, presented in section 6. As the model solely estimates returns relative to the market index, it removes standard variation biases that can arise when news events occur within the estimation window. While the specific event dates have been excluded from the estimation period, increased volatility effects may span past the date itself. This is especially relevant for the high-frequency offender analysis, as these firms are characterized by many previous events within a 1-year lookback period. Therefore, we will conduct the complete two-stage analysis of the CAR, using the Market Adjusted Model.

The results using the Market Adjusted Model can be seen in Appendix A2.2. From table A2.5, we see that the results are robust across models. However, there is a slight significance for carbon-intensive sectors compared to non-carbon-intensive sectors in table 8.4. Nevertheless, as this is at 10% level, we argue that the finding does not sufficiently challenge the results from the main analysis. To further expand on the robustness analysis, a larger number of models can be used to test for consistency in results, as demonstrated by Barroso del Toro et al. (2022).[14]

8.2 Model Fit and Multicollinearity

To formally assess the robustness and validity of our analysis, we perform formal robustness tests. The following subsections address the extent to which our regression models comply with the underlying assumptions for OLS estimation. First, we will address misspecification, omitted variable bias, and multicollinearity before we formally test for heteroskedasticity in residuals and normality. All the results can be found in Appendix A2.3

8.2.1 Misspecification, Multicollinearity and Heteroskedasticity

Firstly, regarding the cross-sectional regression models used in the analysis, there are potential biases arising from the potential misspecification of the model. By conducting a RESET-test on all OLS models, we see that the models appear to be well specified regarding the functional form. Furthermore, with respect to multicollinearity, no models exhibit concerning VIF scores.

[14]Barroso del Toro et al. (2022) require significant results consistent across three models or more in their recent event study of European energy companies to ensure robustness in their findings.

Furthermore, the presence of heteroskedasticity is formally tested through Breusch-Pagan tests on the OLS regression models in line with Wooldridge (2016). The test results strongly suggest heteroskedasticity. The presence of heteroscedasticity does not cause bias or inconsistency in the OLS estimator, however, it causes the t-statistics to be biased (Wooldridge, 2016). We, therefore, employ heteroskedasticity-robust standard errors clustered by firm.

9 Critical Assessment of the Analysis

In this section, we assess the data sample by discussing the variables and possible omitted variable bias, limitations of the sample data, and, lastly, inherent limitations of the methodology.

9.1 Regression Variables and Omitted Variable Bias

In regards to the variables in the regressions, our main concern is related to the lack of control variables in our analysis. Size, risk and industry have most widely been used as these are factors that affect firm performance and sustainable corporate performance (Ullman, 1985), which we also have controlled for. However, due to limited data access to the Bloomberg Terminal at NHH, we have not controlled for several variables widely used in the literature. The literature suggests, among others, it would have been beneficial to control for financial performance measured by for example return on assets (ROA) or return on equity (ROE) (Waddock & Graves, 1997), and R&D expenses may have an impact on the firm's sustainability performance (Andersen & Dejoy, 2011). Controlling for these variables could potentially change the results.

Additionally, concerning the sampling process, our sample data is limited to available data from RepRisk. RepRisk covers a wide set of media sources. However, they have more extensive coverage of the American and European markets. As there is less coverage of the Nordic countries and bias toward the larger firms, smaller firms may be omitted from our sample. By obtaining these additional data points, the results may have changed.

9.2 Limitations of the Sample

9.2.1 Sample Size - Lack of Data

Due to the strict selection criteria for event studies, we have reduced the initial data set substantially. The final sample data is therefore somewhat small (N=316) with a subsequent total of distinct companies = 95, high-frequency offenders (N=145) with subsequent distinct companies = 26 using a 1-year lookback period, and (N=100) with subsequent distinct companies = 22 using a 2-year lookback period.

The results can therefore be sample-specific, thereby invalid for inference. Skewness is often more prominent for small samples as outliers could have a larger impact on the results (Wooldridge, 2016). While the obvious outliers for the full data sample are removed and the data are winsorized, there may be outliers within the subsections of the data, such as within the high-frequency offenders or the carbon-intensive sectors. In addition, due to the type of analysis conducted, our data set may suffer to some extent from sampling bias as only Environmental ESG violators are represented in the data set, leading to unbalanced sector representation. The results must therefore be interpreted with caution.

9.2.2 The Event Data and the RepRisk Database

The analysis is limited to the accuracy and completeness of the RepRisk database. Therefore, we should ideally have run the analysis on multiple ESG news databases to increase the robustness of the results. In addition, to capture the full effect of ESG news incidents on the stock market and get the complete picture of ESG awareness and importance, both positive and negative news should be analyzed. This is in line with analyses done by Serafeim & Yoon (2021) and Capelle-Blancard and Petit (2019).[15]

9.2.3 The Time Period

In regards to the time period of the analysis, we have three main concerns. Firstly, as the data period is only one decade, we do not find a time trend CAR as previously detected among others by Flammer (2013) as discussed in section 7.1. Second, we would have

[15] The studies analyzed positive and negative news using the databases TrueValueLabs and Covalence, respectively

liked to extend the data set to Q1 2022 to actualize the analysis further and increase the time horizon. Lastly, excluding observations from 01.03.2020 to 01.06.2020 to adjust for probable confounding events and extreme return effects from the Covid-19 pandemic has further limited the proximity and actuality of the data sample period.

9.2.4 Event Date and Market Information

An important issue concerns when the news occurs in the market. Griffin and Sun (2013) argue that if the investors do not update their opinion and beliefs regarding the ESG news post of the event as there is already publicly available information in existing channels, there will be no reaction. Thus it seems reasonable to discuss whether these reactions occur because the information may already be known and accordingly incorporated into the prices. As we do not know with certainty when the news occurred, e.i. there could be an ESG news on a former incident, and the reaction may have already occurred.

9.3 Inherent Limitation of the Methodology

9.3.1 The Assumptions of the Event Study Methodology

While the event study methodology is widely accepted within the field of finance, there are several general limitations and weaknesses of the methodology. This is because it builds upon assumptions and methodologies that are disputed among professionals. Most prominent is the market efficiency hypothesis, which is widely researched and debated, and there is still a lack of consensus on whether it holds. Furthermore, the assumption of rational market players has been increasingly challenged by the field of behavioral finance. Lastly, the predictions of normal returns and trading volume are based on a selection of estimation models (See Section 6.3) which are debated in the literature due to the lack of agreement on which model provides the highest precision.

10 Conclusion

Throughout this thesis, we examine the Scandinavian stock market reactions to environmental news incidents. By applying asymmetric information and efficient market theory, we use core concepts within the financial literature to analyze a key challenge in today's society.

While previous studies have mainly focused on the American or European markets, we provide novelty by isolating the Scandinavian market. As these markets are largely characterized by their dominance of carbon-intensive companies, we concentrate the analysis to the market reaction to environmental news. We conduct the analysis by investigating both abnormal price and volume reactions, formally addressed as CAR and CAV. This relationship has, to a limited extent, been applied within the core of the ESG literature. Nevertheless, we argue that a holistic approach is necessary to achieve a profound understanding of the market dynamics before drawing conclusions regarding investors' consideration and incorporation of ESG into their capital allocation. We use the RepRisk database to retrieve news incidents over the time period 2010 to 2020. Based on our two research questions, we test four hypotheses.

The first two hypotheses aim to analyze whether the stock market reaction to environmental news differs based on firms' carbon exposure. Thus, we separate the data sample into carbon-intensive and non-carbon-intensive firms based on the SASB Sustainable Industry Classification System. The first hypothesis regarding the stock price reaction is founded on differences in investors' anticipation and cost assessment of the firms. We argue that these two factors have opposite effects on the relative difference. While environmental news incidents should be more expected within the carbon-intensive sectors, large cost uncertainties related to regulatory risk and future growth opportunities complicate this picture. Hence, we hypothesize that carbon-intensive firms will expect a significantly different abnormal stock price reaction, however, we find no support for this hypothesis. In the second hypothesis, we turn to trading volume. We argue that carbon-intensive firms experience a larger difference of opinions on the occurrence of environmental news based on the outlined cost uncertainties, leading to a higher relative increase in trading volume. However, we find no such notion in our analysis.

To further expand our analysis, we examine whether the firms' recent incident history affects investors' anticipation and expectations of environmental news, by separating the sample into high-frequency and low-frequency offenders. Consequently, our third hypothesis elaborates on the stock-market reaction to high-frequency offenders. We argue that an anticipation effect might arise as the incident rate increases, increasing investors' anticipations of subsequent news incidents. This should lead high-frequency offenders to experience a less negative abnormal stock price reaction to the news incident. However, we find no evidence of the proposed anticipation effect. Lastly, in hypothesis four, we test if the outlined anticipation effect is reflected in the trading volume. We propose that the effect should lead the news to contain a lower degree of unexpectedness for high-frequency offenders. However, we find no difference in abnormal trading volume based on the firm's incident history. Taken together, we conclude that investors do not change their expectations towards the firms, based on our proposed sector affiliation or incident rate. These results are robust when excluding Hydro and Equinor from our analysis, accounting for a substantial amount of the analyzed news incidents.

Examining the full sample, we do not find significant market reactions to the news incidents, on average. This is contradictory to recent analyses performed on the European and American markets. Nevertheless, through the cross-sectional regressions analyzing the CAR and CAV, we encounter two valuable relationships between firm size and market reaction, and time and market reaction, respectively. In our analysis, market capitalization is positively correlated with CAR and negatively correlated with CAV. Accordingly, larger firms experience lower abnormal stock price reactions and trading volume to environmental news incidents. In addition, market capitalization seems to capture the effect of being a high-frequency offender, implying that larger firms are more prone to news incidents. Both these effects can be explained by the fact that larger companies experience higher media and analyst coverage, which is in line with the literature. Furthermore, when controlling for different time periods, we find a less negative reaction to environmental news in more recent years, combined with a decrease in abnormal trading volume. We suggest this finding reflects an increase in ESG awareness over the past decade.

Accordingly, we conclude that no news for investors, is good news for ESG awareness and the transition towards a sustainable future.

10.1 Avenues for Future Research

While we believe our analysis has provided interesting insights into the market valuation of environmental news incidents, there are several important paths yet to be explored.

First, we would encourage future researchers to combine news incidents data from multiple resources to test for consistency and robustness across databases. As each database is based upon its algorithms, methodologies and subjective criteria for tracking and logging news incidents, a comprehensive analysis across databases is necessary before drawing conclusions. We propose including TrueValueLabs and Covalence as a starting point, as these are commonly used in previous literature. Using these databases would further allow for analysis of positive news incidents.

Yet another interesting path to investigate is predictive analyses based on ESG incident history, in line with new research provided by Glossner (2021). He finds negative ROA the subsequent year after news incidents in his analysis. It would be interesting to extend his analysis and focus on the Nordic countries as well as investigate other measures such as changes in sales and cost of debt.

Lastly, it would be valuable to examine the importance of institutional ownership on the stock market reaction to news incidents. This could be implemented in the cross-sectional regressions as a control variable to see if there are systematic differences in investor reactions due to ownership structure. In addition, examining institutional fund managers' reallocation of holdings based on ESG news could give more profound insight into this relationship. For this aspect, it would be interesting to examine fund managers and institutions that have signed up for PRI. Adding this dimension into the analysis, would allow for a debate around active ownership and the effects of committed owners.

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Appendix

A1 Results: Two-Year Lookback Period

Table A1.1 H2.1 OLS Regression of CAR: Comparison 1-year vs. 2-year Lookback Period

	Dependent variable:	
	CAR	
	1 Year	2 Year
	(1)	(2)
High-frequency One-year	0.001	
	t = 0.370	
High-frequency Two-year		0.003
		t = 0.923
ln(Market Capitalization)	0.003***	0.003***
	t = 3.617	t = 3.210
2013-2015	0.009	0.009
	t = 1.613	t = 1.610
2016-2017	0.013**	0.013***
	t = 2.550	t = 2.601
2018-2020	0.015***	0.015***
	t = 3.118	t = 3.121
Reach	−0.002	−0.002
	t = −0.551	t = −0.545
Debt Ratio	−0.006	−0.005
	t = −1.501	t = −1.464
Constant	−0.066***	−0.063***
	t = −4.125	t = −3.783
Time FE	No	No
Entity FE	No	No
Clustered SE	Yes	Yes
Observations	316	316

Note: *$p<0.1$; **$p<0.05$; ***$p<0.01$
We apply Robust standard errors, and report the associated t-statistics.

Table A1.2 H2.2 OLS Regression of CAV: Comparison 1-year vs. 2-year Lookback Period

	Dependent variable:	
	CAV	
	1 Year	2 Year
	(1)	(2)
High-frequency One-year	0.014	
	t = 0.083	
High-frequency Two-year		0.117
		t = 0.709
ln(Market Capitalization)	−0.132**	−0.143**
	t = −2.443	t = −2.389
2013-2015	0.700***	0.701***
	t = 2.726	t = 2.783
2016-2017	0.581	0.594
	t = 1.518	t = 1.581
2018-2020	0.494*	0.485*
	t = 1.758	t = 1.783
Reach	0.151	0.153
	t = 0.737	t = 0.742
Debt Ratio	−0.420*	−0.402*
	t = −1.923	t = −1.818
Constant	1.774**	1.905*
	t = 1.978	t = 1.957
Time FE	No	No
Entity FE	No	No
Clustered SE	Yes	Yes
Observations	316	316

Note: *$p<0.1$; **$p<0.05$; ***$p<0.01$
We apply Robust standard errors, and report the associated t-statistics.

A2 Model Robustness - Research Design Choices

A2.1 Model Robustness - Results without Equinor and Hydro

Table A2.1 H1.1 OLS Regression CAR: Carbon Intensive vs. Non Carbon Intensive without Equinor and Hydro

	Dependent variable:				
	CAR				
	(1)	(2)	(3)	(4)	(5)
Carbon Intensive	−0.005	−0.002	−0.004	−0.004	−0.012
	t = −1.037	t = −0.650	t = −0.964	t = −0.978	t = −0.959
ln(Market Capitalization)		0.005***	0.004***	0.004***	0.004***
		t = 4.472	t = 3.910	t = 3.813	t = 3.933
2013-2015			0.007	0.008	0.008
			t = 1.001	t = 1.032	t = 1.149
2016-2017			0.012*	0.012*	0.008
			t = 1.769	t = 1.739	t = 1.152
2018-2020			0.016**	0.016**	0.006
			t = 2.550	t = 2.519	t = 0.886
Debt Ratio		−0.005	−0.008*	−0.008*	−0.008**
		t = −1.281	t = −1.862	t = −1.852	t = −2.017
High Reach				−0.003	−0.003
				t = −0.654	t = −0.778
Carbon Intensive*(2013-2015)					0.001
					t = 0.054
Carbon Intensive*(2016-2017)					0.008
					t = 0.521
Carbon Intensive*(2018-2020)					0.019
					t = 1.427
Constant	−0.003	−0.074***	−0.072***	−0.069***	−0.067***
	t = −1.171	t = −4.528	t = −4.208	t = −4.045	t = −4.598
Time FE	No	No	No	No	No
Entity FE	No	No	No	No	No
Clustered SE	Yes	Yes	Yes	Yes	Yes
Observations	252	252	252	252	252

Note: *$p<0.1$; **$p<0.05$; ***$p<0.01$
We apply Robust standard errors, and report the associated t-statistics.
This regression provide results for testing H1.1 without Equinor and Hydro

Table A2.2 H1.2 OLS Regression CAV: Carbon-Intensive vs. Non-Carbon-Intensive

	Dependent variable:				
	CAV				
	(1)	(2)	(3)	(4)	(5)
Carbon Intensive	0.041***	−0.025	−0.076	−0.068	0.343
	t = 8.670	t = −0.106	t = −0.326	t = −0.292	t = 0.710
ln(Market Capitalization)		−0.149**	−0.166**	−0.156**	−0.157**
		t = −2.170	t = −2.332	t = −2.225	t = −2.255
2013-2015			0.997***	0.952***	1.106**
			t = 3.449	t = 3.207	t = 2.305
2016-2017			0.928**	0.982**	1.078*
			t = 2.437	t = 2.527	t = 1.867
2018-2020			0.826***	0.854***	1.227***
			t = 3.065	t = 3.041	t = 2.614
Debt Ratio		−0.388*	−0.458**	−0.466**	−0.473**
		t = −1.722	t = −1.962	t = −2.014	t = −2.087
Reach				0.320*	0.332*
				t = 1.659	t = 1.756
Carbon Intensive*(2013-2015)					−0.365
					t = −0.624
Carbon Intensive*(2016-2017)					−0.225
					t = −0.328
Carbon Intensive*(2018-2020)					−0.737
					t = −1.399
Constant	0.173***	2.626**	2.135*	1.803	1.639
	t = 60.286	t = 2.319	t = 1.861	t = 1.613	t = 1.436
Time FE	No	No	No	No	No
Entity FE	No	No	No	No	No
Clustered SE	Yes	Yes	Yes	Yes	Yes
Observations	252	252	252	252	252

Note: *$p<0.1$; **$p<0.05$; ***$p<0.01$
We apply Robust standard errors, and report the associated t-statistics.
This regression provide results for testing H1.2 without Equinor and Hydro

Table A2.3 H2.1 OLS Regressions: High-frequency vs. Low-frequency Offenders

	Dependent variable:				
	CAR				
	(1)	(2)	(3)	(4)	(5)
High Offender	0.015**	0.004	0.002	0.004	−0.009
	t = 2.367	t = 0.739	t = 0.260	t = 0.755	t = −1.144
ln(Market Capitalization)		0.007***	0.006**	0.007***	0.006**
		t = 2.643	t = 2.511	t = 2.639	t = 2.403
2013-2015			0.008		0.006
			t = 0.642		t = 0.456
2016-2017			0.014		0.012
			t = 1.177		t = 0.958
2018-2020			0.023**		0.028**
			t = 2.137		t = 2.438
Debt Ratio		−0.003	−0.006	−0.003	−0.007
		t = −0.513	t = −1.146	t = −0.510	t = −1.347
High Reach				0.001	0.003
				t = 0.154	t = 0.566
High Offender*(2013-2015)					0.018
					t = 1.130
High Offender*(2016-2017)					0.023**
					t = 2.480
Constant	−0.013***	−0.106***	−0.107***	−0.107***	−0.107***
	t = −2.937	t = −2.858	t = −2.699	t = −2.850	t = −2.644
Time FE	No	No	No	No	No
Entity FE	No	No	No	No	No
Clustered SE	Yes	Yes	Yes	Yes	Yes
Observations	252	252	252	252	252

Note: *$p<0.1$; **$p<0.05$; ***$p<0.01$
We apply Robust standard errors, and report the associated t-statistics.
This regression provide results for testing H2.1 without Equinor and Hydro

Table A2.4 H2.2 OLS Regressions CAV: High-frequency vs. Low-frequency Offenders

	Dependent variable:				
	CAV				
	(1)	(2)	(3)	(4)	(5)
High Offender	−0.137	0.157	0.080	0.097	−0.157
	t = −0.519	t = 0.675	t = 0.320	t = 0.383	t = −0.415
ln(Market Capitalization)		−0.218**	−0.210**	−0.203*	−0.205*
		t = −2.130	t = −2.027	t = −1.938	t = −1.943
2013-2015			0.751**	0.724**	0.750*
			t = 2.120	t = 2.093	t = 1.802
2016-2017			0.806*	0.867*	0.656
			t = 1.658	t = 1.795	t = 1.169
2018-2020			0.496*	0.512*	0.628*
			t = 1.653	t = 1.647	t = 1.730
Debt Ratio		−0.555*	−0.560*	−0.571*	−0.610**
		t = −1.748	t = −1.751	t = −1.808	t = −1.984
High Reach				0.267	0.275
				t = 1.075	t = 1.092
High Offender*(2013-2015)					0.153
					t = 0.229
High Offender*(2016-2017)					0.962
					t = 1.156
Constant	0.254	3.645**	2.953*	2.703*	2.739*
	t = 1.123	t = 2.290	t = 1.921	t = 1.728	t = 1.739
Time FE	No	No	No	No	No
Entity FE	No	No	No	No	No
Clustered SE	Yes	Yes	Yes	Yes	Yes
Observations	252	252	252	252	252

Note: *$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$*
We apply Robust standard errors, and report the associated t-statistics.
This regression provide results for testing H2.2 without Equinor and Hydro

A2.2 Alternative Estimation Model: Market Adjusted Model

Table A2.5 H1.1 & H2.1: OLS Regression of CAR using Market Adjusted Model

	Dependent variable:		
	CAR		
	(1)	(2)	(3)
Carbon Intensives	-0.007^{*}		
	t = −1.716		
High-frequency 1-Year		0.002	
		t = 0.655	
High-frequency 2-Year			0.003
			t = 0.670
Market Capitalization	0.004^{***}	0.004^{***}	0.004^{***}
	t = 4.324	t = 3.345	t = 3.154
2013-2015	0.008	0.008	0.008
	t = 1.475	t = 1.367	t = 1.387
2016-2017	0.014^{***}	0.014^{***}	0.015^{***}
	t = 2.589	t = 2.620	t = 2.676
2018-2020	0.015^{***}	0.014^{**}	0.014^{***}
	t = 2.798	t = 2.562	t = 2.631
Reach	0.001	0.001	0.001
	t = 0.339	t = 0.412	t = 0.404
Debt Ratio	−0.007	−0.005	−0.005
	t = −1.292	t = −1.065	t = −1.079
Constant	-0.074^{***}	-0.073^{***}	-0.072^{***}
	t = −4.582	t = −3.952	t = −3.768
Time FE	No	No	No
Entity FE	No	No	No
Clustered SE	Yes	Yes	Yes
Observations	316	316	316

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
We apply Robust standard errors, and report the associated t-statistics.
Model 1 shows the regression for testing H1.1 Carbon-intensives vs. Non-carbon-intensives. Model 2 and 3 shows the regression for H2.1 using one- and two-year lookback period, respectively.

A2.3 Model Robustness - Regression Variables and Omitted Variable Biases

Table A2.6 H1.1: Variance Inflation Factors for All Models Measuring CAR

	(1)	(2)	(3)	(4)
Carbon Intensives	1.035	1.022	1.022	2.618
Market Capitalization	1.019	1.026	1.035	1.064
Debt Ratio	1.035	1.054	1.055	1.058
Time		1.017	1.026	1.655
Reach			1.043	1.044
Carbon Intensives ∗Time				1.971

Table A2.7 H1.2: Variance Inflation Factors for All Models Measuring CAV

	(1)	(2)	(3)	(4)
Carbon Intensives	1.035	1.022	1.022	2.618
Market Capitalization	1.019	1.026	1.035	1.064
Debt Ratio	1.035	1.054	1.055	1.058
Time		1.017	1.026	1.655
Reach			1.043	1.044
Carbon Intensives ∗Time				1.971

Table A2.8 H2.1: Variance Inflation Factors for All Models Measuring CAR

	(1)	(2)	(3)	(4)
Repeat	1.690	1.323	1.326	1.378
Market Capitalization	1.617	1.294	1.295	2.879
Debt Ratio	1.065	1.061	1.062	1.084
Time		1.020	1.027	1.395
Reach				1.745
Carbon Intensives ∗Time			1.033	1.038

Table A2.9 H2.2: Variance Inflation Factors for All Models Measuring CAV

	(1)	(2)	(3)	(4)
Carbon Intensives	1.690	1.323	1.326	1.378
Market Capitalization	1.617	1.294	1.295	2.879
Debt Ratio	1.065	1.061	1.062	1.084
Time		1.020	1.027	1.395
Reach				1.745
Carbon Intensives ∗Time			1.033	1.038

Table A2.10 H1.1 - H1.2 Ramsey RESET Test p-values

	(1)	(2)	(3)	(4)	(5)
H1.1 CAR	1	0.051	0.595	0.677	0.699
H1.2 CAV	1	0.975	1.000	1.000	1.000

Table A2.11 H2.1 - H2.2 Ramsey RESET Test p-values

	(1)	(2)	(3)	(4)
H2.1 CAR	0.092	0.759	0.829	0.844
H2.2 CAV	0.977	1.000	1.000	1.000

Table A2.12 H1.1 - H1.2 Breusch-Pagan Test p-values

	(1)	(2)	(3)	(4)	(5)
H1.1 CAR	0.123	0.002	0.002	0.002	0.005
H1.2 CAV	0.372	0.00000	0.00000	0.00000	0.0001

Table A2.13 H2.1 - H2.2 Breusch-Pagan Test p-values

	(1)	(2)	(3)	(4)	(5)
H2.1 CAR	0.044	0.007	0.020	0.027	0.078
H2.2 CAV	0.003	0.001	0.001	0.003	0.003

Table A2.14 Correlation Matrix for all Regression Variables

	Incident rate	ln(Market Capitalization)	Debt Ratio
Incident rate	1	0.32	-0.230
ln(Market Capitalization)	0.32	1	-0.153
Debt Ratio	-0.230	-0.153	1