

Rising Heat, Rising Risk: The Effect of Greenhouse Gas Emissions on Downside Tail Risk

Tristan M. Neuber¹ and Fabrice J.M. Van Lancker²

Master's Thesis in Finance

December 2023

ABSTRACT. Regulatory and societal attention to environmental pollution is increasing, and greenhouse gas (GHG) emissions are becoming a potential risk factor for investors. This paper uses panel data from S&P 500 firms between 2015 and 2022 to investigate the link between GHG emissions and downside tail risk. We find that high-emitting firms are more vulnerable to extreme stock devaluations. Further, committing to reduce emissions through, for example, emission targets mitigates the effect for carbon-intense firms. We also show that the positive association disappears in years where regulatory attention to climate change is low, indicating that the political environment plays a vital role in how carbon tail risk is perceived.

Keywords: Climate Risk, Downside Risk, GHG Emissions, Sustainable Finance, Tail Risk

Supervisor: Jan Starmans, Assistant Professor at the Department of Finance at the Stockholm School of Economics.

Acknowledgments: We would like to thank our supervisor Jan Starmans for his guidance and support throughout the writing process.



¹E-mail: 42406@student.hhs.se

²E-mail: 42377@student.hhs.se

Table of Contents

1	Introduction	4
2	Literature Review	7
2.1	Tail Risk and Asset Pricing	7
2.2	Carbon Emissions	9
3	Hypothesis Development	10
3.1	Value-Enhancing Theory	10
3.2	Carbon Risk	11
4	Data and Methodology	15
4.1	Sample	15
4.2	Measurement of Variables	16
4.2.1	Greenhouse Gas Emissions	16
4.2.2	Stock Price and Risk Measures	17
4.2.3	Control Variables	20
4.2.4	Descriptive Statistics	21
4.3	Models	23
4.3.1	The Influence of Emissions on Tail risk	23
4.3.2	Signalling and Commitment	24
4.3.3	Paris Agreement and Politics	26
5	Results and Discussion	27
5.1	GHG Emissions and Downside Tail Risk	27
5.1.1	General Results	27
5.1.2	Systematic and Idiosyncratic Tail Risk	29
5.2	Emission Targets and Reduction Plans	33
5.2.1	The Impact of Emission Targets and Reduction Policies	33
5.2.2	The joint effect of CO2e Emissions, Targets, and Policies	33
5.3	The Impact of the Paris Agreement	37
5.3.1	Results Regression	37
5.4	Robustness	39

5.4.1	Alternative Downside Risk Measures	39
5.4.2	General Volatility Control	40
5.4.3	Omitted Variable Bias	41
5.4.4	COVID Control	42
6	Implications	42
7	Limitations and Further Research	44
8	Conclusions	45
	References	47
	Appendix	54

1 Introduction

Investors and scholars often regard risk as both the potential upside and downside movements of security prices (Markowitz, 1952; Tobin, 1958; Engle, 2004). However, scholars have documented that investors are disproportionately averse to downside movements and extreme losses than symmetric risk preferences would suggest (Bawa, 1975; Fishburn, 1977; Menezes et al., 1980). Consequently, downside tail risk has become a pivotal area in asset pricing (e.g., Friend and Westerfield, 1980; Sears and Wei, 1988; Fang and Lai, 1997; Yang and Chen, 2009) and significant efforts have been extended into its determinants (Moore et al., 2013; Kim et al., 2014; Min and Kim, 2016). Additionally, history has shown that systematic crises, such as the Global Financial Crisis (GFC) of 2007/2008 or the COVID-19 pandemic, can be a source of large-scale equity devaluations. These events have exacerbated the focus on tail risk among practitioners and scholars. Another phenomenon with systematic characteristics and potentially devastating consequences is climate change. While it is unclear if the threats of climate change will materialise through a systematic shock or on a more granular basis, the rapid growth in greenhouse gas (GHG)¹ emissions has been determined as a major risk driver (Hui-Min et al., 2021). Existing research suggests a significant link between corporate GHG emissions and stock returns (Bolton and Kacperczyk, 2020; Oestreich and Tsiakas, 2015; Bauer et al., 2022). Yet, little is known of how emissions and downside tail risk are related on a corporate level. With the high attention on tail risk in the asset pricing literature and among risk managers, this research field presents an interesting area of investigation.

This paper aims to analyse whether firm-level emissions can be associated with downside tail risk and explore the intricacies of this hypothesised relationship. Investors' increased attention to corporate emissions and the rising political as well as societal pressures related to climate change (e.g., the Paris Agreement) hint at an economically significant link. The intuition is that high polluters are more vulnerable to events that adversely influence their equity price, such as climate litigation, policy changes, or customer actions resulting in stranded assets or higher operational costs. These carbon risk components appear to be predominantly on the downside. Conversely, cleaner firms are less exposed to these events. This logic is consistent with existing literature, which

¹In the context of this paper the terms greenhouse gas (GHG), CO₂ equivalent (CO₂e), and carbon are used interchangeably

suggests that corporate social responsibility (CSR) in general mitigates tail risks (Kim et al., 2014; Diemont et al., 2016) and contributes positively to shareholder value (Porter and Kramer, 2006). We add to the sustainable finance literature that analyses the ramifications of CSR, specifically GHG emissions, on U.S. firm performance. At the same time, we further expand the literature focused on tail risk by investigating emissions as a potential non-financial determinant.

Our research sample focuses on the constituents of the S&P 500 from 2015 to 2022. The S&P 500, with its broad industry coverage, provides a representative view of the overall U.S. market. Refinitiv Eikon is used to retrieve CDP-sourced emissions data. In line with existing literature on tail risk, we employ expected shortfall (ES) as our main downside risk measure (McNeil, 1999; Archarya et al., 2017; Ciliberti et al., 2007). We start our analysis by evaluating the overall effect of GHG emissions on corporations' downside tail risk. Our results suggest a positive relationship between corporate emission levels and downside risk. Specifically, a 1% increase in total GHG emissions results in a 2.5% increase in expected shortfall. Similar results are obtained for carbon intensity, but no effect was concluded for yearly changes in emission levels.

Second, we determine whether carbon tail risk is of idiosyncratic or systematic nature. On the one hand, company-specific events such as reputational damages or litigation procedures (e.g., the Volkswagen-Diesel scandal) render carbon tail risk non-systematic. On the other hand, regulatory changes, such as emission limits or trading schemes, and fossil fuel price fluctuations, hint at a systematic risk factor. By using downside market beta as measure of systematic tail risk, we find evidence that GHG emission tail risk has both idiosyncratic and systematic components. This distinction is crucial to provide meaningful insights to researchers, practitioners, and scholars. While it is widely accepted that investors are compensated for bearing systematic risk (Sharpe, 1964), idiosyncratic tail risk has been described as virtually undiversifiable in times of crisis (Bégin et al., 2020). These findings support the idea of a carbon premium as investors want to be compensated for bearing these undiversifiable risks. For corporate managers, the fact that carbon tail risk has a systematic component means hedging ought to happen through adjusting financial policies as well as R&D and acquisition expenditures, which results in significant financial implications (Schoar et al., 2023).

Third, we investigate the impact of GHG reduction policies and emission targets on downside risk. The rationale of this analysis is that high emitters may aspire to decrease their CO₂ equivalent (CO₂e) emissions. Hence, the implementation of such policies signals to investors the firms' commitment to reduce their long-term risk exposure. Therefore, companies with the highest current emission levels can significantly improve their emission levels if they take appropriate actions. Our results indicate that neither emission targets nor reduction policies influence downside risk across the board. Nevertheless, when interacted with emissions, emission targets have a significant effect. These findings suggest that signalling a commitment to cut carbon emissions mitigates the tail risk exposure among high emitters but not among low emitters.

Fourth, we analyse the effect of regulatory changes, particularly climate regulations, on downside risk. The theoretical link between emissions and tail risk builds upon regulation as a main driver. Specifically, the exposure of carbon-intense firms to changes in regulation and general political attention to the issue is much higher relative to clean firms, which prompt extreme equity devaluation in adverse events, such as the introduction of carbon taxes. The period under review (2015-2022) provides great insights into the impact of these regulatory changes as it includes the United States' initial participation in the Paris Agreement, the country's withdrawal from the agreement under President Trump, and later, the rejoining under President Biden. These political changes provide a unique opportunity to analyse the influence of changing climate regulations on firms' tail risk. We find that political agendas influence carbon tail risk. Notably, the results show that when the U.S. are a signatory member of the Paris Agreement, corporations with higher emission levels or intensities are more exposed to downside risk. Alternatively, the effect reverses when the U.S. are not part of the agreement. This shows that uncertainty around climate policy is affecting capital markets. Precisely, it suggests that policymakers can effectively use regulations to steer capital towards more sustainable practices.

The remainder of the paper is structured as follows: Section 2 reviews the existing literature. Section 3 develops our hypotheses. Section 4 presents the data and descriptive statistics and introduces the models. Section 5 provides the results and discusses the main findings. Additionally, the section complements the analysis with robustness checks. Section 6 presents implications, while section 7 discusses the limitations of our study. Section 8 provides concluding remarks.

2 Literature Review

2.1 Tail Risk and Asset Pricing

The effects of the Global Financial Crisis in 2007-2008 have intensified the focus on extreme negative shocks. Figure 1 illustrates the impact of these rare events on capital markets over the past two decades. Understanding and managing these tail events is not only important on a systematic level but also on the firm-level. Scholars have investigated tail risks for some time and highlighted the importance in the academic literature (Kelly and Jiang, 2014).

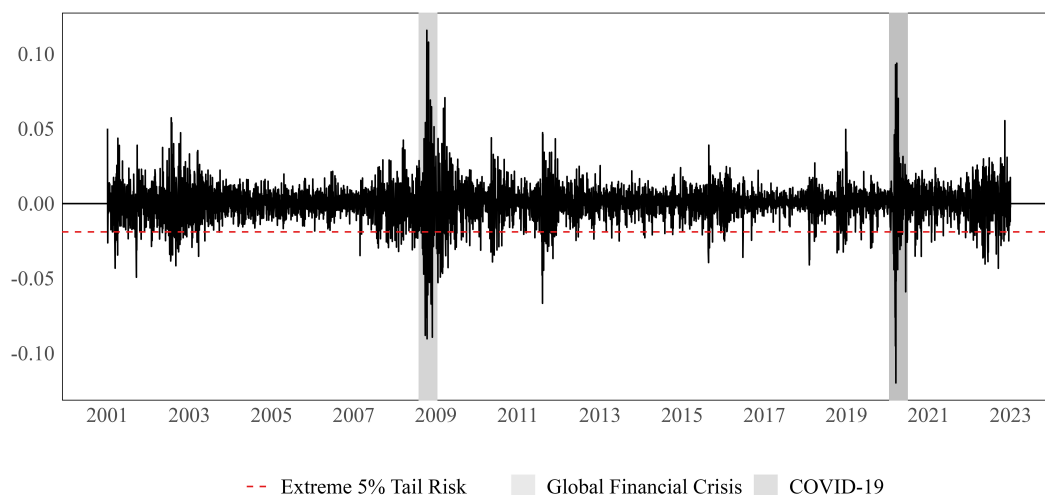


Figure 1: S&P 500 - Historical Returns

Note: The figure plots the daily returns of the S&P 500 between January 1, 2001, and December 31, 2022. The figure also shows the cutoff to the 5% extreme losses over the period.

The original modern portfolio theory (MPT) put forth by Harry Markowitz in 1952 introduced the concept of portfolio optimisation following the trade-off between risk and return (Markowitz, 1952). In this context, Markowitz views risk as the total volatility of asset prices. As such, an optimal portfolio considers assets' co-movement, specifically covariance. However, the framework limits return distributions to be normal and ignores skewness and kurtosis (Bawa and Lindenberg, 1977). At the same time, investors have differential appetites for downside and upside variation. As the disaster avoidance motive demonstrates, investors exhibit a heightened aversion toward extreme negative scenarios (Menezes et al., 1980). Even Markowitz argues that underperformance is much more important for investors than overperformance and that semi-variance, a measure that

captures variation below 0, should be the preferred measure of risk (Markowitz et al., 1993). Thus, further iterations of portfolio theory introduced higher mathematical moments and co-skewness as well as co-kurtosis found their way into asset pricing to assess the distribution of returns more adequately (e.g., Friend and Westerfield, 1980; Sears and Wei, 1988; Fang and Lai, 1997; Yang and Chen, 2009). The non-linear risk appetite of investors, coupled with non-normal return distributions, have introduced downside risk as a central concept of contemporary asset pricing.

Beyond the original notion that investors should only be rewarded for bearing systematic risk (Sharpe, 1964), several studies found that downside risk appears to be a relevant risk factor. For instance, Ang et al. (2006) show that stocks that move further down than the market during downturns have higher required returns to compensate for this increased downside beta exposure. More importantly, the authors find that this reward cannot be explained by other common pricing factors, such as regular market beta, size, value, or momentum. Similarly, Harvey and Siddique (2000) confirm that conditional skewness, a measure of systematic downside risk, is a priced factor even when controlling for Fama-French factors. In addition to the findings on systematic downside risk, Bégin et al. (2020) argue that idiosyncratic tail risk is undiversifiable in times of crisis, which explains their findings of a significant return premium when bearing this risk. Likewise, Huang et al. (2012) define extreme downside risk (EDR) as a measure of idiosyncratic tail risk and demonstrate that there is a premium for loading on EDR when controlling for Fama-French and Carhart's (FFC) four factors. The findings show that tail risk, both in systematic and non-systematic form, is viewed differently in capital markets than other types of risk. Investors are averse to extreme downturns, yet it is very difficult for them to diversify this risk. As such, they require additional compensation for bearing tail risk beyond what traditional risk factors would indicate.

This backs the question of what determines a stock's exposure to extreme equity devaluations. While research is still scarce, some scholars have identified financial metrics, such as leverage, liquidity, balance sheet strength, or profitability to drive downside tail risk (Moore et al., 2013; Thurner et al., 2012; Long et al., 2018; Long et al., 2019; Trinh et al., 2023). Furthermore, non-financial metrics increasingly shift towards the centre of attention and how they may influence corporates' tail risk exposure. Researchers have noted the mitigating effect of high ESG scores on tail risk, citing the insurance properties

of responsible behaviour (Zhang et al., 2021; Shafer and Szado, 2020). Further efforts are needed to disentangle the effect of ESG on tail risk. We aim to shed light on the yet unclear role that carbon emissions play in this.

2.2 Carbon Emissions

From individual households to intergovernmental bodies, the debate over measures to mitigate climate change and adapt to its consequences has gained widespread attention. Within the scientific community, there is a clear consensus that human activities are responsible for the unprecedented increase in greenhouse gas emissions and their impact on global climates (IPCC, 2023). Consequently, GHG emissions have been a central point of discussion in the political and economic debate around the issue. Academia has devoted substantial efforts to investigating the impact of emissions on corporate performance (Houqe et al., 2022; Miah et al., 2021; Hapsoro and Falih, 2020; Khatib et al., 2023). While there is no consensus regarding a clear link between emissions and stock returns, a very influential paper in the sustainable finance area by Bolton and Kacperczyk (2021a) asserts that investors demand a carbon premium. Their argument claims that firms with more carbon emissions earn higher returns as investors require compensation for the increased risk. However, the authors make no detailed inference about the nature of this risk. Similarly, Alessi et al. (2021) stipulate that investors accept lower returns for greener, more transparent companies and use them to hedge their carbon exposure. Many other studies support the positive association between emissions and returns (Oestreich and Tsiakas, 2015; Wen et al., 2020; Bolton and Kacperczyk, 2020). Nonetheless, a large body of literature also challenges the existence of a carbon premium (Houqe et al., 2022). Aswani et al. (2023) suggest that the carbon premium disappears once specific firm characteristics are controlled for, while a study analysing the returns for green and brown firms among G7 nations found evidence of a negative carbon premium (Bauer et al., 2022).

As can be seen, the interplay of carbon emissions and returns has been extensively studied. One area of research suggests that highly emitting firms deliver higher returns due to increased exposure to carbon risk. In this context, Trinks et al. (2020) show that lower carbon efficiency relates to higher systematic risk as carbon-inefficient firms are

more sensitive to uncertain future carbon emission costs. A study across 42 economies also showed that carbon emissions have a significant causal impact on the risk of default (Kabir et al., 2021). The authors argue that the firms’ carbon footprint captures exposure to climate risks, and greater exposure increases the chance of default on their debt obligations. Further, Ilhan et al. (2021) aim to quantify the future impact of climate regulation and find that the cost of option protection against tail risks is higher among carbon-intense firms. It appears that emissions expose firms to risk factors that are predominantly negative. Climate regulation, reputational damages, pollution fines, or technological changes are examples of how high-emissions firms can be adversely affected. This paper explores whether this link between emissions and downside tail risks is observable in equity markets.

We contribute to the existing literature by analysing a potential driver of corporate tail risk. As mentioned before, asset pricing scholars are very concerned with this type of risk due to its complex diversification and investors’ disproportionate risk aversion to extreme negative events. Firm-level CSR initiatives seem to mitigate tail risk, but whether emissions specifically have an impact is unclear. Further, we add to the growing sustainable finance literature by advancing the understanding of how emissions impact corporations and their performance. This may help better understand why or why not a carbon premium exists. Overall, the relationship between emissions and risk, especially the nature of the risk, is a relatively unexplored area and a fruitful avenue for further analysis.

3 Hypothesis Development

3.1 Value-Enhancing Theory

For many years, the dominant perspective in the corporate world was centred around Friedman’s doctrine, also known as the “Shareholders’ Theory” (Friedman, 1970). This theory posits that businesses exist primarily to generate profits for shareholders. Nevertheless, as the world grappled with pressing social and environmental challenges, stakeholders – such as employees and communities – began demanding that companies go beyond profit maximisation and focus on more than just financial returns. The stark

realities of global issues led to a growing realisation that businesses cannot operate in isolation from the societies and environments surrounding them. This changing landscape more recently gave birth to the “Value-Enhancing Theory” (Porter and Kramer, 2006). The theory champions the integration of corporate social responsibility into daily managerial decisions and operational strategies, which ultimately results in long-term shareholder value. Several scholars confirm the relationship between CSR practices and financial performance (Simionescu and Dumitrescu, 2014; Qiu et al., 2021). Interestingly, CSR also appears to make firms more crisis-resilient. Braune et al. (2019) note a negative relationship between social performance and systematic risk, measured by market beta, during times of higher economic instability. At the same time, Lins and Servaes (2017) find that during the GFC, firms with high CSR had stock returns that were four to seven percent higher than low-CSR counterparts. According to the theory, CSR is a source of long-term shareholder value through, for example, reducing risk. Carbon emissions exemplify how firm actions might adversely impact society more than the organisation itself. Consequently, they represent a significant component of corporate socially responsible behaviour, prompting our analysis of whether reduced emissions are related to fewer and less extreme equity devaluations.

3.2 Carbon Risk

There are several risk factors that polluting firms are exposed to, and that can help us understand the hypothesised link between emissions and tail risk. We categorise them into the following areas. First, transition risk describes how structural changes required to reach a greener economic system may cause changes in climate policy, societal sentiment, or shifts in market preferences (Semieniuk et al., 2021). For instance, advancements in technology in the clean energy space may impede the standing of companies relying on fossil technologies (Görge et al., 2020). Similarly, high-emissions companies have extensive exposure to the fossil fuel sector and are thus subject to energy price risks (Bolton and Kacperczyk, 2021b). Arguably, the most important type of climate transition risk relates to climate regulations. A potential shift in regulatory circumstances, such as the introduction of carbon taxes, cap-and-trade schemes, or emissions limits, can force companies to revise their operations or even their business model (Ilhan et al., 2021). As

carbon-intense firms likely require more significant transformations, investors will penalise them more harshly. Many scholars have shown that changes in the political environment raise companies' uncertainty and impact capital markets (Oehler et al., 2021; Durnev, 2010; Kelly et al., 2016). Evidence also shows that high-emissions firms are more exposed to environmental policy risk (Hsu et al., 2023; Seltzer et al., 2022).

Second, heightened focus on climate change mitigation has caused high legal attention around cases where firms disregard environmental policy or disclosure regulations. Consequently, climate change litigation cases have grown substantially in recent years, hurting companies' reputation as well as their financial position (Peel and Osofsky, 2020). A prominent example is the Volkswagen-Diesel scandal, which resulted in the car manufacturer having to pay almost USD 35bn in fines and settlements (Reuters, 2020). In academia, climate litigation risk is yet to be explored further to yield insights in the context of this paper. However, findings by Koh et al. (2014) suggest that irresponsible behaviours, such as high carbon emissions, expose companies to potential legal repercussions. Generally, litigation can cause extreme downward stock movement because bad information about a company suddenly becomes publicly known (Deng et al., 2023).

Third, the general sentiment towards heavy emitters is growing increasingly critical. Public backlash about deceptive reporting or environmental hazards can cause long-term reputational damages. Guastella et al. (2022) argue that failing to meet stakeholder expectations regarding climate objectives, such as limiting carbon emissions, causes reputational and, ultimately, financial damages to a firm. According to the authors, this effect is higher among very carbon-intensive industries. In the short run, such negative news can motivate shareholders to withdraw capital, causing a stock to plummet.

Lastly, physical risk describes the degradation of asset values due to exposure to changing environmental conditions due to climate change. For example, rising sea levels threaten to damage facilities in coastal regions. Several studies investigate the effect of physical risk on asset prices with little conclusive evidence (Hong et al., 2019; Baldauf et al., 2020; Bernstein et al., 2019). In the context of this paper, physical risk is deemed irrelevant as there is no reasonable economic link to carbon emissions. Whether a company emits more or less GHG does not change the exposure of its assets to changing environmental conditions.

Overall, uncertainty around climate and carbon-related topics causes investors to consider their investments cautiously in light of these risks. We hypothesise that carbon-intensive firms display higher downside tail risk due to their higher exposure to events that negatively affect their share price. Increasing attention to climate change mitigation results in policy changes, litigation costs, higher costs of doing business, or reputational damages. Together these factors negatively impact high-emissions companies more frequently and to a greater extent. Thus, the first hypothesis presented in this paper is as follows:

H1a: *Companies with higher greenhouse gas emissions display higher downside tail risk.*

It is essential to understand how we view tail risk in the context of our analysis. Carbon risk and tail risk can be systematic and idiosyncratic. Regulatory interventions such as carbon taxes exemplify how carbon risk can be a systematic factor, given that these interventions affect all companies uniformly (Bolton and Kacperczyk, 2020). In contrast, regulatory changes may be implemented on a sector basis, while cases of climate litigation or technological advancements may have more granular heterogeneous effects, making carbon risk rather non-systematic. While both factors appear reasonable, existing literature does not allow for any inference on the type of risk that may explain tail risk variation. Consequently, we further explore carbon tail risk’s systematic and idiosyncratic components.

H1b: *Companies with higher greenhouse gas emissions display higher systematic downside tail risk.*

H1c: *Companies with higher greenhouse gas emissions display higher idiosyncratic downside tail risk.*

While the disclosure of total emissions is valuable to the market, it does not directly convey information about a company’s commitment to sustainability. Even highly emitting firms may be very ambitious in reducing their carbon footprint and improving their long-term environmental performance. Emission levels and intensities tend to ex-

hibit significant persistence with rather limited year-over-year (Y-o-Y) changes (Bolton and Kacperczyk, 2020). As such, investors may be unable to infer a firm’s intentions to reduce emissions solely from the gradual changes in emission levels or intensities. Given that capital pricing revolves around future expectations, a firm’s commitment to emission reduction and subsequent exposure to downside risk becomes particularly important. Therefore, companies may choose to disclose long-run targets and reduction initiatives to signal their dedication to environmental responsibility. Investors use this forward-looking information, similar to financial performance forecasts, to assess a company’s risk profile. Intuitively, companies’ long-run exposure to carbon risk falls when they aim to cut emissions. As such, the second part of the analysis will focus on the following hypotheses:

H2a: *Companies with emission targets display lower tail risk.*

H2b: *Companies with emission reduction policies display lower tail risk.*

H2c: *The effect is more pronounced among highly emitting companies.*

Note that emission targets refer to quantifiable emission levels that must be achieved at a specific time. In contrast, emission reduction policies outline specific actions to decrease emissions.

Furthermore, we investigate how the link between emissions and tail risk evolves under different regulatory environments. The potential shifts in regulations are particularly important when assessing a firm’s carbon tail risk exposure. High-emissions firms are especially vulnerable to more stringent environmental laws as it means higher costs of doing business, potential penalties, or costly restructuring of current operations. An event that considerably elevated global attention to climate change was the Paris Agreement. This international treaty on climate change was embraced by 196 countries during the 21st United Nations (UN) Climate Change Conference in December 2015 (UNCC, 2023). It became effective a year later in November. This climate agreement aims to prevent catastrophic climate change by reducing the emission of main greenhouse gases that strongly contribute to the ongoing global warming. Given the agreement’s obligations and targets, such as “[limiting] the temperature increase to 1.5°C above pre-industrial lev-

els” and reaching net zero emissions by 2050, the act can have several implications for its members (UNCC, 2023). For instance, a country’s participation in the Paris Agreement can be viewed similarly to companies that voluntarily disclose their CO₂e emissions and targets. Consequently, governments’ participation in the Paris Agreement signals their commitment to combat climate change and implement the required policies (i.e., carbon taxes). This, in turn, means a higher likelihood of restricting regulations and generally higher political attention on carbon-intense firms within the country’s economy.

In the U.S., one of the most significant regulatory changes in recent years with regard to the country’s climate policy was their withdrawal from the Paris Agreement under President Donald Trump. Upon leaving the agreement and Trump’s negligent perspective on climate change, attention to regulatory risk, surrounding carbon-intense firms, drastically dropped in the U.S. A reversed effect occurred when President Biden was elected and re-signed the Paris Agreement. In the context of our argument that the regulatory environment plays a vital role in a firm’s carbon tail risk exposure, we hypothesise that these regime changes should be observable in capital markets. Consequently, the third area of analysis investigates the following hypothesis:

H3: The effect of GHG emissions on downside risk is more pronounced when the United States are signatory of the Paris Agreement

4 Data and Methodology

4.1 Sample

As the study focuses on the United States, we use the current constituents of the S&P 500 as the sample base comprising 500 large-cap U.S. companies. The index spans various industries and gives a good representation of the U.S. stock market. Moreover, focusing on large-cap firms allows easier access to emissions data because smaller companies usually do not report these. The sample comprises the period between 2015 and 2022, as emissions data was largely unavailable before 2015. Eventually, the main dataset was compiled from two different data sources. First, the Refinitiv Eikon database provides company-specific financial and emissions data at the end of the respective financial years. Second, Yahoo!

Finance provides the daily stock prices for the S&P 500 constituents. We use the stock tickers to match the data from the two sources. After removing observations with missing data, the final sample comprises 3,132 firm-year observations for 438 companies across ten industries.

4.2 Measurement of Variables

4.2.1 Greenhouse Gas Emissions

Although sourced through Refinitiv Eikon, the firm-specific carbon emissions are reported originally by CDP, formerly known as the Carbon Disclosure Project. CDP is one of the leading emissions data providers globally and follows the Greenhouse Gas Protocol in measuring emissions (CDP, 2023). At the corporate level, the GHG Protocol stipulates three different types of emissions, which are widely accepted and applied in academia and practice. Scope 1 emissions are emitted directly by a company and include the emissions from sources that the company owns and controls (Greenhouse Gas Protocol, 2023). For instance, the emissions of a manufacturing plant owned and operated by a corporation are classified as scope 1. Furthermore, scope 2 emissions comprise the purchased electricity a company consumes or otherwise brings into its organisational boundaries. As such, scope 2 refers to indirect emissions. Lastly, scope 3 emissions are indirectly emitted through a firm’s value chain. These emissions occur because of the company’s actions, but the company does not directly own the source. Examples include the production of input parts the company uses or the use of the company’s product in downstream activities of the value chain. However, the measurement precision of scope 3 emissions is often criticised for its inaccuracy and inconsistency across data providers (Bolton and Kacperczyk, 2020). Therefore, this paper limits its focus to scope 1 and 2 emissions to avoid measurement biases. Refinitiv Eikon provides total GHG emissions, defined as the sum of scope 1 and 2 emissions, expressed in tonnes of CO₂ equivalent. For a few observations, emission data was unavailable but was substituted with emission estimates provided by CDP. Additionally, previous literature has debated whether empirical analysis should focus on total absolute emissions or a scaled variable to adjust for some size measure (e.g., revenue or market capitalization). Ilhan et al. (2021) use such a scaled measure, commonly referred to as carbon intensity, as they

claim that companies of higher market value are more resistant to regulatory changes. This paper considers both absolute and intensity emission figures. Thus, total carbon emissions were scaled using millions of USD of revenue to derive the intensity variable. When inspecting the data, it becomes evident that carbon emissions, measured in total emission levels and intensity, follow a truncated distribution. Logically, a company cannot emit a negative amount of GHG. Hence, we followed the approach used by Bolton and Kacperczyk (2020) and log-transformed the two variables with the natural logarithm. While total emissions and intensity tend to be persistent over time, reflecting long-term risks, we also include year-over-year emission changes to reflect a corporation's short run environmental performance concerning carbon emissions.

4.2.2 Stock Price and Risk Measures

Generally, downside risk covers the variation of stock movements below a certain threshold, but different procedures to capture these movements exist. The existing literature has developed two methodologies for capturing downside risk (Ali, 2019). On the one hand, asset pricing models incorporate mathematical moments of higher order, namely skewness and kurtosis (Kraus and Litzenberger, 1976; Harvey and Siddique, 2000; Hwang and Satchell, 1999; Friend and Westerfield, 1980; Hassett et al., 1985). On the other hand, a more direct approach focuses on semi-variance (Bawa and Lindenberg, 1977; Estrada, 2002; Hogan and Warren, 1974; Ali, 2019). We use the semi-variance approach, which, in turn, includes multiple approaches to measure downside risk.

Yahoo! Finance served as the source for daily stock prices. Specifically, we use adjusted daily close prices given the long-term nature of the analysis. The adjusted close prices provide a more accurate representation of the historical stock price performance and adjust for relevant stock splits and dividend payments. The stock price data served as the input to calculate daily returns, which we used to derive the downside risk measures. We employ prominent measures from the semi-variance framework, notably expected shortfall (ES) and value at risk (VaR), which feature in previous research (McNeil, 1999; Hoepner et al., 2018; Archarya et al., 2017; Basak and Shapiro, 2001; Ciliberti et al., 2007). VaR measures the most a stock loses given a specific confidence level of $(1 - \alpha)$. This confidence level depends on α , which describes the probability that returns fall

below a certain level of VaR. For example, with $\alpha = 1\%$, the value at risk is the most a stock would lose with 99% confidence. Specifically, VaR describes a point in the extreme left tail of the return distribution and, thus, serves as a good measure of downside risk. Similarly, ES is defined as the expected loss given that returns fall below a certain level of VaR. Therefore, the expected shortfall is calculated as follows using a 5% cutoff value:

$$ES_{5\%} = -\mathbb{E}[r_i | r_i \leq -VaR_{5\%}]$$

where,

r_i = the return of firm i

Throughout this paper, the primary measure used to capture downside risk is ES at the 5% cutoff as academia deems it is superior to VaR when returns are asymmetrically distributed (Ellul and Yerramilli, 2013; Archarya et al., 2017; Ciliberti et al., 2007). By disregarding any returns that occur beyond the cutoff value, VaR underestimates downside risks for stocks that have a large part of their distribution in the extreme left tail. Expected shortfall is superior as it precisely captures these extreme returns. In order to check for the robustness of our results, we calculate VaR and an additional measure called second-order lower partial moment (LPM). We also view LPM as a conceptually different risk measure, providing an additional view of a firm's downside risk. This distinction results from LPM's broader view of downside risk by primarily focusing on asset returns below a minimum acceptable level. Following the definition by Hoepner et al. (2018), LPM captures negative return fluctuations by taking the square root of a stock's semi-variance (variation of negative returns). We use the following formula in the calculation:

$$LPM = \sqrt{\frac{1}{N_1 - 1} \sum_{i=1}^{N_1} (r_{n,i} - \bar{r}_{n,l})^2}$$

where,

$r_{n,i}$ = negative return of firm i

$\bar{r}_{n,l}$ = mean of all $r_{n,i}$ for firm i

N_1 = Number of negative returns of firm i

All three risk measures present methodologically different approaches to capture downside risk. Consequently, they also differ conceptually. ES is based on the returns within the tail and beyond a certain threshold. VaR, on the other hand, simply indicates a point in the distribution, while LPM is a broader measure of downside risk that captures all variations of negative returns. Figure 2 illustrates these differences.

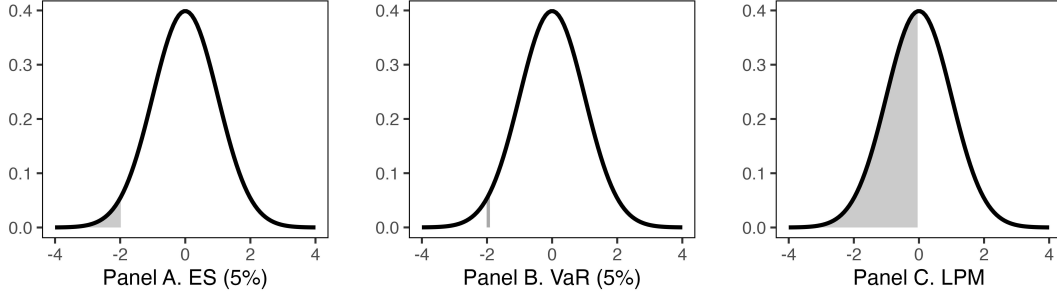


Figure 2: Comparison of Downside Risk Measures

Note: The figure provides an illustrative example of what different downside risk measures capture.

Lastly, we use market returns from the Kenneth French database to calculate downside beta as a measure of systematic downside risk and follow the approach put forth by Bawa and Lindenberg (1977) with one slight modification. The authors stipulate variation below the mean market return in the original formula. We use market variation below zero to be consistent with our other risk measures. Conceptually, the measure captures an asset's sensitivity to negative market movements. We calculate the downside beta using the following formula:

$$\beta_{Down} = \frac{cov(r_i, r_m | r_m < 0)}{var(r_m | r_m < 0)}$$

where,

r_i = return of firm i

r_m = return of the market

Since companies' financials and emissions are annual figures, the downside risk measures are also calculated yearly. Similar to carbon emissions, ES, VaR, and LPM follow a truncated distribution as they cannot be below zero. Thus, the variables are log-transformed.

4.2.3 Control Variables

In order to control for undesired variation and isolate the effect of GHG emissions on downside risk, this paper controls for the following variables. First, we use profitability, a significant determinant of volatility. From a financial perspective, a company's current value is primarily estimated by its profitability, notably its future expected cash flow streams. Hence, the paper employs return on assets (ROA) as a measure of profitability. In addition, Farooq et al. (2021) find compelling evidence that a company's dividend policy influences its downside risk profile. The authors argue that high dividend payouts reduce agency problems and, therefore, extreme negative shocks. Consequently, this paper uses the dividend yield as a control variable. Besides the effect of dividends on the agency problem and, ultimately, tail risk, governance, more generally, is highly relevant. Intuitively, a higher level of governance leads to a closer alignment of interests as well as a more reliable and transparent management team. This, in turn, discourages investors from rapidly selling their stake in bad times. Accordingly, Ali et al. (2022) find that strong governance mechanisms reduce downside risk. Hence, this analysis employs Refinitiv Eikon's governance score as a control. Furthermore, we control for leverage as high debt levels increase the risk of default, which directly links to downside risk. Moreover, the financial leverage effect induces higher earnings volatility as leverage increases (Hoepner et al., 2018). Thus, the debt to total assets ratio, measured in terms of book values, is used to account for the effects. Similarly, the analysis builds upon previous literature and controls for liquidity, defined as the ratio of the book value of cash to total assets (Salama et al., 2011). While leverage provides an indication of long-term financial obligations and risk, liquidity focuses more on the short run and whether a firm can cover short-term liabilities. Additionally, we account for cross-sectional effects such as size and book-to-market ratio through the company's market capitalisation and price-to-book ratio, respectively (Fama and French, 1993). The rationale here is that smaller firms and growth firms, generally tend to display higher risk levels. Lastly, industry and year-fixed effects are included to account for unobserved heterogeneity.

4.2.4 Descriptive Statistics

Table 1 displays the descriptive statistics of all variables used in the analysis. The number of observations varies across variables due to missing data. We excluded the entire firm-year observation from the sample whenever a data point was missing. The average firm within our data sample emits a total of 4.23 million tonnes of CO₂ equivalent, with an average carbon intensity of roughly 300 tonnes per million USD of revenue. Further, the average expected shortfall in the sample is -4.28%. We reversed the sign for interpretability. Specifically, this means that the average 5% worst returns of the sample amount to -4.28% per year.

Table 1: Descriptive Statistics

Variable	N	Mean	Median	SD
ES 5%	3,934	4.28	3.75	2.06
Total Emissions	3,705	4.23	0.29	12.53
Carbon Intensity	3,699	299.50	26.01	920.74
Market Cap	3,928	56,684.38	23,269.82	134,590.36
Dividend Yield	3,992	1.80	1.60	1.62
ROA	3,795	8.29	7.04	7.17
Leverage	3,894	31.11	29.20	23.72
Liquidity	3,947	8.70	5.52	9.44
P/B Ratio	3,695	7.73	3.60	17.70
Governance Score	3,892	62.38	64.94	19.57

Note: This table reports descriptive statistics for the main dependent variable (ES 5%) and the relevant independent variables in the sample. The table presents the number of observations, mean, median, and standard deviation (SD).

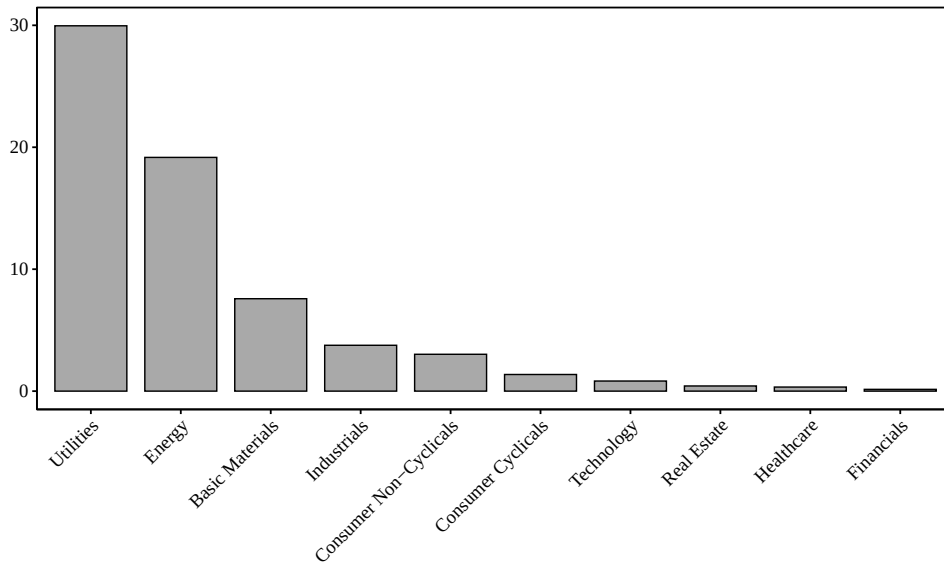
Table 2 depicts the composition of the sample in terms of sector affiliation. Although no sector strictly dominates, the technology sector has the highest number of firm-year observations (504), while basic materials firms constitute the smallest portion (188). In total, the sample includes 3,132 firm-year observations.

Table 2: Sector Observations

Sector	N
Basic Materials	188
Consumer Cyclicals	398
Consumer Non-Cyclicals	259
Energy	154
Financials	397
Healthcare	380
Industrials	444
Real Estate	189
Technology	504
Utilities	219

Note: This table reports the number of firm-year observations per sector within the sample. In total, the sample comprises 3,132 firm-year observations, relatively homogeneously spread across sectors.

Moreover, Figure 3 exhibits the average emissions per industry. Intuitively, the utilities sector displays the highest average emissions in the sample, followed by energy. Financial, healthcare, real estate, and technology companies emit the least. Note that the variable total emissions is defined as scope 1 and 2 emissions, excluding indirect emissions from up- and downstream activities in the value chain.

**Figure 3:** Emissions per Sector

Note: The figure plots the average total GHG emissions (in millions of tonnes) per sector.

4.3 Models

We assess the overall impact of greenhouse gas emissions on firms’ downside risk using a robust linear regression model. Following the literature of Lo (2002) and Momeni et al. (2010), robust or “non-parametric” estimators are adequate to address deviations from the assumptions associated with traditional linear regression models, namely normality and the presence of influential outliers. Specifically, the model employs MM-type estimators, following M-estimation principles with Mallows-type weighting (Wilcox, 2022). In addition, the models control for heteroskedasticity through robust standard errors, employing the Newey and West (1986) robust covariance matrix estimator. Lastly, as we expect high cross-industry variations and politics (i.e., regulations) to be time-sensitive, the statistical analysis includes both industry and time-specific fixed effects to capture the trends that may affect the outcome of the emission variable but remain constant across groups and over time.

The following sections highlight the different regression equations used to test our hypotheses.

4.3.1 The Influence of Emissions on Tail risk

The first model in equation (1.1) investigates the overall effect of greenhouse gas emissions on corporates’ tail risk. In other words, it checks whether the companies with higher CO₂ equivalent emissions have more downside risk exposure. The primary variables of interest are the emissions variables, notably *LOG Total Emissions*, which depicts the total (absolute) amount of GHG emissions that company i emits at time t . Next, *LOG Carbon Intensity* is used as a size-scaled relative measure to determine the carbon efficiency of firms. Lastly, *Change in CO₂*, the year-over-year change in CO₂e emissions, is analysed to investigate whether a company’s yearly changes in emissions influence the extreme downside risk. The three different emission variables are summarised below under the variable *Emissions*. The variable *Controls* includes the firm-specific metrics *LOG Market Cap*, *ROA*, *Leverage*, *Liquidity*, *P/B Ratio*, *Dividend Yield*, and *Governance Score*. The control variable *LOG Market Cap* is excluded from *Controls* when carbon intensity is the main explanatory variable as it already controls for size. This approach avoids the introduction of severe multicollinearity (Aswani et al., 2023).

Hypothesis 1a:

$$\begin{aligned} \text{LOG (ES)}_{i,t} = & \beta_0 + \beta_1 \text{Emissions}_{i,t} + \beta_2 \text{Controls}_{i,t} \\ & + \beta_3 \text{YearFE}_t + \beta_4 \text{IndustryFE}_i + \varepsilon_{i,t} \end{aligned} \quad (1.1)$$

In addition, to test hypotheses 1b and 1c, we run two further regressions. First, we add *Downside Beta* as a measure for systematic downside risk as the dependent variable. This equation allows us to infer the relationship between emissions and systematic downside risk. Then, we modify the original equation (1.1) by adding *Downside Beta* as an explanatory variable to control for systematic downside risk. As argued by Post et al. (2012), downside market beta is a more informative measure of systematic risk compared to the regular market beta. Hence, the use of *Downside Beta* as an additional control variable allows us to single out the effect of emissions on idiosyncratic downside risk.

Hypothesis 1b:

$$\begin{aligned} \text{Downside Beta}_{i,t} = & \beta_0 + \beta_1 \text{Emissions}_{i,t} + \beta_2 \text{Controls}_{i,t} \\ & + \beta_3 \text{YearFE}_t + \beta_4 \text{IndustryFE}_i + \varepsilon_{i,t} \end{aligned} \quad (1.2)$$

Hypothesis 1c:

$$\begin{aligned} \text{LOG (ES)}_{i,t} = & \beta_0 + \beta_1 \text{Emissions}_{i,t} + \beta_2 \text{Downside Beta}_{i,t} + \beta_3 \text{Controls}_{i,t} \\ & + \beta_4 \text{YearFE}_t + \beta_5 \text{IndustryFE}_i + \varepsilon_{i,t} \end{aligned} \quad (1.3)$$

4.3.2 Signalling and Commitment

Moreover, the subsequent hypotheses investigate whether companies that adopt internal emission targets or internal reduction policies, which signals a long-term commitment to reducing their GHG emissions, are less exposed to potential downside risk. In other words, the additional equations (2.1) and (2.2) examine whether corporations that lack emission targets (*Target* = 0) and reduction policies (*Policy* = 0) exhibit greater vulnerability to tail risk. Note that the data quality for the two variables *Target* and *Policy* was significantly lower for 2022 compared to previous years. Therefore, 2022 is excluded from this analysis.

In line with the model in equation (1.1), the regressions with *LOG Carbon Intensity* as the primary variable of interest exclude *LOG Market Cap* from the *Controls* variable. However, unlike the first hypothesis, the models related to the second hypothesis intentionally exclude regressions with *Change in CO2* as the main variable. This decision is based on the understanding that corporate GHG emission targets and policies tend to be long-term in nature, and consequently should not be reflected in yearly, short-term investment decisions made by investors.

Finally, as commitment is expected to mitigate a corporation's carbon risk by reducing its exposure, for example, future environmentally friendly laws or regulations, the equations (2.3) and (2.4) include an interaction variable to assess whether this transition risk is more pronounced in companies with high-emissions as compared to their lower emissions counterparts. The interaction aims to capture this effect.

Hypothesis 2a:

$$\begin{aligned} \text{LOG (ES)}_{i,t} = & \beta_0 + \beta_1 \text{Emissions}_{i,t} + \beta_2 \text{Target}_{i,t} + \beta_3 \text{Controls}_{i,t} \\ & + \beta_4 \text{YearFE}_t + \beta_5 \text{IndustryFE}_i + \varepsilon_{i,t} \end{aligned} \quad (2.1)$$

Hypothesis 2b:

$$\begin{aligned} \text{LOG (ES)}_{i,t} = & \beta_0 + \beta_1 \text{Emissions}_{i,t} + \beta_2 \text{Policy}_{i,t} + \beta_3 \text{Controls}_{i,t} \\ & + \beta_4 \text{YearFE}_t + \beta_5 \text{IndustryFE}_i + \varepsilon_{i,t} \end{aligned} \quad (2.2)$$

Hypothesis 2c:

$$\begin{aligned} \text{LOG (ES)}_{i,t} = & \beta_0 + \beta_1 \text{Emissions}_{i,t} + \beta_2 \text{Target}_{i,t} + \beta_3 (\text{Emissions} \times \text{Target})_{i,t} \\ & + \beta_4 \text{Controls}_{i,t} + \beta_5 \text{YearFE}_t + \beta_6 \text{IndustryFE}_i + \varepsilon_{i,t} \end{aligned} \quad (2.3)$$

$$\begin{aligned} \text{LOG (ES)}_{i,t} = & \beta_0 + \beta_1 \text{Emissions}_{i,t} + \beta_2 \text{Policy}_{i,t} + \beta_3 (\text{Emissions} \times \text{Policy})_{i,t} \\ & + \beta_4 \text{Controls}_{i,t} + \beta_5 \text{YearFE}_t + \beta_6 \text{IndustryFE}_i + \varepsilon_{i,t} \end{aligned} \quad (2.4)$$

4.3.3 Paris Agreement and Politics

Lastly, we aim to dive deeper into the connection between political events and their effect on carbon emitters. As noted above, regulatory risk is one of the main drivers of transition risk and a key component in the theorised connection between carbon emissions and downside risk. In the context of our argumentation, changing political regimes with regard to climate policy ought to influence how capital markets view highly emitting companies. On a global scale, the Paris Agreement is arguably the most comprehensive transnational initiative that aims to tackle climate change. The drastic changes in climate policy in the U.S. with regard to the Paris Agreement may yield valuable insights into how political events influence companies' risk profiles. In order to get a first indication of how the withdrawal from and ultimate rejoining of the Paris Agreement affects the connection between GHG emissions and downside risk, we run the following regression model:

Hypothesis 3:

$$\begin{aligned} \text{LOG (ES)}_{i,t} = & \beta_0 + \beta_1 \text{Emissions}_{i,t} + \beta_2 \text{Paris}_t + \beta_3 (\text{Emissions} \times \text{Paris})_{i,t} \\ & + \beta_4 \text{Controls}_{i,t} + \beta_5 \text{YearFE}_t + \beta_6 \text{IndustryFE}_i + \varepsilon_{i,t} \end{aligned} \quad (3.1)$$

The variable *Paris* in equation (3.1) is a binary variable that takes the value one for firm-year observations at which the U.S. was a signatory of the Paris Agreement and zero for all other years (2017-2021). It is noteworthy that capital markets are generally regarded as being efficient (Fama, 1970). As such, the withdrawal and rejoining may have already been priced into the markets with the change in presidents. To account for this, equation (3.2) investigates the effect of the Trump administration, a regime that was publicly known to be against climate policy.

$$\begin{aligned} \text{LOG (ES)}_{i,t} = & \beta_0 + \beta_1 \text{Emissions}_{i,t} + \beta_2 \text{Trump}_t + \beta_3 (\text{Emissions} \times \text{Trump})_{i,t} \\ & + \beta_4 \text{Controls}_{i,t} + \beta_5 \text{YearFE}_t + \beta_6 \text{IndustryFE}_i + \varepsilon_{i,t} \end{aligned} \quad (3.2)$$

In equation (3.2), the time variable *Trump* comprises the period 2016 to 2020.

5 Results and Discussion

5.1 GHG Emissions and Downside Tail Risk

5.1.1 General Results

The results of the first regression analysis, depicted in Table 3, yield interesting insights. The positive and significant coefficients show that expected shortfall rises when a company has higher total emissions and carbon intensity. Specifically, a 1% increase in total emissions relates to a 2.5% increase in ES, while a 1% increase in intensity translates to a 1.9% increase. Note that these are relative changes and not unit changes. The annual change in GHG emissions displays a negative coefficient close to zero, which is not statistically significant. As suggested by Farooq et al. (2021), dividend yield is negatively related to downside risk across all models. Their argument that higher payouts reduce agency costs may be transferrable to the surprising finding of a positive association between liquidity and downside risk. Further, although liquidity signals financial health in the short run, persistent high liquidity may exacerbate the agency problem because managers have too much excess cash available, which should be distributed to shareholders or invested in productive projects. As such, we find that *Liquidity* is positively related to downside tail risk. Hendrawaty’s (2020) findings, which show that excess cash holdings are negatively related to firm value, support this argument. *ROA*, *Leverage*, and size (*LOG Market Cap*) all show the expected signs. The price-to-book ratio and governance performance are insignificant for all models. Interestingly, the fixed effect coefficients (Appendix A) show that the link between emissions and tail risk is not uniform across industries. Our general finding appears to be driven by a few industries. Consumer non-cyclical and utility companies even display a negative coefficient. While we do acknowledge the influence of the fixed effects, an extensive industry-specific analysis goes beyond the scope of this paper. Moreover, the regression models’ R-squared values of 0.65 to 0.69 illustrate the strength of the models. Specifically, over 65% of the variation in expected shortfall is explained by the models. Additionally, the adjusted R-squared values are very close to the ordinary R-squared values, which suggests no irrelevant variable is included in the model.

Table 3: Regression Results: Carbon Emissions and Downside Risk

	<i>Dependent variable: Expected Shortfall 5%</i>		
	Level (1)	Intensity (2)	Y-o-Y (3)
Constant	1.810*** (0.055)	1.200*** (0.037)	2.060*** (0.055)
LOG Emissions	0.025*** (0.003)		
LOG Intensity		0.019*** (0.004)	
Change in CO2			−0.0001 (0.0001)
Dividend Yield	−0.014*** (0.003)	−0.014*** (0.003)	−0.013*** (0.004)
ROA	−0.005*** (0.001)	−0.007*** (0.001)	−0.007*** (0.001)
Leverage	0.0004 (0.0003)	0.0004 (0.0004)	0.001* (0.0004)
Liquidity	0.006*** (0.001)	0.006*** (0.001)	0.005*** (0.001)
P/B Ratio	0.00001 (0.0003)	−0.0003 (0.0003)	−0.0004 (0.0003)
LOG Market Cap	−0.093*** (0.005)		−0.075*** (0.005)
Governance Score	−0.0002 (0.0002)	−0.0003 (0.0003)	0.0001 (0.0003)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	3,132	3,132	2,746
R ²	0.688	0.657	0.696
Adjusted R ²	0.685	0.655	0.694
Residual Std. Error	0.219	0.230	0.222

Note: This table reports the regression output of equation (1.1). Column (1, Level) presents results using the logarithm of total emissions (LOG Emissions) as GHG emission measure. Column (2, Intensity) presents results using the logarithm of carbon intensity (LOG Intensity) as GHG emission measure. Column (3, Y-o-Y) presents the results using the yearly change in GHG emission levels. The results of the fixed effects (FE) are presented in Appendix A. *** p<0.001, ** p<0.01, * p<0.05.

Overall, our findings provide evidence in support of hypothesis 1a for both total emissions and carbon intensity. These results are consistent with Ilhan et al. (2021) who show that option protection against downside tail risks is more costly for companies with higher carbon intensity. Beyond their findings, we show that investors consider total emissions as well as intensity to assess carbon tail risk exposure while yearly changes play no significant part. The conceptual differences between the absolute and relative metrics

allow for differential views on emissions. On the one hand, total emissions, arguably, are more directly linked to climate regulations. Usually, carbon policies are built around total emission levels rather than on a relative basis. For instance, carbon taxes require companies to pay for every tonne of GHG emitted (World Bank, 2023). Similarly, emission trading schemes primarily focus on a total maximum emission limit within an economy. The fact that the emission level is a significant driver of downside risk supports the argument that investors see regulatory risk as a relevant factor when assessing carbon tail risk. On the other hand, carbon intensity gives better insights into operational efficiency and how effectively companies manage relative emissions. Thus, a higher intensity points towards greater inefficiency, which is an essential metric for investors (Baik et al., 2013). The insignificant Y-o-Y variable indicates that short-term developments in emissions do not influence extreme downside shocks. Overall, these findings support the notion that the long-run exposure to carbon risk factors drives downside tail risk. Intuitively, this makes sense as climate change is a long-term process, and most risk factors related to it only materialise over longer time horizons.

5.1.2 Systematic and Idiosyncratic Tail Risk

The output of equation (1.2), illustrated in Table 4, provides information on the nature of carbon-related risk, notably whether carbon risk is a systematic or idiosyncratic risk component. Consistent with the previous findings, the results show a positive and significant coefficient for emission levels and intensity. Hence, a company's downside beta increases by 0.022 when a firm's level of carbon emissions increases by 1%. Similarly, a 1% increase in carbon intensity increases a firm's downside beta by 0.028 units. Consequently, our model supports our hypothesis (1b) that carbon risk is, at least in part, a systematic risk factor. In line with the previous results, short-term changes in CO₂e emissions yield insignificant findings.

Table 4: Regression Results: Systematic Risk

	<i>Dependent variable: Downside Beta</i>		
	Level (1)	Intensity (2)	Y-o-Y (3)
Constant	1.150*** (0.078)	0.958*** (0.051)	1.360*** (0.081)
LOG Emissions	0.022*** (0.005)		
LOG Intensity		0.028*** (0.005)	
Change in CO2			−0.0001 (0.0001)
Dividend Yield	−0.042*** (0.005)	−0.040*** (0.005)	−0.036*** (0.005)
ROA	−0.005*** (0.001)	−0.006*** (0.001)	−0.007*** (0.001)
Leverage	0.0003 (0.0005)	0.0001 (0.0005)	0.001 (0.001)
Liquidity	0.006*** (0.001)	0.006*** (0.001)	0.007*** (0.001)
P/B Ratio	0.00003 (0.0004)	−0.0001 (0.0004)	−0.0003 (0.0004)
LOG Market Cap	−0.037*** (0.007)		−0.025*** (0.007)
Governance Score	0.0005 (0.0003)	0.0005 (0.0003)	0.001 (0.0004)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	3,132	3,132	2,746
R ²	0.370	0.372	0.369
Adjusted R ²	0.365	0.367	0.363
Residual Std. Error	0.309	0.309	0.321

Note: This table reports the regression output of equation (1.2) and tests for the systematic risk component of GHG emissions, measured by Downside Beta. Column (1, Level) presents results using the logarithm of total emissions (LOG Emissions) as GHG emission measure. Column (2, Intensity) presents results using the logarithm of carbon intensity (LOG Intensity) as GHG emission measure. Column (3, Y-o-Y) presents the results using the yearly change in GHG emission levels. The results of the fixed effects (FE) are presented in Appendix B. *** p<0.001, ** p<0.01, * p<0.05.

Next, the results of equation (1.3) represented in Table 5 provide additional insights into emissions' risk characteristics. In line with the previous findings, emissions levels and intensity are significant. Specifically, a 1% increase in carbon emission levels and intensity positively affects ES by 1.4% or 0.6%, respectively. Yearly changes still display insignificant coefficients. The output provides evidence that emissions impact tail risk beyond the systematic downside risk component captured by *Downside Beta*. This residual effect can be attributed to idiosyncratic downside risk. Thus, equations (1.2) and (1.3) show that the downside risk arising from carbon exposure has both a systematic and idiosyncratic component, providing support for our hypotheses 1b and 1c. The multifaceted risk profile aligns with the findings of Aljughaiman et al. (2021). On the one hand, litigation procedures or reputational damages resulting from excessive pollution are examples of idiosyncratic events that adversely affect individual companies. On the other hand, general changes in the market, such as regulatory changes or technological advancements, can systematically affect all companies and, therefore, constitute a systematic factor. These findings may help us understand why some researchers find a positive carbon premium (Oestreich and Tsiakas, 2015; Wen et al., 2020; Bolton and Kacperczyk, 2020). Exposure to carbon risk means investors take on systematic and idiosyncratic tail risk. The former is undiversifiable and Bégin et al. (2020) show that the latter is virtually undiversifiable during economic turmoil. Consequently, investors want to be compensated for loading on this risk. The R-squared values of all three regressions (i.e., level, intensity, and Y-o-Y change) increased close to 0.8. This drastic improvement shows that the inclusion of *Downside Beta* as an independent variable greatly improves the model's explanatory power regarding the variations in expected shortfall (5%). This does not come as a surprise as both downside beta and expected shortfall capture company risk in the left tail of the distribution.

Table 5: Regression Results: Idiosyncratic Risk

	<i>Dependent variable: Expected Shortfall 5%</i>		
	Level	Intensity	Y-o-Y
Constant	1.270*** (0.043)	0.790*** (0.030)	1.410*** (0.044)
LOG Emissions	0.014*** (0.002)		
LOG Intensity		0.006* (0.003)	
Change in CO2			0.00004 (0.00005)
Downside Beta	0.426*** (0.009)	0.438*** (0.010)	0.430*** (0.010)
Dividend Yield	0.004 (0.003)	0.004 (0.003)	0.005 (0.003)
ROA	−0.003*** (0.001)	−0.005*** (0.001)	−0.004*** (0.001)
Leverage	0.00004 (0.0003)	0.00002 (0.0003)	0.0001 (0.0003)
Liquidity	0.003*** (0.0004)	0.003*** (0.0005)	0.002*** (0.0005)
P/B Ratio	0.00003 (0.0002)	−0.0002 (0.0002)	−0.0001 (0.0002)
LOG Market Cap	−0.069*** (0.004)		−0.059*** (0.004)
Governance Score	−0.0004* (0.0002)	−0.001*** (0.0002)	−0.0003 (0.0002)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	3,132	3,132	2,746
R ²	0.831	0.813	0.842
Adjusted R ²	0.829	0.812	0.840
Residual Std. Error	0.162	0.169	0.161

Note: This table reports the regression output of equation (1.3) and tests for the idiosyncratic risk component of GHG emissions. Downside Beta is added as a control variable. Column (1, Level) presents results using the logarithm of total emissions (LOG Emissions) as GHG emission measure. Column (2, Intensity) presents results using the logarithm of carbon intensity (LOG Intensity) as GHG emission measure. Column (3, Y-o-Y) presents the results using the yearly change in GHG emission levels. The results of the fixed effects (FE) are presented in Appendix C. *** p<0.001, ** p<0.01, * p<0.05.

5.2 Emission Targets and Reduction Plans

5.2.1 The Impact of Emission Targets and Reduction Policies

The regression results of equations (2.1) and (2.2), notably of hypotheses 2a and 2b, are reported in Table 6. Overall, both hypotheses fail to hold, as the dummies are insignificant at the 95% confidence level across all regressions. On a control variable level, the signs and significance levels align with the previous findings. Despite the insignificance, the models yield high R-squared values, ranging from 0.66 to 0.69, with only marginally lower adjusted R-squared values, illustrating the strength of the predictor variables. Note that we excluded Y-o-Y changes as emission targets and policies are hypothesised to determine long-run exposure.

5.2.2 The joint effect of CO₂e Emissions, Targets, and Policies

The regression outputs of hypothesis 2c are illustrated in Table 7. In equations (2.3) and (2.4) the primary variables of interest, namely the interaction terms between emissions and emission targets or reduction policies, present interesting findings. Note that the former refers to limits on total emissions at a given time in the future, while the latter lays out specific steps towards reducing emissions going forward. The regression outputs show significant negative coefficients for the emission target interaction variables. Put differently, implementing emission targets reduces downside tail risk the higher a company's emission level or carbon intensity. For instance, the model of equation (2.3) shows that enacting a public emission target within a company with total emissions 1% higher than its counterparts will decrease its ES by 1% more. Emission reduction initiatives are insignificant. It is worth noting that the coefficients and significance levels of the dummy variables differ from those in equations (2.1) and (2.2), indicating that the introduction of emission targets and policies increase, rather than decrease, companies' expected shortfall. This apparent contradiction to earlier findings can be attributed to the introduction of the interaction variables, which leads to a less accurate estimation of the dummy variables (Wooldridge, 1996). For example, the standard error of the *Target* variable in the total emissions regression of model (2.3) increased fivefold ($0.062/0.012 > 5$), hinting towards a less accurate representation of the true population mean. A reason-

able explanation for this increased inaccuracy is the high correlation between the dummy variable and the interaction term, leading to a potential multicollinearity problem. Furthermore, the control variables' significance remains comparable to the earlier regression models. Similarly, the models maintain high R-squared and adjusted R-squared values. The adjusted R-squared values even increased compared to previous models, showing the strong explanatory power of the interaction terms.

The results show that neither initiative significantly reduces downside risk across the sample. Hence, we find no support for hypotheses 2a and 2b. As the sample includes both best and worst performers regarding carbon emissions, one potential explanation may be that committing to cutting emissions is only relevant for carbon-heavy firms. Among low emitters, commitment to reduce emissions may play no role because carbon risk exposure is already limited. As a result, the effect of these initiatives is absorbed in the cross-section analysis. However, we find evidence that signalling a commitment to carbon betterment can mitigate the negative effect of downside shocks the higher a company's emissions. Specifically, the hypothesised mitigating effect of signalling commitment is significant for emission targets rather than emission reduction policies. Possibly, progress towards the expressed objectives can be more easily monitored for emission targets. At the same time, reduction initiatives are more intangible and do allow for quantitative progress measurement. The fact that the effect only exists in interaction with emissions suggests that the mitigation effects are larger for more carbon-heavy firms. These findings contribute to the academic literature underscoring that the relevance of targets lies not in their standalone impact but in their significance within the context of a firm's emission levels and intensities.

Table 6: Regression Results: Emission Targets and Policies

	<i>Dependent variable: Expected Shortfall 5%</i>			
	<i>Panel A</i>		<i>Panel B</i>	
	Level (1)	Intensity (2)	Level (3)	Intensity (4)
Constant	1.820*** (0.060)	1.190*** (0.040)	1.820*** (0.060)	1.200*** (0.040)
LOG Emissions	0.025*** (0.004)		0.025*** (0.004)	
LOG Intensity		0.019*** (0.004)		0.019*** (0.004)
Target	0.003 (0.012)	−0.024 (0.013)		
Policy			0.007 (0.011)	−0.020 (0.011)
Dividend Yield	−0.011** (0.004)	−0.010** (0.004)	−0.011** (0.004)	−0.010** (0.004)
ROA	−0.006*** (0.001)	−0.009*** (0.001)	−0.006*** (0.001)	−0.009*** (0.001)
Leverage	0.0004 (0.0004)	0.0004 (0.0004)	0.0004 (0.0004)	0.0004 (0.0004)
Liquidity	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)
P/B Ratio	0.00002 (0.0003)	−0.0003 (0.0003)	0.00002 (0.0003)	−0.0003 (0.0003)
LOG Market Cap	−0.095*** (0.006)		−0.095*** (0.006)	
Governance Score	−0.0001 (0.0003)	−0.0002 (0.0003)	−0.0001 (0.0003)	−0.0001 (0.0003)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,735	2,735	2,735	2,735
R ²	0.696	0.669	0.696	0.668
Adjusted R ²	0.694	0.666	0.694	0.665
Residual Std. Error	0.222	0.232	0.222	0.232

Note: This table reports the regression output of equations (2.1) and (2.2). Panel A focuses on the impact of emission targets on downside risk, measured by ES(5%) (equation 2.1). Panel B centers around reduction policies (equation 2.2). Columns (1, Level) and (3, Level) present results using the logarithm of total emissions (LOG Emissions) as GHG emission measure. Columns (2, Intensity) and (4, Intensity) present results using the logarithm of carbon intensity (LOG Intensity) as GHG emission measure. The results of the fixed effects (FE) are presented in Appendix D. *** p<0.001, ** p<0.01, * p<0.05.

Table 7: Regression Results: Emission Targets and Policies Interaction

	<i>Dependent variable: Expected Shortfall 5%</i>			
	<i>Panel A</i>		<i>Panel B</i>	
	Level (1)	Intensity (2)	Level (3)	Intensity (4)
Constant	1.780*** (0.062)	1.180*** (0.040)	1.760*** (0.067)	1.190*** (0.042)
LOG Emissions	0.028*** (0.004)		0.030*** (0.004)	
LOG Intensity		0.023*** (0.004)		0.020*** (0.005)
Target	0.132* (0.062)	0.013 (0.022)		
Policy			0.113* (0.056)	−0.014 (0.022)
Dividend Yield	−0.011** (0.004)	−0.011** (0.004)	−0.011** (0.004)	−0.010** (0.004)
ROA	−0.006*** (0.001)	−0.009*** (0.001)	−0.006*** (0.001)	−0.009*** (0.001)
Leverage	0.0004 (0.0004)	0.0004 (0.0004)	0.0004 (0.0004)	0.0004 (0.0004)
Liquidity	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)
P/B Ratio	0.00000 (0.0003)	−0.0003 (0.0003)	0.00002 (0.0003)	−0.0003 (0.0003)
LOG Market Cap	−0.096*** (0.006)		−0.096*** (0.006)	
Governance Score	−0.0002 (0.0003)	−0.0002 (0.0003)	−0.0002 (0.0003)	−0.0002 (0.0003)
LOG Emissions:Target	−0.010* (0.005)			
LOG Intensity:Target		−0.010* (0.005)		
LOG Emissions:Policy			−0.008 (0.004)	
LOG Intensity:Policy				−0.002 (0.005)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,735	2,735	2,735	2,735
R ²	0.697	0.669	0.697	0.668
Adjusted R ²	0.694	0.666	0.694	0.665
Residual Std. Error	0.222	0.232	0.222	0.232

Note: This table reports the regression output of equations (2.3) and (2.4). Panel A focuses on the interaction between emission targets and emissions. Panel B on the interaction between reduction policies and emissions. Columns (1, Level) and (3, Level) present results using the logarithm of total emissions. Columns (2, Intensity) and (4, Intensity) present results using the logarithm of carbon intensity. The results of the fixed effects (FE) are presented in Appendix E. *** p<0.001, ** p<0.01, * p<0.05.

5.3 The Impact of the Paris Agreement

5.3.1 Results Regression

Lastly, equations (3.1) and (3.2) investigate how the United States' withdrawal from and rejoining the Paris Agreement affected the emissions-tail risk relationship. Note that in our analysis we now include two binary time variables, *Paris* and *Trump*, to account for the time when the United States was a signatory of the Paris Agreement and the time when Donald Trump was president. This accounts for any potential expectation effect.

The results are as expected and support our hypothesis (Table 8). First, the Paris Agreement interaction variable displays a significant positive sign. This implies that companies with higher emissions and emission intensities had significantly higher downside risk when the U.S. was a signatory of the agreement. Specifically, a 1% percent increase in firms' emission level or carbon intensity increases the expected shortfall by 2.4% and 2.5%, respectively. The Trump regression shows that the President's administration and related politics reversed the effect. In the latter case, a 1% increase in GHG emissions, measured in emission or intensity levels, decreases the expected shortfall by 1.7% and 2.0%, respectively. However, the analysis only gives limited statistical robustness and requires careful interpretation due to noise during the time horizon (e.g., COVID-19) within the model. The lower adjusted R-squared values partially reflect the models' restrictions.

Nevertheless, the regression output supports hypothesis 3. These findings confirm the notion that political agendas are an essential driver of carbon risk. This risk is mostly reflected in the firm's transition risk, which may lead to costs, such as changing firms' supply chains, investing in more carbon-efficient technologies, or paying higher taxes if a carbon tax is implemented. Investors' anticipation of these potential costs is what drives our results. First, the U.S. entrance into the Paris Agreement leads to potential future regulations that negatively affect high-emitting companies, increasing their downside risk. Alternatively, Donald Trump's campaign provided an opposite view of climate change. Some examples are his intentions to maximise the production of coal, oil, and gas, and withdraw from previously implemented climate agreements such as Obama's Climate Plan and the Paris Agreement (Inside Climate News, 2016). Consequently, Trump's election decreased regulatory uncertainty and provided a friendlier business environment for high-emitting companies, explaining the positive interaction coefficient. These findings

Table 8: Regression Results: Impact of Paris Agreement

	<i>Dependent variable: Expected Shortfall 5%</i>			
	<i>Panel A</i>		<i>Panel B</i>	
	Level (1)	Intensity (2)	Level (3)	Intensity (4)
Constant	1.920*** (0.098)	1.400*** (0.058)	1.690*** (0.105)	1.350*** (0.059)
LOG Emissions	−0.004 (0.006)		0.015* (0.007)	
LOG Intensity		−0.009 (0.006)		0.013 (0.007)
Paris	−0.280** (0.087)	−0.055 (0.031)		
Trump			0.192* (0.086)	0.057 (0.030)
Dividend Yield	−0.008 (0.006)	−0.010 (0.006)	−0.007 (0.006)	−0.009 (0.006)
ROA	−0.005*** (0.001)	−0.006*** (0.001)	−0.005*** (0.001)	−0.006*** (0.001)
Leverage	0.0004 (0.001)	0.0003 (0.001)	0.0003 (0.001)	0.0002 (0.001)
Liquidity	0.006*** (0.001)	0.007*** (0.001)	0.006*** (0.001)	0.007*** (0.001)
P/B Ratio	0.0003 (0.0004)	0.0002 (0.0004)	0.0003 (0.0004)	0.0002 (0.0004)
LOG Market Cap	−0.054*** (0.009)		−0.055*** (0.009)	
Governance Score	0.001* (0.0004)	0.001 (0.0004)	0.001* (0.0004)	0.001 (0.0004)
LOG Emissions:Paris	0.024*** (0.007)			
LOG Intensity:Paris		0.025*** (0.007)		
LOG Emissions:Trump			−0.017** (0.007)	
LOG Intensity:Trump				−0.020** (0.007)
Industry FE	Yes	Yes	Yes	Yes
Year FE	No	No	No	No
Observations	3,132	3,132	3,132	3,132
R ²	0.165	0.144	0.161	0.138
Adjusted R ²	0.160	0.139	0.156	0.133
Residual Std. Error	0.324	0.332	0.325	0.336

Note: This table reports the regression output of equations (3.1) and (3.2). Panel A shows the interaction between *Paris* and emissions. Panel B shows the interaction between *Trump* and emissions. Columns (1, Level) and (3, Level) present results using the logarithm of total emissions. Columns (2, Intensity) and (4, Intensity) present results using the logarithm of carbon intensity. The results of the fixed effects (FE) are presented in Appendix F. *** p<0.001, ** p<0.01, * p<0.05.

are in line with the research by Hsu et al. (2023) and Ilhan et al. (2021). The former found that high-emissions firms displayed significant positive abnormal returns relative to their low-emission counterparts shortly after Trump’s election. Similarly, Ilhan et al. (2021) show that the price of put option protection against downside tail risk significantly decreased for carbon-intense firms after Trump was elected president. Consistent with our findings, this suggests that downside risk for high-emissions firms fell during the administration. Lastly, the results of equation (3.2) go even beyond our initial hypothesis. The interaction’s negative sign shows that the election of the 46th U.S. President did not only favour carbon-intense companies but negatively affected low emitters. A possible explanation could be the low emitters’ high upfront capital expenditures into greener technologies. Since the presidential election and the withdrawal from the Paris Agreement did not provide a competitive advantage for environmentally friendly companies, the new regulatory environment might negatively impact these firms’ future cash flows and profitability, requiring them more time to repay their initial investments.

5.4 Robustness

5.4.1 Alternative Downside Risk Measures

As described above, we follow the approach by Hoepner et al. (2018) and employ alternative downside risk measures for hypotheses 1 and 2 to check the robustness of our models. Specifically, the second-order lower partial moment (LPM) and value at risk (VaR) at the 5% confidence level are used. Additionally, we use the expected shortfall at the 1% cutoff level as a third robustness measure, which captures even more extreme downside variation.

The outputs generally support our main findings. For hypothesis 1 (Appendix G), the level and intensity of emissions remain significant, while yearly emission changes are still insignificant. Similarly, the findings of hypotheses 2a and 2b (Appendices H and I) are robust. The effect of emission targets and reduction policies on downside risk is not significant at the 95% confidence level. For hypothesis 2c (Appendices J and K), which includes the interaction effect of targets and reduction policies with emissions, the picture is not as clear. While the same mitigating effect of emission targets on downside risk is found when looking at VaR 5%, the effect disappears for ES 1% and LPM. The conceptual

differences of the downside measures may help us understand these findings. ES 1% and LPM measure variation on the downside. The former focuses on the extreme left tail of the distribution, while the latter measures general variation below 0. Given that these two measures do not support earlier findings while VaR 5% is consistent, it may be that this interactive effect of emissions and targets is only observable in a specific part of the return distribution. Reduction policies, on the other hand, appeared insignificant at first. The robustness checks show that both ES 1% and LPM are significantly affected by the interaction term (at the 95% confidence level). Hence, it seems that the effectiveness of reduction policies in mitigating downside risk appears only in the very extreme left tail as well as in general downside volatility. The findings highlight the importance of considering different risk measures when investigating downside risk. Generally, the robustness check confirms our findings of hypotheses 1 as well as 2a and 2b. Given that we do not observe any reversal in the sign of the coefficients for the interaction regression (hypothesis 2c), the results are considered fairly robust.

5.4.2 General Volatility Control

One potential shortcoming of our findings is that GHG emissions positively link to risk overall. If this was the case, downside risk would also be affected, but the effect would not be specific to the left tail of the distribution. Thus, we run our main model again and include the upside variation as a control factor. Since the main measure of our dependent variable (ES) is a measure of variation itself, specifically in the extreme left tail, including general volatility makes little econometric sense. Thus, we include upside volatility, *Volatility*, calculated simply as the standard deviation of positive returns.

$$\begin{aligned} \text{LOG (ES)}_{i,t} = & \beta_0 + \beta_1 \text{Emissions}_{i,t} + \beta_2 \text{LOG (Volatility)}_{i,t} \\ & + \beta_3 \text{Controls}_{i,t} + \beta_4 \text{YearFE}_t + \beta_5 \text{IndustryFE}_i + \varepsilon_{i,t} \end{aligned} \quad (1.4)$$

The results, presented in Appendix L, show that our findings for total emission levels are robust. The coefficient remains positive and significant. However, the carbon intensity coefficient is now insignificant. This suggests that higher carbon intensity increases companys' overall risk. However, beyond that, no marginal effect on downside tail risk can be observed. This effect is only observable when looking at total emission

levels. Note that including the upside volatility renders almost all other control variables insignificant except size and dividend yield. The positive significant coefficient on log-transformed upside volatility is intuitive because if total volatility increases, both the upside and downside components of risk increase.

5.4.3 Omitted Variable Bias

Although a large portion of the variation in downside risk is explained by our models, the possibility of an omitted variable to distort the results persists. When one or more of the explanatory variables are correlated to this unobserved factor, regression estimates may be inconsistent. Assuming the potential effect is time-constant, we run the main analysis again using a lagged version of the dependent variable (ES 5%) to account for this potential bias. Wooldridge (1996) stipulates this approach as a helpful tool to eliminate omitted variable bias in cross-section analyses. Therefore, the following model is used as a robustness check:

$$\begin{aligned} \text{LOG (ES)}_{i,t} = & \beta_0 + \beta_1 \text{Emissions}_{i,t} + \beta_2 \text{LOG (ES)}_{i,t-1} \\ & + \beta_3 \text{Controls}_{i,t} + \beta_4 \text{YearFE}_t + \beta_5 \text{IndustryFE}_i + \varepsilon_{i,t} \end{aligned} \quad (1.5)$$

As expected, the regression output (Appendix M) shows that the lagged version of ES is highly significant. At the same time, level of emissions as well as intensity remain significant and positive, but the size of the coefficients has reduced. In light of these findings, the original results are robust to omitted variable bias.

Overall, the main analysis regarding emission levels is robust for different measures of downside risk and omitted variable bias. Additionally, we were able to single out the effect of total emissions on downside risk when controlling for upside volatility as well. The significant findings with regard to carbon intensity also hold for different measures of downside volatility. However, the general volatility check demonstrates that intensity affects risk as a whole rather than downside risk specifically. Moreover, reduction policies and emission targets seem to be somewhat significant among carbon-heavy firms, but the effect seems to appear only in a specific part of the distribution.

5.4.4 COVID Control

To control for the noise during the period the U.S. withdrew from the Paris Agreement as well as Trump’s presidential term, we further control for COVID-19 using another time dummy variable (*COVID*). The global pandemic is a particularly interesting event since it can be defined as a Black Swan event (Taleb, 2007), an unexpected event with a very low probability of occurrence, which caused extreme and widespread equity shocks to global capital markets (Zhang et al., 2021). Hence, we perform the following regression models to control for the effects of COVID-19:

$$\begin{aligned} \text{LOG (ES)}_{i,t} = & \beta_0 + \beta_1 \text{Emissions}_{i,t} + \beta_2 \text{Paris}_t + \beta_3 \text{COVID}_t \\ & + \beta_4 (\text{Emissions} \times \text{Paris})_{i,t} + \beta_5 \text{Controls}_{i,t} + \beta_6 \text{IndustryFE}_i + \varepsilon_{i,t} \end{aligned} \quad (3.3)$$

$$\begin{aligned} \text{LOG (ES)}_{i,t} = & \beta_0 + \beta_1 \text{Emissions}_{i,t} + \beta_2 \text{Trump}_t + \beta_3 \text{COVID}_t \\ & + \beta_4 (\text{Emissions} \times \text{Trump})_{i,t} + \beta_5 \text{Controls}_{i,t} + \beta_6 \text{IndustryFE}_i + \varepsilon_{i,t} \end{aligned} \quad (3.4)$$

The output (Appendix N) shows a large and significant negative coefficient of the *COVID* variable, as one would expect. Nonetheless, the interaction terms remain significant, with the exception of carbon intensity in interaction with the *Paris* dummy. Overall, this shows that our models are robust to the statistical noise induced by the COVID-19 pandemic.

6 Implications

This study adds to the existing literature by connecting two empirical research areas that are highly relevant in their respective fields. First, corporate-level carbon emissions and their ramifications on numerous facets of corporate performance have been a central research area in light of the focus on climate change and its mitigation. Second, scholars have identified downside risk, in its various forms, as an integral factor in asset pricing. We discovered a significant link between carbon emissions and extreme equity devaluations, providing crucial insight for corporate risk managers and asset managers.

For a corporation, avoiding downside stock movements is positively reflected in their equity cost of capital (Chong and Phillips, 2012). As such, carbon betterment can be a valuable source to manage stock risk and smooth capital raising costs. Among highly emitting companies, having emission targets in place can be a valuable instrument as it is positively perceived in capital markets and has a mitigating effect on extreme downside risk. Arguably, these signals must be backed by tangible actions to be credible. Moreover, corporations ought to be aware of the multifaceted risk profile of emissions (i.e., its systematic and idiosyncratic components). Company-specific news about, for example, excess pollution may have reputational and legal repercussions. This information typically impacts only a particular firm and can thus be effectively managed by the company. Conversely, broad market shifts, such as regulatory changes, which classify as systematic carbon risk, are much more challenging to manage as they lie outside corporations' control. Internal financing policies (e.g., dividend payouts) as well as the productivity of future investments through R&D or acquisition expenditure ought to be adjusted to manage this type of risk (Schoar et al., 2023). Hence, risk managers should be aware of this dual exposure to enhance their resilience against low-probability events.

The distinction between systematic and idiosyncratic risk is also relevant for fund managers. The dual risk characteristics of carbon emissions allow asset managers only to diversify part of the downside risk away, notably emissions' idiosyncratic component. Since a significant part of carbon tail risk is systematic, portfolio diversification still leaves investors with considerable downside risk exposure. Hence, active owners may seek to implement initiatives to cut emissions or enforce more firm-level transparency to assess carbon risk exposure adequately. The findings by Hoepner et al. (2018) support this notion as they showed that ESG shareholder engagement effectively lowers downside risk. Following the argument by Bégin et al. (2020), asset owners may even be unable to diversify idiosyncratic tail risk during times of crisis. This further incentivises investors to engage with their target companies or redirect capital to firms with less carbon-intense operations. Lastly, we find that the regulatory environment is a significant driver of the link between emissions and downside tail risk. This finding explains why carbon risk is, at least in part, a systematic risk factor and is highly relevant to policymakers. Specifically, it shows that policymakers have a significant power to influence investors' sentiment towards polluting firms. Consequently, policymakers can leverage this relationship to

penalise carbon-heavy firms indirectly in capital markets and motivate them to reduce their emissions.

7 Limitations and Further Research

There are a number of limitations to take into account when assessing our study. First, endogeneity is a potential concern for our findings, which occurs when the explanatory variable correlates with the model’s residuals. When endogeneity is present, all coefficient estimators are inconsistent. By running the lagged regression model as a robustness test, we excluded the possibility of omitted variable bias, a type of endogeneity issue, under the time-constant effect assumption. However, the effect might be time-varying, or other endogeneity biases, such as reverse causality or measurement error, may induce inconsistency in our estimations. For instance, companies that report disappointing earnings figures and experience a stock devaluation may strategically shift to more highly emitting operations in pursuit of cost-cutting benefits. This reverse causality effect would distort our findings.

Second, the findings of our third hypothesis may be influenced by external factors. We showed that the interplay of emissions and downside tail risk changes under different climate political regimes, which is consistent with the findings of other scholars (Hsu et al., 2023; Ilhan et al., 2021). However, our time dummies span a considerable period, with other potentially influential events that may affect the results. While we did check the robustness of our findings by controlling for the COVID-19 period, the U.S.-China trade war is another example with significant effects on capital markets, which may cloud the true relationship between emissions and tail risk during the period (Wang et al., 2021). Hence, further investigation is required to single out the effect of these regime changes on the hypothesised relationship.

Third, the paper restricts its focus to scope 1 and 2 carbon emissions at the firm level. It is reasonable to exclude scope 3 as scholars agree that the available data suffers from significant inconsistencies across providers. Nonetheless, scope 3 constitutes the majority of most companies’ emissions and is increasingly gaining attention in practice. For example, in November 2022, the European Commission published new standards

under the Corporate Sustainability Reporting Directive (CSRD), obliging large European corporations to report scope 3 emissions (European Union, 2022). The aim is to make companies and stakeholders more aware of where carbon hotspots occur in the value chain. From a regulatory perspective, the focus on holding companies responsible for their supply chain is increasing (Kaplinsky and Morris, 2018). Therefore, it is conceivable that investors will increasingly consider scope 3 emissions in evaluating a company’s risk profile. Once the measurement of scope 3 emissions reaches adequate data quality, future researchers may find this an attractive research area.

Besides looking into scope 3 emissions, future research could focus on entangling the effect of all three different scopes in relation to downside risk. While our paper focused on the combined effect of scope 1 and 2, our findings may be driven by either direct or indirect emissions. Diving into the differential effects can yield valuable insights for practitioners, regulators, and academics. Further, industry-specific analysis could help future researchers to better understand what drives the link between emissions and tail risk. Lastly, future research may expand on our general findings of hypothesis 2. While our analysis considers only the binary options between having or not having emission targets or reduction policies, the stringency and ambition of these initiatives can be investigated further. Arguably, for companies with more ambitious targets/reduction policies, higher mitigating effects on downside risk should be observed. Within the generally increasing empirical interest in carbon emissions, these topics can serve as the basis for further analysis of how emissions impact downside risk and how this can be mitigated.

8 Conclusions

Awareness of climate change mitigation has risen substantially in recent years. In particular, greenhouse gas emissions have moved to the centre of attention as one of the major causes of climate-related problems. Investors increasingly account for carbon emissions, and scholars have identified multiple avenues in how they affect company performance. This paper investigates the interplay of GHG emissions and downside tail risk for U.S. companies. Specifically, we hypothesise that firms with higher emissions are more exposed to adverse events arising from the regulatory environment and society’s general view of heavy polluters. First, we find a positive link between carbon emissions, measured in

emission level and carbon intensity, and the average of the worst 5% stock returns among S&P 500 companies. The robustness check revealed that high carbon intensity relates to higher general volatility without a specific effect on the left tail. On the other hand, emission levels increase the downside-tail portion of a return distribution. Yearly changes have no significant effect, which suggests investors consider long-run exposure as opposed to short-term changes. Further, the analysis showed that carbon tail risk has both a systematic and idiosyncratic component, providing valuable insights to practitioners.

Second, we demonstrate that emission targets effectively mitigate the risk of extreme stock devaluations as they signal to the market a commitment to carbon betterment. This effect, however, is only observable among highly emitting companies. Many companies also implement carbon reduction policies, which lay out specific steps toward reducing emissions. Whether these policies also have a mitigating effect is unclear. It appears to affect a specific portion of the downside distribution. Further research is required to find a definitive link.

Lastly, we investigated how climate political events influence the relationship between emissions and downside risk. The findings demonstrate that when the Trump administration withdrew the United States from the Paris Agreement, highly emitting firms benefitted from reduced tail risk. These findings are consistent with previous research, which showed that capital markets view polluting firms differently under these heterogeneous political regimes.

Overall, this paper adds to the sustainable finance literature by positing GHG emissions as a determinant of downside tail risk. Future research may build upon this paper as the data quality and coverage of carbon emissions improve. A deeper analysis of industry-specific effects and the ramifications of scope 3 emissions, which become increasingly important, yield interesting fields for future research.

References

- Alessi, L., Ossola, E., and Panzica, R. (2021). What greenium matters in the stock market? the role of greenhouse gas emissions and environmental disclosure. *Journal of Financial Stability*, 54:100869.
- Ali, H. (2019). Does downside risk matter more in asset pricing? evidence from china. *Emerging Markets Review*, 39:154–174.
- Ali, S., Liu, B., and Su, J. (2022). Does corporate governance have a differential effect on downside and upside risk? *Journal of Business Finance and Accounting*, 49(9-10):1642–1695.
- Aljughaiman, A. A., Cao, N. D., and Albarrak, M. S. (2021). The impact of greenhouse gas emission on corporate’s tail risk. *Journal of Sustainable Finance Investment*, pages 1–18.
- Ang, A., Chen, J., and Xing, Y. (2006). Downside risk. *The review of financial studies*, 19(4):1191–1239.
- Archarya, V., Pedersen, L., Philippon, T., and Matthew, R. (2017). Measuring systemic risk. *The Review of Financial Studies*, 30(1):2–47.
- Aswani, J., Raghunanda, A., and Rajgopal, S. (2023). Are carbon emissions associated with stock returns? reply. *Review of Finance, Forthcoming*.
- Baik, B., Chae, J., Choi, S., and Farber, D. B. (2013). Changes in operational efficiency and firm performance: A frontier analysis approach. *Contemporary Accounting Research*, 30(3):996–1026.
- Baldauf, M., Garlappi, L., and Yannelis, C. (2020). Does climate change affect real estate prices? only if you believe in it. *The Review of Financial Studies*, 33(3):1256–1295.
- Basak, S. and Shapiro, A. (2001). Value-at-risk-based risk management: optimal policies and asset prices. *The review of financial studies*, 14(2):371–405.
- Bauer, M. D., Huber, D., Rudebusch, G. D., and Wilms, O. (2022). Where is the carbon premium? global performance of green and brown stocks. *Journal of Climate Finance*, 1:100006.
- Bawa, V. S. (1975). Optimal rules for ordering uncertain prospects. *Journal of Financial Economics*, 2(1):95–121.
- Bawa, V. S. and Lindenberg, E. B. (1977). Capital market equilibrium in a mean-lower partial moment framework. *Journal of financial economics*, 5(2):189–200.
- Bernstein, A., Gustafson, M., and Lewis, R. (2019). Disaster on the horizon: The price effect of sea level rise. *Journal of Financial Economics*, 134(4):253–272.
- Bolton, P. and Kacperczyk, M. T. (2020). Carbon premium around the world. *National Bureau of Economic Research*, page 70.
- Bolton, P. and Kacperczyk, M. T. (2021a). Do investors care about carbon risk? *Journal of Financial Economics*, 142(2):517–549.

- Bolton, P. and Kacperczyk, M. T. (2021b). Global pricing of carbon-transition risk. *Journal of Finance*.
- Braune, E., Charosky, P., and Hikkerova, L. (2019). Corporate social responsibility, financial performance and risk in times of economic instability. *Journal of Management and Governance*, 23:1007–1021.
- Bégin, J. F., Dorion, C., and Gauthier, G. (2020). Idiosyncratic jump risk matters: Evidence from equity returns and options. *The Review of Financial Studies, Society for Financial Studies*, 33(1):155–211.
- CDP (2023). Climate change 2023 reporting guidance. <https://www.cdp.net/en/guidance/guidance-for-companies>.
- Chong, J. and Phillips, G. M. (2012). Measuring risk for cost of capital: The downside beta approach. *Journal of Corporate Treasury Management*, 4:344.
- Ciliberti, S., Kondor, I., and Mézard, M. (2007). On the feasibility of portfolio optimization under expected shortfall. *Quantitative Finance*, 7(4):389–396.
- Deng, H., Xiong, L., and Xiao, L. (2023). Does patent infringement litigation affect stock price crash risk? evidence from china. *Accounting & Finance*.
- Diemont, D., Moore, K., and Soppe, A. (2016). The downside of being responsible: Corporate social responsibility and tail risk. *Journal of business ethics*, 137(2):213–229.
- Durnev, A. (2010). The real effects of political uncertainty: Elections and investment sensitivity to stock prices.
- Ellul, A. and Yerramilli, V. (2013). Stronger risk controls, lower risk: Evidence from u.s. bank holding companies. *The Journal of Finance*, 68:1757–1803.
- Engle, R. (2004). Risk and volatility: Econometric models and financial practice. *American economic review*, 94(3):405–420.
- Estrada, J. (2002). Systematic risk in emerging markets: the d-capm. *Emerging Markets Review*, 3(4):365–379.
- European Union (2022). Directive (eu) 2022/2464 of the european parliament and of the council. *Official Journal of the European Union*, 322(15).
- Fama, E. and French, K. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.
- Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, 25(2):383–417.
- Fang, H. and Lai, T. Y. (1997). Co-kurtosis and capital asset pricing. *Financial Review*, 32(2):293–307.
- Farooq, O., Satt, H., Bendriouch, F. Z., and Lamiri, D. (2021). Dividend policy and the downside risk in stock prices: Evidence from the mena region. *The Journal of Risk Finance*, 22:261–278.

- Fishburn, P. C. (1977). Mean-risk analysis with risk associated with below-target returns. *The American Economic Review*, 67(2):116–126.
- Friedman, M. (1970). A friedman doctrine - the social responsibility of business is to increase its profits. *The New York Times*.
- Friend, I. and Westerfield, R. (1980). Co-skewness and capital asset pricing. *The Journal of Finance*, 35(4):897–913.
- Greenhouse Gas Protocol (2023). A corporate accounting and reporting standard. <https://ghgprotocol.org/sites/default/files/standards/ghg-protocol-revised.pdf>.
- Guastella, G., Matteo, M., Stefano, P., and Xepapadeas, A. (2022). Climate reputation risk and abnormal returns in the stock markets: A focus on large emitters. *International Review of Financial Analysis*, 84.
- Görge, M., Jacob, A., Nerlinger, M., Riordan, R., Rohleder, M., and Wilkens, M. (2020). Carbon risk.
- Hapsoro, D. and Falih, Z. N. (2020). The effect of firm size, profitability, and liquidity on the firm value moderated by carbon emission disclosure. *Journal of Accounting and Investment*, 21(2):240–257.
- Harvey, C. R. and Siddique, A. (2000). Conditional skewness in asset pricing tests. *The Journal of finance*, 55(3):1263–1295.
- Hassett, M., Sears, R. S., and Trennepohl, G. L. (1985). Asset preference, skewness, and the measurement of expected utility. *Journal of Economics and Business*, 37(1):35–47.
- Hendrawaty, E. (2020). Examining the excess cash holdings as an indicator of agency problems. *International Business and Accounting Research Journal*, 4(2):71–80.
- Hoepner, A., Oikonomou, I., Sautner, Z., Starks, L., and Zhou, X. (2018). Esg shareholder engagement and downside risk.
- Hogan, W. W. and Warren, J. M. (1974). Toward the development of an equilibrium capital-market model based on semivariance. *Journal of Financial and Quantitative Analysis*, 9(1):1–11.
- Hong, H., Li, F. W., and Xu, J. (2019). Climate risks and market efficiency. *Journal of Econometrics*, 208(1):265–281.
- Houqe, M. N., Opare, S., ul Hassan, Z., Kaleem, M., and Ahmed, K. (2022). The effects of carbon emissions and agency costs on firm performance. *Journal of Risk and Financial Management*, 15(4):152.
- Hsu, P.-H., Li, K., and Tsou, C. Y. (2023). The pollution premium. *Journal of Finance*, 78(3):1343–1392.
- Huang, W., Liu, Q., Rhee, S. G., and Wu, F. (2012). Extreme downside risk and expected stock returns. *Journal of Banking & Finance*, 36(5):1492–1502.
- Hui-Min, L., Xue-Chun, W., Xiao-Fan, Z., and Ye, Q. (2021). Understanding systemic risk induced by climate change. *Advances in Climate Change Research*, 12(3):384–394.

- Hwang, S. and Satchell, S. E. (1999). Modelling emerging market risk premia using higher moments. *International Journal of Finance & Economics*, 4(4):271–296.
- Ilhan, E., Sautner, Z., and Vilkov, G. (2021). Carbon tail risk. *The Review of Financial Studies*, 34(3):1540–1571.
- Inside Climate News (2016). Trump: America first on fossil fuels, last on climate change. <https://insideclimatenews.org/news/27052016/donald-trump-republican-party-election-fossil-fuels-coal-oil-gas-fracking-climate-change-paris/>.
- IPCC (2023). Ar6 synthesis report: Climate change 2023. <https://www.ipcc.ch/report/sixth-assessment-report-cycle/>.
- Kabir, M. N., Rahman, S., Rahman, M. A., and Anwar, M. (2021). Carbon emissions and default risk: International evidence from firm-level data. *Economic Modelling*, 103:105617.
- Kaplinsky, R. and Morris, M. (2018). Standards, regulation and sustainable development in a global value chain driven world. *International Journal of Technological Learning, Innovation and Development*, 10(3-4):322–346.
- Kelly, B. and Jiang, H. (2014). Tail risk and asset prices. *The Review of Financial Studies*, 27(10):2841–2871.
- Kelly, B., Pástor, L., and Veronesi, P. (2016). The price of political uncertainty: Theory and evidence from the option market. *Journal of Finance*, 70(5):2417–2480.
- Khatib, S. F., Ismail, I. H., Salameh, N., Abbas, A. F., Bazhair, A. H., and Sulimany, H. G. H. (2023). Carbon emission and firm performance: The moderating role of management environmental training. *Sustainability*, 15(13):10485.
- Kim, Y., Li, H., and Li, S. (2014). Corporate social responsibility and stock price crash risk. *Journal of Banking & Finance*, 43:1–13.
- Koh, P. S., Qian, C., and Wang, H. C. (2014). Firm litigation risk and the insurance value of corporate social performance. *Strategy Management Journal*, 35(10):1464–1482.
- Kraus, A. and Litzenberger, R. H. (1976). Skewness preference and the valuation of risk assets. *The Journal of finance*, 31(4):1085–1100.
- Lins, K. V. and Servaes, H. (2017). Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *Journal of Finance*, 72(4):1785–1824.
- Lo, A. W. (2002). The statistics of sharpe ratios. *Financial analysts journal*, 58:36–52.
- Long, H., Zhu, Y., Chen, L., and Jiang, Y. (2019). Tail risk and expected stock return around the world. *Pacific-Basin Finance Journal*, 56:162–178.
- Long, H., Zhu, Y., and Jiang, Y. (2018). Idiosyncratic tail risk and expected stock returns: Evidence from the chinese stock markets. *Finance Research Letters*, 24:129–136.
- Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, 7(1):77–91.

- Markowitz, H., Todd, P., Xu, G., and Yamane, Y. (1993). Computation of mean-semivariance efficient sets by the critical line algorithm. *Annals of operations research*, 45:307–317.
- McNeil, A. J. (1999). Extreme value theory for risk managers. *Departement Mathematik ETH Zentrum*, 12(5):217–37.
- Menezes, C., Geiss, C., and Tressler, J. (1980). Increasing downside risk. *The American Economic Review*, 70(5):921–932.
- Miah, M. D., Hasan, R., and Usman, M. (2021). Carbon emissions and firm performance: evidence from financial and non-financial firms from selected emerging economies. *Sustainability*, 13(23):13281.
- Min, B.-K. and Kim, T. S. (2016). Momentum and downside risk. *Journal of Banking & Finance*, 72:S104–S118.
- Momeni, M., Nayeri, M. D., Ghayoumi, A. F., and Ghorbani, H. (2010). Robust regression and its application in financial data analysis. *World Academy of Science, Engineering and Technology*, 47:521–526.
- Moore, K., Sun, P., de Vries, C. G., and Zhou, C. (2013). The drivers of downside equity tail risk. *Available at SSRN 2240135*.
- Newey, W. K. and West, K. D. (1986). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix.
- Oehler, A., Walker, T. J., and Wendt, S. (2021). Effects of election results on stock price performance: Evidence from 1980 to 2008. *Managerial Finance*, 39(8):714–736.
- Oestreich, A. M. and Tsiakas, I. (2015). Carbon emissions and stock returns: Evidence from the eu emissions trading scheme. *Journal of Banking Finance*, 58:294–308.
- Peel, J. and Osofsky, H. M. (2020). Climate change litigation. *Annual Review of Law and Social Science*, 16:21–38.
- Porter, M. E. and Kramer, M. R. (2006). The link between competitive advantage and corporate social responsibility. *Harvard business review*, 84(12):78–992.
- Post, T., Van Vliet, P., and Lansdorp, S. (2012). Sorting out downside beta. *Available at SSRN 1980614*.
- Qiu, S., Jiang, J., Liu, X., Chen, M. H., and Yuan, X. (2021). Can corporate social responsibility protect firm value during the covid-19 pandemic? *International Journal of Hospitality Management*, 93:102759.
- Reuters (2020). Volkswagen says diesel scandal has cost it 31.3 billion euros. <https://www.reuters.com/article/us-volkswagen-results-diesel-idUSKBN2141JB>.
- Salama, A., Anderson, K., and Toms, S. (2011). Does community and environmental responsibility affect firm risk? evidence from uk panel data 1994–2006? *Business ethics: a European review*, 20(2):192–204.

- Schoar, A., Yeung, K., and Zuo, L. (2023). The effect of managers on systematic risk. *Management Science*.
- Sears, R. S. and Wei, K. C. J. (1988). The structure of skewness preferences in asset pricing models with higher moments: An empirical test. *The Financial Review, Eastern Finance Association*, 23(1):25–38.
- Seltzer, L., Starks, L. T., and Zhu, Q. (2022). Climate regulatory risks and corporate bonds. *National Bureau of Economic Research*, 20.
- Semieniuk, G., Campiglio, E., Mercure, J.-F., Volz, U., and Edwards, N. R. (2021). Low-carbon transition risks for finance. *WIREs Climate Change*, 12(1):678.
- Shafer, M. and Szado, E. (2020). Environmental, social, and governance practices and perceived tail risk. *Accounting Finance*, 60(4):4195–4224.
- Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance*, 19(3):425–442.
- Simionescu, L. and Dumitrescu, D. (2014). Corporate social responsibility and financial crisis. *Journal of Public Administration, Finance and Law*, 1(1):31–37.
- Taleb, N. (2007). *The black swan: The impact of the highly improbable*. Random House.
- Thurner, S., Farmer, J. D., and Geanakoplos, J. (2012). Leverage causes fat tails and clustered volatility. *Quantitative Finance*, 12(5):695–707.
- Tobin, J. (1958). Liquidity preference as behavior towards risk. *The review of economic studies*, 25(2):65–86.
- Trinh, V. Q., Duong, C. N., and Elnahass, M. (2023). Financial stability: A ‘vaccine’ for tail risk of the global banking sector in the shadow of the pandemic. *The European Journal of Finance*, 29(7):726–753.
- Trinks, A., Mulder, M., and Scholtens, B. (2020). An efficiency perspective on carbon emissions and financial performance. *Ecological Economics*, 175:106632.
- UNCC (2023). The paris agreement. <https://unfccc.int/process-and-meetings/the-paris-agreement>.
- Wang, X., Wang, X., Zhong, Z., and Yao, J. (2021). The impact of us–china trade war on chinese firms: Evidence from stock market reactions. *Applied Economics Letters*, 28(7):579–583.
- Wen, F., Wu, N., and Gong, X. (2020). China’s carbon emissions trading and stock returns. *Energy Economics*, 86:104627.
- Wilcox, R. (2022). *Introduction to robust estimation and hypothesis testing (fifth edition)*. Academic Press.
- Wooldridge, J. M. (1996). *Introductory Econometrics: A Modern Approach 3rd edition*. Thomson/South-Western, Mason.

World Bank (2023). Carbon pricing dashboard.
<https://carbonpricingdashboard.worldbank.org/>.

Yang, C. Y. and Chen, M. C. (2009). The role of co-kurtosis in the pricing of real estate. *Journal of Real Estate Portfolio Management*, 15(2):185–195.

Zhang, J., De Spiegeleer, J., and Schoutens (2021). Implied tail risk and esg ratings. *Mathematics*, 9(14):1611.

Appendix

Appendix A: Carbon Emissions and Downside Risk (Fixed Effects)

	<i>Dependent variable: Expected Shortfall 5%</i>		
	Level (1)	Intensity (2)	Y-o-Y (3)
Main Variables	(Table 3)	(Table 3)	(Table 3)
FE Consumer Cyclical	0.111*** (0.023)	0.085*** (0.024)	0.077** (0.024)
FE Consumer Non-Cyclical	-0.130*** (0.024)	-0.194*** (0.025)	-0.153*** (0.025)
FE Energy	0.227*** (0.027)	0.187*** (0.028)	0.221*** (0.029)
FE Financials	0.052 (0.027)	-0.032 (0.028)	-0.041 (0.025)
FE Healthcare	0.034 (0.024)	-0.040 (0.026)	-0.033 (0.024)
FE Industrials	-0.033 (0.022)	-0.065** (0.023)	-0.072** (0.023)
FE Real Estate	-0.054 (0.029)	-0.113*** (0.028)	-0.139*** (0.028)
FE Technology	0.154*** (0.024)	0.061* (0.025)	0.098*** (0.024)
FE Utilities	-0.323*** (0.025)	-0.335*** (0.026)	-0.312*** (0.027)
FE 2016	0.077*** (0.018)	0.065*** (0.019)	
FE 2017	-0.255*** (0.018)	-0.273*** (0.019)	-0.333*** (0.018)
FE 2018	0.185*** (0.018)	0.180*** (0.019)	0.108*** (0.018)
FE 2019	0.009 (0.018)	-0.015 (0.019)	-0.068*** (0.018)
FE 2020	0.824*** (0.018)	0.789*** (0.019)	0.742*** (0.018)
FE 2021	0.112*** (0.018)	0.067*** (0.019)	0.026 (0.018)
FE 2022	0.384*** (0.018)	0.359*** (0.019)	0.300*** (0.018)
Observations	3,132	3,132	2,746
R ²	0.688	0.657	0.696

Note: This table reports the fixed effects regression results of equation (1.1). It serves as an extension to Table 3. *** p<0.001, ** p<0.01, * p<0.05.

Appendix B: Systematic Risk (Fixed Effects)

	<i>Dependent variable: Downside Beta</i>		
	Level (1)	Intensity (2)	Y-o-Y (3)
Main Variables	(Table 4)	(Table 4)	(Table 4)
FE Consumer Cyclical	0.075* (0.033)	0.095** (0.033)	0.031 (0.035)
FE Consumer Non-Cyclical	-0.326*** (0.035)	-0.327*** (0.034)	-0.385*** (0.037)
FE Energy	0.112** (0.039)	0.100** (0.039)	0.091* (0.043)
FE Financials	0.207*** (0.039)	0.210*** (0.039)	0.100** (0.037)
FE Healthcare	-0.141*** (0.035)	-0.134*** (0.035)	-0.218*** (0.035)
FE Industrials	0.022 (0.032)	0.031 (0.032)	-0.012 (0.034)
FE Real Estate	-0.177*** (0.041)	-0.201*** (0.039)	-0.272*** (0.042)
FE Technology	0.159*** (0.034)	0.153*** (0.034)	0.122*** (0.035)
FE Utilities	-0.567*** (0.036)	-0.592*** (0.036)	-0.581*** (0.039)
FE 2016	0.021 (0.026)	0.016 (0.026)	
FE 2017	-0.110*** (0.026)	-0.118*** (0.026)	-0.132*** (0.027)
FE 2018	-0.084*** (0.025)	-0.084*** (0.025)	-0.108*** (0.026)
FE 2019	-0.034 (0.025)	-0.042 (0.025)	-0.056* (0.026)
FE 2020	0.051* (0.025)	0.038 (0.025)	0.022 (0.026)
FE 2021	-0.143*** (0.026)	-0.155*** (0.025)	-0.177*** (0.027)
FE 2022	-0.086*** (0.026)	-0.091*** (0.026)	-0.114*** (0.027)
Observations	3,132	3,132	2,746
R ²	0.370	0.372	0.369

Note: This table reports the fixed effects regression results of equation (1.2). It serves as an extension to Table 4. *** p<0.001, ** p<0.01, * p<0.05.

Appendix C: Idiosyncratic Risk (Fixed Effects)

	<i>Dependent variable: Expected Shortfall 5%</i>		
	Level (1)	Intensity (2)	Y-o-Y (3)
Main Variables	(Table 5)	(Table 5)	(Table 5)
FE Consumer Cyclical	0.058*** (0.017)	0.027 (0.019)	0.040* (0.018)
FE Consumer Non-Cyclical	-0.003 (0.019)	-0.060** (0.020)	-0.007 (0.020)
FE Energy	0.163*** (0.021)	0.131*** (0.022)	0.161*** (0.022)
FE Financials	-0.051* (0.021)	-0.129*** (0.022)	-0.097*** (0.019)
FE Healthcare	0.075*** (0.019)	0.012 (0.020)	0.043* (0.018)
FE Industrials	-0.050** (0.017)	-0.077*** (0.018)	-0.073*** (0.017)
FE Real Estate	0.012 (0.022)	-0.028 (0.022)	-0.032 (0.021)
FE Technology	0.064*** (0.018)	-0.018 (0.019)	0.032 (0.018)
FE Utilities	-0.069*** (0.020)	-0.068** (0.021)	-0.063** (0.021)
FE 2016	0.052*** (0.014)	0.044** (0.015)	
FE 2017	-0.258*** (0.014)	-0.274*** (0.015)	-0.305*** (0.014)
FE 2018	0.233*** (0.014)	0.230*** (0.014)	0.184*** (0.014)
FE 2019	0.028* (0.014)	0.010 (0.014)	-0.024 (0.013)
FE 2020	0.811*** (0.014)	0.784*** (0.014)	0.758*** (0.013)
FE 2021	0.167*** (0.014)	0.134*** (0.015)	0.113*** (0.014)
FE 2022	0.429*** (0.014)	0.410*** (0.015)	0.374*** (0.014)
Observations	3,132	3,132	2,746
R ²	0.831	0.813	0.842

Note: This table reports the fixed effects regression results of equation (1.3). It serves as an extension to Table 5. *** p<0.001, ** p<0.01, * p<0.05.

Appendix D: Emission Targets and Policies (Fixed Effects)

	<i>Dependent variable: Expected Shortfall 5%</i>			
	<i>Panel A</i>		<i>Panel B</i>	
	Level (1)	Intensity (2)	Level (3)	Intensity (4)
Main Variables	(Table 6)	(Table 6)	(Table 6)	(Table 6)
FE Consumer Cyclical	0.104*** (0.025)	0.073** (0.026)	0.104*** (0.025)	0.072** (0.026)
FE Consumer Non-Cyclical	-0.118*** (0.026)	-0.182*** (0.028)	-0.119*** (0.027)	-0.180*** (0.028)
FE Energy	0.219*** (0.030)	0.168*** (0.031)	0.220*** (0.030)	0.169*** (0.031)
FE Financials	0.062* (0.030)	-0.024 (0.030)	0.062* (0.030)	-0.022 (0.030)
FE Healthcare	0.052* (0.026)	-0.023 (0.028)	0.051 (0.026)	-0.021 (0.028)
FE Industrials	-0.023 (0.024)	-0.056* (0.025)	-0.023 (0.024)	-0.054* (0.025)
FE Real Estate	-0.053 (0.031)	-0.117*** (0.031)	-0.052 (0.031)	-0.117*** (0.031)
FE Technology	0.168*** (0.026)	0.069* (0.027)	0.167*** (0.026)	0.071** (0.027)
FE Utilities	-0.324*** (0.027)	-0.338*** (0.029)	-0.323*** (0.027)	-0.339*** (0.029)
FE 2016	0.077*** (0.018)	0.065*** (0.019)	0.077*** (0.018)	0.066*** (0.019)
FE 2017	-0.254*** (0.018)	-0.269*** (0.019)	-0.254*** (0.018)	-0.272*** (0.019)
FE 2018	0.183*** (0.019)	0.191*** (0.020)	0.185*** (0.018)	0.180*** (0.019)
FE 2019	0.009 (0.019)	-0.002 (0.020)	0.010 (0.018)	-0.014 (0.019)
FE 2020	0.821*** (0.019)	0.800*** (0.020)	0.823*** (0.018)	0.789*** (0.019)
FE 2021	0.112*** (0.020)	0.083*** (0.020)	0.114*** (0.018)	0.070*** (0.019)
Observations	2,735	2,735	2,735	2,735
R ²	0.696	0.669	0.696	0.668

Note: This table reports the fixed effects regression results of equation (2.1) and (2.2). It serves as an extension to Table 6. *** p<0.001, ** p<0.01, * p<0.05.

Appendix E: Emission Targets and Policies Interaction (Fixed Effects)

	<i>Dependent variable: Expected Shortfall 5%</i>			
	<i>Panel A</i>		<i>Panel B</i>	
	Level (1)	Intensity (2)	Level (3)	Intensity (4)
Main Variables	(Table 7)	(Table 7)	(Table 7)	(Table 7)
FE Consumer Cyclical	0.103*** (0.025)	0.073** (0.026)	0.106*** (0.025)	0.073** (0.027)
FE Consumer Non-Cyclical	-0.118*** (0.026)	-0.182*** (0.028)	-0.117*** (0.026)	-0.179*** (0.028)
FE Energy	0.213*** (0.030)	0.163*** (0.031)	0.217*** (0.030)	0.169*** (0.031)
FE Financials	0.063* (0.030)	-0.023 (0.030)	0.064* (0.030)	-0.021 (0.030)
FE Healthcare	0.052 (0.026)	-0.025 (0.028)	0.052* (0.026)	-0.021 (0.028)
FE Industrials	-0.022 (0.024)	-0.056* (0.025)	-0.021 (0.024)	-0.053* (0.025)
FE Real Estate	-0.053 (0.031)	-0.119*** (0.031)	-0.051 (0.031)	-0.116*** (0.031)
FE Technology	0.169*** (0.026)	0.068* (0.027)	0.169*** (0.026)	0.071** (0.027)
FE Utilities	-0.322*** (0.027)	-0.337*** (0.029)	-0.320*** (0.027)	-0.338*** (0.029)
FE 2016	0.077*** (0.018)	0.065*** (0.019)	0.077*** (0.018)	0.066*** (0.019)
FE 2017	-0.252*** (0.018)	-0.268*** (0.019)	-0.253*** (0.018)	-0.272*** (0.019)
FE 2018	0.185*** (0.019)	0.192*** (0.020)	0.185*** (0.018)	0.180*** (0.019)
FE 2019	0.013 (0.019)	-0.00000 (0.020)	0.012 (0.018)	-0.014 (0.019)
FE 2020	0.824*** (0.019)	0.803*** (0.020)	0.824*** (0.018)	0.789*** (0.019)
FE 2021	0.115*** (0.020)	0.085*** (0.020)	0.115*** (0.018)	0.071*** (0.019)
Observations	2,735	2,735	2,735	2,735
R ²	0.697	0.669	0.697	0.668

Note: This table reports the fixed effects regression results of equation (2.3) and (2.4). It serves as an extension to Table 7. *** p<0.001, ** p<0.01, * p<0.05.

Appendix F: Impact of Paris Agreement (Fixed Effects)

	<i>Dependent variable: Expected Shortfall 5%</i>			
	<i>Panel A</i>		<i>Panel B</i>	
	Level (1)	Intensity (2)	Level (3)	Intensity (4)
Main Variables	(Table 8)	(Table 8)	(Table 8)	(Table 8)
FE Consumer Cyclical	0.033 (0.038)	0.007 (0.039)	0.038 (0.038)	0.008 (0.040)
FE Consumer Non-Cyclical	−0.178*** (0.041)	−0.222*** (0.041)	−0.174*** (0.041)	−0.223*** (0.041)
FE Energy	0.173*** (0.046)	0.146** (0.046)	0.173*** (0.046)	0.146** (0.046)
FE Financials	−0.112* (0.046)	−0.162*** (0.045)	−0.111* (0.046)	−0.163*** (0.045)
FE Healthcare	−0.041 (0.041)	−0.092* (0.041)	−0.037 (0.041)	−0.092* (0.041)
FE Industrials	−0.091* (0.037)	−0.110** (0.038)	−0.086* (0.037)	−0.110** (0.038)
FE Real Estate	−0.176*** (0.049)	−0.202*** (0.046)	−0.173*** (0.049)	−0.199*** (0.046)
FE Technology	0.061 (0.040)	0.002 (0.039)	0.065 (0.040)	0.003 (0.040)
FE Utilities	−0.398*** (0.043)	−0.391*** (0.043)	−0.392*** (0.043)	−0.380*** (0.043)
Observations	3,132	3,132	3,132	3,132
R ²	0.165	0.144	0.161	0.138

Note: This table reports the fixed effects regression results of equation (3.1) and (3.2). It serves as an extension to Table 8. Note that time fixed effects were not used here due to the use of time dummies (*Paris* and *Trump*). *** p<0.001, ** p<0.01, * p<0.05.

Appendix G: Alternative Downside Risk Measures

	<i>Expected Shortfall 1%</i>			<i>Value at Risk 5%</i>			<i>Lower Partial Moment</i>		
	Level (1)	Intensity (2)	Y-o-Y (3)	Level (4)	Intensity (5)	Y-o-Y (6)	Level (7)	Intensity (8)	Y-o-Y (9)
Constant	2.230*** (0.068)	1.550*** (0.046)	2.530*** (0.068)	1.400*** (0.052)	0.858*** (0.036)	1.580*** (0.053)	-3.350*** (0.115)	-4.610*** (0.079)	-2.810*** (0.116)
LOG Emissions	0.026*** (0.004)			0.024*** (0.003)			0.048*** (0.007)		
LOG Intensity		0.017*** (0.004)			0.021*** (0.004)			0.036*** (0.008)	
Change in CO2			-0.0001 (0.0001)						-0.0001 (0.0001)
Dividend Yield	-0.010* (0.004)	-0.010* (0.004)	-0.008 (0.005)	-0.018*** (0.003)	-0.018*** (0.003)	-0.015*** (0.004)	-0.029*** (0.007)	-0.031*** (0.007)	-0.027*** (0.008)
ROA	-0.005*** (0.001)	-0.008*** (0.001)	-0.007*** (0.001)	-0.005*** (0.001)	-0.007*** (0.001)	-0.006*** (0.001)	-0.009*** (0.002)	-0.013*** (0.002)	-0.012*** (0.002)
Leverage	0.001* (0.0004)	0.001 (0.0004)	0.001** (0.0005)	0.0001 (0.0003)	0.0001 (0.0003)	0.0003 (0.0004)	0.001 (0.001)	0.001 (0.001)	0.002* (0.001)
Liquidity	0.005*** (0.001)	0.006*** (0.001)	0.005*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.005*** (0.001)	0.011*** (0.001)	0.011*** (0.001)	0.010*** (0.001)
P/B Ratio	-0.00002 (0.0003)	-0.0004 (0.0003)	-0.0004 (0.0003)	0.00005 (0.0002)	-0.0003 (0.0003)	-0.0002 (0.0003)	0.0001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
LOG Market Cap	-0.105*** (0.007)		-0.086*** (0.006)	-0.085*** (0.005)		-0.067*** (0.005)	-0.189*** (0.011)		-0.154*** (0.010)
Governance Score	-0.0002 (0.0003)	-0.0005 (0.0003)	-0.00002 (0.0003)	-0.0001 (0.0002)	-0.0002 (0.0002)	0.0002 (0.0003)	-0.0002 (0.001)	-0.001 (0.001)	0.0005 (0.001)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,132	3,132	2,746	3,132	3,132	2,746	3,132	3,132	2,746
R ²	0.611	0.579	0.619	0.687	0.660	0.699	0.662	0.630	0.670

Note: This table reports the robust regression output of equation (1.1). Expected Shortfall 1%, Value at Risk (5%), and Lower Partial Moment are used as downside risk variables. Columns (1, Level), (4, Level), and (7, Level) present results using the logarithm of total emissions (LOG Emissions) as GHG emission measure. Columns (2, Intensity), (5, Intensity), and (8, Intensity) present results using the logarithm of carbon intensity (LOG Intensity) as GHG emission measure. Columns (3, Y-o-Y), (6, Y-o-Y), and (9, Y-o-Y) present the results using the yearly change in GHG emission levels. *** p<0.001, ** p<0.01, * p<0.05.

Appendix H: Alternative Downside Risk Measures - Target Dummy

	Expected Shortfall 1%			Value at Risk 5%			Lower Partial Moment		
	Level (1)	Intensity (2)	Level (3)	Intensity (4)	Level (5)	Intensity (6)	Level (5)	Intensity (6)	Intensity (6)
Constant	2.260*** (0.074)	1.530*** (0.049)	1.410*** (0.057)	0.840*** (0.039)	-3.300*** (0.126)	-4.650*** (0.085)			
LOG Emissions	0.025*** (0.004)		0.025*** (0.003)		0.046*** (0.008)				
LOG Intensity		0.018*** (0.005)		0.022*** (0.004)		0.037*** (0.008)			
Target	0.016 (0.015)	-0.016 (0.016)	0.005 (0.012)	-0.019 (0.012)	0.018 (0.026)	-0.038 (0.027)			
Dividend Yield	-0.007 (0.005)	-0.008 (0.005)	-0.015*** (0.004)	-0.015*** (0.004)	-0.024** (0.008)	-0.025** (0.008)			
ROA	-0.006*** (0.001)	-0.008*** (0.001)	-0.006*** (0.001)	-0.009*** (0.001)	-0.011*** (0.002)	-0.015*** (0.002)			
Leverage	0.001 (0.0005)	0.001 (0.0005)	0.001 (0.0004)	0.001 (0.0004)	0.001 (0.001)	0.001 (0.001)			
Liquidity	0.005*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.011*** (0.001)	0.012*** (0.001)			
P/B Ratio	0.00001 (0.0003)	-0.0003 (0.0003)	0.00004 (0.0003)	-0.0002 (0.0003)	0.0002 (0.001)	-0.0005 (0.001)			
LOG Market Cap	-0.108*** (0.007)		-0.088*** (0.005)		-0.194*** (0.012)				
Governance Score	-0.0001 (0.0003)	-0.0003 (0.0003)	0.00001 (0.0002)	-0.00004 (0.0003)	-0.00003 (0.001)	-0.0003 (0.001)			
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes			
Year FE	Yes	Yes	Yes	Yes	Yes	Yes			
Observations	2,735	2,735	2,735	2,735	2,735	2,735			
R ²	0.629	0.598	0.690	0.662	0.676	0.645			

Note: This table reports the robust regression output of equation (2.1), with the emission target dummy. Expected Shortfall 1%, Value at Risk (5%), and Lower Partial Moment are used as downside risk variables. Columns (1, Level), (3, Level), and (5, Level) present results using the logarithm of total emissions (LOG Emissions) as GHG emission measure. Columns (2, Intensity), (4, Intensity), and (6, Intensity) present results using the logarithm of carbon intensity (LOG Intensity) as GHG emission measure. *** p<0.001, ** p<0.01, * p<0.05.

Appendix I: Alternative Downside Risk Measures - Policy Dummy

	Expected Shortfall 1%		Value at Risk 5%		Lower Partial Moment	
	Level (1)	Intensity (2)	Level (3)	Intensity (4)	Level (5)	Intensity (6)
Constant	2.260*** (0.074)	1.530*** (0.049)	1.420*** (0.057)	0.847*** (0.038)	-3.300*** (0.126)	-4.630*** (0.084)
LOG Emissions	0.025*** (0.004)		0.025*** (0.003)		0.046*** (0.008)	
LOG Intensity		0.018*** (0.005)		0.022*** (0.004)		0.038*** (0.008)
Policy	0.021 (0.013)	-0.013 (0.014)	0.007 (0.010)	-0.018 (0.011)	0.025 (0.023)	-0.030 (0.023)
Dividend Yield	-0.007 (0.005)	-0.008 (0.005)	-0.015*** (0.004)	-0.014*** (0.004)	-0.024** (0.008)	-0.025** (0.008)
ROA	-0.006*** (0.001)	-0.008*** (0.001)	-0.006*** (0.001)	-0.009*** (0.001)	-0.011*** (0.002)	-0.015*** (0.002)
Leverage	0.001 (0.0005)	0.001 (0.0005)	0.00005 (0.0004)	0.0001 (0.0004)	0.001 (0.001)	0.001 (0.001)
Liquidity	0.005*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.011*** (0.001)	0.012*** (0.001)
P/B Ratio	0.00001 (0.0003)	-0.0003 (0.0003)	0.00004 (0.0003)	-0.0002 (0.0003)	0.0002 (0.001)	-0.0005 (0.001)
LOG Market Cap	-0.109*** (0.007)		-0.088*** (0.005)		-0.194*** (0.012)	
Governance Score	-0.0002 (0.0003)	-0.0003 (0.0003)	-0.00001 (0.0002)	-0.00001 (0.0003)	-0.0001 (0.001)	-0.0002 (0.001)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,735	2,735	2,735	2,735	2,735	2,735
R ²	0.629	0.598	0.690	0.662	0.676	0.644

Note: This table reports the robust regression output of equation (2.2), with the reduction policy dummy. Expected Shortfall 1%, Value at Risk (5%), and Lower Partial Moment are used as downside risk variables. Columns (1, Level), (3, Level), and (5, Level) present results using the logarithm of total emissions (LOG Emissions) as GHG emission measure. Columns (2, Intensity), (4, Intensity), and (6, Intensity) present results using the logarithm of carbon intensity (LOG Intensity) as GHG emission measure. *** p<0.001, ** p<0.01, * p<0.05.

Appendix J: Alternative Downside Risk Measures - Target and Emissions Interaction

	Expected Shortfall 1%		Value at Risk 5%		Lower Partial Moment	
	Level	Intensity	Level	Intensity	Level	Intensity
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	2.230*** (0.076)	1.520*** (0.050)	1.370*** (0.059)	0.828*** (0.039)	-3.370*** (0.130)	-4.660*** (0.086)
LOG Emissions	0.028*** (0.005)		0.030*** (0.004)		0.053*** (0.008)	
LOG Intensity		0.020*** (0.005)		0.026*** (0.004)		0.044*** (0.009)
Target	0.135 (0.076)	0.008 (0.027)	0.164** (0.059)	0.020 (0.021)	0.252 (0.130)	0.023 (0.047)
Dividend Yield	-0.007 (0.005)	-0.008 (0.005)	-0.015*** (0.004)	-0.015*** (0.004)	-0.024** (0.008)	-0.026** (0.008)
ROA	-0.006*** (0.001)	-0.008*** (0.001)	-0.006*** (0.001)	-0.009*** (0.001)	-0.011*** (0.002)	-0.015*** (0.002)
Leverage	0.001* (0.0005)	0.001 (0.0005)	0.0001 (0.0004)	0.0001 (0.0004)	0.001 (0.001)	0.001 (0.001)
Liquidity	0.005*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.011*** (0.001)	0.012*** (0.001)
P/B Ratio	0.0000 (0.0003)	-0.0003 (0.0003)	0.0002 (0.0003)	-0.0002 (0.0003)	0.0001 (0.001)	-0.001 (0.001)
LOG Market Cap	-0.109*** (0.007)		-0.090*** (0.005)		-0.196*** (0.012)	
Governance Score	-0.0002 (0.0003)	-0.0004 (0.0003)	-0.0001 (0.0002)	-0.0001 (0.0003)	-0.0001 (0.001)	-0.0003 (0.001)
LOG Emissions:Target	-0.009 (0.006)		-0.012** (0.004)		-0.018 (0.010)	
LOG Intensity:Target		-0.007 (0.006)		-0.011* (0.005)		-0.017 (0.011)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,735	2,735	2,735	2,735	2,735	2,735
R ²	0.629	0.598	0.691	0.663	0.677	0.645

Note: This table reports the robust regression output of equation (2.4), with the emission target interaction term. Expected Shortfall 1%, Value at Risk (5%), and Lower Partial Moment are used as downside risk variables. Columns (1, Level), (3, Level), and (5, Level) present results using the logarithm of total emissions (LOG Emissions) as GHG emission measure. Columns (2, Intensity), (4, Intensity), and (6, Intensity) present results using the logarithm of carbon intensity (LOG Intensity) as GHG emission measure. *** p<0.001, ** p<0.01, * p<0.05.

Appendix K: Alternative Downside Risk Measures - Policy and Emissions Interaction

	Expected Shortfall 1%		Value at Risk 5%		Lower Partial Moment	
	Level (1)	Intensity (2)	Level (3)	Intensity (4)	Level (5)	Intensity (6)
Constant	2.190*** (0.082)	1.530*** (0.052)	1.380*** (0.063)	0.851*** (0.040)	-3.440*** (0.139)	-4.650*** (0.089)
LOG Emissions	0.032*** (0.006)		0.028*** (0.004)		0.058*** (0.009)	
LOG Intensity		0.019** (0.006)		0.021*** (0.005)		0.042*** (0.011)
Policy	0.155* (0.069)	-0.004 (0.027)	0.066 (0.053)	-0.025 (0.021)	0.279* (0.117)	-0.009 (0.046)
Dividend Yield	-0.008 (0.005)	-0.008 (0.005)	-0.015*** (0.004)	-0.014*** (0.004)	-0.026** (0.008)	-0.026** (0.008)
ROA	-0.006*** (0.001)	-0.008*** (0.001)	-0.006*** (0.001)	-0.009*** (0.001)	-0.011*** (0.002)	-0.015*** (0.002)
Leverage	0.001* (0.0005)	0.001 (0.0005)	0.001 (0.0004)	0.001 (0.0004)	0.001 (0.001)	0.001 (0.001)
Liquidity	0.005*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.011*** (0.001)	0.012*** (0.001)
P/B Ratio	0.0002 (0.0003)	-0.0003 (0.0003)	0.0004 (0.0003)	-0.0002 (0.0003)	0.0002 (0.001)	-0.001 (0.001)
LOG Market Cap	-0.110*** (0.007)		-0.089*** (0.005)		-0.196*** (0.012)	
Governance Score	-0.0002 (0.0003)	-0.0003 (0.0003)	-0.00002 (0.0002)	-0.00001 (0.0003)	-0.0002 (0.001)	-0.0002 (0.001)
LOG Emissions:Policy	-0.010* (0.005)		-0.005 (0.004)		-0.020* (0.009)	
LOG Intensity:Policy		-0.002 (0.006)		0.002 (0.005)		-0.006 (0.011)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,735	2,735	2,735	2,735	2,735	2,735
R ²	0.630	0.598	0.690	0.662	0.676	0.644

Note: This table reports the robust regression output of equation (2.4), with the reduction policy interaction term. Expected Shortfall 1%, Value at Risk (5%), and Lower Partial Moment are used as downside risk variables. Columns (1, Level), (3, Level), and (5, Level) present results using the logarithm of total emissions (LOG Emissions) as GHG emission measure. Columns (2, Intensity), (4, Intensity), and (6, Intensity) present results using the logarithm of carbon intensity (LOG Intensity) as GHG emission measure. *** p<0.001, ** p<0.01, * p<0.05.

Appendix L: Upside Volatility Control

	<i>Dependent variable: Expected Shortfall 5%</i>		
	Level (1)	Intensity (2)	Y-o-Y (3)
Constant	1.470*** (0.038)	1.170*** (0.025)	1.580*** (0.039)
LOG Emissions	0.009*** (0.002)		
LOG Intensity		0.004 (0.002)	
Change in CO2			0.00000 (0.00004)
LOG Volatility	0.663*** (0.012)	0.693*** (0.012)	0.677*** (0.012)
Dividend Yield	0.005* (0.002)	0.006** (0.002)	0.006* (0.002)
ROA	-0.0004 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Leverage	0.00001 (0.0002)	0.00004 (0.0002)	0.0001 (0.0003)
Liquidity	0.0005 (0.0004)	0.0003 (0.0004)	0.0001 (0.0004)
P/B Ratio	-0.00004 (0.0002)	-0.0002 (0.0002)	-0.0002 (0.0002)
LOG Market Cap	-0.044*** (0.004)		-0.036*** (0.003)
Governance Score	0.0001 (0.0002)	0.0001 (0.0002)	0.0003 (0.0002)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	3,132	3,132	2,746
R ²	0.855	0.848	0.865

Note: This table reports the robust regression output of equation (1.2) by controlling for upside volatility (LOG Volatility). Column (1, Level) presents results using the logarithm of total emissions (LOG Emissions) as GHG emission measure. Column (2, Intensity) presents results using the logarithm of carbon intensity (LOG Intensity) as GHG emission measure. Column (3, Y-o-Y) presents the results using the yearly change in GHG emission levels. *** p<0.001, ** p<0.01, * p<0.05.

Appendix M: Lagged Regression

	<i>Dependent variable: Expected Shortfall 5%</i>	
	Level (1)	Intensity (2)
Constant	1.080*** (0.060)	1.110*** (0.060)
LOG Emissions	0.012*** (0.003)	
LOG Intensity		0.007* (0.003)
LAG ES	0.450*** (0.017)	0.456*** (0.017)
Dividend Yield	−0.011*** (0.003)	−0.009** (0.003)
ROA	−0.002* (0.001)	−0.003** (0.001)
Leverage	0.0002 (0.0003)	0.0002 (0.0003)
Liquidity	0.003*** (0.001)	0.003*** (0.001)
P/B Ratio	−0.0002 (0.0003)	−0.0003 (0.0003)
LOG Market Cap	−0.051*** (0.005)	−0.040*** (0.004)
Governance Score	−0.0001 (0.0002)	0.00002 (0.0002)
Industry FE	Yes	Yes
Year FE	Yes	Yes
Observations	2,694	2,694
R ²	0.765	0.764

Note: This table reports the robust regression output of equation (1.5) by controlling for lagged expected shortfall (LAG ES). Column (1, Level) presents results using the logarithm of total emissions (LOG Emissions) as GHG emission measure. Column (2, Intensity) presents results using the logarithm of carbon intensity (LOG Intensity) as GHG emission measure. *** p<0.001, ** p<0.01, * p<0.05.

Appendix N: Paris Agreement - COVID Control

	<i>Dependent variable: Expected Shortfall 5%</i>			
	<i>Panel A</i>		<i>Panel B</i>	
	Level (1)	Intensity (2)	Level (3)	Intensity (4)
Constant	1.880*** (0.082)	1.170*** (0.051)	1.730*** (0.092)	1.180*** (0.053)
LOG Emissions	0.012* (0.005)		0.026*** (0.006)	
LOG Intensity		0.006 (0.006)		0.016* (0.007)
Paris	−0.044 (0.073)	0.141*** (0.028)		
Trump			0.239** (0.075)	0.119*** (0.027)
COVID	0.476*** (0.016)	0.448*** (0.016)	0.406*** (0.015)	0.375*** (0.015)
Dividend Yield	0.002 (0.005)	0.0001 (0.005)	0.004 (0.005)	0.002 (0.005)
ROA	−0.005*** (0.001)	−0.008*** (0.001)	−0.005*** (0.001)	−0.007*** (0.001)
Leverage	0.001 (0.0005)	0.0005 (0.001)	0.001 (0.001)	0.0004 (0.001)
Liquidity	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)
P/B Ratio	−0.00001 (0.0004)	−0.0003 (0.0004)	−0.0001 (0.0004)	−0.0004 (0.0004)
LOG Market Cap	−0.092*** (0.007)		−0.092*** (0.008)	
Governance Score	0.001 (0.0003)	0.0003 (0.0003)	0.001 (0.0003)	0.0003 (0.0004)
LOG Emissions:Paris	0.017** (0.005)			
LOG Intensity:Paris		0.011 (0.006)		
LOG Emissions:Trump			−0.013* (0.006)	
LOG Intensity:Trump				−0.013* (0.007)
Industry FE	Yes	Yes	Yes	Yes
Year FE	No	No	No	No
Observations	3,132	3,132	3,132	3,132
R ²	0.332	0.298	0.309	0.272

Note: This table reports the robust regression output of equations (3.1) and (3.2), by controlling for COVID-19. Panel A focuses on the interaction terms Paris and emissions, and the control dummy COVID. Panel B centers around the interaction terms Trump and emissions, and the control dummy COVID. Columns (1, Level) and (3, Level) present results using the logarithm of total emissions (LOG Emissions) as GHG emission measure. Columns (2, Intensity) and (4, Intensity) present results using the logarithm of carbon intensity (LOG Intensity) as GHG emission measure. *** p<0.001, ** p<0.01, * p<0.05.