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The energy transition: The impact of extreme energy price changes on U.S.-listed firms

An event study approach

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ABSTRACT

Motivated by the ongoing energy crisis and the growing focus on sustainability, this study investigates the impact of extreme changes in oil, natural gas and coal prices on the stock performance of 1,326 U.S.-listed firms from March 2020 to October 2022, while also taking into account a firm's greenness. Using an event study methodology, the results do not show clear and consistent evidence of the expected relationship between energy price changes and the performance of U.S. stocks. The effects of energy price fluctuations vary across subperiods and different event windows and do not have statistical and economical significance. Moreover, using pooled OLS regression, this study finds no statistically significant evidence supporting the influence of a firm's greenness, as measured by ESG scores, individual E-, S-, and G-score, CO_2 intensity and political affiliation, on abnormal returns following extreme energy price changes. These mixed and ambiguous findings highlight the complexity of the relationship between energy prices, stock performance, and a firm's greenness. This calls upon policymakers and investors to consider various factors when analysing the effects of energy price changes on stocks amidst the ongoing energy crisis and transition.

Keywords: Event study, Energy crisis, ESG scores, CO_2 emissions, Political affiliation

JEL Classification: G14, Q50, Q40, C33, G00

TABLEOF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1 Introduction

In the last couple of stirring years, energy price movements have been extensive. Headlines such as "Climbing energy prices are roiling markets" and "Oil prices are falling, but Wall Street isn't buying it" dominated newspapers, highlighting the impact of these dramatic shifts (Sorkin et al., 2022; Henderson, 2022). The plethora of such articles reveal a consensus among news reporters and market analysts that these extreme changes in energy prices have a notable effect on the stock performance of US-listed firms. This effect is not surprising, given the importance and reliance on energy commodities such as oil, natural gas, and coal in fuelling industries, ensuring companies' economic stability, and safeguarding national security (Ahmed & Sarkodie, 2021). With fossil fuels accounting for about 80% of global energy consumption, price fluctuations of these cause great uncertainty and concerns among investors regarding economic activity and firm performance (Sonenshine & Cauvel, 2017). Throughout history, several events have given rise to this uncertainty leading to varying degrees of energy crises. The recent combination of the Covid-19 pandemic (2020) and the Russian/Ukraine war (2022) has intensified the challenges surrounding the energy sector, resulting in an ongoing energy crisis. Both events caused disruptions in energy trade, triggered shocks in demand, extreme energy price swings, impeded energy investments, and raised concerns about the magnitude of the impact on stock markets (Zakeri et al., 2022; Cohen, 2020).

The current energy crisis is distinguished by the parallel growing focus on sustainability, driven by the need to accelerate the transition to clean energy and mitigate the threat of climate change. This trend makes it necessary for companies to actively engage in the transition to a low-carbon economy by, for example, reducing the use of fossil fuels and associated CO_2 emissions. Simultaneously, investors are more critical and aware of a company's sustainability performance, which is valued in their stock price. ESG scores have become crucial in evaluating a firm's greenness, as these scores provide insights into a firm's behaviour regarding dealing with Environmental (E), Social (S) and Governance (G) matters (Drempetic et al., 2020). A better rating on ESG performance can positively influence a firm's financial performance and increases the likelihood of attracting, engaging and retaining employees and capital (Friede et al., 2015). Moreover, studies suggest that ESG scores, particularly the environmental pillar, can serve as a hedge against negative environmental conditions and, more specifically, against bad climate-related news (Pastor et al., 2021). In recent years, additional measures have been developed to evaluate a firm's greenness, including measures such as a firm's CO_2 intensity and its political affiliation. CO_2 intensity seems to have a negative impact on a company's stock price, while a democratic-leaning company shows better ESG performance and higher stock valuation (Jung et al., 2016; Di Giuli & Kostovetsky, 2014). However, research on this relationship is quite limited.

Although academic research on ESG-related topics has grown steadily in recent years, conclusions about the impact of a firm's greenness on stock price responses to negative events is highly dependent on the context, leading to inconclusive findings. The current period is characterized by a unique combination of drastic energy price fluctuations resulting from the energy crisis, alongside the ongoing energy transition.

Hence, it presents an interesting opportunity to examine the impact of these extreme energy price fluctuations on stock performance, while also investigating how a firm's level of greenness influences this relationship. Therefore, this study aims to answer the following research question:

How are the stocks of U.S.-listed firms affected by extreme changes in energy prices, and is this effect influenced by the greenness of a firm?

This paper uses an event study approach to investigate the impact of a 15% or more change in daily oil, natural gas and coal prices on the stock performance of 1,326 U.S.-listed firms from March 2020 to the end of October 2022. Cumulative abnormal returns are measured as a proxy for stock returns and various variables are examined to identify the main factors driving these abnormal returns. All these variables can be seen as proxies for firm's greenness and consist of a firm's overall ESG score, the individual pillar of ESG (i.e., environmental, social and governance), CO_2 intensity and political affiliation. Cumulative abnormal returns are estimated on the event day and during a 3- and 7-day event window of [-1,1] and [-3,3], respectively, using a constant mean return model. Afterwards, a regression is performed on the obtained cumulative abnormal returns using several explanatory variables, representing a firm's greenness, and a set of control variables. Finally, the statistical significance of all these results is tested using a range of significance tests.

Although extremely positive (negative) energy prices were expected to have a negative (positively) effect on U.S. stock performance, this event study finds no supporting evidence for this assumption. For each energy commodity, the results were mixed and ambiguous with varying trends and magnitudes of (C)AARs across the three different event windows. In fact, when considering all energy commodities together, a positive relationship was found between energy price changes and stock prices, contradicting what was assumed. Some clearer trends, or even little evidence of time series momentum, emerge when analysing four subperiods consisting of the (1) Covid-19 outbreak phase, (2) Covid-19 follow-up phase, (3) Covid-19 recovery phase, and (4) Russia-Ukraine war. However, these results were still ambiguous, and with this lack of clarity, there is no conclusive evidence of and how U.S.-listed firms are affected by extreme changes in energy prices. Furthermore, this study finds no economically and statistically significant evidence for the influence of a firm's ESG score or individual environmental, social or governance scores on abnormal returns around extreme energy price changes. The use of other less conventional indicators of a firms' greenness, namely CO_2 intensity and political affiliation, in the regression models also yielded only very low and insignificant coefficients. The absence of convincing evidence suggests that, contrary to expectations, a firm's ESG performance may not serve as a hedge against bad climate-related news, such as extreme energy price changes.

This paper makes valuable contributions to the existing literature in various ways. First, it fills a gap in the literature by examining the influence of oil, natural gas, and coal prices on stock performance of the overall U.S. stock market, which is a comprehensive approach compared to previous studies that focus primarily on the influence of only one energy commodity. Additionally, this study reassesses the relationship between energy price fluctuations and stock performance in light of the recent energy crisis and ongoing energy transition, which have potentially shifted macroeconomic conditions and financial markets. Furthermore, this study builds upon the existing literature related on the relationship between a firm's greenness and stock performance. Previous papers already showed that ESG performance can positively influence stock reactions following bad climate-related news. However, this study expanded these findings by focussing specifically on one type of climate-related news: extreme energy price changes. Consequently, this is, to the best of my knowledge, the first study that measures the impact of extreme energy price changes on stock performance, considering both overall ESG ratings and the individual scores. Most research only focusses on the ESG scores as proxies for a firm's greenness, however, these scores can be inaccurate and biased. Therefore, this study added value by including CO_2 intensity and political affiliation as extra measures of a firm's greenness and to see how these variables influences the relationship between extreme energy price changes and stock performance. By addressing all above aspects, the research contributes to a deeper understanding of the complex relationship between energy price changes, firm greenness, and stock performance, shedding light on the role of different factors within the framework of a firm's greenness. These findings will show how the energy crisis may impact the pace of the energy transition. Consequently, this can help politicians with the formulation of policy recommendations to tackle (negative) effects caused by the energy crisis.

The remainder of this thesis paper is organized as follows. Chapter 2 provides an overview of the related literature and introduces the hypotheses related to the research question. Chapter 3 shows a description of the process of data collection and discusses the associated descriptive statistics. Next, chapter 4 describes the methodology used to analyse these data and chapter 5 reveals the results of the empirical tests. Finally, chapter 6 contains the conclusions of this paper in combination with the limitations and recommendations for further research.

2 Literature Review

This chapter presents key concepts, definitions, and theories to better understand the research question. It provides an overview of energy markets, (efficient) stock markets, and the relation between both markets. Also, literature on a firm's greenness and its impact on stock performance will be explained using concepts like ESG performance, carbon dioxide (CO_2) intensity and political affiliation. Finally, research gaps are identified, and hypotheses are derived to answer the research question.

2.1 Energy market

2.1.1 The fundamentals and trends of fossil fuels

For decades, the energy commodities oil, natural gas, and coal have been essential resources used by firms and countries as inputs to ensure their economic stability and national security (Ahmed & Sarkodie, 2021). These fossil fuels, formed in the earth over millions of years from the remains of plants and animals, are non-renewable and exhaustible. Moreover, extracting and burning fossil fuels emit CO_2, a greenhouse gas, with significant environmental consequences. Despite all this, fossil fuels continue to play a crucial role in global energy systems and economies (Change, z.d.). They currently account for about 80% of the world's total energy consumption, with increasing demand in developing countries, including India and China, and emerging markets (IEA, 2022). The United States (U.S.) is one of the largest consumers of oil and natural gas worldwide, accounting for 19.9% and 20.5% of world's consumption by 2021, respectively. In terms of coal use, China (53.8%) and India (12.5%) surpasses the U.S. which had a coal use share of 6.6% in 2021 (BP, 2022). Nevertheless, forecasters expect an end to the peak in worldwide demand for fossil fuels, in part due to climate commitments by governments and firms. Therefore, natural gas demand will plateau by the end of the decade, coal demand will soon peak, and oil demand will reach its highest point by the mid-2030s before declining. The share of fossil fuels in the global energy mix is expected to drop below 75% by 2023 and just above 60% by the middle of the century (IEA, 2022). There will be a long-term negative sentiment on fossil fuel prices due to the increasing share of renewable energies in total energies.

Historically, several events have led to energy crises of varying degrees, such as the 1973' oil crisis, the turmoil in the Middle East, and the 2008' global financial crisis (GFC). The 1973' oil crisis, driven by geopolitical factors, exposed vulnerabilities and dependencies in the energy system, leading to high oil prices, inflation, economic harm and concerns about global energy security (IEA, 2022). Currently, the world is facing an energy crisis due to the Covid-19 pandemic (2020), especially its opening up phase, and the Russian invasion of Ukraine (2022), with a ban on commodity imports from Russia. To combat the spread of Covid-19 in 2020 far-reaching measures were taken, such as lock downs, travel restrictions and quarantines. This caused global disruption and negative economic impact, leading to reduced industrial output and huge changes in energy demand and supply (Zakeri et al., 2022; BP, 2021). For instance, this led to oil price shocks and impeded energy investments, with oil prices even falling below $37 a barrel, the lowest price level in 17 years (Zakeri et al., 2022; Cohen, 2020). After the lockdowns were lifted in early 2021, industries returned to full capacity, driving up energy demand and prices. Additionally, rising natural gas demand in Asia and Europe drove up prices further. The Russian invasion of Ukraine in February 2022 further worsened the energy crisis. The disruption of Russia's energy trade due to blockades and sanctions has disturbed its role as worldwide exporter of fossil fuels (Zakeri et al., 2022). This Russia-Ukraine war is expected to have lasting effects on the global energy system, including greater focus on energy security, economic growth slowdown, and alterations of the energy supply mix (BP, 2023). As a result, all three fossil fuel prices hit record levels (IEA, 2022).

Today's energy crisis has some similarities to past energy crises but is more complex and far-reaching. Previous crises were mostly limited to oil and policy makers had to take straightforward measures like scaling down oil dependency. However, today's energy crisis spans various dimensions, including oil, gas, coal, electricity, food security and climate change, due to greater integration of fuel markets. As a result, the consequences and solutions are also all-encompassing (IEA, 2022; Gilbert et al., 2021).

Prior to 2008, natural gas and oil prices shared a pattern, however, after the GFC they have diverged (Ordu & Soytas, 2016). Consequently, the three fossil fuels have developed somewhat different patterns around the pandemic and Russia-Ukraine war. There have been concerns about global oil resources and potential shortages for years, with expected small increase in oil prices leading to a shift towards alternative energy sources (Henriques & Sadorsky, 2008). Oil prices are influenced by various factors such as supply and demand, geopolitical events, political stability, institutional arrangements of the organization of petroleum exporting countries (OPEC), and futures markets (Basher & Sadorsky, 2006). The pandemic and Russia-Ukraine war led to oil price changes at an unexpectedly rapid pace, with record-low prices in 2020 followed by extreme increases to the second highest level since 2015 of $70.91 per barrel, creating a desire to reduce oil imports (BP, 2021, 2022, 2023). Simultaneously, there has been a fundamental shift towards the use of natural gas as a global commodity, driven by its ability as a substitute for oil (Gilbert et al., 2021; Brown & Yucel, 2008). Natural gas plays an essential role in domestic and commercial heating, as well as in industrial production and electricity generation. Moreover, it is a relatively clean fuel that emits considerably less CO_2 than oil and coal and its prices are influenced by factors as demand and supply, international trade flows, meteorological conditions, substation effects among energy commodities and business cycles (Nick & Thoenes, 2014). During the pandemic, natural gas markets were under pressure, but the biggest blow came shortly after the Ukraine invasion in early 2022. This disrupted the supply chain from Russia that was needed to meet demand, leading to skyrocketing natural gas prices, exacerbated by increased uncertainty (Gilbert et al., 2021). Finally, global coal demand rose prior to the pandemic and Russia-Ukraine war, mainly driven by China and India, and is expected to continue rising in the next years (IEA, 2021, 2022). Although the pandemic caused lower demand and prices, the major setback occurred after the Ukraine invasion. High natural gas prices led to increased demand for coal as a substitute, driving coal prices even higher.

2.1.2 The ongoing energy transition

Another factor that sets apart today's energy crisis from predecessors is the growing attention on sustainability, which is part of the ongoing energy transition (IEA, 2022). There is a global urgency to hasten clean energy transitions to reduce the threat of climate change (IEA, 2020). Rising CO_2 concentrates in the atmosphere have led to alarming global warming effects, emphasizing the need for emission reductions (Henriques & Sadorsky, 2008). Non-renewable energies, with their high emissions, contribute significantly to this climate change problem, making the shift to renewable energies crucial. Renewable energies are obtained from natural sources that replenish themselves faster than they are consumed, such as solar, wind, hydropower, and bioenergy. Unlike fossil fuels, renewable energy generation produces less CO_2 emissions (United Nations, z.d.). Governments play an important role in driving this low-carbon energy transition through initiatives such as the Sustainable Development Goals (SDGs) and guidelines to focus investments on clean energy initiatives and innovations (IEA, 2021). These developments require active involvement for companies, for example, by reducing the use of fuels making them more sustainable. Simultaneously, investors place greater value on a firm's sustainability, with higher level of sustainability positively impacting its stock price. Consequently, all firms now want to boast about their firm's greenness.

Thereby, the ongoing energy transition is impacted by today's energy crisis. Covid-19 caused a rapid change in lifestyle and behaviour and emphasized the significance of science-based policy advise, while the Russia-Ukraine war highlighted the importance of energy diversification and dependence on local renewables (Zakeri et al., 2022). While some argue that opportunities have arisen for low-carbon transitions, others argue that many firms still rely heavily on fossil fuels. Therefore, extreme fossil fuel price fluctuations affect their cash flows and operating costs, impacting their revenues and economic activity (Benkraiem et al., 2018). Likewise, these firms will face return shocks, especially those that rely heavily on fossil fuels, making it likely that these firms will have higher costs and less money available for green energy investments and innovations (Zakeri et al., 2022). Indeed, Deng et al. (2022) show that the transition to a low-carbon economy in the U.S. is expected to slow down for this reason. Hence, it is crucial to evaluate the exact reaction of stock markets to these energy price fluctuations before formulating policy recommendations to address negative effects through subsidies, for example (Zakeri et al., 2022).

2.2 Energy prices and the macro economy

For a long time, researchers have been interested in investigating the macroeconomic effects of energy price changes, initially focusing on the impact of oil price fluctuations (Benkraiem et al., 2018). Unexpected energy price swings can be seen as exogenous shocks to a country's economy, now that fossil fuel supplies and prices are crucial factors in industrial production (Mohanty et al., 2013). Subsequently, this greatly affects macroeconomic conditions and indicators, such as inflation rates, interest rates, exchange rates, gross domestic product (GDP) per capita, and unemployment levels (Hsiao et al., 2019).

Pioneer Hamilton (1983) shed light on the relationship between crude oil prices and the U.S. macroeconomy since World War II. He demonstrated a puzzling pattern in which dramatic oil price hikes were followed by recessions, apart from the 1960-1961 economic downturn. After conducting several tests, Hamilton (1983) concluded that this pattern can be traced to a significant and nonspurious correlation between increasing oil prices and U.S. recessions from 1948 to 1972. This suggests that extreme oil price changes have, to some degree, contributed to at least some of the U.S. recessions. Thereafter, numerous academics have explored the relation between energy prices and macroeconomic indicators using various estimation techniques and datasets. For example, Ahmed & Sarkodie (2021) used (stochastic simulated) ARDL models to show that increasing prices of energy commodities – oil, natural gas and coal – limits firms' production, leading to inflationary pressure, reduced purchasing power, and reduced aggregate demand. Additionally, it decreases the long-term employment rate (Papapetrou, 2001). Research by Darby (1982) already highlighted this positive relation between oil price and inflation rates, attributing it to increased production costs and subsequent price hikes in goods and services. Moreover, given the key role of coal and natural gas in electricity and heating, price increases of these fuels are likely to adversely affect household cashflows, further deteriorating purchasing power (Ahmed & Sarkodie, 2021). Besides, higher inflation rates generally affect interest rates, as the Federal Reserve raises them to dampen rising inflation. According to Gronwold (2008), large energy price increases affect also a country's GDP per capital. His findings revealed that large oil price shocks, particularly those in 1973-1974, 1979, and 1991, triggered a negative response of real U.S. GDP, while normal oil price increases did not significantly affect GDP.

Over time, doubts about Hamilton's (1983) findings emerged due to potential biases in his dataset, which mostly included upward oil movements. Consequently, it raised uncertainty about the correlation during periods of oil price declines. Therefore, Mork (1989) conducted a comparable study extending the sample period to 1988. He confirmed a significant negative effect of oil price hikes on U.S. gross national product (GNP). Moreover, Mork (1989) found that rising oil prices have adverse effects on GNP, while oil price declines do not lead to positive effects of the same magnitude, indicating an asymmetrical relationship. Later, Mory (1993) argued that oil price declines do not significantly benefit the economy in the short term. A drop in oil prices may increase disposable income in oil-importing regions, but it also leads to unemployment in oil-producing regions and will distort oil demand, supply and trade. This suggests different effects of energy price changes on energy importing or exporting countries. Mork (1994) confirmed this conclusion and showed that asymmetry was strongest in the U.S., at that time the largest oil-importing country. Increased volatility in energy prices also contributes to this asymmetrical effect, causing uncertainties in investment decisions, real consumption growth, and resource allocation (Mohtanty et al., 2013). In short, it is generally agreed that energy prices have substantial effects on economic activities, where climbing energy prices can be destructive to the macroeconomy. This inspired subsequent researchers to explore the applicability of these findings to the stock market.

2.3 The stock market

2.3.1 Efficient Market Hypothesis

Decades ago, Fama et al. (1969) proposed the Efficient Market Hypothesis (EMH), which states that stock markets are efficient and reflect all available information while incorporating all projections of future returns and profits. It suggests that when new information emerges, investors process this information rapidly and completely. Therefore, stocks are traded at their fair value, eliminating the possibility to buy undervalued stocks, sell overvalued stocks, or consistently generate alpha. Investors response to unforeseen events when they contain new information by assessing the news, predicting the consequences, and responds through transactions prior to, during or after the implementation of the news. The investors' response is contingent upon whether the news is positive or negative, affecting the direction of change in stock value. These stock price changes shortly after events thus reflect changes in investor expectations and measure the short-term effects of events (Hall & Kenjegaliev, 2017). Fama et al. (1969) expect these changes, or so-called abnormal returns, to be transitory, as stock prices eventually revert to their mean level, with the speed with which the new information is fully absorbed providing insights into market efficiency.

Fama (197) identified three conditions under which the EMH can exist: (1) lack of transition costs, (2) freely available information without costs, and (3) agreement on the implication of information. However, in real-life these are not fully met due to costs for information and trading. Nevertheless, the EMH still helps assess how stock prices respond to news. Furthermore, the EMH has three forms: (1) weak, (2) semi-strong, and (3) strong. The weak form integrates historical prices into current stock prices, while the semi-strong form evaluates if current stock prices adjusted to historical and public information. Finally, the strong form established when current stock prices reflect all public and private information. Event studies use the semi-strong form to study the effects of unforeseen events on firm valuation and returns.

Consequently, events can cause abnormal returns only if they are significant and unforeseen, otherwise the information has already been processed. These events include announcements such as stock splits, dividends, and earning reports, as well as unexpected catastrophic, social, and political events such as terrorism, natural disasters, and war. These events, initiated by firms or arising externally, introduce new information that may impact future financial outlook, causing investors to reassess stock prices. Consequently, stock markets may experience increased uncertainty, greater volatility, diminishing investments, and lower firm valuation (Grinblatt et al., 1984; Worthington & Valadkhani, 2004).

2.4 Energy prices and the stock market

2.4.1 Existence of a relationship

The two last decades, scholars have extensively examined the effects of energy prices on stock markets in various scenarios, building upon existing knowledge of their effects on the macroeconomy. Changes in oil, natural gas and coal prices are expected to affect stock prices due to their economic significance. An efficient stock market should quickly react to news, including shocks in energy prices (Huang et al., 1996). Higher oil prices can increase business costs and reduce earnings, cashflows and gross margins, thereby negatively impacting stock markets. In contrast, an oil price drop is expected to have a reversed effect on stock markets (Mohanty et al., 2013). Although there is a large body of literature on the relationship between energy price changes and stock markets, the results are mixed and inconclusive.

The pioneering work of Chen et al. (1986) investigated the effects of innovative macroeconomic variables on stock price returns. Based on the EMH, they argued that stock prices should be influenced by a specific set of economic variables that describe the state of the economy. This set includes traditional metrics, but Chen et al. (1986) notably introduces the price of oil as an innovative addition. Indeed, their findings showed that industrial production, inflation rates, interest rates and bond yield spreads are priced into the stock market as risk. However, they found no evidence supporting the hypothesis that oil price risk is priced separately into the stock market. Similar results were found by Huang et al. (1996) who examined the relation between oil futures returns and U.S. stock returns from 1979 to 1990. Using a multivariate vector autoregressive (VAR) approach, Huang et al. (1996) proved that oil futures returns only lead to stock returns for a few individual companies, such as firms in the oil industry, but had minimal impact on market indices such as the S&P 500. Overall, the absence of correlation in these studies suggests that there is no significant relationship between stock returns and changes in oil prices.

Controversy, Jones and Kaul (1996) and Sadorsky (1999) provide evidence of a significant negative relationship between the prices of oil and aggregated stock market returns within the U.S. Jones and Kaul (1996) examined whether the response of various international equity markets to oil price shocks can be explained by present and future changes in a firm's cash flows and/or expected returns. For their research, they include the stock markets of the U.S., Canada, Japan, and the United Kingdom (UK) over a total period from 1947 until 1991. Using standard dividend discount models, they found that the negative response of U.S. and Canadian stock prices to oil price shocks could be entirely explained by their influence on cash flows, indicating rationality. Contrary, the results for Japan and the UK are less conclusive, making it impossible to explain the impact of oil price shocks. Spurred by these conflicting findings, Sadorsky (1999) dives deeper into the relationship between oil prices, economic activities, and stock performance. He started with a VAR model that used U.S. monthly data on stock returns, interest rates, industrial production and oil prices, and used a different approach to estimate oil price shocks than previous researchers (Jones and Kaul, 1996; Huang et al., 1996). The analysis pointed out that both oil prices and its volatility significantly affect economic activities, including U.S. stock returns. Additionally, impulse response functions present that oil price changes are indeed explanatory for the movements of U.S. stock returns. Oil price increases are found to significantly depress U.S. stock returns, attributed to their adverse effects on economic activity and company's earnings (Sadorsky, 1999). Finally, Sadorsky (1999) observed a shift in the dynamics of oil prices. Since 1986, oil price fluctuations have explained a greater proportion of the forecast error variance in stock returns than interest rates. This suggests that the relationship between oil prices and stock returns is not constant, but rather depend on various factors. The impact of oil prices on the stock market will fluctuate over time due to shifts in the macroeconomic environment and financial markets (Sadorsky, 1999). Miller and Ratti (2009) supported these findings by examining the relationship between oil prices and stock markets in six OECD countries over a long period from 1971 to 2008, allowing them to identify breaks in the relationship. Using a cointegrated vector error correction model, they find evidence for several breaks. During the period 1971-1980 and 1988-1999, they showed a significant negative relation between oil prices and stock performance, as expected given the dependence of modern economies on oil. Contrary, Miller and Ratti (2009) found no significant relationship from 1980 to 1988. Surprisingly, the significant negative relationship disappeared after 1999 and even became positive. Indeed, this suggests that the dynamics of oil prices relative to stock prices may change over time. Therefore, there is an ongoing need for research to analyse and fully understand this dynamic relationship.

Early research mainly focused on the effects of oil prices, while some later studies expanded to include all three fossil fuels. Oberndorfer (2009) evaluated the relationship between energy market developments, including oil, natural gas and coal, and European energy stocks in 2002-2007. According to his results, rising oil prices negatively influences the stock prices of energy utility companies, while benefiting oil and gas companies. Moreover, coal price changes also affected energy utility's stocks, albeit to a lesser extent than oil, even though coal plays a more important role in electricity generation than oil. Finally, no significant relationship was found between natural gas prices and European energy stocks. Additionally, Benkraiem et al. (2018) did not focus on a specific industry but investigated the effects of oil and natural gas prices on the S&P 500 from 1999 through 2015. They demonstrate a negative association between oil and natural gas prices on the one side and S&P 500 stock prices on the other side. However, this relationship is found to be significant only for medium and high quantiles, both in the long- and short-run. This suggest that oil and natural gas prices have explanatory value for the S&P 500 returns, with circumstances determining which energy price will dominate at the time. Ahmed and Sarkodie (2021) expanded on this research by extending the sample period to 1991 to 2019 and adding coal prices. Using (stochastic stimulated) ARDL models, they validated the negative long-term relation between movements in oil price, natural gas prices, and the S&P 500. However, no significant evidence is found for a long-run relationship between coal prices and the S&P 500. Contrary, in the short-term a positive link was found between all three energy commodities and the S&P 500. These findings indicate a consensus on the link between oil prices and stock performance, while the link between natural gas, coal, and stock prices remains uncertain and depends on various circumstances.

Furthermore, most researchers typically use VAR or VEC models to investigate the relationship between energy prices and stock performance. However, Aggarwal et al. (2012) took a different approach by using an event study methodology in which they used daily data on oil prices and stock returns for 71 companies in the S&P transportations index from January 1986 to July 2008. In this analysis, large changes in oil prices, or so-called oil shocks, are treated as events to see how these extreme changes impact stock returns, oil and market betas, return variances, and trading volume of the transportation firms. The findings revealed that an oil price change of 5% or more had a negative impact on stock performance, betas, variances, and trading volumes. Besides, Aggarwal et al. (2012) conclude that other firm characteristics, such as firm size and return on assets (ROA) are also important in explaining this found relationship. Mohanty et al. (2013) employed an event study like Aggarwal et al. (2012), but now they focus on companies in the U.S. oil and gas industry from 1968 to 2008. As expected, Mohanty et al. (2013) found a positive relationship between oil price increases and stock performance for oil and gas companies, as these firms primarily sell oil as output rather than using it as inputs. Again, they emphasized the influence of firm-specific factors on the impact of energy price changes on stock performance. In line with this, Hall & Kenjegaliev (2017) reviewed whether oil price fluctuations affect oil companies' stocks in emerging economies and Western countries. Their event study from 2000 until 2008 revealed considerable abnormal returns after an oil shock happened. Besides, discrepancies were observed among firms from diverse economic areas, particularly with Russian and Chinese firms showing unusual patterns, likely influenced by high political factors in these countries.

Although a substantial body of literature exists, the effects of energy prices on stock performance have yielded diverse findings ranging from negative, positive, to no effects. At the end of this chapter, table 1 summarizes the most relevant literature on this topic. Most studies focus on the impact of oil price fluctuations and agree that oil affects stock prices regardless of direction (Chen et al., 1986; Sadorsky, 1999; Miller & Ratti, 2009). Limited research examines the impact of gas and coal price changes on stock performance, usually within specific sectors rather than the stock market as a whole (Aggarwal, 2012; Hall & Kenjegaliev, 2017). Therefore, this study contributes to the existing literature by concentrating on the overall U.S. stock market and including the prices of oil, natural gas and coal. Moreover, few studies have focussed on the relationship between energy prices and stock prices in recent years, while Covid-19 and the Russian-Ukraine war were unexpected, new events that potentially caused shifts in macroeconomic conditions and financial markets (Sadorsky, 1999; Millar & Ratti, 2009). Therefore, the previously found relationship should be reassessed. For example, Mugaloglu et al. (2021) showed that the impact of oil price shocks on oil and gas stocks declined after the Covid-19 outbreak, while Ali et al. (2022) argued that U.S. stock markets continue to be impacted by oil price changes during and after the pandemic. However, these studies focused only on one energy commodity and do not consider the period surrounding the Russian-Ukraine war, which affected all energy prices. Since this study focuses on the overall U.S. stock market rather than on a specific sector, it is generally agreed that a rise in energy prices tends to have a negative impact on stock performance (Jones and Kaul 1996; Benkraiem, 2018). Therefore, this pattern is expected to persist over the last two stirring years, leading to the following hypothesis:

Hypothesis 1: *An extreme positive (negative) energy price change has a negative (positive) effect on the stock price of U.S.-listed firms.*

2.5 ESG

2.5.1 Development of ESG

The interest in sustainability and its integration within companies has a long history, with Bowen (2013) introducing the concept of Corporate Social Responsibility (CSR) as early as 1953. With this, he underlined the ethical obligations and responsibilities of companies towards societal stakeholders, emphasizing their important role in creating a positive impact on society while meeting shareholders' objectives. This concept has evolved further and now encompasses addressing environmental issues by considering the economic, environmental and social aspects of a company (Drempetic et al., 2020). In recent years, more and more firms and investors have integrated sustainability practices into their investment decisions, making CSR a worldwide business standard (Barros et al., 2022). Commitments to CSR offer valuable insights into a firm's values and internal culture but are entirely based on self-regulation and therefore can vary considerably. To provide more transparency and guidance, sustainability ratings have been created by third-party rating agencies, evaluating firms based on three types of criteria: environmental, social, and corporate governance (Drempetic et al., 2020).

Environmental (E), Social (S) and Governance (G) ratings, originally developed in 1980, became popular among investors in the last decade (Berg et al., 2022). In the early 2005s, the United Nations Principle for Responsible investment (UN PRI) was established to encourage integration environmental, social and governance concerns into investment and ownership decisions. Not much later, this network reintroduced and supported the concept of ESG ratings (UN PRI, 2021). With the growing interest in sustainable investing and the inability of investors to assess a firms' sustainability on their own, all investors rely heavily on ESG ratings (Drempetic et al., 2020). As a result, ESG disclosers has grown significantly, along with the emergence of numerous rating agencies (Berg et al., 2022). Consequently, ESG has become a crucial factor in attracting, engaging and retaining employees and capita, contributing to a company's success (Atkins, 2020). ESG rating agencies assess and rate a company's behaviour in addressing Environmental (E), Social (S) and Governance (G) concerns, using specific weighting schemes to obtain an overall ESG score (Refinitiv, 2022). The environmental pillar includes metrics related to climate change, pollution, resource depletion, waste, and more. Secondly, the social aspect evaluates how companies perform in areas such as working conditions, employee relations, human rights, and various other relevant factors. Finally, under the governance pillar, a company's performance is assessed on issues such as board diversity, executive compensation and political lobbying, to name a few (UN PRI, 2021). However, ESG ratings face challenges due to ever-changing interpretations of corporate values, lack of a global measurement standard and unstandardized (voluntary) ESG reporting by companies, leading to biases, manipulation and subjectivity (Berg et al., 2022). For example, studies have shown that some firms intentionally disclose their sustainable performance in a way that inflates their ESG ratings while some suspect collusions between firm and rating agencies. Simultaneously, it is difficult to detect these problems because of agency problems and high monitoring costs (Bams & Van der Kroft, 2022; Clementino & Perkins, 2020; Drempetic et al., 2020). Although the assessment of rating agencies relies on the same public available information such as annual reports, NGO websites, and sustainability reports, considerable inconsistent ESG ratings arise due to different rating methodologies among rating agencies, leading to confusion among investors (Chatterji et al., 2016). All these issues undermine the reliability of ESG ratings, which is why harmonization is desirable in the future (Berg et al., 2022).

2.5.2 ESG and firm's financial performance

Given the growing recognition of corporate sustainability, extensive research is conducted on the relation between a firm's ESG rating and its financial performance, particularly regarding long-term shareholder value. A summary of the relevant literature on the topic can be found in table 1. This research is important as massive money flows to companies with high ESG performance, raising investor considerations (Ferriani & Natoli, 2021). However, establishing an ambiguous relationship is difficult as improvements in ESG ratings may not be directly visible in a company's financial statement (Engelhardt et al., 2021). This reflects the ongoing debate between short-term profits and long-term value creation under shareholder versus stakeholder theory (Zumente & Bistrova, 2021).

On one hand, improving corporate sustainability and achieving higher ESG ratings require financial resources to invest in, for example, environmentally friendly inputs and sustainable operational practices. There are also costs associated with disclosing ESG-related information (Drempetic et al., 2020). According to Friedman's (1970), a proponent of the shareholder's theory, CSR lies in the pursuit of profit maximization. Therefore, investments in ESG activities are undesirable flows of money from shareholders to a firm's stakeholders. Consequently, socially responsive firms have higher costs, lower profits and thus a competitive disadvantage compared to unresponsive counterparts (Engelhardt et al., 2021). Furthermore, investing in ESG activities can be driven by agency problems, with managers prioritizing personal image over shareholders' interests (Krüger, 2015). Therefore, the shareholders theory predicts either no or a negative relation between ESG ratings and a firm's financial performance. On the other hand, participating in ESG activities can increase a firm's long-term value through better stakeholders' relations, improved reputation, higher profits and better capital access (Engelhardt et al., 2021). Consequently, the short-term costs overshadow the long-term benefits. This aligns with the stakeholder's theory, which argues that ethical behaviour improves financial performance by taking responsibilities towards all stakeholders, including employees, customers, institutions, local communities and shareholders (Freeman, 2010). This means that if a firm acts in the best interest of all stakeholders, it also aligns with shareholders' objectives. Thus, adopting an ESG framework benefits both shareholders and stakeholders by addressing the shareholders' financial aims while benefiting a wider network of stakeholders (Zumente & Bistrova, 2021).

The latter view is supported by a plethora of research. For instance, Friede et al. (2015) reviewed over 2,200 individual studies, using primary and second-level data, and found that 90% of them observed a non-negative relationship between ESG scores and a firm's financial performance. In fact, many studies showed a positive and stable relationship. Even clearer findings emerge when differentiating between portfolio and nonportfolio studies, various regions, and different assets classes, such as emerging markets (Friede et al., 2015). Similar findings were observed by Clark and Viehs (2014), who concluded that 88% of the related literature showed a financial positive effect associated with increased sustainability. The great diversity of the study area and the variations in definitions and approaches to CSR and financial performance pose challenges to drawing conclusions. Comparing studies is further complicated by the changing relevance of sustainability practices and their metrics over time (Brooks & Oikonomou, 2018). In light of this, Wheland et al. (2021) examined more than 1,000 studies to reassess the relationship between ESG and financial performance, considering more recent periods and different research frameworks related to financial performance. Using this more sophisticated approach, they found a positive impact of ESG on firms' financial performance, expressed in metrics as ROA, return on equity (ROE) and stock prices. Similar results were found for risk-adjusted attributes and climate change studies. Despite variations in time and methodology, the positive relationship between ESG and financial performance persist. This means that initiatives to improve ESG performance not only benefit the environment and society, but also aim to create shareholder value by improving a firm's financial performance (Zumente & Bistrova, 2021).

This positive relationship is supported by empirical evidence, although the exact impact on a firm's value drivers remains limited and unclear (Brooks and Oikonomou, 2018). Higher ESG scores have been linked to higher operating efficiency, firm value, lower cost of capital, lower financial risks and higher firm valuation (Dai et al., 2020; El Ghoul et al., 2011). Additionally, companies without (good) ESG ratings are perceived as disadvantageous and riskier investments (Atkins, 2020). Using a resource-based view, Barney (1991) argues that a firm's financial performance relies on firm-specific resources that are valuable, unique, inimitable, and non-replicable, including tangible and intangible assets. Improving ESG performance often enhances intangible assets, such as employee attraction and reputation, as well as tangible assets, like lower energy costs (Branco & Rodrigues, 2006). These ESG initiatives have thus internal and external benefits leading to long-term value creation. Therefore, it is imperative that a company's management and investors consider ESG performance as part of their overall strategy (Atkins, 2020).

2.5.3 ESG and extreme events

Due to the value-creating nature of ESG activities, sustainable companies are likely to achieve higher future profits and firm value. However, the impact of ESG scores on expected returns ultimately depends on which type of investors prevail in stock markets. Investors who consider ESG scores in their portfolios are using this information to reconsider their expectations of a company's risk-return pattern. In this light, stronger ESG performance also provide risk-reduction benefits and facilitate capital raisings, resulting in greater resilience of these firms' stock prices during crises (Pedersen et al., 2021). In part, this resilience stems from the idea that ESG activities help create social capital and faith in a company, which fosters shareholders' loyalty and helps a company overcome challenges resulting from crises (Demers et al., 2020). Considering this, stock market investors can anticipate future stock prices concerning future bad news and forthcoming costs for firms with varying ESG ratings (Boldeanu et al., 2022).

The study by Lins et al. (2017) is one of many that focus on the 2008-2009 global financial crisis to see if the level of CSR can serve as a mitigator of downside risk. This is seen as a period where public confidence in companies, capital markets, and institutions unexpectedly diminished. Lins et al. (2017) showed that companies with higher CSR scores outperformed those with low scores by 4 to 7 percent, even after accounting for firm characteristics and risk factors. Furthermore, high CSR firms had higher profitability, sales growth, margins, and employee productivity in this period. A high level of CSR therefore acts as an insurance policy against downside risk that prove beneficial when the world experiences a negative shock.

Since 2020, research in this area has expanded to include the Covid-19 pandemic that affected nearly every aspect of life and the global economy. Engelhardt et al. (2021) examined the relationship between ESG scores and the stock performance of 1,452 publicly listed European firms during the pandemic. In their research, they identified Covid-19 as an unexpected and exogenous shock, or a so-called event, to the economy. They found that European firms with higher ESG ratings have higher abnormal returns and lower stock price volatility following the Covid-19 outbreak. Furthermore, they break down the overall ESG rating and identified the social pillar as the main driver of this positive relationship. This makes sense since this has started as a health crisis that affects employee well-being and working conditions, which are assessed under the social component of the ESG score. In addition, Albuquerque et al. (2020) focused on the U.S. stock market during the beginning of the Covid-19 crisis and discovered that firms with higher E- and S-ratings experienced significantly higher returns, lower volatility, and greater operating profit margins. Moreover, return volatility is even lower when stocks are hold by investors who are more environmentally and socially oriented. Another kind of crisis occurred as well, namely the Russian invasion of Ukraine that triggered, among others, a global energy crisis and unpredictable stock markets. Kick and Rottmann (2022) decided to test whether ESG ratings could also mitigate risk during this type of crisis. Using an event study, they investigated if and how ESG ratings affect the (cumulative) abnormal returns of 1,452 European companies around the invasion of Ukraine. Kick & Rottmann (2022) revealed that only the environmental pillar of ESG had a significantly positive effect on firms' cumulative abnormal stock returns before and after the event. However, these effects were considerable small and had no economic relevance. Consequently, their findings do not fully support the idea of ESG as a protective measure against extreme adverse events, suggesting that this effect of ESG is not automatic generalizable across crises. Additionally, Bae et al. (2021) and Demers et al. (2021), both focusing on Covid-19, found limited evidence of down-side risk protections from high ESG ratings. Demers et al. (2021) revealed that the positive explanatory power of ESG scores for stock returns during Covid-19 disappeared after considering industry affiliation and other risk measures. Similarly, Bae et al. (2021) found no evidence of firms with higher ESG ratings outperforming those with low ratings during Covid-19 outbreak. Their findings suggest a potential gap between a firm's ESG rating and their actual actions, requiring investors to distinguish between true ESG and firms making cheap talk.

Recently, Pastor et al. (2021) investigated the effectiveness of using firms with better ESG performance as hedges against climate-related news. They divided their sample into 'green' and 'brown' companies that generate positive or negative externalities for the society, respectively. Besides, Pastor et al. (2021) incorporates in their models the varying investor preferences for sustainability, proxied by ESG scores. Using various equilibrium models, Pastor et al. (2021) showed that green firms have basically lower expected returns, suggesting the attractiveness to investors of holding these firms and their ability to hedge climate risks. However, green firms show remarkable outperformance during positive shocks to ESG factors, reflecting changes in investors' sustainability preferences. Pastor et al. (2021) therefore concluded that ESG scores can be explicitly viewed as hedges against climate-related news, which is aligned with the findings of Engle et al. (2020). Engle et al. (2020) used a dynamic hedging method to construct climate risk hedged portfolios based on ESG performance of U.S.-listed firms. Using textual analysis, they extracted bad news about climate changes from various news sources, including events as floods, sea level changes, as well as advances in alternative fuel supply and extreme fossil fuel price changes. Unlike Pastor et al. (2021), they used only environmental scores because it can be argued that this pillar is strongly related to news about climate changes. Engle et al. (2020) found that mimicking portfolios based on a firm's environmental score outperforms alternative portfolios, serving as a hedge against bad climate news. These findings suggest that firms with higher environmental ratings will react less negative to unexpected changes in fossil fuel prices, which is perceived as bad climate news, compared to firms with lower environmental ratings. The findings of Pastor et al. (2021) were tested for credibility by Ardia et al. (2020) by using a firm's carbon emissions as a proxy of their environmental performance. They focused on S&P 500 firms and found indeed that green firms outperformed brown firms when concerns according climate change rose unexpectedly during 2010-2018. In summary, the evidence points in the direction that ESG ratings, particularly the environmental pillar, can be used to hedge against unexpected climate-related changes.

So, extensive research has shown a relationship between ESG scores and stock performance, but the results have led to ambiguity in understanding this relationship. Nevertheless, most studies have shown positive impacts of a firm's ESG performance on its stock performance across several equity markets, including the U.S. (Friede et al., 2015; Clark & Viehs, 2014; Wheland et al., 2021). Moreover, the valuation of firms' ESG ratings depends on their recognition by investors and their inclusion in their portfolios (Pedersen et al., 2021). The interest in ESG valuation has grown, especially after the Covid-19 outbreak and the start of the Russia-Ukraine war (Atkins, 2020). This trend makes it interesting to examine whether the positive relationship between ESG ratings and stock returns in the U.S. still exists or has become event stronger over the past two years. Furthermore, including a firm's ESG rating in investors' investment decisions can serve as a mechanism to mitigate risk against adverse economic environments, or so-called negative events. However, the impact of ESG on stock price reactions to these events varies by sector and context, resulting in inconclusive findings. ESG has shown a positive impact on stock reactions to the pandemic, but not necessarily to the Russia-Ukraine war (Engelhardt et al., 2021; Kick & Rottmann, 2022). Some other scholars revealed that firms with better ESG ratings can be seen as a hedge against climate-related news (Engle et al., 2020; Pastor et al., 2021). However, the impact of climate-related news on stocks, considering ESG ratings, has not been extensively researched and mainly focuses on a broad range of climate-related news. No research focuses specifically on the impact of the energy crisis, where extreme energy price changes are considered as (bad) climate-related news. Nevertheless, it can be inferred from the literature that firms with higher ESG ratings are likely to experience a more positive stock performance following an extreme change in energy prices (Engle et al., 2020). Therefore, the following hypothesis is proposed:

Hypothesis 2: *A higher ESG performance positively influences the abnormal returns of a firm following an extreme energy price change.*

Research have shown that the impact of ESG ratings on the relationship between events and stock performance can vary across the three separate pillars of ESG: Environmental (E), Social (S) and Governance (G) (Engelhardt et al., 2021; Kick & Rottmann, 2022; Engle et al., 2020). The significance of each pillar in influencing the overall ESG score's impact depends on the nature of the event and investor preferences. This study examines the impact of extreme changes in energy prices on the performance of U.S. stocks. These events are associated to climate change concerns and are therefore strongly related to the environmental pillar, as this pillar includes metrics such as climate change and emissions. For example, how a firm will react to unexpectedly extreme changes in oil, natural gas, or coal prices will strongly depend on their dependence of these fossil fuels. So, this is analogous to the degree of greenness of a firm. Simultaneously, it is important to note that this type of event is not directly related to the social and governance components of the ESG score, suggesting that these components will not be considered as driving factors. Additionally, research by Engle et al. (2020) highlights that specifically the environmental component of ESG ratings has a positive influence on stock prices after receiving bad climate news, such as fossil fuel price changes. Accordingly, the third hypothesis is as follows:

Hypothesis 3a: *The positive effect of a firm's ESG performance on its abnormal returns following an event is driven by the firm's environmental performance, proxied by the environmental (E) pillar of the ESG score.*

2.6 Carbon dioxide intensity

As discussed earlier, a firm's environmental performance is important for their reaction to extreme changes in energy prices. Among investors and financial institutions, diverse metrics and methodologies are used to evaluate environmental performance, the main literature of which summarized in table 1. One such measure is the environmental pillar of ESG scores, however, this score may be vulnerable to inaccuracies and biases, as discussed in section 2.5.1. Hence, some studies have demonstrated that a firm's CO_2 intensity can serve also as a credible proxy for assessing environmental performance. This measure is reliable because it is an objective outcome being independent of artificial scoring mechanisms and firms' resources (Drempetic et al., 2020; Kick & Rottmann, 2022).

Drempetic et al. (2020) analysed the impact of firm size on the availability, quality, and level of a firm's ESG performance. They used two proxies for environmental performance: the Environmental score and CO_2 emissions. Drempetic et al. (2020) argued that using a firm's CO_2 emissions is suitable for two reasons. First, there is a global trend among politicians and investors in which they focus, among other things, on achieving the Sustainable Development Goals (SDGs), in which there is a lot of focus on climate mitigation. This movement focusses on reducing CO_2 emissions at the national and firm level as this emission has a negative impact on the environment, as discussed in section 2.1.2. Consequently, nowadays high levels of CO_2 emissions are penalized through taxes and lower business valuation. Therefore, a firm's CO_2 emissions can be seen as a reflection of their environmental performance. Second, when it comes to conducting empirical research on the performance of companies, CO_2 emissions expressed in equivalent units of measurement are widely accepted and frequently used. Most literature uses a firm's CO_2 intensity, obtained by scaling CO_2 emissions with firm size (Drempetic et al., 2020). Considering all this, high CO_2 intensity implied greater dependence on fossil fuels and lower environmental performance, and vice versa. Jung et al. (2016) examined whether investors incorporated a firm's environmental performance, proxied by CO_2 emissions, into their lending decisions through the cost of financing. Using a sample 255 firms during 2009 until 2013, they found a positive relationship between a firm's cost of debt and its CO_2 emissions. Therefore, Jung et al. (2016) suggest that lower CO_2 intensity will positively affect a company's stock price, as it will be positively valued by investors. Additionally, Ilhan et al. (2021) revealed that S&P 500 companies with poor ESG performance, measured by their CO_2 intensity, have higher tail risks, indicating greater costs of protection against extreme downside risks is greater. These findings are even more evident during periods of climate policy uncertainty, which increases attention to climate risks (Ilhan et al., 2021). Furthermore, Kick & Rottmann (2022) also used both ESG ratings and CO_2 intensity as a proxy for a firm's greenness. They found that companies with high CO_2 intensity performed abnormally poorly in the period following the Russian invasion of Ukraine. A logical explanation for this underperformance can be found in the fact that Russia plays a prominent role in the supply of fossil energy and the war has raised concerns about the security of energy supply and its prices.

Thus, in general, it can be inferred from literature that higher CO_2 intensity is a signal of poor environmental performance, resulting in a high dependence on fossil fuels and a lower firm valuation. Given that CO_2 intensity can serve as an alternative to companies' environmental scores, a similar effect to what was described in section 2.5.3 can be expected. However, there is little literature focusing on CO_2 intensity as a proxy, and to my knowledge no research is available on linking the impact of CO_2 intensity to the relationship between energy price changes and stock performance. The second part of the third hypothesis is therefore formulated as follows:

Hypothesis 4b: *The positive effect of a firm's ESG performance on its abnormal returns following an event is driven by the firm's environmental performance, proxied by a lower CO_2 intensity.*

2.7 Political affiliation

Studies have provided evidence that a firm's political affiliation can play a role in its level of sustainability and thus its "greenness". One of the important studies in this field has been carried out by Di Giuli & Kostovetsky (2014), who investigated whether Democratic-leaning firms have better socially responsible policies than Republican-leaning firms by analysing the elections results from 2003 to 2009. They used two different measures for a firm's political affiliation. First, they measure the internal political environment using information about campaign contributions of the firm's CEO, directors, and founders. After all, one can reason that if the management of a firm make generously donates to a particular politician or his/her party, it can be assumed that they adhere to that political party. Second, Di Giuli & Kostovetsky (2014) measure the external political environment by looking at the voting patterns of the home state where a firm's headquarter is located. This pattern will represent the views of the stakeholders now they are more likely to cluster in the state where the headquarter of the firm is located. Stakeholders' norms, values and goals are largely traceable to their political preferences and will permeate the management and policies of a company. The findings of Di Giuli & Kostovetsky (2014) revealed that Democratic-leaning firms are more socially responsible, including spending significantly more money on environmental protection. For example, a Democratic-leaning firm tend to allocate, on average, an additional $18 million per year on ESG activities relative to Republican-leaning firms. This positive relationship is found for both the internal and external political environment. This is not surprising now Democrats can be seen as liberal prioritizing environmental and social responsibility. This while the Republicans are more conservative and tend to focus less on these areas. This remarkable difference between the two parties is confirmed by the National Consumers League, which conducted a survey in 2007 showing that 96% of Democrats want Congress to ensure that firms address social issues, as opposed to 65% of Republicans. Another study was conducted by Rubin (2008), who investigated whether policies on CSR activities are correlated to the political ideologies of individuals living near the firm's headquarters. Again, the external political environment is used, and Rubin (2008) gives several reasons for this use. First, the geographical distance between investors and a firm's headquarter plays a decisive role in their trading and portfolio decisions. Besides, there is a tendency for companies' executives to live near their company's headquarter as well as other stakeholders. Finally, even if elections do not appear to be a suitable proxy for stakeholders' political beliefs, they argue that the community where firm's executives live still influences political values. Indeed, the results of Rubin (2008) demonstrated that firms with high CSR ratings are more often headquartered in a Democratic state, while firms with low CSR ratings tend to be based in Republican states.

Thus, the scant literature suggests that a firm's political affiliation affects their investments in ESG activities, which is reflected in their ESG ratings. However, the literature on this topic is very limited. This study thereby fills a research gap by connecting the potential impact of a firm's political affiliation on the relationship between energy price changes and stock performances. Especially since researchers argue that political beliefs have further polarized within the last decades, potentially leading to even more pronounced differences in empirical results related to the impact of political affiliation on ESG activities and stock performance (Rubin, 2008). Besides, previous research has shown that better ESG performance will positively influence a firm's stock performance after extreme negative climate-related events. Since democratically minded companies can deliver better ESG performance, it is equally likely that democratic properties have a positive impact on a company's stock performance after an event. Therefore, the last hypothesis is defined as follows:

Hypothesis 5: *Being a Democratic-leaning firm will positively influence the abnormal returns of a firm following an event.*

Table 1: Overview of literature on the relationship between energy prices, stock performance, and a firm's greenness

This meta Table summarizes key findings from previous empirical studies investigating the relationship between energy prices, stock performance, and a firm's greenness. Panel A shows the literature related to the existence of a relationship between energy price changes and stock performance. Panel B presents studies who investigates the influence of ESG performance, proxied by ESG scores, on a firm's financial performance, particularly during extreme negative events. Panel C displays literature on the influence of ESG performance, proxied by CO_2 intensity and political affiliation, on a firm's financial performance. Per panel, the studies are presented in chronological order, providing an overview of the developments in the literature over time. The Table includes information on the time period, region, the applied method, type of energy price or ESG proxies, the control variables accounted for, and the relevant results.

Panel A - Literature on the relationship between energy prices and stock performance (hypothesis 1)

Author(s)	Time period	Region	Method	Energy price proxies	Control variable(s)	Results
Chen et al. (1986)	1953-1983	U.S.	Factor models, Fama-Macbeth (1973) method	Producer Price Index/Crude Petroleum series (oil)		Oil price changes and risks are not separately priced into the stock market
Huang et al. (1996)	1979-1990	U.S.	Cross- and serial correlation structures, VAR models	Daily closing price of NYMEX oil futures	Interest rate, seasonality's	Except for oil companies, there is no relation between oil futures returns and individual stock market returns or the S&P 500
Jones and Kaul (1996)	1947-1991	U.S., Canada, Japan, U.K.	Standard cash-flow/dividend valuation models	Producer Price Index by country	Inflation rate, industrial production	U.S. and Canadian stock prices react negatively to oil price shocks, while the impact on Japanese and UK stocks remains uncertain
Sadorsky (1999)	1947-1996	U.S.	GARCH (1,1) model, unrestricted VAR model, IRF	Producer Price Index for fuels	Interest rates, industrial production, inflation rate	Oil prices and volatility affect economic activities U.S. stock returns, with an asymmetric and time- and context-dependent relationship.
Miller and Ratti (2009)	1971-2008	Canada, France, Germany, Italy, U.K, U.S.	Cointegrated VEC model	Crude oil price	Interest rate, industrial production	Real stock prices and crude oil prices exhibit a long-term relationship, but the dynamics of this relationship change over time.
Oberndorfer (2009)	2002-2007	Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain	Standard regression model (OLS), GARCH (1,1) model using two different portfolios (utilities versus oil and gas companies)	Crude Oil – Brent One Month Forward, ICE Natural Gas One Month Forward, Coal index based on GI Australia Freight, GI Columbia Freight, GI South Africa Freight	Interest rate, exchange rate	Higher oil prices hurt energy utility stocks but benefit oil and gas companies. Coal prices have a minor impact on utility stocks. No significant relationship exists between natural gas prices and European energy stocks.
Aggarwal et al. (2012)	1986-2008	U.S.	Event study approach with a market model, cross-sectional regression model	WTI light sweet crude oil spot price	Profitability, investment growth, leverage, size, run-up, industry specifications, oil price change	Oil price changes negatively affect transportation firms' stock prices and increases risks. Firm characteristics play a significant role in this relationship.
Mohanty et al. (2013)	1986-2008	U.S.	Event study with a market model, cross-sectional regressions	WTI light sweet crude oil spot price	ROA, future growth opportunities, run-up, industry concentration, size, leverage, industry effects, % oil price change	Oil company stocks react positively to oil price increases, which is influenced by firm-characteristics
Benkraiem et al. (2018)	1999-2005	U.S.	ARDL models, QARDL-ECM models	WTI crude oil, regular gasoline, diesel fuel, heating oil, HH natural gas		Negative short-term relationship between oil and natural gas price and S&P 500 firms for medium and high quantiles and not on the long-term.

Ahmed and Sarkodie (2021)	1991-2019	U.S.	ARDL and dynamic ARDL stochastic simulated models	UK Brent oil, WTI oil, Australian coal, U.S. natural gas	Interest rates, industrial production index, consumer & producer price index	The S&P 500 is negatively impacted by oil and natural gas prices in the long-term, while coal prices show no significant relationship. In the short run, oil, natural gas, and coal prices show a positive relation with the S&P 500.

Panel B - Literature on the impact of ESG performance on firm's financial performance (hypothesis 2 & 3a)

Author(s)	**Time period**	**Region**	**Method**	**ESG proxies**	**Control variable(s)**	**Results**
Lins et al. (2017)	2001-2003, 2008-2009, 2007-2013	U.S.	Event study approach with market model, panel data regression models	CSR data from MSCI ESG STATS	Market capitalization, long- and short-term debt, cash, profitability, B/M, negative B/M, momentum, idiosyncratic risk	Firms with high CSR scores outperform those with lower CSR scores by at least 4% during the financial crisis, but not during the subsequent recovery period.
Albuquerque et al. (2020)	2017-2020	U.S.	Cross-sectional regressions, difference-in-difference analysis,	Thomson Reuters‘ Refinitiv ESG, MSCI ESG	Size, cash to assets, Tobin's Q, dividend yield, volatility, leverage, industry	Firms with higher E and S scores have significantly higher ARs, lower volatility, and higher operating profit margins during Q1 2020
Demers et al. (2020)	2018-2020	U.S.	Event study approach with buy and hold AR, regression analysis, Owen-Shapley decomposition, construction of hedge portfolios	Thomson Reuters' Refinitiv ESG, MSCI	Industry specifications, cash, long- and short-term debt, ROA, size, market share, dividend payout ratio, market share, B/M, momentum, investor horizon, institutional ownership, CEO's tenure, idiosyncratic risk	ESG is not an important factor for explaining the level of ARs after the Covid-19 outbreak. ESG scores are negatively related with ARs during the Covid-19 recovery period.
Engle et al. (2020)	2009-2016	U.S.	Dynamic hedging approach, mimicking portfolios	MSCI ESG, Sustainalytics ESG scores	Firm size, firm value, market	Portfolios consisting of firms with high E scores outperform those with lower E scores
Ardia et al. (2020)	2010-2018	U.S.	Multivariate linear regression framework, panel regressions	Greenhouse gas (GHG) emissions	The five Fama-French factors (Fama & French, 2015), momentum factor	Support Pastor et al.'s (2020) conclusion that green firms outperform brown firms during increased climate change worries
Pastor et al. (2021)	2015-2020	U.S.	ESG-asset pricing models, equilibrium models, cross-sectional regressions	MSCI ESG	Industry specification, firm size	Green firms outperform brown firms during positive shocks to ESG factors, which leads to ESG being used as a hedge against climate-related news
Engelhardt et al. (2021)	2020	Europe	Event study approach with market-adjusted model, multivariate OLS regressions	Thomson Reuters Refinitiv's ESG scores	Tobin's Q, firm size, ROE, profitability, (negative) market-to-book, cash/assets, short-term debt/assets, long-term debt/assets, leverage, volatility, momentum	High ESG firms have significantly higher abnormal returns and lower volatility during Covid-19 with the social component having the greatest effect.

Bae et al. (2021)	2020	U.S.	Cross-sectional regression analysis	MSCI ESG, Thomson Reuters‘ Refinitiv ESG	Long-term and short-term debt, cash holdings, profitability, B/M, negative B/M, momentum, idiosyncratic risk	Firms with higher ESG ratings do not outperform those with low ESG ratings after the Covid-19 outbreak
Kick & Rottmann (2022)	2021-2022	Europe	Event study with market model, cross-sectional regression models	Thomson Reuters' Refinitiv ESG, CO_2 intensity	Industry specification, firm size, B/M, profitability, cash and debt rate	Higher environmental scores cause higher positive ARs before and after the Russian invasion of Ukraine, however the magnitudes are not economically relevant. Lower CO_2 intensity cause protective effects in the period after the Ukraine invasion.

Panel C - Literature on alternative measures of a firm's environmental performance (hypothesis 3b & 4)

Author(s)	**Time period**	**Region**	**Method**	**ESG proxies**	**Control variable(s)**	**Results**
Rubin (2008)	1972-2005	U.S.	Regression analyses	External political environment	Size, M/B, return volatility, firm's age, leverage, insiders' ownership, institutional HHI	Firms with higher CSR scores are often located in Democratic states rather than in Republican states
Di Giuli & Kostovetsky (2014)	2003-2009	U.S.	OLS regression models, instrumental variable regressions (2SLS)	CSR data from KLD, political contributions from the FEC website, external political environment	Firm size, ROA, cash, dividends, debt, B/M	Democratic-leaning firms score higher on CSR compared to republican-leaning firms
Jung et al. (2016)	2009-2013	Australia	Regression analyses	Greenhouse gas (GHG) emissions	Size, leverage, default risk, tangible assets, asset age, cash	A significant positive relationship between cost of debt and carbon risk
Drempetic et al. (2020)	2004-2015	U.S., Japan, U.K., Canada	Linear mixed-effects models, structural equation models	Greenhouse gases (GHG), ASSET4	EPS/P, return on invested capital, operating profit margin, EMS certification	ESG ratings are not reliable measures of firms' sustainability performance, as it depends on firm size
Ilhan et al. (2021)	2009-2016	U.S.	Regression analysis, selection model	Carbon emissions from CDP	Assets, dividends/net income, debt/assets, EBIT/assets, CapEx/assets, B/M, returns, CAPM beta, volatility, institutional ownership, oil beta	Cost of protection against extreme downside risks is greater for companies with higher CO_2 intensity, especially during increased climate change concerns

3 Data

This chapter presents which data is used to examine the impact of extreme changes in energy prices on U.S.-listed firms' stock prices. First, a detailed explanation will be given about the selection of the events and stock prices. Second, the data used for the creation of independent variables are described in detail, followed by a brief explanation of the used control variables. Finally, descriptive statistics of the data and their associated correlations are given and explained in the last subsection.

3.1 Event selection

Since an event study analysis will be performed, it is essential to define the events of interest. In this paper, all events are extreme changes in daily energy prices from March 2020 to October 2022. Different energy commodities are considered, namely oil, natural gas and coal. For each of these three, the most representative benchmark was chosen. All benchmarks are extracted from Datastream and consist of the daily time series of the trading price. Daily stock prices are used as the most reliable evidence of market efficiency is derived from event studies using daily stock returns (Fama, 1991). Afterwards, events were selected using event criteria.

3.1.1 Energy prices

Most literature uses the West Texas Intermediate (WTI) oil price or the Brent oil price. This paper, following Tsai (2015), uses the WTI crude oil spot price in Cushing, Oklahoma as a benchmark to reflect the price of oil per barrel for several reasons. First, WTI prices are most used indices in the U.S. (Mohanty et al., 2013). As indicated by the U.S. Energy Information Administration (EIA), the WTI crude oil price can be seen as the U.S. benchmark for oil prices, while the Brent oil price is more of a global benchmark (French, 2023). As this paper's scope is limited to the U.S. market, WTI crude oil price is preferred over Brent crude oil. Second, many firms opt for forwards, futures and over-the-counter derivatives tied to WTI when utilizing hedging instruments. Given that the WTI serves as the basis of firms' hedging strategies, it is more appropriate to use as a benchmark (Aggarwal et al., 2012). The benchmark used to reflect the price of natural gas per Million British thermal units (MMBtu) is the Henry Hub (HH) natural gas spot price. According to the EIA, the HH prices can be seen as a national benchmark for the natural gas price within the U.S (Short-Term Energy Outlook, 2023). The use of HH as a benchmark is also supported by the existing literature. Benkraiem et al. (2018) used for example the HH natural gas spot price to represent the U.S. gas price while examining the impact of gas price changes on the U.S. stock market. Finally, finding an appropriate benchmark for coal prices within the U.S. is difficult. The scarce literature mostly uses the Rotterdam Coal futures or the Australian coal market (Wang et al., 2021; Ahmed & Sadorkie, 2021). Besides, U.S. coal spot prices are available but vary by region, lacking an overall national spot price. This makes it too difficult to use. Unfortunately, no suitable and complete data was available for the Australian coal market and the regionally U.S. coal spot prices. Hence, following Wang et al. (2021), the Rotterdam Coal 1-month Futures is used in this paper. However, it should be noted that the Rotterdam Coal 1-month Futures is more of a European benchmark rather than a U.S. benchmark (Tan et al., 2020). Therefore, this may limit the impact on U.S. stock prices compared to the impact of a specific U.S. coal benchmark.

Though, it can be assumed that there will still be a relationship now that the U.S. is partially dependent on coal from other (European) countries, reducing this limitation (Coal, 2022)

In this paper, daily spot prices are preferred over futures prices based on various reasons. First, many studies that focus primarily on short-term impacts of extreme energy price changes on stock prices uses spot prices rather than futures prices (Aggarwal et al., 2012; Benkraiem et al., 2018; Nick & Thoenes, 2014). Second, Aggarwal et al. (2012) argued that only a small fraction of changes in energy prices might be anticipated by energy futures. Here, this possibility is even lower considering the focus on large energy price changes. So, it is expected that short-term impacts will be more reflected in spot markets than in futures markets (Nick & Thoenes, 2014; Ma et al., 2021). Indeed, a comparison of spot and futures prices of oil and natural gas shows that somewhat more events take place, especially for natural gas, when focusing on spot prices, see figures 1-3 in Appendix A. For example, significant increases in natural gas spot prices were observed in February 2021, while comparatively modest fluctuations were observed in its futures prices.[1] Besides, it has been shown that the impact of energy futures on stock market returns is insignificant. Instead, stock prices primarily react to fluctuations in energy spot prices (Aggarwal et al., 2012; Kristjanpoller & Concha, 2016). Finally, futures prices are often preferred to spot prices because they exhibit less noise, as spot prices are more strongly affected by temporary (random) events (Sadorsky, 2001; Oberndorfer, 2009). For this paper, however, this counterargument does not outweigh the benefits of using spot prices. After all, the focus is only on short-term effects where noise is less important. Moreover, the effect of extreme price changes is examined regardless of the cause of the price change, making it irrelevant whether the cause is ‘noise’ or not. So, energy spot prices provide stronger signals for stock prices making their use preferable. However, no suitable spot price is available for coal and its futures price is therefore used, which may introduce a potential limitation. Yet, the effect is expected to be so small that the results will not be biased. For example, figure 1 shows that the differences between the spot and futures prices of oil is minimal indicating that similar results are likely to be obtained. This is supported by Fan & Xu (2011), who stated that using spot or futures prices only slightly change the results, while the conclusions remain the same.

3.1.2 Event criteria

The event selection period is from the beginning of March 2020 through the end of October 2022 and was chosen since it consists of stirring years where people have been surprised by extreme energy price movements. This period starts around the global outbreak of Covid-19 and extends until the end of this crisis. It also captures the turmoil around the Russian invasion of Ukraine, which has, among others, major implications for energy supplies.

An event is an extreme change in the daily price of oil, natural gas, or coal and are categorized as either positive or negative price changes. To find a sufficient number of events, a grid search is used in which several thresholds are considered (Hall & Kenjegaliev, 2017). The thresholds reflect the percentage

[1] A reason for this was a winter storm hitting Oklahoma and Texas in February 2021. This led to a strain on the markets of natural gas and electricity, resulting in a short spike in U.S. natural gas (spot) prices. After the winter storm, inventories were low and so the aftermath of the winter storm in early 2021 continued into the following months, even if the impact was less severe than that of February 2021 (Comstock, 2022)

daily change in energy prices and consist of 5%, 10%, 15% and 20%, based on existing literature (Mohanty et al., 2013; Himmelman et al., 2012; Bremer & Sweeney, 1985). Suppose a threshold of 5% is maintained; this implies that if the price of oil, natural gas or coal is higher (lower) by 5% than the price of the previous day, that day is considered as a positive (negative) event. On one hand, it can be argued that energy price changes must exceed a certain threshold limit to ensure that they are significant enough to potentially impact the U.S. stock market (Huang et al., 2005). Corrado and Jordan (1997) argued for example that a 2.5% threshold is too low generating too many (insignificant) events, while Himmelmann et al. (2012) showed that a threshold of 20% is high enough resulting in significant abnormal returns. Logically, the higher the threshold reflecting a larger drop or rise in daily energy prices, the greater the expected effects on U.S. stock prices (Aggarwal, 2012). On the other hand, it can be expected that the higher the threshold, the fewer events take place. Nevertheless, a sufficient number of events is needed to conduct proper research.

The grid search showed that a threshold of 5% or 10% give too many events for all three energy commodities. A 20% threshold gives enough and equally distributed events for the oil and natural gas benchmark, but not for the coal benchmark, now that the preferred minimum is five for either a positive or negative event.[2] A threshold of 15% results in sufficient events for all three benchmarks, but they do not show an equal distribution now that gas has more positive events. In the end, having sufficient events for each energy benchmark outweighed the disadvantage of an unequal distribution. Therefore, a 15% threshold is used, resulting in a total of 47 events, of which 29 are positive events and 18 being negative, which are shown in Table 2. As earlier discussed, the Covid-19 pandemic has the most notable effect on oil prices, leading to series of extreme events in the first half of 2020. Conversely, the events due to extreme changes in natural gas and coal prices were more spread out over the period of interest, with both experiencing a surge of events around the time of the invasion of Ukraine in early 2022. Although the distribution of events over the period of interest varies by energy commodity, the events related to the three energy commodities follow each other closely, resulting in event clustering. This problem is further discussed in chapter 4. Besides, Table 1 displays that there are some double extreme increases or decreases in energy prices. In total, there are six times two days when an extreme energy price increase (decrease) is followed by another extreme increase (decrease), including two double decreases and four double increases. Additionally, three times an increase (decrease) is reversed to a decrease (increase) within one single day. These different developments in energy prices within the sample period could potentially contribute to the occurrence of momentum increases or momentum crashes, and thus potentially affect the event study results (Daniel & Moskowitz, 2016; Dierkes & Krupski, 2022). Furthermore, all events took place on weekdays. Therefore, no problems arise with events taking place on days that the stock market was closed. However, there are some days within the event window or estimation window when the market is closed due to a public holiday. These days were removed from the sample and the following trading day is used instead.

[2] A threshold of 20% result in eight, nine and four positive events for respectively the oil, natural gas, and coal benchmark. In addition, for the oil, natural gas, and coal benchmark five, five, and two negative events occur, respectively, when a threshold of 20% is maintained.

Table 2: Overview of events from March 2020 to October 2022
This Table lists the extreme energy price changes, or so-called events, examined during the sample period from March 2020 to October 2022. An extreme energy price change is referred to as an event if the daily energy price is at least 15% higher than the previous day. The total of 47 events are categorized by extreme changes in the prices of (1) oil, (2) natural gas, (3) coal, and (4) all three energy commodities. The left side of the Table shows extreme energy price increases, and the right side shows extreme energy price decreases. The date the event occurred is presented as well as the percentage change in energy price. For each type of energy commodity and direction, the total average percentage change in energy prices is calculated.

Extreme changes in oil prices							
Events	Event date	Direction	Magnitude	Events	Event date	Direction	Magnitude
1	19-03-2020	Positive	23.81%	1	09-03-2020	Negative	-24.59%
2	30-03-2020	Positive	29.53%	2	18-03-2020	Negative	-24.42%
3	02-04-2020	Positive	24.67%	3	20-04-2020	Negative	-305.97%
4	22-04-2020	Positive	35.02%	4	21-04-2020	Negative	-123.68%
5	23-04-2020	Positive	28.84%	5	27-04-2020	Negative	-20.82%
6	29-04-2020	Positive	22.04%				
7	30-04-2020	Positive	25.10%				
8	05-05-2020	Positive	20.45%				
Mean			26.18%	Mean			-99.90%
Extreme changes in natural gas prices							
Events	Event date	Direction	Magnitude	Events	Event date	Direction	Magnitude
1	03-06-2020	Positive	16.46%	1	04-09-2020	Negative	-22.41%
2	29-06-2020	Positive	16.90%	2	17-09-2020	Negative	-19.90%
3	08-09-2020	Positive	30.56%	3	08-10-2020	Negative	-25.87%
4	23-09-2020	Positive	16.11%	4	18-02-2021	Negative	-64.12%
5	05-10-2020	Positive	36.17%	5	19-02-2021	Negative	-42.06%
6	09-10-2020	Positive	51.01%	6	22-02-2021	Negative	-36.29%
7	30-11-2020	Positive	22.98%	7	07-02-2022	Negative	-16.85%
8	05-02-2021	Positive	16.72%	8	10-05-2022	Negative	-15.88%
9	11-02-2021	Positive	72.87%				
10	16-02-2021	Positive	84.97%				
11	17-02-2021	Positive	110.78%				
12	28-01-2022	Positive	28.44%				
13	02-02-2022	Positive	22.94%				
14	18-07-2022	Positive	15.91%				
15	06-10-2022	Positive	18.32%				
Mean			37.41%	Mean			-30,42%
Extreme changes in coal prices							
Events	Event date	Direction	Magnitude	Events	Event date	Direction	Magnitude
1	01-06-2020	Positive	16.49%	1	01-11-2021	Negative	-41.54%
2	27-09-2021	Positive	16.96%	2	03-03-2022	Negative	-18.96%
3	28-02-2022	Positive	31.74%	3	28-03-2022	Negative	-16.76%
4	01-03-2022	Positive	23.89%	4	02-05-2022	Negative	-19.53%
5	02-03-2022	Positive	38.57%	5	31-10-2022	Negative	-20.32%
6	04-03-2022	Positive	22.26%				
Mean			24,99%	Mean			-23.42%
Total changes in energy prices							
Events	Event date	Direction	Magnitude	Events	Event date	Direction	Magnitude
29	2020-2022	Positive	31.74%	18	2020-2022	Negative	-47.48%

3.2 Stock market data

One of the objectives of this paper is to investigate the impact of extreme energy price changes on stock prices for firms with different ESG scores. As mentioned before, both a firm’s reaction to energy price fluctuations and its ESG rating can be dependent on the size of the firm. This makes it crucial to obtain an extensive and diverse dataset that incorporates both small and large firms, as argued by Sadorsky (2008). Therefore, the list of firms was selected from the S&P 1500 which includes 600 small firms, 400 medium-sized firms, and 500 large firms. The composition of the S&P 1500 as of October 31, 2022, was maintained, resulting in a total of 1505 firms. Daily closing prices for all these firms are obtained from the Eikon

Datastream database for the period of March 1, 2020, to October 31, 2022. Some firms have missing data on stock prices during this period, for example, because of a spin-off took place. Consequently, these firms are removed from the sample as the analysis cannot be conducted for these firms. As a result, the sample size is reduced by 41 firms, leaving a total of 1464 firms, shown in Table 3 in Appendix A. Although firm-specific events may also affect stock prices during the sample period, it would be too time-consuming to assess and remove these events for all firms. Moreover, given the sample size of this study, it is assumed that the effects of firm-specific information on the event day are minimized (Ramiah et al., 2015).

3.3 ESG data

In order to assess the ESG performance of a firm, the Refinitiv's ESG ratings are collected from the Thomson Reuters' Refinitiv ESG database, which is an enhancement and replacement of the formerly known ASSET4 database (Refinitiv, 2022). Many other databases also offer ESG ratings such as the MSCI ESG rating, Moody's ESG, Sustainalytics ESG score and S&P Global ESG rank (Deng et al., 2022). Selecting the appropriate ESG database is a difficult process. The wide variety of data providers all have their own rating processes, scope and information sources, making it difficult to compare the actual quality of ESG information from different databases. Among investors, the ESG ratings from Sustainalytics are preferred the most, which has the advantage of publishing monthly ratings (SustainAbility, 2020). However, due to the inaccessibility of Sustainalytics' ESG ratings, it is impossible to use these ratings in this research. Berg et al. (2022) showed that ESG ratings from Moody's, S&P Global and Refinitiv has the highest correlation with Sustainalytics' ESG ratings. Among these options, Refinitiv is preferred. Reasons for this are its data accessibility, its objective and transparent method of ESG measurement, and its extensive coverage of U.S. firms. Furthermore, Refinitiv's ESG ratings have been used extensively by prior studies (Albuquerque et al., 2020; Deng et al., 2022; Engelhardt et al., 2021; Kick & Rottman, 2022).

The Thomson Reuters' Refinitiv ESG database is a comprehensive ESG database and covers more than 85% of the global market. For the data collection, Refinitiv uses many public available information, resulting in ESG data for more than 12,000 private and public firms worldwide, across 630+ ESG metrics. The ESG performance is categorized into ten different categories forming the basis of three individual pillar scores: environmental, social, and corporate governance. Environmental performance is measured in three subcategories: resource use, emissions, and innovation. A firm's social performance is evaluated using four subcategories: workforce, human rights, community, and product responsibility. Finally, corporate governance performance is covered by the three subcategories: management, shareholders, and CSR strategy. The definitions are elaborated in Table 4 of Appendix A. The ratings are determined by comparing a firm's ESG performance with industry peers and its country of registration. All ten categories are included and weighted in the total ESG score, reflecting a firms' overall ESG performance. Additionally, Refinitiv offers a total ESG score that is discounted for significant ESG controversies impacting the firms with the aim of correcting the ESG score in response to negative media coverage. The ESG scores are provided as percentile ranks ranging from 0 (worst) to 100 (best). Although the ESG scores are revised every week, a definitive score is issued at the end of each fiscal year based on the firm's disclosures (Refinitiv, 2022).

For this paper's analysis, the Thomson Reuters' Refinitiv total ESG ratings as well as its individual environmental (E), social (S) and corporate governance (G) components are collected for the years 2019, 2020 and 2021. Based on the literature, the 'normal' total ESG score without a controversies overlay is used (Engelhardt et al., 2021; Kick & Rottmann, 2022). Firms listed in the U.S. are known to pursue transparent and reliable ESG reporting, resulting in a relatively large amount of available ESG data. ESG data was collected for all firms in the sample; with only 115 firms lacking ESG scores for any of the three years. These firms are therefore excluded from the sample. It should be noted that these companies differ from companies with an ESG rating of zero. The omitted firms lack ESG scores entirely, while firms with an ESG score of zero are rated but score very low on ESG performance. Table 5 in Appendix B show the descriptive statistics of ESG scores per year. One can see a trend of yearly increases in the mean of both the overall ESG scores and the three individual pillars. This indicates a slow shift towards greater ESG alignment among the firms in the sample, which is aligned with the global focus on sustainability.

3.4 Carbon dioxide intensity

Following the existing literature, additional data is collected related to a firm's environmental performance. This paper focusses on a firm's carbon dioxide (CO_2) intensity as a proxy for its environmental performance. Specifically, CO_2 intensity is considered as an appropriate measure of a firm's environmental performance as it is an objective ESG outcome and it consists of a firm's total CO_2 and CO_2 equivalent emissions in tonnes, divided by its total assets (Kick & Rottmann, 2022; Drempetic et al., 2020). For all emission classifications by type the greenhouse gases (GHG) protocol is followed. The CO_2 intensity was collected for all firms in the sample for the years 2019, 2020 and 2021. The availability of this data is unfortunate limited, resulting in 715 companies whose CO_2 intensity is missing. However, the sample will be reduced to 616 firms only for the model that incorporates the variable related to CO_2 intensity. For this model, sufficient observations are still available to draw some general conclusions.

3.5 Political affiliation

Based on previous studies, one can measure a firm's political affiliation internally and externally. The internal political environment can be measured using information about campaign contributions of a firm's CEO, directors, and founders to proxy a firm's political affiliation. Although this measurement was the preferred choice, obtaining reliable data would consume too much time within the scope of this research.[3]

Following the research of Di Giuli & Kostovetsky (2014), the external political affiliation environment is used and measured by using a firm's political geography. This refers to the political leanings of a firm's employees, customers, suppliers, shareholders, and regulators. The political geography is determined by the voting patterns of the state in which the firm's headquarter is currently located. The information on the current headquarter location of the firms is collected with the help of the Erasmus

[3] BoardEx, among others, could be consulted to gather information of a firm's CEOs, directors and founders. The website of the Federal Election Committee (FEC) could be used to collect data on the political contributions. However, merging multiple databases increases the likelihood of data errors. Especially now that these databases use different ways of writing down information on a firm's CEOs, directors and founders, and contain many missing data. Collecting, merging and verifying these databases would therefore have taken too much time for this study, and at the same time the risks of errors in the data and thus in the results was too great.

Service Data Centre. Information on the location of the headquarters was missing for 49 companies. After conducting a manual review, the headquarters' locations were added for 24 companies based on (online) firm documentation. The remaining 23 companies were removed from the sample now their headquarters are not located in the U.S. Furthermore, information on the voting patterns of the states is derived from the outcome of the 2020 presidential election in the U.S. This election is the only presidential election held during the period of interest. Additionally, this presidential election is particularly suitable because it represents two opposing perspectives and had the highest voting turnout since 1900.[4] Joe Biden belongs to the Liberal Democrats, whereas Donald Trump is a conservative Republican. These obvious differences between the candidates' values provide a clear choice for the American voters (Rubin, 2008). However, it could be argued that this election took place in 2020 while the sample period in this study is 2020-2022. It is possible that the opinion and thus residents' voting pattern has changed in the years following the presidential election. Nevertheless, it is assumed that residents' opinions will not change so drastically in the first few years after the presidential election as to directly influence decisions within companies. Therefore, it will not bias this analysis' results. Specially, information is collected on whether the Democrats or Republicans has won in a particular state. Besides, per state the percentage of votes that is received by both the Democratic candidate and Republican candidate in the presidential election are collected. Next, data on location of the firms' headquarters are linked to the voting patterns of the respective state, shown in Table 6 of Appendix B. Table 6 presents that many firms' headquarters are clustered in the democratic states California and New York, while Republican Texas is also home to many companies. No additional data is lost in this process. Therefore, the main (additional) sample consist of 1326 (611) firms as shown in Table 3.

3.6 Control variables

Following the literature, a set of control variables are used in this paper (Engelhardt et al., 2021). These control variables are incorporated into the regression models in order to improve the internal validity of the analysis, as control variables have the potential to affect the stock reactions as well. In this way, the presence of an omitted variable bias is reduced. Consistent with previous studies, control variables are included to describe the financial characteristics of a firm consisting of industry classification, firm size, leverage, ROA and cash. All data for the construction of these control variables are collected from Datastream for the years 2019 until 2022. Besides, all accounting variables are winsorized at the top and bottom 1% to correct for outliers.

3.6.1 Industry classification

Previous literature on the relationship between energy price fluctuations and stock performance has been criticized for assuming homogeneity across all sectors and firms within a market. Narayan and Sharma (2011) argued that sectors are heterogenous now each have different market structures, leading to varying impacts of energy price changes on stock prices depending on the sector. Indeed, they found sectoral differences in the reaction of stock prices to energy price changes, showing that most sectors experience a

[4] Most of the data were obtained from www.uselectionatlas.org, and were verified using other online sources.

drop in their stock returns, except for the energy and transportation sectors. This difference could be explained by the fact that firms experience a different degree of energy dependency, which in turn depends on their sectoral location. This is supported by other economics, who argued that a stock index can never fully reflect these sectoral differences (Tsai, 2015). Lee et al. (2012) also found short-run negative relationships for only 2 out of 7 sector indices in the U.S. Here, the information technology and consumer staples sectors experience the greatest consequences of an oil price increase now both are sectors where energy is an important input. Consequently, it is essential to account for these sectoral differences.

Following Tsai (2015), industry-specific information is collected using the first two digits of the Standard Industrial Classification (SIC) codes. Numerous other industry classification systems exist as well such as the Global Industry Classification Standards (GICS), which is widely used in studies (Engelhardt et al., 2021; Mohanty et al., 2013). However, data on GICS were unavailable for this study. SIC codes are granted by the U.S. authorities to firms to identify their primary business and consist of four-digit numeric codes. All firms have a primary SIC code indicating their main activity, and some have additional SIC codes representing their ancillary activities. Furthermore, SIC codes are categorized into eleven divisions which are further divided into 83 major groups, 426 industry groups and 1,005 specific industries (SICCODE, 2021). This paper focuses on primary SIC codes and the eleven divisions (Tsai, 2015). After collecting these SIC codes, only two firms had missing codes which were manually added using online firm information. Table 7 in Appendix B show that most firms fall within the manufacturing industry, while only 23 firms fall under mining industry. In the regressions will be controlled for industry classification using industry-specific dummy variables based on the SIC-codes of firm i (Aggarwal et al., 2012).

3.6.2 Firm size

Many studies have examined the impact of firm size on the relationship between energy price shocks and stock performance. Some argue that larger firms have better economic performances shown by productivity, efficiency, and profitability. This leads to more resources, capabilities, and experiences, resulting in economies of scale suggesting that they have no difficulties with adjusting their input mix quickly and cost-effectively. However, others argue that smaller firms are more efficient now they are more innovative, less bureaucratic, and have less principal agent problems (Sadorsky, 2008). Indeed, a relationship is found between energy price changes and stock prices varies with firm size, with a medium-sized firm having the strongest relationship (Sadorsky, 2008). Later research confirms this size effect, but only a statistical positive relationship for small firms is found, which becomes less positive and even insignificant as firm size increases (Tsai, 2015; Narayan & Sharma, 2011). Moreover, firm size is considered to affect a firm's ESG score. Some studies show a positive relationship between firm size and ESG scores due to more capital and resources for ESG disclosure, leading to more available data in the ESG databases resulting in higher scores (Drempetic et al., 2020). However, Gregory (2022) argues that this positive relationship is only driven by a few outliers. Despite conflicting evidence, all studies highlight the influence of firm size on the impact of energy prices on stocks, as well as on ESG scores. Therefore, a variable size is included to control for a possible size bias. Various methods are used in the literature to account for firm size and includes the number of employees, sales volume, market capitalization and total assets. Despite the varying measures, the literature indicates no (significant) discrepancies in results when different measures of firm sizes are used. (Drempetic et al., 2020; Tsai, 2015; Sadorsky, 2008). In this study, the natural logarithm of a firm's total assets is chosen as a proxy for firm size, which is in line with Aggarwal et al. (2012). The value of the total assets represents the total value of all assets owned by a firm.

3.6.3 Leverage

The leverage effect, proposed by Bhandari (1988), suggests that high-leverage firms outperform low-leverage firms because they can have higher stock returns, trading volumes and risk (Aggarwal et al., 2012). Nevertheless, high leverage ratios coupled with low cash reserves may indicate low financial strength, leaving firms at high risk of financial distress (Andrade & Kaplan, 1998). Logically, the leverage-risk effect converts cash flow risk into equity risk and limit the firm's ability to respond to changing circumstances. This reduces a firm's resilience during unexpected negative events. Accordingly, literature demonstrate that during events as the GFC, Covid-19 and the Ukraine invasion, a high leverage negatively affect firms' stock reaction (Deng et al., 2020; Albuquerque et al., 2020). Besides, a firm's leverage ratio may affect its ESG rating, but there is no agreement on the direction of this relationship. Higher debt may result in higher ESG ratings due to the greater influence of stakeholders, but it may also lead to lower ESG ratings as less money is available for investments in ESG activities (Drempetic et al., 2020). It can be argued that especially in times of unexpectedly high energy prices, financial strength is important for a firm. Therefore, it is hypothesized that a firm's leverage ratio negatively influences its abnormal returns. Following Engelhardt et al. (2021), the debt-to-asset ratio is used as a proxy for a firm's leverage. This is calculated by dividing the total amount of short-term and long-term debt by the market value of total assets.

3.6.4 Return on assets (ROA)

Haugen and Baker (1996) illustrate that, in general, higher average stock returns have been earned by firms with greater profitability. Likewise, high profitability firms are more likely to have a lower market risk, return volatility and trading volume. Furthermore, they are less sensitive to (extreme) changes in energy price. Consequently, it is expected that a firm's profitability positively affects its stock reaction following an event (Aggarwal et al., 2012; Mohanty et al., 2013). Moreover, incorporating a variable for profitability also reduces endogeneity in the ESG ratings. Yu et al. (2018) show that profitable firms allocate more resources to ESG issues, leading to better ESG reporting resulting in higher ESG ratings. Hence, ROA is used to proxy profitability and is calculated by dividing a firm's net income by its total assets.

3.6.5 Cash

Like the leverage ratio, a company's cash holdings may reflect its financial strength and are therefore important in explaining firms' stock returns. Cash-rich firms are more likely to survive challenging periods like extreme changes in energy prices. These firms have enough money to anticipate and continue investing, while firms with less cash may be unable to do so (Lins et al., 2017). For example, cash-rich firms were less affected by the Covid-19 crisis. Especially, when they also had a low leverage ratio (Albuquerque et al., 2020). Therefore, the available cash holdings, defined as the natural logarithm of cash divided by total assets, is predicted to positively influence the stock's reaction (Engelhardt et al., 2021).

3.7 Descriptive statistics

Table 8 contains the descriptive statistics for all variables during the sample period, showing the number of observations, mean, standard deviation, median, minimum, maximum, skewness, and kurtosis. First, preliminary results of the (cumulative) abnormal returns ((C)ARs) of the positive, negative, and all events demonstrate a non-normal distribution, as shown by their skewness and kurtosis values deviating from 0 and 3, respectively. These results are presented in Table 9 of Appendix B. Skewness gives an indication of the level of asymmetry presented in the distribution of the data, while kurtosis evaluates whether the distribution of the data departs from normality in the tails. High levels of skewness and kurtosis can undermine the analysis' validity since the use of Ordinary Least Squares (OLS) regressions assumes a normal distribution. Here, skewness ranged from slightly negative on the negative event day (-1.994) to positive on the positive event days (4.384). Although these values are not extreme, they suggest that the first (second) has a more prominent presence of negative (positive) abnormal returns than their counterparts. Furthermore, extreme positive kurtosis values are presented where especially the value of the abnormal returns on the event days of positive (80.682), negative (18.231) and all (54.519) events are extreme. A kurtosis value above three indicates a higher peak, skinny in the centre and thicker tails compared to a normal distribution. This high kurtosis primarily stems from the presence of extreme minimum and maximum values, as showed earlier. To mitigate kurtosis and skewness, the (cumulative) abnormal returns are winsorized at the bottom and top at a 1% level; the winsorized results are shown in table 8.

Panel A summarizes the winsorized (C)ARs of the positive, negative, and all events. For positive events, one can see that the average (C)ARs are slightly positive on the event day (0.40%) and during the 3-day event window (1.10%). However, if the event window is increased to seven days the positive (C)ARs changes to an average CAR of -0.60%. A plausible reason for this may be that a longer event window is more affected by noise (McWilliams & Siegel, 1997). Furthermore, it can be concluded that among all three event windows, the 3-day event window contains the most extreme CARs shown by the highest average CAR as well as the large minimum and maximum values, -35.8% and 36.0%, respectively. Although less negative events occurred, the impact appeared to be bigger. The mean of the (C)ARs on the event day and during the 3- and 7-day event windows are all negative, -1.10%, -0.30% and -2.20%, respectively. Again, the 3-day event window shows the largest reaction, suggesting that the impact of both positive and negative events is primarily noticed and processed by investors shortly before and after the event. Finally, considering all events together, the values of the CARs considerably diminished, resulting in an average CAR of -0.10%, -0.50% and -0.20% on the event day and during a 3- and 7-day event window, respectively. It is notable that the 7-day event window has now the highest average CAR, while on the same time, the 3-day window still has the largest minimum and maximum value, since the minimum (maximum) 3-day CAR is -362.60% (227.80) compared to -114.10% (114.80%) in the 7-day event window.

Panel B of Table 8 provides more insights in the characteristics of the overall ESG rating and the three individual pillars. The average ESG rating amounts 51.6% with a standard deviation of 18.4%. Among the three pillars, corporate governance has the highest value (59.3%), while the environmental pillar has the lowest value (37.8%). In addition, it is noteworthy that only the environmental pillar has a minimum value of 0, suggesting that companies were rated on their environmental performance, but performed so poorly that they received no points at all. All ESG variables show a negative kurtosis and are slightly positive skewed except the corporate governance variable, which is negatively skewed.

The descriptive statistics of the environmental proxies can be found in panel C of Table 8. First, it is presented that 67.6% of all firms are headquartered in a Democratic-leaning state. Besides, the average firm is headquartered in a state that cast 53.5% of the votes for the Democratic Biden in the 2020 presidential election. The presence of many firms in the Democratic-leaning states California and New York contributes to the fact that the overall political affiliation of firms in the dataset tends to be slightly more Democratic than those of the rest of the country, aligning with the findings of Di Giuli and Kostovetsky (2014) and Rubin (2008). Political affiliation has negative skewness and kurtosis, while presidential vote has it the other way around. Nevertheless, both variables show only a small deviation. With respect to $\mathrm{CO_2}$ intensity, a mean of 0.391 is found with a standard deviation of 1.305. Despite the winsorization of the variable, it still has a high positive value of kurtosis. This can be traced to the large differences in emissions between companies, resulting in a higher peak in the distribution.

Finally, panel D of Table 8 displays the descriptive statistics of the control variables. As for the control variables, the average company in the dataset has a size of $15.440 billion and cash holdings of 10.9%, which is in line with similar studies (Engelhardt et al., 2021; Albuquerque et al., 2020). Besides, average financial leverage and ROA have values of 0.290 and 0.109, respectively. Although, the winsorization of all control variables there is still some skewness and kurtosis.

Table 3: Descriptive statistics

This Table reports the descriptive statistics of all variables during the sample period from March 2020 to October 2022. The final sample consist of 1,326 firms listed on the S&P 1500 and are obtained from Datastream. Panel A provides information on the dependent variables consisting of constant mean return model event day, 3- and 7 day (cumulative) abnormal returns. Panel B shows the independent variables consisting of the total ESG score and its individual pillars Environmental (E), Social (S), and Corporate Governance (G) scores. Panel C presents additional independent variables consisting of a firm's political affiliation, presidential votes and CO_2 intensity. Political affiliation denotes the dummy variable that takes a value of one if the firm's headquarter is located in a state where a Democrat won, and zero otherwise. Presidential votes reflect the percentage of votes that is received by the Democratic candidate Biden in the 2020 presidential election in the state where the firm's headquarter is located. CO_2 intensity is a firm's total CO_2 and CO_2 equivalent emissions in tonnes, divided by its total assets. Panel D displays the control variables consisting of firm size calculated as the natural logarithm of a firm's total assets, leverage as the ratio of a firm's total debt to total assets, total cash holdings, and ROA is a firm's total net income relative to its total assets. For each variable, the total number of observations, average, standard deviation, median, minimum, maximum, skewness and kurtosis are shown.

Panel A. (Cumulative) abnormal returns								
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Median**	**Min**	**Max**	**Skewness**	**Kurtosis**
Event study – positive events								
AR_0	38,454	0.004	0.038	0.002	-0.134	0.133	0.477	5.192
$\mathrm{CAR}_{(-1,1)}$	38,454	-0.006	0.068	-0.003	-0.220	0.212	-0.224	4.576
$\mathrm{CAR}_{(-3,3)}$	38,454	0.011	0.116	0.009	-0.358	0.360	-0.034	4.174
Event study – negative events								
AR_0	23,868	-0.010	0.041	-0.005	-0.134	0.133	-0.595	4.784
$\mathrm{CAR}_{(-1,1)}$	23,868	-0.003	0.071	-0.003	-0.220	0.212	0.217	4.522
$\mathrm{CAR}_{(-3,3)}$	23,868	-0.022	0.123	-0.024	-0.358	0.360	0.230	4.356
Event study – all events								
AR_0	62,322	-0.001	0.040	0.001	-0.134	0.133	-0.026	5.268
$\mathrm{CAR}_{(-1,1)}$	62,322	-0.005	0.069	-0.003	-0.220	0.212	-0.041	4.577
$\mathrm{CAR}_{(-3,3)}$	62,322	-0.002	0.120	-0.004	-0.358	0.360	0.053	4.154

Panel B. ESG data								
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Median**	**Min**	**Max**	**Skewness**	**Kurtosis**
ESG	3,978	0.516	0.184	0.515	0.040	0.948	0.018	2.103
E	3,978	0.378	0.285	0.362	0.000	0.979	0.206	1.770

S	3,978	0.530	0.209	0.520	0.019	0.979	0.099	2.054
G	3,978	0.593	0.197	0.612	0.006	0.996	-0.353	2.458

Panel C. Environmental proxies								
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Median**	**Min**	**Max**	**Skewness**	**Kurtosis**
Political affiliation	1,326	0.676	0.468	1.000	0.000	1.000	-0.751	1.564
President vote (%)	1,326	0.535	0.090	0.541	0.297	0.922	0.140	3.892
CO_2 intensity	1,779	0.391	1.305	0.017	0.000	9.559	5.316	33.509

Panel D. Control variables								
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Median**	**Min**	**Max**	**Skewness**	**Kurtosis**
Firm size	3,651	15.440	1.600	15.326	12.020	19.508	0.355	2.732
Leverage	3,651	0.290	0.209	0.287	0.000	1.000	0.643	3.4683
ROA	3,651	0.048	0.083	0.043	-0.242	0.293	-0.238	5.571
Cash	3,651	0.109	0.112	0.073	0.001	0.536	1.721	6.014

Furthermore, a correlation analysis was performed and the Pearson correlation coefficients for all variables are shown in Table 10. The correlation coefficients can take a value between of -1 and +1 representing the degree of the linear relationship between the two variables. When correlation coefficients surpass -0.7 or +0.7, it indicates a very strong relationship between the two variables. This may lead to multicollinearity and reduce the reliability and robustness of the results (Brooks, 2019). Therefore, caution is needed and for clarification, the relevant coefficients are shown in bold in Table 10. As expected, there is a strong positive correlation between the 3-day and 7-day event window. This makes sense because the longer event window includes the shorter event window, significantly increasing the correlation between both. Nevertheless, this does not impact the validity of this study as both CARs will be included separately as dependent variables in the regression models. Besides, there is a strong positive correlation between the environmental and social pillars and the overall ESG rating. Although the correlation between the governance pillar and the overall ESG score does not exceed 0.7, it is still so high that it should be treated with caution. This strong correlation stems from the fact that the total ESG rating is based on a mix of the three individual pillars. Therefore, in the main analysis, the overall ESG rating and the individual pillars will be separated in the regression models to mitigate the issue of multicollinearity. Furthermore, the environmental and social pillars are strongly correlated. Hence, the regression model that includes all three pillars will also be run with the pillars separately. Finally, a strong correlation exists between a firm's political affiliation and the Democratic percentages votes and will be included independently in the regression models.

Most of the other correlations are generally weak, although there are three other correlations that exhibit modest collinearity, being greater than -0.5 or +0.5. There is a considerable positive relationship between the size of a firm and its environmental, social, and overall ESG rating. This suggests that a firms' overall ESG and individual pillar scores increase with firm size, which is also found in the literature (Drempetic et al., 2020). Hence, this should be treated with caution when analysing the findings.

In addition, univariate tests were conducted to compare the characteristics of firms with low and high ESG scores, as displayed in Table 11. Most notable is firm size, which shows that firms with high ESG ratings are significantly larger than those with low ESG ratings. This aligns with the characteristics of the dataset used by Engelhardt et al. (2021). Besides, firms with high ESG ratings are more located in Democratic-leaning states, while firms with low ESG ratings logically have considerably higher CO2 intensity.

Table 4: Pearson correlation matrix

This Table presents the calculated Pearson correlation coefficients between all variables used in this study. Correlation coefficients higher than -0.7 or +0.7 are shown in bold and indicate caution. The correlation coefficients are tested for statistical significance and this significance is indicated by ***, ** and * at the 1%, 5% and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) AR_0	1.000													
(2) $CAR_{(-1,1)}$	0.445***	1.000												
(3) $CAR_{(-1,1)}$	0.526***	**0.739*** **	1.000											
(4) ESG	0.002	0.019***	0.021***	1.000										
(5) Environmental	0.001	0.018***	0.018***	**0.863*** **	1.000									
(6) Social	0.000	0.011***	0.014***	**0.893*** **	**0.756*** **	1.000								
(7) Governance	0.005	0.024***	0.025***	0.654***	0.383***	0.349***	1.000							
(8) Political affiliation	-0.006	-0.020***	-0.017***	0.069***	0.063***	0.108***	-0.026***	1.000						
(9) President vote (%)	-0.005	-0.019***	-0.015***	0.065***	0.057***	0.098***	-0.024***	**0.761*** **	1.000					
(10) CO_2 intensity	0.005	0.002	0.003	-0.170***	-0.158***	-0.148***	-0.079***	-0.059***	-0.029***	1.000				
(11) Firm size	-0.010**	0.009**	0.006	0.588***	0.591***	0.544***	0.286***	-0.022***	-0.043***	-0.282***	1.000			
(12) Leverage	-0.012***	-0.010**	-0.012***	0.101**	0.142**	0.095***	0.048***	-0.083***	-0.067***	-0.087***	0.208***	1.000		
(13) ROA	-0.006	-0.014***	-0.006	0.083**	0.073**	0.079***	0.044***	0.052***	0.042***	0.012**	-0.013***	-0.141***	1.000	
(14) Cash	0.011**	-0.006	-0.003	-0.159**	-0.185**	-0.097***	-0.165***	0.128***	0.196***	0.047***	-0.340***	-0.239***	0.191***	1.000

Table 5: Descriptive statistics of firms with low and high ESG scores

This Table reports the descriptive statistics and the corresponding univariate tests for the characteristics of firms with low and high ESG scores. A firm is classified as a low ESG firm if its ESG score is lower than the median score of all firms in the sample, and vice versa for firms with high ESG scores. A t-test is performed to check whether the differences in means between characteristics of low ESG and high ESG firms is significantly different from 0. This significance is indicated by ***, ** and * at the 1%, 5%, and 10% level.

	Low ESG		**High ESG**		
	Observations	**Mean**	**Observations**	**Mean**	**Difference**
Political affiliation	1,991	0.643	1,987	0.709	-0.066***
Presidential vote (%)	1,991	0.530	1,987	0.541	-0.011***
CO_2 intensity	302	0.678	309	0.332	0.346***
Firm size	1,754	14.610	1,897	16.208	-1.599***
Leverage	1,754	0.267	1,897	0.311	-0.043***
ROA	1,754	0.043	1,897	0.052	-0.010***
Cash	1,754	0.125	1,897	0.093	0.032***

4 Methodology

This chapter outlines the research methodology used to answer the research question and hypotheses. First, the statistical design of an event study will be explained. Subsequently, the regression models will be specified and linked to the hypotheses. Accordingly, statistical tests are conducted to ensure the validity of the model. The chapter is concluded with an explanation of the robustness tests that are used.

4.1 Event study

An event study approach is used to test the first hypothesis, which states that an extreme positive (negative) energy price change has a negative (positive) effect on the stock prices of U.S.-listed firms. This methodology is a well-known research approach that is widely used in financial economics to assess the impact of events on stock prices and is especially a popular method when short-term effects are examined (Fama et al., 1969; Brown and Warner, 1980, 1985; Aggarwal et al., 2012; Hall & Kenjegaliev, 2017). Since this study focusses only on short-term effects of extreme energy price changes, an event study is the appropriate method to use (Oberndorfer, 2013). Assuming market efficiency, stock prices represent all expectations and projections for a firm's future returns and earnings. When an event happens, investors immediately process this new information influencing stock prices positively or negatively (Fama et al., 1969). Therefore, this post-event stock price change reflects shifts in investors' expectations and measure event's short-term impact on firms (Hall & Kenjegaliev, 2017). To measure this effect, an event study approach compares actual returns to expected returns in a scenario where the event did not occur (Brown and Warner, 1980). This study follows an event study procedure as proposed by MacKinlay (1997), following research by Hall & Kenjegaliev (2017).

To conduct an event study, the initial step is defining the event of interest that is expected to result in an abnormal return on the event day. An event is defined as an increase (decrease) of at least 15% in the daily oil, natural gas, or coal price compared to the previous day's price, as explained in section 3.1.2. Consistent with Aggarwal et al. (2012), energy price changes are considered events once they reach the 15% threshold, regardless of cause. It is beyond this study's scope to distinguish between energy price fluctuations caused by exogenous shocks or by endogenous responses, as it is too challenging to precisely attribute a specific cause to such changes. To illustrate, there is no distinction made between an oil supply shock driven by a global pandemic, war, or a permanent shift in global aggregate demand (Kilian, 2008). Nevertheless, it can be argued that extreme changes in daily energy prices are unforeseen and exogenous to the U.S. stock market resulting in a surprise reaction among investors. This exogenous nature makes these events suitable for an event study approach allowing a causal interpretation of how such an event caused abnormal returns (Aggarwal et al., 2012). The day of an event is denoted as t_0.

After the events have been defined, the period over which the firms' stock prices will be examined needs to be identified, also known as the event window. The length of this window varies greatly now researchers have the discretion to choose this length according to their own opinion (Benbachir et al., 2022).

Nevertheless, it is common to include at least one day prior and after the event. This captures any pre-event leakage effects and delaying effects after the event (MacKinlay, 1997). This analysis uses two event windows. Following Aggarwal et al. (2012), the first event window consists of one day before the event (t_1) and one day after the event (t_2). This results in an event window of three days which is denoted as [-1,1]. This short timeframe is chosen for several reasons. First, it reduces problems caused by confounding or overlapping events (Curran & Moran, 2007). Given the rapid succession of events in this analysis, it becomes important to keep the event window (relatively) short. Second, a shorter horizon is more reliable now the short timeframe tests are most effective in identifying abnormal returns (Brown and Warner, 1980, 1985). Finally, too long horizons have lower explanatory power leading to inaccurate conclusions regarding the significance of events (McWilliams & Siegel, 1997). Although a short horizon is preferred, a somewhat longer event window is used as well. This longer window is necessary to address market inefficiencies by loosening the assumption of perfect efficiently markets, as this longer window checks for information leaks or a delay in processing new information in the U.S. stock market. Following Boldeanu et al. (2022), an event window of three days before and three days after the event is used, resulting in a one-week timeframe, denoted as [-3,3].

To determine the abnormal returns, it is necessary to calculate the expected normal returns. Normal returns reflect expected stock performance if the event did not occur and serve as a benchmark against which actual returns are compared. There are several methods to calculate normal returns. The most used models are the market model and the constant mean return model (MacKinlay, 1997). The market model assumes a steady linear relationship between market returns and stock returns. However, this study focusses on all firms in the S&P 1500, representing approximately 90% of the U.S. stock market (S&P Composite 1500, n.d.). Due to this high coverage of the U.S. stock market, it is hard to find a U.S. market index that deviates sufficiently from the S&P 1500 to create unbiased abnormal returns. Thus, the market model is not best suited for this analysis, yet a variant of the market model will be used as a robustness test. Like previous studies, the constant mean return model is therefore adopted, which presumes that the mean return of a stock is constant over time (Hall & Kenjegaliev, 2017). It is a simple model that does not consider market factors or risk. Although the model's simplicity, it is proved that its predicted results are not inferior to those of more sophisticated models (Brown and Warner, 1980, 1985). Furthermore, it is assumed that the stock returns follow a jointly multivariate normal distribution and are identically and independently distributed over time.

When using a constant mean return model, the estimation window must be specified. This is the period before the event in which the normal stock returns are predicted, without the impact of the event. Following similar studies, an estimation window of eight trading days is used, from day 11 through 4 prior to the event day (McKenzie & Thomsen, 2001; Milonas, 2006). This 8-day estimation window is considerably shorter than the 120- or 250-day estimation windows commonly used (MacKinlay, 1997). The option to use a relatively short estimation window is an important advantage of using a constant mean return model. It is assumed that an 8-day window is sufficiently long to avoid being biased by short-term price fluctuations, but also short enough to be not affected by price sensitive information other than the relevant event (Schroeder et al., 1990). In this study, the main reason for this short window are the problems created by event clustering. Here, as explained by McKenzie (2004), event clustering refers to situations where two or more events happen shortly after each other, which is common in this study, as seen in Table 2. This leads to overlapping event windows and estimation windows, potentially resulting in inaccurate estimates and unreliable test statistics. For example, if the actual abnormal return is either positive or negative, normal periods that comprise previous event(s) result in biased estimations of the average abnormal returns. Moreover, abnormal returns will be correlated due to the lack of independence between normal returns if there are multiple estimation windows that overlap (McKenzie, 2004). The use of an 8-day estimation window does not eliminate the problem of event clustering, however, it significantly reduces the occurrence of event clustering. Moreover, an estimation window and the corresponding event window do not overlap to prevent the event from affecting the parameter estimations of the normal performance model. Additionally, no days are dropped between the estimation and event windows. Although this deletion would control for information leaks before the event day, it will also increase the problems with event clustering. Since the latter is a bigger issue in this study, this was decisive. This is supported by Schroeder et al. (1990), who concluded that dropping the days between event windows and estimation windows leads to comparable conclusions and identical implications. Besides, by using a somewhat longer event window, the estimation window already starts four days prior to the event reducing potential problems with information leakage. Figure 4 presents an overview of the entire timeline of the event study.

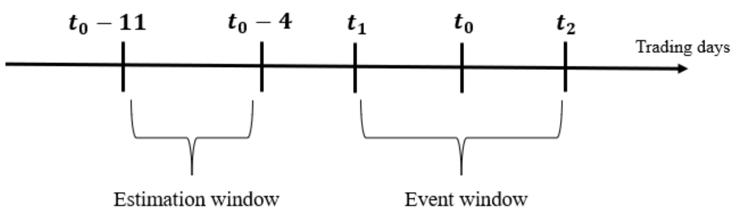

Figure 1: Timeline event study
This figure presents a general overview of the entire timeline of the event study. The estimation window starts eleven trading days prior to the event day (t_0) and ends four trading days prior to the event. The largest event window starts and ends three days before and after the event day ($t_1 = -3,\ t_2 = 3$), respectively, while the smallest event window starts and ends one day before and after the event day ($t_1 = -1,\ t_2 = 1$).

After defining the features of the event study, the next step is to calculate the (cumulative) abnormal returns (MacKinlay, 1997). First, the stock prices need to be transformed into daily stock returns. A firm's daily stock return during the period of interest is measured as follows:

$$R_{it} = \frac{P_{it} - P_{it-1}}{P_{it-1}} \tag{1}$$

Where R_{it} is the (actual) stock market return of firm i at day t. Furthermore, P_{it} designates the closing stock price of firm i at day t and P_{it-1} is the closing stock price of firm i at day $t - 1$, being the prior day's closing stock price.

Subsequently, the abnormal return is measured by taking the difference between a firm's actual stock return and its expected normal return at time t. This is done for all companies in the sample over all days of the event window. Therefore, the following formula is used:

$$AR_{it} = R_{it} - E(R_{it}|X_t) \tag{2}$$

Where the abnormal, actual, and normal return for firm i at time t are designated by AR_{it}, R_{it}, and $E(R_{it}|X_t)$. The preconditioning information for the normal return model is specified by X_t. As argued, the normal returns are modelled using the constant mean return model. Herewith, the normal returns are calculated by taking the average returns of firm i during the estimation window. This model is described by the following formula:

$$E(R_{it}|X_t) = \bar{R}_{it} = \frac{1}{\tau_1 - \tau_0} \sum_{t \in [\tau_0 - \tau_1]} R_{it} \tag{3}$$

Where $\bar{R}_{it}$ is the mean return of firm i during the estimation window (τ_0, τ_1), or in other words the expected normal return of firm i. τ_0 and τ_1 represent the first and last day of the estimation window, respectively. Finally, R_{it} show the (actual) stock market return of firm i at time t.

To draw general conclusion about the overall impact of the events on the U.S. stock market, it is necessary to aggregate the abnormal returns, which can be done across securities and over time. First, to examine the impact on the U.S. stock market on a particular day in the event window, the average abnormal returns (AAR) are measured. Therefore, the abnormal returns of each individual company are aggregated across all companies for each day in the event window, represented by the following formula:

$$AAR_t = \frac{1}{N} \sum_{i=1}^{N} AR_{it} \tag{4}$$

Where AAR_t show the average abnormal return on day t of the event window, N represents the total numbers of firms in the sample, and AR_{it} is the abnormal return for firm i on day t from equation 2.

Nevertheless, observations of single day events still lack informative value due to variation in returns across the days within the event window. Therefore, the abnormal returns for each firm are aggregated over the days within the event window. As a result, the firm-specific cumulative abnormal returns are calculated by summing up each daily abnormal return of firm i over both event windows. The cumulative abnormal returns are described by the following formula:

$$CAR_i = CAR_{i,(T_1,T_2)} = \sum_{T_1}^{T_2} AR_{it} \tag{5}$$

Where $CAR_{i,(T_1,T_2)}$ stand for the cumulative abnormal returns of firm i for time period T_1 until T_2, measured by adding up the abnormal returns (AR_{it}) from equation 2. Specifically, T_1 and T_2 will have a value of -1 or -3 and +1 or +3, respectively.

Furthermore, to analyse the impact of an event of interest on the overall U.S. stock market, the cumulative average abnormal returns (CAAR) will be defined. Accordingly, all cumulative abnormal returns will be aggregated across the total portfolio of firms in the sample, defined as follows:

$$CAAR_t = CAAR_{(T_1,T_2)} = \frac{1}{N}\sum_{i=1}^{N} CAR_{(T_1,T_2)} \tag{6}$$

Where $CAAR_{(T_1,T_2)}$ denotes the cumulative average abnormal returns for the portfolio of firms for the period between T_1 until T_2, inferred by the summation of cumulative abnormal returns from equation 5. N represents the total number firms in the portfolio that is used.

As a result, the impact of each individual event on the U.S. stock market will be known, with each event classified as a positive or negative event. To draw conclusions about the specific impact of either all positive or all negative events on the U.S. stock market, cumulative average abnormal returns must be aggregated across all positive and negative events in the sample, respectively. Thereby, the samples of respectively positive and negative events are further divided into four categories that include events resulting from: (1) oil price changes, (2) natural gas price changes, (3) coal price changes, and (4) all energy price changes. Specifically, the mean of the (cumulative) average abnormal return over all the positive or negative events is calculated using the following formulas:

$$\overline{AAR_t} = \overline{AAR_{(T_1,T_2)}} = \frac{1}{E}\sum_{i=1}^{E} AAR_t \tag{7}$$

Where $\overline{AAR_t}$ show the mean of the average abnormal return over all events on day t of the event window, E represents the total positive or negative event in the sample, and AAR_{it} is the average abnormal return on day t of the event window.

$$\overline{CAAR_t} = \overline{CAAR_{(T_1,T_2)}} = \frac{1}{E}\sum_{i=1}^{E} CAAR_{(T_1,T_2)} \tag{8}$$

Where $\overline{CAAR_{(T_1,T_2)}}$ denotes the mean of the cumulative average abnormal returns over all events for the period between T_1 until T_2, inferred by dividing the summation of cumulative average abnormal returns from equation 6 by the total number of events (E).

To test hypothesis 3a, both an event study method and regression analysis are used. The latter one will be explained in detail in section 4.2. Hypothesis 3a predicts that the positive effect of a firm's ESG performance on its abnormal returns during an event is driven by the firm's environmental performance, proxied by the environmental (E) pillar of the ESG score. Following Boldeanu et al. (2022), the expected positive effect of a firm's environmental performance on its abnormal returns during an event is examined by calculating the $\overline{CAAR}$ for two different portfolios. Ranking the firms in the sample based on the average value of their environmental pillar score is employed to determine which firms are included in these portfolios. One portfolio consists of 662 firms that have an environmental pillar score above the median score, denoted as ($\overline{CAAR_{High\ E}}$). The other portfolio consists of 664 firms that have an environmental pillar score below the median score, denoted as ($\overline{CAAR_{Low\ E}}$). These two portfolios are compared to see the difference between reactions of firms with low and high environmental pillars. Subsequently, a two-sample t-test is performed to test whether the $\overline{CAAR}$s of these two portfolios are significantly different. It is expected that ($\overline{CAAR_{High\ E}}$) has a higher value than ($\overline{CAAR_{Low\ E}}$).

4.1.1 Significance tests

The $\overline{AAR_{(T_1,T_2)}}$ and $\overline{CAAR_{(T_1,T_2)}}$ are used to test hypothesis 1 and 3a. To answer these hypotheses, it is necessary to see if the results are statistically significant. Therefore, several tests are performed consisting of both parametric and non-parametric tests. First, a two-sided t-test is conducted which can be seen as a traditional t-test in the literature (MacKinlay, 1997; Brown, 1980). Nevertheless, this simple t-test may fail considering the issue of event clustering. The BMP test, as explained by Boehmer, Musumeci, and Poulsen (1991), considers heteroskedasticity since it is reasonable to assume that periods of events are prone to event-induced variance. This event-induced variance is especially present in event studies where the events are clustered, as in this study. Therefore, additionally this BMP test is used (Ma et al., 2021). Moreover, a non-parametric test will be performed to verify the conclusions drawn from parametric tests. Compared to parametric tests, non-parametric tests do not rely on assumptions concerning the distribution of abnormal returns such as the normality assumption and are often used alongside parametric tests (MacKinlay, 1997). Consequently, the generalised sign test will be used, which can be considered as a widely used test due to its powerful nature (Kolari & Pynnonen, 2011).

4.2 Regression analysis

To address the remaining hypotheses and find potential drivers for the (cumulative) abnormal returns, multiple models are constructed using pooled Ordinary Least Squares (OLS) regressions using panel data (MacKinlay, 1997). An OLS regression is a popular method for determining the coefficients of linear regression models. Subsequently, these coefficients explain whether and to what extent a relationship exists between one or multiple independent variables and a dependent variable. In this paper, numerous regressions have been carried out, covering both univariate and multivariate analyses. In all regression models, the dependent variable consists of AR_{it}, $CAR[-1,1]_{it}$ *or* $CAR[-3,3]_{it}$, measured for all firms in the sample. Furthermore, each model includes a different independent variable in addition to a set of control variables. The inclusion of these control variables should increase the explanatory power of the regression models and are the same for each model. The control variables are industry classification ($Industry$), firm size ($FirmSize$), leverage ($Leverage$), return on assets (ROA) and cash ($Cash$). Before running the regression analysis, the data should be checked to ensure that OLS assumptions are met (James et al., 2013). Table 12 in Appendix C lists the definitions of all dependent and independent variables used in this paper.

First, multicollinearity arises when two or more independent variables are highly correlated with each other, leading to unreliable estimates of regression coefficients and potentially misleading findings. Based on the correlation matrix and the individual inclusion of independent variables in the regressions, as discussed in section 3.7, no problems of multicollinearity are detected. However, to ensure that there is no multicollinearity between three or more variables, Variance Inflation Factor (VIF) tests are conducted. This resulted in unique and average VIF values well below the threshold of five or ten, indicating that multicollinearity problems are negligible (James, 2013).

Another assumption potentially at issue is the presence of homoscedasticity. Homoscedasticity describes a situation where the variance of the error terms remains constant, while heteroskedasticity refers to varying error term variance (James et al., 2013). This latter leads to incorrect standard errors which are necessary to test hypotheses accurately. The presence of heteroskedasticity will be tested by performing Breusch-Pagan tests that assumes a null hypothesis of constant variance of the error terms. The results of these tests led to rejection of the null hypothesis, demonstrating heterogeneity in the residuals' distribution and exhibit non-constant variance. Moreover, concerns arise about the assumption that the error terms in a regression model are uncorrelated. There will be a tendency to underestimate the true standard errors if the error terms are correlated, resulting in incorrect confidence intervals (Brooks, 2019). Therefore, Breusch-Godfrey tests are used to assess the existence of autocorrelation. It follows that the null hypothesis of no serial correlation in regression models is rejected at a threshold of five percent. Besides, the rapid sequence of events results in event clustering, necessitating a correction for this potential bias caused by the lack of independence between normal returns. To overcome the problems of event clustering, heteroskedasticity and autocorrelation, robust standard errors are estimated and applied, clustered by events. Additionally, all models consider industry and year fixed effects.

Furthermore, the distribution of residuals of the regression models should be normal. To test if this assumption hold, quantile-quantile (Q-Q) plots are made of the regression models' residuals, where a straight line represents a normal distribution. All Q-Q plots show a similar pattern with roughly straight lines but deviate from this in the ends of the distributions. Nevertheless, this poses no problems now that this study's sample size is large enough to assume an approximately normal distribution following the central limit theorem (Brooks, 2019). One remaining issue is potential the problem of endogeneity. This is a situation where one or multiple independent variables are correlated with the error term in a regression model. Endogeneity can have different causes, such as omitted variable bias, simultaneity, selection bias and measurement errors (Brooks, 2019). For this study, endogeneity issues are likely to arise from omitted variable biases where one or multiple independent variables are affected by factors that are not included in the model. Consequently, the estimations of regression coefficients are inaccurate. To solve this problem, potential omitted variables are included in the models as a robustness tests, as explained in section 5.3.

4.2.1 ESG ratings

The second hypothesis predicts that higher ESG performance positively affects a firm's abnormal returns. To test this positive relationship, two regression models are constructed to analyze the impact of the total ESG rating. In the first model, the independent variable of interest is a firm's total ESG score, which reflects its total performance on environmental, social, and corporate governance aspects. This results in the following model:

$$Y_{it} = \beta_0 + \beta_1 ESG_{it} + \beta_2 Leverage_{it} + \beta_4 Cash_{it} + \beta_3 ROA_{it} + \beta_5 FirmSize_{it} + \sum_{k=1}^{11} \beta_k\, Industry_{it} + \varepsilon_t \qquad (9)$$

Where Y_{it} takes the value of one of the dependent variables, being AR_{it}, $CAR[-1,1]_{it}$ or $CAR[-3,3]_{it}$ of firm i at event date t. β_0 denotes the intercept of the regression line and ESG_{it} represent the total ESG score of firm i in the year-end prior to the event at time t. $Leverage_{it}$ is the ratio of total debt to total assets of firm i, $Cash_{it}$ represents the ratio of total cash to total assets of firm i, and both represents the financial strength of a firm. The variable ROA_{it} proxies the firm's profitability and is the net income of firm i relative to its total assets. $FirmSize_{it}$ represents the total assets of firm i. All these firm-level control variables using accounting data are computed based on the year-end prior to the extreme price change (Mohanty et al., 2013). Besides, industry-specific dummy variables are included to indicate within which industry firm i operates. This is represented by the variable $Industry_{it}$. This same set of control variables is consistently added and interpreted for all regression models discussed in the rest of this paper. Finally, the error term is included by ε_t.

In this regression model the coefficient of interest is the one of the total ESG rating, represented by β_1. Previous studies demonstrated that a higher ESG score can be seen as a hedge against negative events, such as climate changes or pandemics (Pastor et al., 2021). Hence, the first hypothesis expects β_1 to be positive, following a one-sided t-test.

In line with research by Engelhardt et al. (2021), a second model is constructed with another proxy for the total ESG score. For this model, a dummy variable $High\ ESG$ is created, which takes a value of one if a firm's total ESG score is above the median score of all respective firms within the sample, and zero otherwise. Again, the ESG score of firm i is based on the year-end prior to the event. The model is described by the following equation:

$$Y_{it} = \beta_0 + \beta_1 High\ ESG_{it} + \beta_2 Leverage_{it} + \beta_4 Cash_{it} + \beta_3 ROA_{it} + \beta_5 FirmSize_{it} + \sum_{k=1}^{11} \beta_k\ Industry_{it} + \varepsilon_t \qquad (10)$$

Where $High\ ESG_{it}$ denote the dummy variable which is set to one if firm i's total ESG score at time t is higher than the median score of all respective firms within the sample at time t, and zero otherwise.

For the coefficient of interest, the same expectation and reasoning discussed for equation 9 applies. Consequently, the coefficient of firms with an ESG score above the median score, denoted as β_1, is expected to be positive related to a firm's (C)ARs, following a one-sided t-test.

Hypothesis 3a states that the positive effect of a firm's ESG performance on abnormal returns during an event is driven by the firm's environmental performance, as proxied by the Environmental (E) pillar of the ESG score. In addition to the event study approach, a regression model is constructed that provides a different view of the effect of ESG on a firm's abnormal returns following an extreme energy price change by breaking down the total ESG score into its individual components environment (E), social (S), and corporate governance (G). As a result, the ESG variable of equation 9 has been substituted with its individual pillar scores, while the total ESG score has been omitted to address the issue of multicollinearity. Therefore, the following model is applied to investigate the hypothesis:

$$Y_{it} = \beta_0 + \beta_1 Env_{it} + \beta_2 Soc_{it} + \beta_3 Gov_{it} + \ \beta_2 Leverage_{it} + \beta_4 Cash_{it} + \beta_3 ROA_{it} + \beta_5 FirmSize_{it} + \sum_{k=1}^{11} \beta_k \, Industry_{it} + \varepsilon_t \qquad (11)$$

Where Env_{it}, Soc_{it} and Gov_{it} denote the individual environment (E), social (S), and corporate governance (G) scores of firm i in the year-end prior to the event at time t.

Hypothesis 3a predicts that a firm's environmental performance, proxied by its environmental score, positively impact a firm's abnormal returns as an extreme change in energy prices can be considered as an issue related to environmental aspects. Consequently, the coefficient of interest is the coefficient of the environmental score, being β_1. A positive impact of β_1 is hypothesized, using a one-sided t-test. Even though the coefficients of the social and corporate governance scores are not the main coefficients of interest, they are included in the regression model for comparison. The coefficient of the environmental score (β_1) is expected to have the most positive effect on the dependent variables, compared with the coefficients of the social (β_2) and corporate governance (β_3) scores.

4.2.2 Carbon dioxide intensity

Hypothesis 3b predicts that the positive effect of a firm's ESG performance on abnormal returns during an event is driven by the firm's environmental performance, proxied by $\mathrm{CO_2}$ intensity. This can be seen as an alternative proxy for the environmental score of a firm. Accordingly, a regression model is established where the main independent variable is the $\mathrm{CO_2}$ intensity per firm, being a firm's total $\mathrm{CO_2}$ and $\mathrm{CO_2}$ equivalent emissions in tonnes, divided by its total assets. The results in the following regression equation:

$$Y_{it} = \beta_0 + \beta_1 CO_2 intensity_{it} + \ \beta_2 Leverage_{it} + \beta_4 Cash_{it} + \beta_3 ROA_{it} + \beta_5 FirmSize_{it} + \sum_{k=1}^{11} \beta_k \, Industry_{it} + \varepsilon_t \qquad (12)$$

Where $CO_2 intensity_{it}$ is the carbon dioxide intensity of firm i in the year-end prior to the event at time t. The coefficient of interest in this regression model is the coefficient of a firm's $\mathrm{CO_2}$ $\mathrm{intensity}$, being β_1. It is expected that the higher a firm's $\mathrm{CO_2}$ intensity, the worse its environmental performance is leading to worse abnormal returns, and vice versa. Likewise, hypothesis 3b predicts that β_1 has a negative influence on the dependent variables.

4.2.3 Political affiliation

Two sets of regression models are constructed to examine the fourth hypothesis, which predict that a Democratic-leaning firm will positively influence the abnormal returns of a firm following an extreme energy price change. Therefore, the main independent variable in these regression models is a firm's political affiliation which is proxied in two different ways. First, a dummy variable is used that equals one if the firm's headquarter is located in a state where a Democrat has won, and zero otherwise. By also adding the previously used set of control variables as, the model is as follows:

$$Y_{it} = \beta_0 + \beta_1 Democratic_{it} + \ \beta_2 Leverage_{it} + \beta_4 Cash_{it} + \beta_3 ROA_{it} + \beta_5 FirmSize_{it} + \sum_{k=1}^{11} \beta_k \, Industry_{it} + \varepsilon_t \qquad (13)$$

Where $Democratic_{it}$ denote the dummy variable that takes a value of one if the firm's headquarter is located in a state where a Democrat, and zero otherwise. This is based on the outcome of the U.S. presidential election in 2020. Previous literature demonstrated that Democratic-leaning firms are more concerned about the environment and therefore pays more attention to the sustainability of its firm. Consequently, hypothesis 4 predicts that the coefficient of being a Democratic-leaning firm, denoted by β_1, positively influences the dependent variables, following a one-sided t-test.

In addition, the hypothesis is tested by replacing the above dummy variable with a more detailed proxy of a firm's political affiliation. A proportion variable is included, defined as the percentage votes that is received by the Democratic candidate in the presidential election where a firm is headquartered. This leads to the following model:

$$Y_{it} = \beta_0 + \beta_1 DemocratVotes_{\,it} + \ \beta_2 Leverage_{it} + \beta_4 Cash_{it} + \beta_3 ROA_{it} + \beta_5 FirmSize_{it} + \sum_{k=1}^{11} \beta_k \, Industry_{it} + \varepsilon_t \qquad (14)$$

Where the variable $DemocratVotes_{it}$ reflect the percentage of votes that is received by the Democratic candidate in the presidential election of 2020 in the state where the headquarter of firm i is located at time t. Likewise, the coefficient of interest is the coefficient related to the percentage votes received by the Democratic candidate, depicted as β_1. Like the prediction of equation 13, it is hypothesized that $\beta_1$have a positive impact on the (cumulative) abnormal returns.

4.3 Robustness tests

Several robustness checks will be performed to test the robustness of the main results to see if changes in key parameters cause changes in the results. Diverse adjustments will be made for the event study including a longer estimation window and excluding the 'finance, insurance & real estate' sector. Furthermore, a market-adjusted model without an estimation window will be used to calculate the expected normal returns. This approach was specifically chosen because it is an appropriate solution to mitigate the effects of event clustering since no estimation window is used (MacKinlay, 1997). Finally, to reduce the presence of omitted variable biases, extra variables are included in the regression models. In this robustness check, a variable related to a firm's price to earnings ratio is added. Besides, a variable is added representing the percentage change in decrease or increase in daily energy prices.

5 Results

This chapter reviews the empirical results obtained by applying the methodology to the sample dataset in chapter 3. Next, the findings from the event study and OLS regressions are evaluated in relation to the hypotheses for acceptance or rejection. Finally, some findings of the robustness tests are discussed.

5.1 Market reaction to extreme energy price changes

To answer the first hypothesis, which states that extreme positive (negative) energy price changes have negative (positive) effects on stock prices of US-listed firms, an event study methodology is applied. Table 13 in Appendix D lists by event the (C)AARs of S&P 1500 firms during the day of the event and the 3- and 7-day event windows, showing significance with a t-test, generalized sign test and BMP test. The BMP test, which corrects for event-induced volatility, is particularly comprehensive and serves as the main significance test in this paper unless otherwise noted.

The impact of energy price changes varies extremely across events, even when categorized by energy commodity type and event direction, leading to ambiguous findings. Table 13 shows surprisingly mixed (C)AARs for oil price increases, with directional changes observed across different event windows. For example, on March 19, 2020, despite a 23.81% rise in oil price, the market showed a significant positive reaction of 8.909% on the event day. However, this initial positive response became negative in the 3-day CAAR, possibly indicating a delayed response, and then returned to a positive CAAR when the event window was extended to seven days. Reversals in market reactions are also observed for natural gas and coal prices, although relatively less frequently than for oil prices, suggesting that these divergent reactions may be due to high levels of panic and uncertainty surrounding the Covid-19 outbreak that primarily affected oil. Moreover, the largest (C)AARs are observed in events triggered by oil price declines, such as a significant negative market reaction of -17.683% on April 20, 2020. Slightly smaller outliers are also observed for natural gas events, but not for coal prices. This difference may be partly attributed to greater dependence on oil and the perception among investors that changes in oil and natural gas price have greater effects on corporate costs, leading to more extreme reactions (Ahmed & Sarkodie, 2021). Furthermore, regarding potential limitations of event clustering, Table 13 reveals no observable trend or differences in the (C)AARs associated with clustered or non-clustered events. However, the absence of such a trend or differences does not negate the possible influence that clustering might have had on the results. Finally, it should be noted that almost all event-day, 3-day, and 7-day (C)AARs are significant at the 1%, 5% or 10% level according to at least one of the significance tests. In fact, these tests show relatively high t- or z-statistics, indicating a strong level of statistical significance. In summary, changes in all three energy prices significantly impact the U.S. stock market, albeit with varying magnitudes and levels of consistency, making it challenging to find a clear trend.

Next, the (C)AARs are aggregated across positive and negative events to draw conclusions about the specific impact of either all positive or all negative events on the U.S. stock market for the 3- and 7-day event windows, presented in Table 14. Furthermore, Figures 5 and 6 illustrate the AARs over the seven days (i.e. [-3,3]) around the positive and negative event days, respectively, to see the overall trend and to make sure that fluctuations after the event are not negated by pre-event fluctuations.

Table 14 shows that with respect to oil, there is a notable positive market reaction of 1.478% on the day of an oil price increase, being significant at 1%. This contradicts Benkraiem et al. (2018) who found a negative short-term reaction of S&P 500 firms to WTI oil price increases. This divergence in findings could be due to this study's focus on a sample of S&P 1500 firms, which includes more small firms. These smaller firms may experience different or heighted effects from energy price increases compared to the sample in Benkraiem et al. (2018). However, over the 3-day event window, there is a turnaround to a CAAR of -2.827% which is the largest negative reaction found. Although the 7-day CAAR decreases in magnitude, it remains negative. This directional shift may indicate slow information processing leading to market inefficiencies (Narayan & Sharma, 2011). However, it should be noted, for example, that figure 5 shows an increase in AARs from one day after the event, resulting in a positive post-event window [0,3], further elaborated in Table 15 in Appendix D. Yet, these post-event spikes are offset by pre-event drops when the days before and after are taken together, resulting in the slightly negative 7-day CAAR. Additionally, the negative 7-day reaction is mainly driven by the oil increase on May 5, 2020, but this event window includes also negative Covid-19 statements from the White House. This raises suspicion that this negative CAAR may be affected not only by energy price changes, but also by the presence of noise, especially for longer event windows (CDC Museum, 2023; Oberndorfer, 2009). Therefore, the 7-day CAARs should be interpreted with caution. Conversely, an extreme drop in oil prices caused the highest significant negative reaction of -3.912% on the event day. However, the 3-day event window reveals a positive but insignificant reaction of 0.438%, while when extended to seven days, a significant negative CAAR of -2.286% is found. This unexpected positive relationship aligns with the findings of Ahmed & Sarkodie (2021), who found a positive short-term relation between oil prices and the (real) U.S. stock index adjusted for inflation. Furthermore, natural gas price increases show only a small positive reaction on the event day of 0.047%, significant at the 10% level. The stock markets reacted even more positively in the 3- and 7-day event windows by 0.493% and 1.404%, respectively, significant at 1% with a slightly higher reaction after the event than before the event. Negative natural gas price changes follow a similar trend, albeit in a different direction. On the event day there is a slightly small negative reaction of -0.135%, while this response becomes more severe to -1.240% and -2.428% for the 3- and 7-day event windows, respectively. Again, these findings support Ahmed and Sarkodie (2021), but contradicts the evidence of Benkraiem et al. (2018) of a significant negative relation between HH gas prices and stock prices of specific quantiles of S&P 500 firms. However, unlike Benkraiem et al. (2018), this study focuses on a broader range of companies and does not distinguish between quantiles. Moreover, changes in coal prices show mixed results based on the direction of change and event window duration. Both extreme rises and falls in coal prices produce significant positive changes in stock performance during the day itself, 0.331% and 0.197%, respectively. For positive changes in coal prices, this response changes to a 3-day CAAR of -0.328% before changing again to a positive CAAR of 1.082% during a 7-day event window, both significant at 1%. This reversal trend occurs inversely for negative changes in coal prices. These divergent outcomes of coal events align with the scarce literature (Oberndorfer, 2009; Ahmed & Sarkodie, 2021).

When considering all energy commodities, an energy price rise causes an abnormal stock return of 0.501% on the event day, thus a positive reaction. Besides, the suspicion of a delayed response is supported by a negative 3-day CAAR of -0.593%. However, this reverses to a positive reaction in the 7-day window, while the response to falling energy prices remains negative and becomes stronger when the event window is extended which is mainly driven by highly negative post-event responses, shown in figure 6. Surprisingly, energy price decreases do not benefit stock performance, contrasting previous studies (Sadorsky, 1999; Sonenshine & Kauvel, 2017; Benkraiem et al., 2018). This unexpected positive relationship may be attributed to the specific time period, as argued by Miller & Ratti (2009). Furthermore, despite the use of balanced event windows in this study (i.e. [-3,3] and [-1,1]), figures 5 and 6 present that post-event responses are generally not cancelled out by pre-event changes. An exception to this is found in the 7-day event window surrounding a positive coal event, however, this may be attributed to the increased noise in higher event windows. Therefore, it may be useful for follow-up research to split longer event windows into pre- and post-event windows. Moreover, the graphs show that the responses over the same number of days before and after the event have often the same direction and appear to be somewhat symmetrical, albeit with slightly varying magnitudes. In general, positive (negative) abnormal returns on the day after an event are not followed by another positive (negative) abnormal return. Thus, although cancellation will not be a major concern, the varying magnitudes may cause more negative or positive balanced 3- and 7-day CAARs than when looking only at post-event reactions, and caution is needed in interpreting the results.

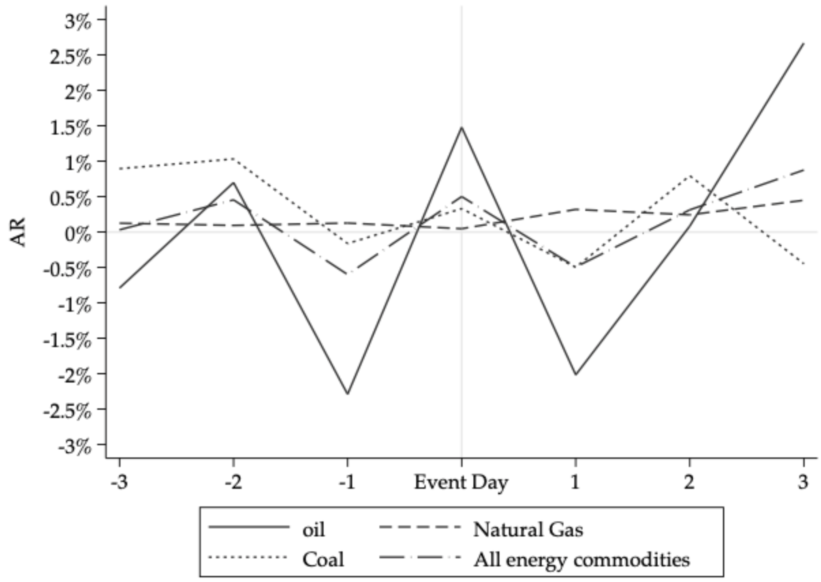

Figure 2: the daily average abnormal returns before and after positive events
This figure shows the trend of the average abnormal returns in percentage (%) on the Y-axis over the seven days consisting of three days before and three days after an extreme energy price increase, denoted as the event day on the X-axis. The AARs are calculated for 1,326 firms using the constant mean return model with an 8-day estimation window during a sample period from March 2020 to October 2022. Afterwards, these AARs are aggregated across all firms and all positive and negative events categorized by energy commodity. This study focuses on the cumulative average abnormal returns consisting of [-1,1] and [-3,3] whose trend around positive events can be derived from this figure.

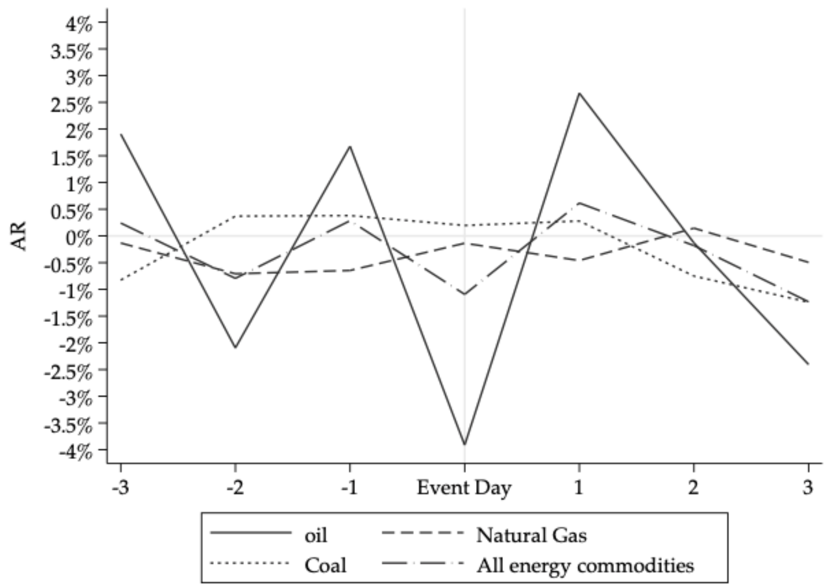

Figure 3: the daily average abnormal returns before and after negative events
This figure shows the trend of the average abnormal returns in percentage (%) on the Y-axis over the seven days consisting of three days before and three days after an extreme energy price increase, denoted as the event day on the X-axis. The AARs are calculated for 1,326 firms using the constant mean return model with an 8-day estimation window during a sample period from March 2020 to October 2022. Afterwards, these AARs are aggregated across all firms and all positive and negative events categorized by energy commodity. This study focuses on the cumulative average abnormal returns consisting of [-1,1] and [-3,3] whose trend around negative trends can be derived from this figure.

Thus, Tables 13 and 14 show no unambiguous results or trends for the impact of extreme changes in oil, natural gas and coal prices on stock performance. This lack of clarity can perhaps be attributed to the presence of structural breaks within the overall sample period. Structural breaks indicate significant changes in economic or market conditions affecting stock performance and can result from various factors such as macroeconomic events, shifts in market sentiment, or unforeseen crises. If such breaks coincide with the estimation and event windows, it could potentially affect the observed abnormal returns. In this study, four subperiods can be distinguished and the associated (C)AARs can be found in Table 16, and in Table 17 and figures 7-14 in Appendix D. First, the Covid-19 outbreak phase (March 2020 to June 2020) characterized by panic, far-reaching economic restrictions, and complete lockdowns leading to a negative demand shock for energy commodities. Second, the Covid-19 follow-up phase (July 2020 to June 2021) resembles the Covid-19 outbreak phase in many ways. However, the initial panic and novelty has subsided, and measures now fluctuate between moderate and severe. Therefore, this phase is distinguished from the initial phase to assess whether there are divergent findings despite the ongoing negative trend in energy commodity demand. The third subperiod begins at early 2020 when the spread of Covid-19 diminishes, and countries gradually reopen and resume daily activities. This recovery phase (July 2021 to February 21, 2022) is marked by a positive energy demand shock. Finally, the Ukraine invasion in February 2022 leads to measures against Russia and physical blockades of trade routes, while high energy demand remains. Therefore, this period of war (February 21, 2022, to October 2022) shows a negative energy supply shock.

In the initial phase of Covid-19, events are mainly triggered by oil price changes. Again, on days that energy prices rise (fall) sharply, a significant positive (negative) AAR is found of 1.432% (-3.192%), contrary to older literature (Sadorsky 1999; Sonenshine & Kauvel, 2017). However, the AAR for both positive and negative returns reverses direction during a 3-day event window to -2.271% and 0.438%, respectively, suggesting a slowdown in processing news of changing energy prices (Narayan & Sharma, 2011). Finally, all 7-day event windows are significantly negative, with the largest negative effect observed, contrary to expectations, when energy prices fall. It was expected that the greatest negative impact would be found when energy prices rise, as this is indicative of rising operating costs and falling profits that depress stock prices. However, these remarkable findings are supported by other researchers studying the same period (Zhou et al., 2023; Karamati, 2022). For example, Ali et al. (2022) found that negative movements in oil prices are related to bearish trends in the U.S. stock market, with increased volatility and uncertainty playing an important role. With respect to positive events, it should be noted that the negative 7-day CAAR is dominated by negative pre-event responses while post-event responses (i.e. [0,3]) are positive, shown in Figure 7 and Table 17. This pattern is also observed with natural gas and coal events, where the 3-day pre- and post-event reactions partially offset each other, leading to an overall negative 7-day CAAR, despite the positive post-event CAAR. This indicates that a balanced event window for this subperiod may not be sufficient to draw unambiguous conclusions and further research including different pre- and post-event windows is recommended.

In the Covid-19 follow-up phase, events are solely driven by natural gas price changes. All three event windows show significant negative (C)AARs, regardless of the event's direction. For example, a 3-day event window gives a CAAR of -0.545% and -0.993% after positive or negative changes, respectively. Again, the magnitude of the CAARs increase with the length of the event window, indicating more noise. Unlike the Covid-19 outbreak phase, consistent results are seen here, possibly caused by decreasing overall panic and stabilization due to government measures (Shet et al., 2022). A clear negative trend of (C)AARs can be deduced, independent of different event windows or energy price change direction. Zhou et al. (2023) attribute this to a possible momentum crash in which the U.S. stock market faced an adverse shock caused by Covid-19 panic, creating negative returns over a long period of time. Figures 8 and 12 indeed shows a clear trend of negative AARs on all seven days around the event, except on day 3 prior to the event, supporting the possibility of the presence of a momentum crash. The Covid-19 recovery phase covers only a few events caused by natural gas and coal price changes. Interestingly, the previously found negative trend is reversed, with all event windows showing a positive (C)AAR, irrespective of event direction. In particular, energy price increases have large significant positive effects on stocks of 1.650%, 2.583% and 6.855% on the event day and during a 3- and 7-day event window. Moreover, Figure 9 demonstrates that this positive response is found mostly in the pre-event period and drops somewhat quickly after an energy price increase but becomes positive again in the days following. It is possible that this overall positive reaction can be attributed to the recovery phase of the momentum crash. According to Jegadeesh et al. (1993), a momentum crash is followed by a recovery phase of market collapse that leads to high positive returns, making it logical that this phase consists of a large flow of positive stock returns (Zhou et al., 2023).

Finally, the Russia/Ukraine war caused a ban on coal imports to the U.S., leading to many extreme price changes for coal. Here, energy price increases result in positive (C)AARs of 0.125%, 0.825% and 4.496% on the event day and during the 3- and 7-day event windows, respectively. These relatively large positive effects are partly attributed to pre-event reactions, as post-event reactions are also positive, but with a slightly smaller magnitude, as shown in Figure 10. Conversely, energy price falls lead to negative (C)AARs of -0.266%, -0.496% and -3.321% within the same time frames. Nonetheless, CAARs to negative gas prices decreases show an overall climbing trend. So, both positive and negative events show a trend with increasing magnitudes for longer event windows. This short-term positive relationship aligns with the work of Ahmed and Sarkodie (2021) but contradicts the plethora of research. The circumstances of the war may have played a role, as Boubaker et al. (2022) found an unexpected positive reaction of the U.S. stock market to the Ukraine invasion. They stated that investors may believe that this war will not escalate globally and that solutions will be found to mitigate the impact on energy supplies.

Overall, the event study results are mixed and ambiguous, with different fuzzy trends and magnitudes of (C)AARs across different event windows. If one focuses on the effect of all positive or all negative events on stocks during the total sample, one finds exactly the opposite results than hypothesis 1 states. These are, however, varying between energy commodity type and the length of event windows. Nevertheless, when considering subperiods, a clearer trend is found. Although there is evidence of time series momentum in three of the four subperiods, indicating a consistent influence of energy price movements during specific periods, the Covid-19 outbreak phase stands out as an exception with inconsistent results. Additionally, there is a tendency for (C)AARs to become larger as the event window lengthens, indicating the influence of increasing noise. Moreover, it should be kept in mind that the results may be slightly affected by the chosen balanced event windows as the pre- and post-reactions sometimes differ somewhat. Especially for the longer event window of [-3,3] the momentum trend of the times series becomes somewhat fuzzy and debatable. So inconsistent results and trends are found, sometimes even against the hypothesis. Yet even in the pre- and post-event reactions it is challenging to detect a clear trend. Therefore, this insufficient and varying evidence ensures that hypothesis 1 cannot be accepted.

Table 6: Significance of the (cumulative) average abnormal returns

This Table reports the event study results of AAR_0, $CAAR_{(-1,1)}$, and $CAAR_{(-3,3)}$ indicating the (cumulative) average abnormal returns on the event day and over a 3- and 7-day event window, respectively. The (C)AARs are calculated for 1,326 firms using a constant mean return model with an 8-day estimation window during a sample period from March 2020 to October 2022. An extreme energy price change is referred to as an event if the daily energy price is at least 15% higher than the previous day, resulting in a total of 47 events, of which 29 energy price increases and 18 energy price decreases. Afterwards, these AARs are aggregated across all firms and all positive and negative events categorized by energy commodity. To test whether the (C)AARs are significantly different from zero a two-sided t-test (MacKinlay, 1997), a BMP test correcting for event-induced volatility (Boehmer et al., 1991) and a generalized sign test (Kolari & Pynnonen, 2011) are used. The statistical significance is indicated by ***, **, and * at the 1%, 5% and 10% level.

Extreme changes in oil prices													
Event direction	**Obs.**	**AAR_0**	**t-value**	**Z-value**	**BMP**	**$CAAR_{(-1.1)}$**	**t-value**	**Z-value**	**BMP**	**$CAAR_{(-3.3)}$**	**t-value**	**Z-value**	**BMP**
Positive	10,608	1.478%	20.497***	16.050***	18.165***	-2.827%	-27.073***	-33.058***	-24.601***	-0.168%	-0.982	-2.018**	-3.524***
Negative	6,630	-3.912%	-43.067***	-41.174***	-42.692***	0.438%	2.895***	-1.176	0.125	-2.286%	-8.824***	-12.483***	-16.711***
Extreme changes in gas prices													
Event direction	**Obs.**	**AAR_0**	**t-value**	**Z-value**	**BMP**	**$CAAR_{(-1.1)}$**	**t-value**	**Z-value**	**BMP**	**$CAAR_{(-3.3)}$**	**t-value**	**Z-value**	**BMP**
Positive	19,890	0.047%	2.134**	1.186	1.675*	0.493%	12.168***	12.172***	14.088***	1.404%	18.123***	18.632***	19.926***
Negative	10,608	-0.135%	-4.836***	-4.745***	-6.873*	-1.240%	-22.017***	-21.947***	-23.842***	-2.428%	-26.601***	-28.964***	-29.961***
Extreme changes in coal prices													
Event direction	**Obs.**	**AAR_0**	**t-value**	**Z-value**	**BMP**	**$CAAR_{(-1.1)}$**	**t-value**	**Z-value**	**BMP**	**$CAAR_{(-3.3)}$**	**t-value**	**Z-value**	**BMP**
Positive	7,956	0.331%	9.352***	8.444***	11.408***	-0.328%	-4.895***	-2.364**	-3.971***	1.945%	17.173***	18.641***	27.531***
Negative	6,630	0.197%	6.046***	3.092***	10.008***	0.858%	14.760***	17.254***	16.114***	-1.587%	-13.337***	-16.147***	-11.637***
Total changes in energy prices													
Event direction	**Obs.**	**AAR_0**	**t-value**	**Z-value**	**BMP**	**$CAAR_{(-1.1)}$**	**t-value**	**Z-value**	**BMP**	**$CAAR_{(-3.3)}$**	**t-value**	**Z-value**	**BMP**
Positive	38,454	0.501%	20.610***	13.490***	12.495***	-0.593%	-15.228***	-13.735***	-3.503***	1.082%	16.332***	19.389***	28.038***
Negative	23,868	-1.092	-34.504***	-30.877***	-24.293***	-0.191%	-3.683***	-9.256***	-9.269***	-2.155%	-24.210***	-33.904***	-34.471***

Table 7: Significance of the (cumulative) average abnormal returns distributed over four subperiods

This Table reports the event study results of AAR_0, $CAAR_{(-1,1)}$, and $CAAR_{(-3,3)}$ indicating the (cumulative) average abnormal returns on the event day and over a 3- and 7-day event window, respectively, divided into four different subperiods. The (C)AARs are calculated for 1,326 firms using a constant mean return model with an 8-day estimation window during a sample period from March 2020 to October 2022. An extreme energy price change is referred to as an event if the daily energy price is at least 15% higher than the previous day, resulting in a total of 47 events, of which 29 energy price increases and 18 energy price decreases. Afterwards, these AARs are aggregated across all firms and all positive and negative events categorized by energy commodity. The first subperiods is the Covid-19 outbreak phase from March 2020 to June 2020. The second subperiod represents the Covid-19 follow-up phase from July 2020 until June 2021, while the third subperiod covers the recovery phase of Covid-19 from July 2021 to February 21, 2022. Finally, the last subperiods represents the period around the Russia-Ukraine war from February 21, 2022, to October 2022. To test whether the (C)AARs are significantly different from zero a two-sided t-test (MacKinlay, 1997), a BMP test correcting for event-induced volatility (Boehmer et al., 1991) and a generalized sign test (Kolari & Pynnonen, 2011) are used. In this table, statistical significance is shown only for the two-sided t-test, with significance indicated by ***, **, and * at the 1%, 5% and 10% level. No significant differences were found with the other statistical tests.

Positive events

Covid-19 outbreak phase			**Covid-19 follow-up phase**			**Covid-19 recovery phase**			**Russia/Ukraine war**		
Oil prices (10,608)			*Oil prices (0)*			*Oil prices (0)*			*Oil prices (0)*		
$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$
1.478%***	-2.827%***	-0.168%	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Gas prices (2,652)			*Gas prices (11,934)*			*Gas prices (2,652)*			*Gas prices (2,652)*		
$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$
2.195%***	0.609%***	-1.547%***	-0.771%***	-0.545%***	-0.776%***	1.670%***	3.509%***	8.364***	-0.072%*	2.036%***	7.203%***
Coal prices (1,326)			*Coal prices (0)*			*Coal prices (1,326)*			*Coal prices (5,304)*		
$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$
-0.461%***	-3.583%***	-4.735%***	N/A	N/A	N/A	1.549%***	0.730%***	3.836%***	0.224%***	0.221%**	3.142%***
Total energy prices (14,586)			*Total energy prices (11,934)*			*Total energy prices (3,978)*			*Total energy prices (7,956)*		
$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$
1.432%***	-2.271%***	-0.834%***	-0.771%***	-0.545%***	-0.776%***	1.650%***	2.583%***	6.855%***	0.125%***	0.826%***	4.496%***

Negative events

Covid-19 outbreak phase			**Covid-19 follow-up phase**			**Covid-19 recovery phase**			**Russia/Ukraine war**		
Oil prices (6,630)			*Oil prices (0)*			*Oil prices (0)*			*Oil prices (0)*		
$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$
-3.192%***	0.438%***	-2.286%***	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Gas prices (0)			*Gas prices (7,956)*			*Gas prices (1,326)*			*Gas prices (1,326)*		
$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$
N/A	N/A	N/A	-0.105%***	-0.993%***	-1.958%***	0.047%	1.457%***	-0.791%***	-0.499%***	-5.423%***	-6.883%***
Coal prices (0)			*Coal prices (0)*			*Coal prices (1,326)*			*Coal prices (5,304)*		
$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$
N/A	N/A	N/A	N/A	N/A	N/A	1.181%***	1.349%***	1.792%***	-0.207%***	0.735%***	-2.431%***
Total energy prices (6,630)			*Total energy prices (7,956)*			*Total energy prices (2,652)*			*Total energy prices (6,630)*		
$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1,1)}}$	$\mathbf{CAAR_{(-3,3)}}$
-3.192%***	0.438%***	-2.286%***	-0.105%***	-0.993%***	-1.958%***	0.929%***	1.403%***	0.501%***	-0.266%***	-0.496%***	-3.321%***

5.2 Firm characteristics in stock reactions to energy price changes

Once the significance of the (C)AARs has been tested, the remaining hypotheses are analyzed using several pooled OLS regressions in which different independent variables are regressed on the CARs of all individual firms in the sample. All these models incorporate a unique independent variable consisting of a firm's total ESG score, its individual pillars Environmental (E), Social (S) and Corporate Governance (G) scores, political affiliation or $\mathrm{CO_2}$ intensity. Finally, every model incorporates a set of control variables consisting of a firm's leverage, cash, ROA, firm size, and industry classification.

5.2.1 Influence of ESG scores

To examine the second hypothesis, on the positive impact of higher ESG performance on a firms' abnormal returns, two regression models are created. The first model measures the effect of total ESG ratings, the results of which are presented in columns 1 of Table 18 with total ESG rating as the variable of interest. For the day of the event, the 3- and 7-day windows, the coefficients are 0.001, 0.003 and 0.006, respectively. As can be seen, the positive influence of ESG scores on the abnormal reaction to energy price changes increases as the event window increases. In principle, these results support Pastor et al.'s (2021) findings that stocks of firms with higher ESG scores can be used as hedges against negative climate-related news, such as unexpected energy price changes. However, the coefficients are not statistically significant for all event windows, offering no clear evidence of this positive relationship. Besides, the coefficients are quite low to have real economic value. These findings align with Bae et al. (2021), who argue that ESG performance does not provide protection for firms' stocks against negative events during specific periods, such as Covid-19. The constant term remains negative and insignificant across all three regressions. Moreover, a second model is employed with a dummy variable $High\,ESG$ as main independent variable, shown in columns 2 of Table 18. Using this alternative proxy for a firm's ESG performance results in considerably lower coefficients. A coefficient close to zero on $High\,ESG$ was found when the AAR on the event day is used as the dependent variable. Furthermore, the output reveals relatively small coefficients of 0.001 and 0.002 for the 3- and 7-day event windows, respectively, indicating that firms with high ESG ratings experience around 0.2% higher abnormal stock returns compared to those with low ESG ratings during a 3-day event window. This aligns with Engelhardt et al. (2020), who employed a similar dummy variable and found better performance of high ESG-rated firms during the Covid-19 period. Nevertheless, his findings exhibit significance and higher estimates, while here the variable $High\,ESG$ lack statistical significance, as does the negative constant term. Regarding control variables, all firm-specific variables, except for ROA, are statistically insignificant and present similar patterns in both models. ROA has a negative impact of -0.032 at the 10% level for $\mathrm{CAR}_{(-3,3)}$. This suggest that more profitable firms are more sensitive to changes in energy prices, contradicting previous studies (Haugen & Baker, 1996; Aggarwal et al., 2012). However, this negative influence is weaker and insignificant for AR_0 and $\mathrm{CAR}_{(-1,1)}$, questioning the reliability of this influence. Statistical insignificance of the remaining control variables prevents drawing definitive inferences; however, some insights emerge. Leverage negatively affects firm's abnormal returns following energy price changes, consistent with Deng et al. (2020). Higher cash availability has a positive impact on a firm's abnormal returns on the event day but turns into a negative impact during the 3- and 7-day event windows, contrary to expectations (Albuquerque et al., 2020). Finally, firm size does not appear to affect firms' abnormal returns following events with coefficients close to zero.

Finally, the relatively small (adjusted) R^2 in both models is notable. The adjusted R^2 ranges from 0.68% to 1.89%, depending on the specific dependent variable employed. The regression models with $CAR_{(-1,1)}$ have the highest explanatory power, while the AR_0 model shows the lowest. These low R^2 values suggest that the independent variables have limited explanatory power for the variation of the dependent variables (Brooks, 2019). Possible reasons include the somewhat futile nature of firms' ARs and the potential omission of relevant variables, especially in models with CARs as dependent variables, which is further discussed in section 5.3. Additional reasons could be the presence of outliers or high multicollinearity, however, in this study these potential problems have already been tested and corrected. Furthermore, the high level of noise during this turbulent period may affect the explanatory value. Besides, it is even shown that the (adjusted) R^2 decreases when the event window is extended from three to seven days, supporting the notion of sufficient explanatory power in short-term windows (Brown & Warner, 1980). Finally, the inclusion of annual ESG data rather than shorter-term ESG data, such as monthly data, may play a role as well (Kothari & Warner, 2007). This latter reduces accuracy and possibly explanatory value, leading to difficulties in determining market efficiency. In conclusion, the model assessing the impact of total ESG scores reveals only small effects on U.S. stock performance. However, these coefficients lack statistical significance. The second regression model yields even smaller insignificant coefficients. More specifically, the influence of higher ESG performance on abnormal returns is practically negligible the day of an extreme energy price change. These insignificant independent variables and low (adjusted) R^2 indicate that higher ESG performance does not positively affect a firm's abnormal returns during extreme changes in oil, natural gas, or coal prices. Therefore, the second hypothesis is not accepted.

5.2.2 Influence of a firm's environmental score

To answer hypothesis 3a, two different methods are used. This hypothesis states that the positive effect of a firm's ESG performance on its abnormal returns during an event is driven by its environmental performance, proxied by the environmental (E) pillar of the ESG score. First, an event study is employed where the $\overline{\text{CAAR}}$s of two portfolios are compared, where the first (second) portfolio consist of firms with an average environmental score below (above) the median score. A two-sample t-test was performed to test the significance of the differences in their $\overline{\text{CAAR}}$s, summarized in Table 19 in appendix D.

Consistent with the findings of the general event study, Table 19 does not show unambiguous results, making it difficult to draw definitive interpretations. On the day of an extreme increase or decrease in energy prices, there was no meaningful and statistically significant difference between both type of firms. Examining the specific energy commodity, it is revealed that firms with low environmental scores perform better after positive oil and negative coal events but perform weaker after positive natural gas events. However, these significant differences are primarily driven by a few specific events (Table 13, Appendix D). For example, the better performance of firms with low environmental scores after positive oil events can be traced to the strong reactions on March 19, 2020, and April 29, 2020. A 3-day event window shows that both portfolios have negative CAARs, however, firms with low environmental scores perform worse than those with high scores, resulting in a significant difference of -0.368%. This underperformance may be primarily due to weaker responses to gas and coal price increases, supporting the findings of Engle et al. (2017). Similarly, they ranked firms based on their environmental score and found that firms with high scores can be used as a hedge against negative climate-related news, such as fossil fuel price increases. Conversely, firms with a low environmental score respond less negative to energy price decreases than firms with a high score. This difference in CAARs amounts to 0.357%, significant at the 1% level. In the 7-day event window there is no significant difference in reaction to energy price decreases. However, after an energy price increase, low-scoring firms exhibit significantly worse negative CAARs of -0.618% than high-scoring firms (Engle et al., 2017). Overall, surprisingly, it appears that firms with low environmental scores are less sensitive to energy price changes, which can either benefit or harm them depending on the direction of the price change. One possible reason could be that the low-scoring portfolio contains relatively many energy-producing firms because they tend to have lower environmental scores, so they may react differently to energy price changes because they use energy commodities differently, such as an output.

Next, hypothesis 3a is also tested using a pooled OLS regression in which the total ESG score is broken down into its three pillars, environmental (E), social (S), and governance (G), shown in Table 18. To address potential multicollinearity, columns 3 present regression models with only the environmental pillar as independent variable. Additionally, columns 4 include all three pillars, as it can be assumed that multicollinearity is not a significant issue, as the VIF value of this model remains well below five.

Columns 3 of Table 18 show that a firm's environmental score does not affect the abnormal returns on the day of an extreme energy price change. Once the event window is extended to three or seven days, a firm's environmental score comes into play with estimates of 0.002 and 0.005, respectively. However, none of this show significance and the constants of all models are insignificantly negative. Moreover, none of the control variables are significant, except for ROA, and all show similar estimates as observed in previous models. Columns 4 confirm that none of the environmental, social, and governance pillars has a significant effect on the relationship between energy price changes and stock performance. This aligns with the findings of Boldeanu et al. (2022), who also concluded that environmental, social and governance scores had no significant impact on stocks during Covid-19. One possible reason for this similarity is the overlapping periods covered by both studies, as many energy price changes occurred during the Covid-19 pandemic. Despite the insignificance, some interesting patterns emerge. For example, the regressions with AR_0 as independent variable display that only the governance pillar has a modest impact on firms' abnormal returns. Again, there is no effect of the environmental score. Nevertheless, both the environmental and governance pillars have a positive effect on the 3-day CAR while the social pillar has no effect. Again, this influence becomes more pronounced when considering a longer event window, with the environmental pillar having the largest impact of 0.005 during a 7-day window. These positive estimates of environmental scores suggest that firms with higher environmental performance react less negatively to unexpected changes in fossil fuel prices, supporting the findings of Pastor et al. (2020). Besides, good governance performance has a positive impact of 0.003, while surprisingly the social pillar negatively affects firms' abnormal returns during a 7-day event window. Again, all models have low (adjusted) R^2, indicating low explanatory value. This is logic since the models replicate earlier ones by using the individual components of the total ESG rating. Therefore, the same reasons can be given for this low explanatory value.

In conclusion, both methods show no impact of a firm's environmental performance on its abnormal returns on the event day. Nonetheless, the event study results reveal that firms with high environmental scores outperformance those with low scores after energy prices increases. This, however, is reversed when energy prices decrease, resulting in contradictory findings. Moreover, the regressions with the separate pillars of ESG scores show that a firm's environmental score has a small but insignificant impact on abnormal returns over longer event windows. So, the lack of economic and statistical significance is evident in all these interpretations. Consequently, there is no sufficient evidence to accept hypothesis 3a.

5.2.3 Influence of carbon dioxide intensity

To examine hypothesis 3b, which predicts that the positive effect of a firm's ESG performance on its abnormal returns during an event is driven by a firm's environmental performance, proxied by CO_2 intensity, a regression model is constructed. In this model, the variable of interest is a firm's CO_2 intensity and serves as an alternative and more objective measure of a firm's environmental performance than its ESG ratings. These results are presented in columns 1 of Table 19, although it should be noted that the number of observations is considerably lower than in previous regression models due to limited data availability on firms' CO_2 intensity. On the day of an extreme energy price increase or decrease, there is no influence of a firm's CO_2 intensity on abnormal returns. Yet, this outcome is statistical insignificant. When the dependent variable is changed to a 3-day event window, there is still no impact of CO_2 intensity on the reaction of stocks to energy price changes. However, this outcome has become statistically significant, allowing for interpretation. This contradicts the findings of Jung et al. (2016), who argued that lower CO_2 intensity positively affects a company's stock price, as it will be positively valued by investors. Here, the opposite result indicates that during this more recent and turbulent period, investors valued CO_2 intensity less or not at all. Surprisingly, for the model with the 7-day CAR a coefficient of 0.001 is found, significant at 5%. This suggests that firms with higher CO_2 intensity will have more positive abnormal returns following extreme energy price changes than firms with lower CO_2 intensity, even if this generally means greater reliance on fossil fuels. This conflicts with the findings of Kick & Rottmann (2022), who focussed on the period following the Ukraine invasion, which is also covered in this study. Yet, they find abnormal underperformance for firms with higher CO_2 intensity, arguing that this is because the war has far-reaching implications for energy supplies and prices. The unexpected findings may be due to the low sample size, which may not accurately represent all firms and lead to different results than larger samples (Jung et al., 2016; Kick & Rottmann, 2022). Finally, the constant term is still negative and insignificant, and the coefficients of the control variables are still quite similar. However, firm size show now a positive effect during a 7-day event window, consistent with Lins et al. (2017), although insignificant. The explanatory value remains low, with a slightly higher value observed for the 3-day event window model. In this model, another possible reason for the generally low explanatory value is the smaller sample size.

In conclusion, it was expected that the higher a firm's CO_2 intensity, the worse its environmental performance and therefore a negative coefficient was expected. However, the results indicate that a firm's

CO_2 intensity has no or a modest positive effect on its abnormal returns after extreme energy price changes. Nevertheless, the economic significance of these results is quite low. Hence, hypothesis 3b is not accepted.

5.2.4 Influence of political affiliation

Finally, the last hypothesis is tested by including two different independent variables in the models. This hypothesis predicts that a Democratic-leaning firm will positively influence a firm's abnormal returns following extreme energy price changes. First, the impact of a firm's political affiliation on its abnormal returns is examined using a dummy variable that equals one if the firm's headquarter is located in a state where Democrats has won, and zero otherwise. Columns 3 of Table 19 show that this variable coefficient estimate of this independent variable is negative but very close to zero on the day of an extreme energy price change. Yet this value shows no significance. When the dependent variable is changed to the 3- and 7-day CAR, this negative influence increases to -0.002 and -0.004, respectively, with only the latter being significant at 5%. This implicates that Democratic-leaning firms have lower abnormal performance in the seven days around an energy price change than Republican-leaning firms, contradicting the expectations based on the work of Di Giuli and Kostovetsky (2014). They showed that Democratic-leaning firms spend more money on their environmental performance, such as investments in energy use innovations that reduce dependence on fossil fuels. This environmental-friendly strategy should theoretically make them less vulnerable to fossil fuel price changes, therefore, the opposite effect found in this study is surprising. In addition, the dummy variable is replaced by a variable that represents the percentage of votes the Democratic candidate received in the state where a firm is headquartered during the presidential election. Columns 3 of Table 19 demonstrate similar results to the dummy variable, although slightly larger coefficients. According to this model, being a Democratic-leaning firm result in lower 7-day CARs of -0.016, significant at 10%. This contradicts Rubin (2008), who concluded that Republican-leaning firms have a worse environmental performance of -0.0125. One possible reason for these contrary findings may be that the relation between Democratic (Republican) ties and a firm's better (worse) environmental performance has blurred in recent years. Again, both models show a low (adjusted) R^2. Therefore, another regression model is employed including both the dummy and CO_2 intensity variable, since both are proxies for a firm's environmental performance without significant correlation. The president votes (%) is excluded from this model to avoid multicollinearity problems, as it highly correlates (0.761) with the Democratic dummy variable. Columns 4 of Table 19 show somewhat different results to the earlier analysis. The negative effect of the Democratic dummy increased slightly to -0.004 and is significant for the 3-day event window. Besides, the (adjusted) R^2 increases but remains relatively low, suggesting that the combination of these variables only contributes slightly to the explanatory power. Finally, the estimates of the control variables remain similar. Ooverall, the regression models yield findings contrasting expectations, which shows that a firm's Democratic disposition negatively impacts abnormal returns during extreme energy price changes. However, this effect is relatively small for all event windows and only significant for the 7-day event window. So, in addition to the opposite result than the hypothesis states, many interpretations lack both economic and statistical significance, leading to non-acceptance of hypothesis 4.

Table 8: Regression model results measuring the influence of ESG performance on abnormal returns

This Table presents the results of the pooled OLS regressions in which a firm's ESG performance is regressed on the (C)ARs of all 1,326 individual firms. The dependent variable consists of a firm's AR_0, $CAR_{(-1,1)}$, or $CAR_{(-3,3)}$ indicating the (cumulative) abnormal returns on the event day and over a 3- and 7-day event window, respectively. The (C)ARs are calculated for all 1,326 firms using a constant mean return model with an 8-day estimation window during a sample period from March 2020 to October 2022. An extreme energy price change is referred to as an event if the daily energy price is at least 15% higher than the previous day, resulting in a total of 47 events, of which 29 energy price increases and 18 energy price decreases. Columns 1 shows the regression results with the total ESG score as main independent variable, while columns 2 presents the influence of having a total ESG score higher than the median score of the whole sample. Columns 3 show the results of the models using only the individual environmental pillar of the total ESG score as the main independent variable. Columns 4 present the results of the models including all three individual pillars of the total ESG score: environmental, social, and corporate governance. All regression models include a set of control variables including firm size calculated as the natural logarithm of a firm's total assets, leverage as the ratio of a firm's total debt to total assets, total cash holdings, and returns on assets (ROA) a firm's total net income relative to its total assets. All regression models include industry and year fixed effects and control for autocorrelation and heteroskedasticity by using robust standard errors, clustered by events. The p-values are reported in parentheses and the statistical significance is indicated by ***, **, and * at the 1%, 5% and 10% level, respectively.

	AR_0				**$CAR_{(-1,1)}$**				**$CAR_{(-3,3)}$**			
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
ESG	0.001				0.003				0.006			
	(0.002)				(0.003)				(0.006)			
High_ESG		0.000				0.001				0.002		
		(0.000)				(0.001)				(0.001)		
Environmental			0.000	-0.000			0.002	0.002			0.005	0.005
			(0.001)	(0.001)			(0.002)	(0.002)			(0.004)	(0.004)
Social				0.000				0.000				-0.002
				(0.002)				(0.003)				(0.004)
Governance				0.001				0.002				0.003
				(0.001)				(0.002)				(0.002)
Leverage	-0.002	-0.002	-0.002	-0.002	-0.005	-0.005	-0.005	-0.005	-0.009	-0.009	-0.010	-0.010
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)
Cash	0.002	0.001	0.001	0.002	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005	-0.004	-0.004
	(0.004)	(0.004)	(0.004)	(0.003)	(0.007)	(0.007)	(0.007)	(0.007)	(0.011)	(0.011)	(0.011)	(0.011)
ROA	-0.005	-0.005	-0.005	-0.005	-0.009	-0.008	-0.009	-0.009	-0.032*	-0.032	-0.033*	-0.033*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.010)	(0.010)	(0.010)	(0.010)	(0.018)	(0.018)	(0.018)	0.018)
Firm size	-0.000	-0.000	-0.000	-0.000	-0.000	0.000	-0.000	-0.000	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-0.001	-0.002	-0.002	-0.002	-0.007	-0.007	-0.006	-0.007	-0.003	-0.003	-0.000	-0.002
	(-0.001)	(0.010)	(0.010)	(0.010)	(0.014)	(0.014)	(0.019)	(0.014)	(0.024)	(0.024)	(0.023)	(0.023)
Observations	57,199	57,199	57,199	57,199	57,199	57,199	57,199	57,199	57,199	57,199	57,199	57,199
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0071	0.0071	0.0071	0.0071	0.0191	0.0191	0.0191	0.0192	0.0190	0.0190	0.0190	0.0190
Adjusted R^2	0.0068	0.0068	0.0068	0.0068	0.0189	0.0189	0.0189	0.0189	0.0187	0.0187	0.0187	0.0188

Table 9: Regression model results measuring the influence of several proxies of a firm's environmental performance on abnormal returns

This Table presents the results of the pooled OLS regressions in which a several proxies for a firm's environmental performance is regressed on the (C)ARs of all 1,326 individual firms. The dependent variable consists of a firm's AR_0, $\mathrm{CAR}_{(-1,1)}$, or $\mathrm{CAR}_{(-3,3)}$ indicating the (cumulative) abnormal returns on the event day and over a 3- and 7-day event window, respectively. The (C)ARs are calculated for all 1,326 firms using a constant mean return model with an 8-day estimation window during a sample period from March 2020 to October 2022. An extreme energy price change is referred to as an event if the daily energy price is at least 15% higher than the previous day, resulting in a total of 47 events, of which 29 energy price increases and 18 energy price decreases. Columns 1 shows the regression results with CO_2 intensity as main independent variable, where CO_2 intensity is a firm's total CO_2 and CO_2 equivalent emissions in tonnes, divided by its total assets. Columns 2 show the results of the models using a firm's political affiliation as independent variable of interest, which is denoted as a dummy variable that takes a value of one if the firm's headquarter is located in a state where a Democrat won, and zero otherwise. Columns 3 presents the results of the models that proxied a firm's political affiliation with the help of the variable presidential votes that reflect the percentage of votes that is received by the Democratic candidate Biden in the 2020 presidential election in the state where the firm's headquarter is located. Finally, columns 4 demonstrate the results of the models that combines two independent variables: CO_2 intensity and political affiliation. All regression models include a set of control variables including firm size calculated as the natural logarithm of a firm's total assets, leverage as the ratio of a firm's total debt to total assets, total cash holdings, and returns on assets (ROA) a firm's total net income relative to its total assets. All regression models include industry and year fixed effects and control for autocorrelation and heteroskedasticity by using robust standard errors, clustered by events. The p-values are reported in parentheses and the statistical significance is indicated by ***, **, and * at the 1%, 5% and 10% level, respectively.

	$\mathbf{AR_0}$				$\mathbf{CAR_{(-1,1)}}$				$\mathbf{CAR_{(-3,3)}}$			
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
CO2 intensity	0.000			0.000	0.000**			0.000*	0.001**			0.001
	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)
Democratic dummy		-0.000		-0.001		-0.002		-0.004**		-0.004**		-0.007
		(0.001)		(0.001)		(0.001)		(0.002)		(0.002)		(0.003)
Democratic percentage			-0.002				-0.006				-0.016*	
			(0.004)				(0.006)				(0.009)	
Leverage	-0.001	-0.002	-0.002	-0.001	-0.004	-0.005*	-0.005	-0.005*	-0.005	-0.010	-0.010	-0.007
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.006)	(0.006)	(0.005)
Cash	0.003	0.002	0.002	0.004	-0.003	-0.005	-0.004	-0.001	0.004	-0.004	-0.003	0.009
	(0.004)	(0.003)	(0.003)	(0.004)	(0.009)	(0.007)	(0.007)	(0.009)	(0.015)	(0.011)	(0.010)	(0.015)
ROA	-0.007	-0.005	-0.005	-0.007	-0.014	-0.008	-0.008	-0.013	-0.044	-0.031*	-0.032*	-0.042
	(0.011)	(0.007)	(0.007)	(0.011)	(0.017)	(0.010)	(0.010)	(0.016)	(0.030)	(0.018)	(0.018)	(0.029)
Firm size	-0.000	-0.000	-0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-0.004	-0.002	-0.001	-0.004	-0.015	-0.008	-0.006	-0.013	-0.020	-0.005	0.001	-0.016
	(0.012)	(0.011)	(0.012)	(0.012)	(0.016)	(0.015)	(0.017)	(0.016)	(0.027)	(0.026)	(0.028)	(0.027)
Observations	27,871	57,199	57,199	27,871	27,871	57,199	57,199	27,871	27,871	57,199	57,199	27,871
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0077	0.0071	0.0071	0.0078	0.0215	0.0192	0.0191	0.0221	0.0194	0.0191	0.0191	0.0201
Adjusted R^2	0.0072	0.0068	0.0068	0.0073	0.0210	0.0190	0.0189	0.0216	0.0189	0.0189	0.0188	0.0195

5.3 Robustness test

To examine the robustness of the main results, several robustness tests are conducted. The main findings of these tests are documented in Appendix E. In the event study analysis various minor changes were made to see if the results remained robust. First, this study retains firms in the ‘finance, insurance & real estate’ sector whereas these types of firms are usually removed from the sample due to specific rules surrounding this sector. Here, 309 of such firms were included in this sample, but removing them did not affect the results, suggesting that the findings are robust to this selection criteria. Secondly, this study used an 8-day estimation window, however following McKenzie (2004) this was also expended to 31 and 61 days, to examine the sensitivity of (C)AARs to different estimation windows. While the change in reactions varied for different events, the overall findings remained unchanged, still indicating no clear trend.

According to the first hypothesis, several methods are available for calculating normal returns in the event study. The baseline model uses the constant mean return model with an 8-day estimation window. However, the rapid sequence of events results in event clustering, potentially leading to inaccurate results. To test the robustness of these estimations, the normal returns are also calculated using a market-adjusted model without an estimation window, ensuring no overlap between event windows and estimation windows (MacKinlay, 1997). The only overlap left is for event windows of different events. This model requires the use of a market portfolio, which in this case should represent the entire U.S. stock market as closely as possible because this study already focuses on a large sample of U.S.-listed firms. Therefore, the CRSP U.S. Total Market Index is used, which includes almost 4,000 stocks across mega, large, small, and micro capitalizations (CRSP U.S. Total Market Index | CRSP – The Centre for Research in Security Prices, z.d.). Tables 20 to 22 show the results of this robustness test. Aggregation of the (C)AARs across all positive and negative events leads to different results, shown in Table 21. Now, a positive reaction is found for both types of events regardless of the event window length, leading to a clearer trend. The previously found negative 3-day CAAR on energy price increases now changes to a significantly positive reaction, albeit still small. Even more surprising, all energy price decreases lead to positive reactions, aligning with the existing literature (Oberndorfer, 2009; Benkraiem et al., 2018). This rigorous change in the directional reaction to negative events can be predominantly attributed to several events that previously showed an extremely negative reaction but now significantly decreased in magnitude or even changed to a positive reaction. For example, oil price decrease on April 20, 2020, previously caused a 7-day CAAR of -17.683% but now changes to a negative CAAR of only -1.056%, seen in Table 20. When the (C)AARs are divided into subperiods, the results are also somewhat different, shown in Table 22. Focussing on the Covid-19 outbreak phase, a clear trend in direction or magnitudes remains elusive. Although a positive response is found after energy price increases for all event windows, the magnitudes still vary inconsistently. For negative events, the magnitudes decrease considerably when using the market-adjusted model. Moreover, all results for the Covid-19 follow-up phase change direction, so the negative reaction to positive energy price changes is now consistent with expectations (Ahmed & Sarkodie, 2021). The findings for the Covid-19 recovery phase are quite similar, although the size of the CAARs decreases for positive events and changes to a modest negative 7-day CAAR. Finally, during the period around the Russia/Ukraine war it is only notable that the

3- and 7-day CAAR appear to be positive, supporting earlier research (Boubaker et al., 2022). Thus, in general, using a different model to calculate normal returns yields somewhat different results. This difference in findings may be partially attributed to the removal of the estimation window or the specific choice to use the CRSP U.S. Total Market Index as a benchmark, all during an exceptionally turbulent period. Regardless of the exact reason for these changing findings, it can be concluded that the baseline results are sensitive to the choice of model employed for calculating normal returns. This means that the results should be interpreted with caution.

As discussed in section 4.2, one potential problem in this study may be endogeneity, which can be caused by a variety of reasons. In this study, endogeneity is most likely to result from biases due to omitted variable, where one or multiple independent variables are affected by factors that are not included in the models. To address this endogeneity concern, two control variables are added to the regression models to correct for possible omitted variables. First, a firm's P/E ratio is incorporated which is calculated by dividing the closing price of a common share by their earnings per share. A firm with a high P/E ratio is considered as a growth stock which is expected to grow above average and future high profits. This bright prospect is incorporated in the stock price while the current earnings are still relatively low. Therefore, if operating costs rise due to energy prices, these growth firms are expected to have smaller buffers than value firms to absorb such declines, because they rely heavily on future cash flows and success that are also expected to decline (Drempetic et al., 2020). Accordingly, it is expected that a high P/E ratio negatively influence abnormal returns after an extreme energy price change. Like the other accounting variables, the P/E ratio is winsorized at the 1% level. Second, a variable EXP is added, which reflects the percentage change in decrease or increase in daily oil, natural gas or coal prices. A larger percentage change in energy prices is expected to have a greater impact on firm's businesses hypothesizing a positive relationship (Mohanty et al., 2013). The results of these new regression models are reported in Tables 23 and 24 of Appendix E. First, Table 23 presents the findings for the regression models incorporating the total ESG rating and its individual pillars E, S and G. The result for all main independent variables remains the same after adding extra control variables. In addition, the P/E ratio has an insignificant effect very close to zero while the EXP variable has a large positive influence on abnormal returns. However, the latter effect is significant only for the event-day and 7-day CAAR. Table 24 present the results for the models that include a firm's CO_2 intensity and political affiliation, showing again that the additional variables P/E and EXP change little in the estimates of the main independent variables. The only notable difference is a decrease in magnitude and loss of significance for the Democratic votes (%) variable in the 7-day CAR model. Although all coefficients remain the same in both models, there is a remarkable increase in the (adjusted) R^2, especially after including the variable EXP. This indicates that the relatively low explanatory value may be due to missing variables in the models that do explain variation in the models. In conclusion, there may be an omitted variable bias that cause a relatively low (adjusted) R^2. However, one must be careful when adding controls to regression models, as too many control variables can lead to overfitting, despite the higher (adjusted) R^2. Nevertheless, adding these omitted variables increases the explanatory value but leaves the estimates of the regression coefficients the same leading to unchanged conclusions. This indicates that the findings are relatively robust against endogeneity problems.

6 Conclusion

This paper aimed to examine the impact of extreme energy price changes on the stock performance of U.S.-listed firms, with a special focus on the influence of a firm's greenness. This study was motivated by the large fluctuations in energy prices observed in recent years due to the outbreak of Covid-19 (2020) and the Russia-Ukraine war (2022). Given the crucial role of energy commodities like oil, natural gas, and coal in global society and its industries, it is not surprising that previous studies have found notable effects of energy price swings on stock markets (Ahmed & Sarkodie, 2021). Moreover, in parallel with this energy crisis, the focus on sustainability is increasing, driven by the need to switch to clean energy and mitigate climate change. Investors now look critically at a firm's sustainability performance, as reflected in its ESG scores, for example. These recent developments may have led to possible shifts in macroeconomic conditions and financial markets. Therefore, this paper contributes to the existing literature by reassessing the previously found relationship between energy prices and stock markets considering the current energy transition and energy crisis. Furthermore, this study expands on previous literature by going beyond conventional measures for considering influences of a firm's sustainability performance, expressed not only through ESG scores as usual, but also through CO_2 intensity and political affiliation (Di Giuli & Kostovetsky, 2014; Ilhan et al., 2021). Examining this inventive combination of various aspects enhances understanding of the complex relationship between energy prices, stock performance and a firm's greenness and provides valuable insights for policymakers and investors. Therefore, this study seeks to answer the following research question:

How are the stocks of U.S.-listed firms affected by extreme changes in energy prices, and is this effect influenced by the greenness of a firm?

This analysis uses a sample of 1,326 U.S.-listed firms from March 2020 to October 2022 to study the impact of a 15% or more change in daily oil, natural gas and coal prices on their stock performance. Subsequently, the research question is answered by testing several hypotheses. The first hypothesis predicts that extreme positive (negative) energy price changes have negative (positive) effects on the stock performance of U.S.-listed firms, and to examine these effects, an event study methodology is applied. The resulting findings are mixed and ambiguous, with varying trends and magnitudes of (C)AARs across different event windows. In fact, when considering all energy commodities, a positive relationship was found between energy price fluctuations and stock prices, contradicting what was assumed (Benkraiem et al., 2018). However, clearer trends emerge when analyzing subperiods with some showing evidence of time series momentum and more consistent effects. Yet, the existence of structural breaks and increased noise with longer event windows contribute to the lack of conclusive evidence. Hence, the absence of clarity, ambiguous results, and sometimes contradictory findings do not support the acceptance of hypothesis 1 meaning that there is no clear effect of extreme energy price changes on the U.S. stock market. Moreover, using a market-adjusted model without an estimation window shows slightly different results, leading to a clearer trend, but still not enough supporting evidence for the acceptance of hypothesis 1. Yet, it highlights the sensitivity of the main results to the chosen model for calculating normal returns, indicating caution in interpreting the results.

Based on Pastor et al. (2021), the second hypothesis states that a higher ESG performance positively affects a firm's abnormal returns after an event, which is examined using regression models. The results of the first model, considering a firm's total ESG score, seems initially consistent with previous research showing that higher ESG scores act as hedges against bad climate-related news (Pastor et al., 2021). A small positive influence of ESG scores on abnormal returns to energy price changes is found on the event day (0.001) and during the 3-day (0.003) and 7-day (0.006) event windows, with the magnitude increasing as the length of the event window increases. Nevertheless, these coefficients lack statistical and economic significance. The second model, with a dummy variable for firms with high ESG scores, also yields insignificant results with even lower magnitudes (Bae et al., 2021). For instance, it appears that firms with high ESG scores experience only around 0.2% higher abnormal stock returns compared to those with low scores during a 3-day event window (i.e. [-1,1]). These small effects lack economic value in addition to their statistical insignificance. Overall, the analysis provides no evidence of a positive influence of a firm's higher ESG performance on its abnormal returns after an extreme energy price change, leading to the non-acceptance of hypothesis 2. This non-acceptance holds even when a firm's P/E ratio and the percentage change in decrease or increase in energy prices are added to the regression models as a robustness test.

Moreover, as the events in this study are related to climate change concerns, the positive effect of a firm's ESG performance on its abnormal returns during extreme energy price changes is assumed to be driven by its environmental performance, proxied by the environmental (E) pillar of the ESG score in hypothesis 3a. Both the event study and regression analysis fail to show significant influences of a firm's environmental score. While event study results indicate that firms with high environmental scores outperform firms with low scores after energy price increases, the opposite is observed when energy prices fall, leading to contradictory findings (Engle et al., 2017). Moreover, regression models examining the individual pillars of ESG scores show a small but insignificant coefficient of 0.005 of a firm's environmental score only in the 7-day event window (i.e. [-3,3]). Consequently, there is insufficient evidence supporting the assumption that a firm's environmental performance positively influences its abnormal returns after an event, and hypothesis 3a is not accepted. In addition, hypothesis 3b tested the same relationship, but now expressing a firm's environmental performance in terms of its CO_2 intensity. The regression outputs present either no effect or modest positive effects, contradicting the expectation of better abnormal returns for firms with lower CO_2 intensity because they are expected to be less dependent on fossil fuels (prices). However, the economic significance of these extremely small coefficient results is minimal, resulting in the non-acceptance of hypothesis 3b. This indicates that there is no evidence of better abnormal returns after an event when a firm has low CO_2 intensity. Both variants of hypothesis 3 are robust against adding the P/E ratio and the percentage change in decrease or increase in energy prices. Finally, hypothesis 4 suggests that being a Democratic-leaning firm positively affects abnormal returns after energy price changes. The regression results contradict expectations, indicating that a firm's democratic disposition negatively affects abnormal returns (Di Giuli & Kostovetsky, 2014). However, this is only significant for the 7-day event window (i.e. [-3,3]) with a coefficient of -0.004 but lacks economic and statistical significance for the other event windows, which remains consistent in the robustness test. Hence, hypothesis

4 cannot be accepted implying that a firm's Democratic disposition does not positively affect its abnormal returns after extreme energy price changes.

In conclusion, none of the hypotheses can be accepted due to ambiguous and insignificant results. Contrary to assumptions, a positive relationship is initially observed between energy price changes and the U.S. stock market. However, this relation is insignificant and changes direction and magnitude across subperiods and different event windows. A possible reason for this insignificance, is the focus on balanced event windows of [-1,1] and [-3,3] where pre- and post-event (C)AARs are more likely to cancel each other out compared to the use of pre- and post-event windows, like [0,1] and [0,3]. Although, it shown that this issue of eliminating pre- and post-event effects is not a major problem in this analysis, it does increase with the longer 7-day event window. For example, positive changes in oil prices result in a pre-event window [-3,0] of -0.904% while the post-event window [0,3] show a positive reaction of 2.215%. Consequently, the balanced event window [-3,3] presents a positive effect while this would be different if one focus on the pre- and post-effects separately. Moreover, the quite similar pre- and post-event reactions reinforce or diminish each other, resulting in somewhat different (insignificant) results than if one were to focus on both separately. This is for example shown in the reaction to gas price changes where the pre-event window [-3,0] of -1.620% is more negative than the post-event window [0,3] of -0.943%, making the balanced event window [-3,3] more negative. Furthermore, the sensitivity of baseline results to the choice of model used to calculate normal returns underscores the need for cautious interpretation. Therefore, the analysis revealed no clear effects of extreme energy price changes on the performance of U.S.-listed firms. This suggests that policymakers, when formulating energy and economic policies, should consider the possibility of no clear relation between energy prices and stock prices and that if there is a relationship, it will be complex and multidimensional. Furthermore, this study finds not economically and statistically significant evidence of influences of a firm's ESG score, environmental score, CO_2 intensity, or political affiliation on abnormal returns around extreme energy price changes. This indicates that a firm's greenness may not be a (sole) driver of stock market reactions to these events. Therefore, investors should consider a wide range of factors and indications when assessing the effects of energy price change on stock performance rather than using firms with a high level of greenness as a hedge.

6.1 Limitations and recommendations

This subsection discusses the limitations of the research and provides recommendations for future research. First, there are several limitations associated with the use of ESG data. While this paper examines daily changes in energy prices and stock returns, it uses Refinitiv's ESG scores, drawn from the Thomson Reuters ESG database, which are published annually. The inclusion of annual ESG data rather than shorter-term ESG data reduces accuracy of the results, leading to difficulties in determining the impact of ESG performance on the market efficiency following energy price changes (Kothari & Warner, 2007). Here, more frequent ESG data was not available, but for follow-up research it is recommended to do so, for example by including monthly ESG data from Sustainalytics. Furthermore, it is crucial to recognize that the choice of an ESG database can affect the results, as each rating agency has its own rating methodologies leading to different ESG scores. According to Berg et al. (2022), obtaining identical ESG scores from different rating agencies is almost impossible. This discrepancy can even lead to situations where firms receive high scores from one rating agency but receive low scores from another. It is thus interesting to examine the same research question using more than one ESG dataset to test the findings' reliability, as argued by Halbritter and Dorfleitner (2015).

Secondly, an event is defined as a 15% or more change in daily energy prices; in short, a fixed percentage is used to determine events. Despite using a comprehensive grid search, this remains a one-size-fits all threshold determined manually based on certain trade-offs. For example, consideration of a 15% threshold that resulted in more events may have led to different results than if a higher threshold of 20% or 25% with fewer events had been preferred. This makes the event study results sensitive to the author's personal preference. Moreover, this study chose to define events based on exceeding a certain level of return with respect to energy prices, as commonly found in literature (Hall & Kenjegaliev, 2017). In view of the rather turbulent period during the sample period when energy prices move in all directions, it would also be interesting to look at a volatility trigger. For example, Chiou and Lee (2009) proved that oil price volatility shocks cause slightly different responses in stock returns than just an oil price change. Therefore, identifying events based on a predefined threshold based on energy price volatility to see if such events cause significant market reactions is of interest for further research. However, this is still a predefined threshold, which creates a potential selection bias. Picolli et al. (2017) argue that fixed thresholds can affect outcomes because, for example, a 15% energy price change may be more surprising to investors during a calm period than during a turbulent period, such as a crisis. Since this study covers a period with a lot of uncertainty, it is advisable to conduct further research that includes a moving threshold, such as Picolli et al. (2017) to see if clear relationships between energy price fluctuations and stock performance can be found. Moreover, it is possible that an 15% energy price change may be seen as a considerably large price change for one energy market, such as the coal market with large cap stocks, while in another energy market it may be seen as a relatively small price change, such as the oil and gas market with small cap stocks. Furthermore, the underlying reason for an energy price change of 15% or more is not considered, as it is beyond the scope of this study. However, Kilian (2008) argued that it is necessary to separate the sources of energy price changes, such as an energy price change caused by a supply or demand shock, as this can have considerable effects on the impact of these change on stock prices. Future research might therefore consider grouping extreme energy price changes by cause to see if this plays a role in the outcomes.

Thirdly, this study suffers from event clustering, which can lead to inaccurate estimates and unreliable test statistics (Picolli et al., 2017). This problem has been addressed in several ways, such as short estimation and event windows and robust standard errors clustered by events. Although, there is no trend in the results for clustered events, the robustness test shows that event study results are sensitive to differences in estimation models for calculating normal returns where event clustering is less of an issue. This indicates that event clustering is indeed a limitation, which can be eliminated by removing overlapping events (MacKinaly, 1997). However, this may introduce a selection, as it requires manual determination of which event are removed. Further research is needed to determine if this event selection approach yields more reliable findings than with the event clustered standard errors used in this study. But not only event clustering can influence the results, other notable events that are not energy price changes can also undesirably influence the estimation and event windows, such as Covid-19 declarations and news reports about the Russia-Ukraine war. Identifying these specific events that affected stock market reactions during the sample period had been too challenging. Moreover, these events are closely correlated with energy price changes, making it difficult to remove all event days associated with news releases related to Covid-19 or the Russia-Ukraine war. In addition, due to time constraints, it was not verified whether any firm-specific events occurred on the event dates, making it possible that the event study results were influenced by responses to these types of events. All this leads to a potentially high level of short-term noise and may be a limitation for this study. Focusing on the long-term effects of extreme energy price changes can dampen this short-term noise, isolating the true impact of these energy price changes on stock performance. A possible method for this is using buy-and-hold abnormal returns (BHAR), as proposed by Friedhoff and Krahnhof (2022).

Finally, other recommendations can be proposed for further research. Due to data limitations, this sample is limited to publicly traded U.S. firms, disregarding private firms. Nonetheless, private firms are less scrutinized than publicly traded firms, which may result in private firms having fewer incentives and resources to disclose ESG data to obtain ESG scores (Berg et al., 2022). Moreover, private firms also differ from publicly listed firms in other business areas, such as the ease of raising new capital, flexibility in decision-making and investor expectations. These differences may cause private firms to react differently to extreme energy price changes resulting in the fact that the findings of this study cannot be applied to private firms. This leaves room for future research to include a sample of private firms to examine their response to extreme changes in energy prices. Moreover, as discussed in section 3.1.2., six extreme increases (decreases) in energy prices on day one is followed by another extreme increase (decrease) the next day, while three increases (decreases) are followed by an opposite extreme energy price change. These different developments could potentially contribute to the occurrence of momentum increases or crashes in the stock market, and thus potentially affect the event study results. For further research, it is therefore interesting to single out these specific events and examine their effects on the U.S. stocks separately. Moreover, this change in data selection allows to directly examine whether the results found in this study change if the double-day extreme energy price increases and declines are omitted. This becomes even more interesting if the sample period is made slightly larger to include potentially more double-day extreme price changes, making the conclusions even stronger.

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APPENDIX A Data collection and selection

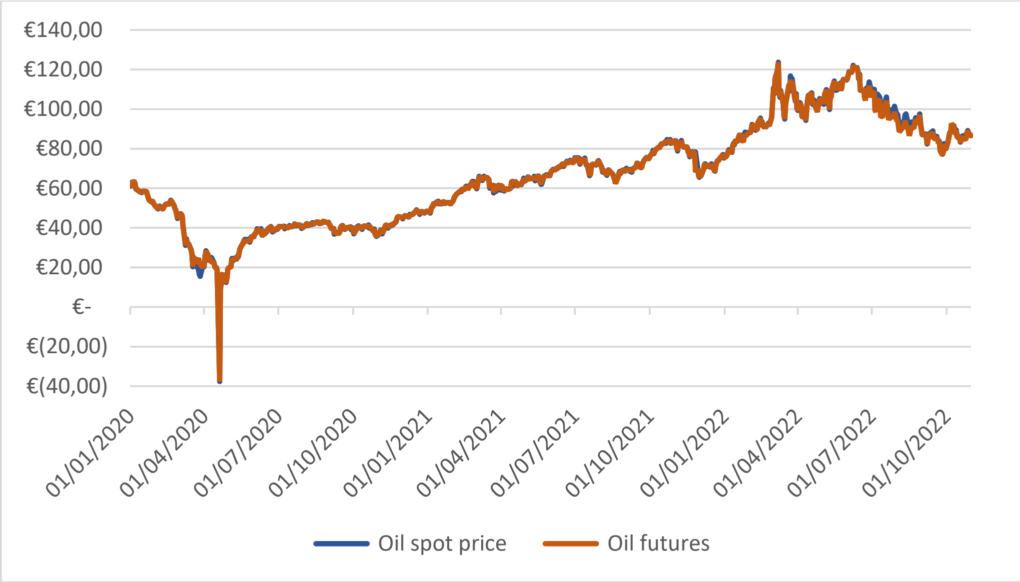

Figure 4: overview of spot and futures prices of oil
This Graph presents a comparison of the prices of the WTI crude oil spot price in Cushing, Oklahoma (blue line) and the NYM-Light Crude Oil TRc1 (red line) in the period from January 1, 2020, until October 30, 2022.

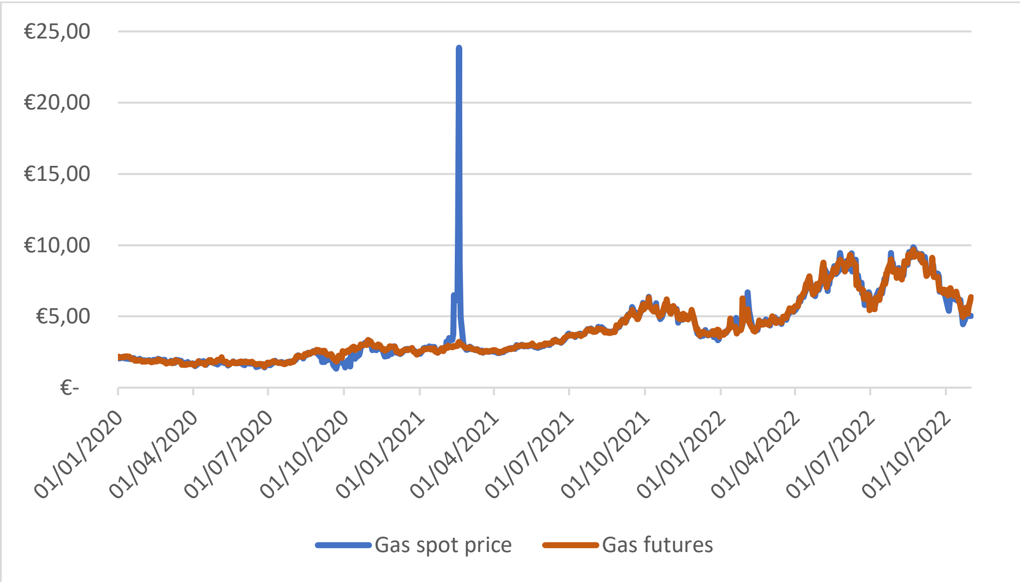

Figure 5: overview of spot and futures prices of natural gas
This Graph presents a comparison of the spot prices of the SNL Natural Gas Henry Hub (HH) CST Gulf Coast (blue line) and the futures prices of NYM-Natural Gas TRc1 (red line) in the period from January 1, 2020, until October 30, 2022.

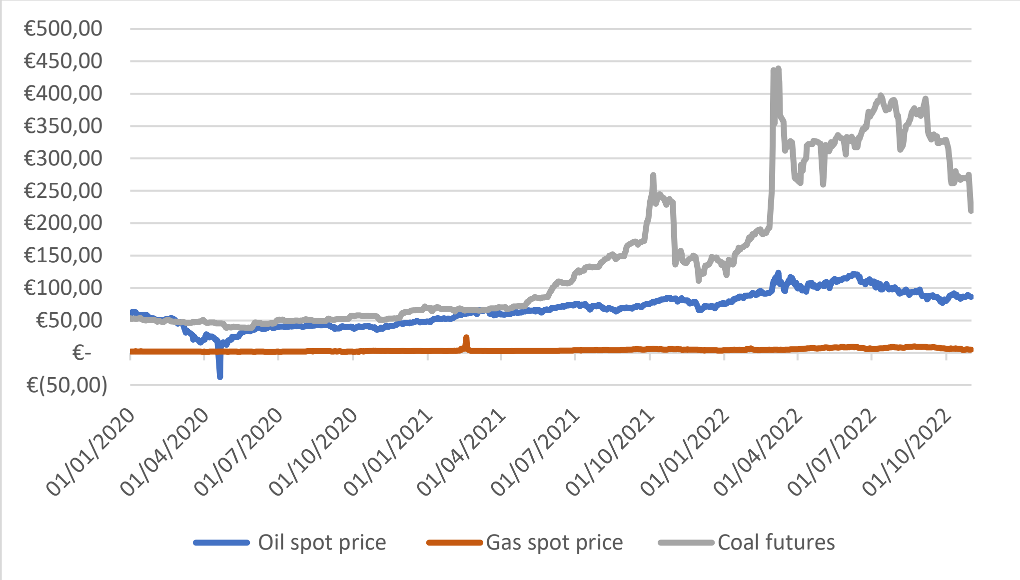

Figure 6: overview of oil, natural gas and coal spot and futures prices
This Graph shows oil and natural gas spot prices and coal futures used for this analysis to determine events in the period from January 1, 2020, until October 30, 2022. The blue line indicates the WTI crude oil spot price in Cushing, Oklahoma. The red line presents the spot prices of the SNL Natural Gas Henry Hub (HH) CST Gulf Coast. The grey line displays the futures prices of the ICE-Coal Rotterdam TRc1.

Table 10: sampling procedure
This Table lists all the data filtering criteria used to collect and select the stock prices, ESG scores and environmental proxies (i.e., CO_2 intensity and political affiliation) of U.S.-listed firms in the S&P 1500. This selection process reduces the raw dataset from 1,505 firms obtained from Datastream to a final sample of 1,326 (main sample) and 611 (additional sample). Column 1 represents the phase in the sampling procedure. Column 2 shows the number of firms removed associated with the filtering step in column 1. Column 3 presents the total number of firms remaining at each phase.

Selection criteria	**Number of firms removed**	**Number of firms remaining**
All firms within the S&P 1500		1,505
Missing data on stock prices	36	1,464
Missing data on ESG scores	115	1,349
Missing data on political affiliation	23	1,326
Number of firms – main sample		**1,326**

Selection criteria	**Number of firms removed**	**Number of firms remaining**
Number of firms – main sample		1,326
Missing data on CO_2 intensity	715	611
Number of firms – additional sample		**611**

Table 11: Overview of the individual pillars of the Refinitiv's total ESG score

This Table gives a summary of the three individual pillars Environmental (E), Social (S), and Corporate Governance (G) of the total ESG rating provided by the Thomson Reuters' Refinitiv ESG database. The Environmental (E), Social (S) and Corporate Governance (G) performance are categorized into ten different subcategories shown in column 2. The specific definition of these subcategories is further explained in column 3. Column 4 provides the weights in the ESG score per subcategory.

Individual pillar	Subcategories	Category definitions	Metrics
Environmental	Resource use	Measures a firm's performance and capacity to decrease usage of energy, materials, or water, and to find more eco-efficient solutions by enhancing supply chain management	20
	Emissions	Measures a firms' commitment and effectiveness in decreasing environmental emissions throughout its production and operational processes	28
	Innovation	Measures a firm's capacity to decrease environmental costs and burdens for its customers, consequently leading to new market opportunities via new environmental technologies and processes, or eco-designed products	20
Social	Workforce	Measures a firm's effectiveness in terms of providing job satisfaction, a safe and healthy workspace, maintaining diversity and equal opportunities, and creating development opportunities for its workforce	30
	Human rights	Measures a firm's effectiveness in terms of respecting fundamental human rights conventions	8
	Community	Measures a firm's commitment to being a good citizen, safeguarding public health and respecting business ethics	14
	Product responsibility	Measures a firm's capacity to produce quality products and services that integrate the customer's health and safety, integrity, and data privacy	10
Governance	Management	Measures a firm's level of commitment and effectiveness in adhering to best practices of corporate governance principles	35
	Shareholders	Measures a firm's effectiveness in providing equal treatment to shareholders and utilizing anti-takeover mechanisms	12
	Corporate Social Responsibility (CSR) strategy	Measures a firm's practices to communicate that it integrates the economic (financial), social, and environmental aspects into its day-to-day decision-making processes	9
Total ESG score			186

APPENDIX B Descriptive statistics

Table 12: Descriptive statistics of the total ESG score and its individual pillars per year

This Table reports the descriptive statistics of the total ESG score and its individual pillars Environmental (E), Social (S) and Corporate Governance (G) categorized by year 2019, 2020 and 2021. The ESG scores are obtained from the Thomson Reuters' Refinitiv ESG database for the final sample of 1,326 firms. The descriptive statistics consist of the mean, median, standard deviation (Std. Dev), minimum (Min) and maximum (Max).

	ESG					
Year	**Obs.**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
2019	1,326	47.675%	45.940%	18.706	4.390%	92.960%
2020	1,326	51.621%	51.930%	18.282	4.040%	93.840%
2021	1,326	55.553%	56.880%	17.469	6.340%	94.790%

	Environmental (E)					
Year	**Obs.**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
2019	1,326	33.486%	28.875%	28.672	0.000%	97.640%
2020	1,326	38.040%	36.990%	28.318	0.000%	97.510%
2021	1,326	41.929%	41.560%	27.778	0.000%	97.630%

	Social (S)					
Year	**Obs.**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
2019	1,326	48.982%	46.985%	21.266	5.790%	97.880%
2020	1,326	53.200%	51.750%	20.815	4.920%	97.510%
2021	1,326	56.691%	56.975%	19.877	1.920%	97.310%

	Corporate Governance (G)					
Year	**Obs.**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
2019	1,326	55.814%	57.840%	20.560	0.630%	97.250%
2020	1,326	58.865%	60.295%	19.596	7.260%	99.480%
2021	1,326	63.336%	65.400%	18.103	13.510%	99.620%

Table 13: Distribution of political affiliation of firms and states

This Table presents an overview of the distribution of the political affiliation of all 1,326 firms within the sample and U.S. states. The information in this Table is based on the U.S. presidential election in 2020. All states within the U.S. are listed and the corresponding number of firms headquartered in that particular state is shown. Percent Biden represents the percentage of the population that voted for Biden in the respective state. The political environment indicates whether Republicans or Democrats won in the 2020 presidential election and represents the political affiliation of the respective state.

State	**Number of firms**	**Percent Biden**	**Politic environment**	**State**	**Number of firms**	**Percent Biden**	**Politic environment**
Alabama	8	36.57%	Republican	Montana	2	40.55%	Republican
Alaska	0	42.77%	Republican	Nebraska	7	39.17%	Republican
Arizona	25	49.22%	Democrat	Nevada	13	50.06%	Democrat
Arkansas	10	34.78%	Republican	New Hampshire	4	52.71%	Democrat
California	191	63.44%	Democrat	New Jersey	38	57.14%	Democrat
Colorado	33	55.40%	Democrat	New Mexico	1	54.29%	Democrat
Connecticut	33	59.24%	Democrat	New York	113	60.76%	Democrat
Delaware	11	58.74%	Democrat	North Carolina	30	48.59%	Republican
District of Columbia	8	92.15%	Democrat	North Dakota	2	31.76%	Republican
Florida	54	47.76%	Republican	Ohio	57	45.16%	Republican
Georgia	41	49.47%	Democrat	Oklahoma	9	32.29%	Republican
Hawaii	5	63.73%	Democrat	Oregon	6	56.45%	Democrat
Idaho	5	32.98%	Republican	Pennsylvania	62	49.87%	Democrat

Illinois	69	57.39%	Democrat	Rhode Island	4	59.39%	Democrat
Indiana	18	40.87%	Republican	South Carolina	4	43.43%	Republican
Iowa	5	44.89%	Republican	South Dakota	23	35.61%	Republican
Kansas	6	41.40%	Republican	Tennessee	23	37.45%	Republican
Kentucky	7	36.13%	Republican	Texas	134	46.44%	Republican
Louisiana	5	39.85%	Republican	Utah	10	37.20%	Republican
Maine	2	52.09%	Democrat	Vermont	0	66.09%	Democrat
Maryland	23	65.36%	Democrat	Virginia	43	54.11%	Democrat
Massachusetts	63	65.60%	Democrat	Washington	25	57.97%	Democrat
Michigan	23	50.55%	Democrat	West Virginia	2	29.69	Republican
Minnesota	38	52.40%	Democrat	Wisconsin	22	49.45%	Democrat
Mississippi	6	41.04%	Republican	Wyoming	0	25.55%	Republican
Missouri	23	41.34%	Republican				

Table 14: Distribution of industry classification
This Table provides an overview of the industry classification of all 1,326 firms within the sample based on the first two digits of the Standard Industrial Classification (SIC) codes. Column 1 shows the classification based on the first two digits of the SIC codes and column 2 gives the corresponding industry definition. Column 3 demonstrate the number of firms of the final sample that fall within the specific industry.

Classification	**Industry**	**Number of firms**
01-09	Agriculture, Forestry & Fishing	2
10-14	Mining	37
15-17	Construction	23
20-39	Manufacturing	501
40-49	Transportation & Public Utilities	121
50-51	Wholesale Trade	38
52-59	Retail Trade	99
60-67	Finance, Insurance & Real Estate	309
70-89	Services	196
91-98	Public Administration	0
99	Non-classifiable Establishment	0

Table 15: Descriptive statistics of (C)AR before winsorization
This Table reports the descriptive statistics of the dependent variables during the sample period from March 2020 to October 2022. The final sample consist of 1,326 firms listed on the S&P 1500 and are obtained from Datastream. Panel A provides information on the dependent variables consisting of constant mean return model event day, 3- and 7 day (cumulative) abnormal returns before winsorization. For each variable, the total number of observations, average, standard deviation, median, minimum, maximum, skewness and kurtosis are shown.

Panel A. (Cumulative) abnormal returns								
Variable	**Obs.**	**Mean**	**Std. Dev.**	**Median**	**Min**	**Max**	**Skewness**	**Kurtosis**
Event study – positive events								
AR_0	38,454	0.005	0.048	0.002	-0.444	1.588	4.384	80.682
$\mathrm{CAR}_{(-1,1)}$	38,454	0.011	0.130	0.009	-3.626	2.278	-0.241	31.699
$\mathrm{CAR}_{(-3,3)}$	38,454	-0.006	0.076	-0.003	-1.412	1.148	-0.177	17.269
Event study – negative events								
AR_0	23,868	-0.011	0.049	-0.005	-0.635	0.492	-1.994	18.231
$\mathrm{CAR}_{(-1,1)}$	23,868	-0.022	0.138	-0.024	-1.134	1.804	0.547	11.731

$CAR_{(-3,3)}$	23,868	-0.002	0.080	-0.003	-0.806	1.078	0.649	14.811
Event study – all events								
AR_0	62,322	-0.001	0.049	-0.001	-0.635	1.588	1.740	54.519
$CAR_{(-1,1)}$	62,322	-0.002	0.134	-0.004	3.626	2.278	0.071	22.299
$CAR_{(-3,3)}$	62,322	-0.004	0.078	-0.003	-1.411	1.148	0.172	16.275

APPENDIX C Variable explanation

Table 16: Summary of all dependent and independent variables
This table lists all the variables of interest used in the regression models and their corresponding definitions. The first column presents the name of variable as used in the regression models. Column 2 defines the variables, while column 3 gives the expected sign of the coefficients of the variables.

Variable	Definition	Expected sign
Dependent variables		
AR_{it},	The abnormal returns of firm i on the day of an extreme change in energy prices, calculated with the constant mean return model	
$CAR[-1,1]_{it}$	The cumulative abnormal return of firm i over the three-day event window	
$CAR[-3,3]_{it}$	The cumulative abnormal return of firm i over the seven-day event window	
Independent variables		
ESG	The total ESG score of firm i	+
ESG_High	Dummy variable, which takes a value of 1 if a firm i's total ESG score at time t is higher than the median score of all respective firms within the sample at time t, and 0 otherwise.	+
Environmental	The environmental (E) score of firm i	+
Social	The social (S) score of firm i	?
Governance	The Governance (G) score of firm i	?
CO_2 intensity	CO_2 intensity is the carbon dioxide intensity of firm i, measured by dividing its total CO_2 and CO_2 equivalent emissions in tonnes by total assets.	+
Political affiliation - democratic	Dummy variable that equals 1 if firm i's headquarter is located in a state where a Democrat has won, and 0 otherwise	+
Political affiliation – democratic votes	Proportion variable defined as the percentage votes that is received by the Democratic candidate in the presidential election where firm i is headquartered.	+
Control variables		
Industry-specific information	Industry-specific dummy variables based on the SIC-code of firm i, that takes a value of 1 if firm i belongs to industry j, and 0 otherwise	?
Firm size	The natural logarithm of the total assets of firm i	?
Leverage	Debt-to-asset ratio of firm i calculated by dividing its total amount of short-term and long-term debt by the market value of long-term debt by its market value of total assets	-
Return on assets (ROA)	Dividing the net income of firm i by its total assets	+
Cash	Cash holdings of firm i calculated by dividing the cash available by its total assets	

APPENDIX D Event study results

Table 17: Significance of the (cumulative) average abnormal returns

This Table reports per event the results of AAR_0, $\mathrm{CAAR}_{(-1,1)}$, and $\mathrm{CAAR}_{(-3,3)}$ indicating the (cumulative) average abnormal returns on the event day and over a 3- and 7-day event window, respectively. The (C)AARs are calculated for 1,326 firms using a constant mean return model with an 8-day estimation window during a sample period from March 2020 to October 2022. An extreme energy price change is referred to as an event if the daily energy price is at least 15% higher than the previous day, resulting in a total of 47 events, of which 29 energy price increases and 18 energy price decreases. Afterwards, these AARs are aggregated across all firms and all positive and negative events categorized by energy commodity. To test whether the (C)AARs are significantly different from zero a two-sided t-test (MacKinlay, 1997), a BMP test correcting for event-induced volatility (Boehmer et al., 1991) and a generalized sign test (Kolari & Pynnonen, 2011) are used. The statistical significance is indicated by ***, **, and * at the 1%, 5% and 10% level.

Extreme changes in oil prices

Event date	Obs.	AAR_0	t-value	Z-value	BMP	$\mathrm{CAAR}_{(-1.1)}$	t-value	Z-value	BMP	$\mathrm{CAAR}_{(-3.3)}$	t-value	Z-value	BMP
Positive													
19-03-2020	1,326	8.909%	23.808***	23.585***	23.888***	-1.702%	-4.062***	-7.992***	-7.034***	6.962%	11.271***	11.582***	10.425***
30-03-2020	1,326	1.698%	11.569***	14.359***	16.298***	-3.241%	-12.736***	-12.517***	-10.430***	0.866%	1.412	1.802*	3.344***
02-04-2020	1,326	0.332%	2.206**	4.464***	7.735***	-10.621%	-30.807***	-26.494***	-32.347***	-2.169%	-4.003***	-1.565	2.236**
22-04-2020	1,326	-0.429%	-4.282***	-3.463***	-0.377	-5.039	-24.738***	-24.464***	-26.454***	-3.889%	-10.811***	-11.747***	-11.611***
23-04-2020	1,326	0.034%	0.3085	-1.414	-1.959	0.269%	1.427	2.988***	4.289***	-2.964%	-9.422***	-10.181****	-11.868***
29-04-2020	1,326	5.356%	31.865***	27.470***	35.436***	4.563%	17.237***	16.665***	14.756***	6.342%	17.771***	16.724***	16.077***
30-04-2020	1,326	-2.938%	-29.180***	-26.234***	-30.995***	-1.294%	-6.780***	-11.195***	-11.225***	5.642%	16.734***	16.921***	15.852***
05-05-2020	1,326	-1.123%	-10.373***	-9.504***	-5.185***	-5.550%	-25.120***	-22.596***	-21.865***	-12.133%	-34.461***	-26.841***	-32.503***
Negative													
09-03-2020	1,326	-8.209%	-42.956***	-30.940***	-47.766***	-3.046%	-11.224***	-12.980***	-11.735***	-14.251%	-36.197***	-28.653***	-39.775***
18-03-2020	1,326	-7.444%	-29.340***	-24.626***	-27.808***	11.074%	28.665***	24.804***	29.719***	13.843%	23.002***	21.226***	22.895***
20-04-2020	1,326	-4.400%	-41.842***	-29.005***	-45.047***	-6.348%	-34.792***	-26.890***	-36.082***	-17.683%	-47.287***	-30.267***	-54.418***
21-04-2020	1,326	-3.890%	-45.085***	-29.047***	-42.925***	-7.803%	-38.994***	-28.833***	-42.875***	-7.267%	-19.130***	-19.23***	-19.313***
27-04-2020	1,326	4.382%	40.773***	28.991***	44.025***	8.316%	37.095***	27.897***	38.787***	13.928%	33.063***	27.056***	34.484***

Extreme changes in gas prices

Event date	Obs.	AAR_0	t-value	Z-value	BMP	$\mathrm{CAAR}_{(-1.1)}$	t-value	Z-value	BMP	$\mathrm{CAAR}_{(-3.3)}$	t-value	Z-value	BMP
Positive													
03-06-2020	1,326	1.709%	17.914***	18.718***	14.906***	7.110%	4.219***	2.101**	-0.634	1.367%	4.223***	1.489	2.321**
29-06-2020	1,326	2.681%	31.773***	26.016***	32.038***	0.507%	4.472***	5.450***	6.280***	-4.456%	-21.761***	-20.091***	-20.283***
08-09-2020	1,326	-2.554%	-35.072***	-27.346***	-36.679***	-2.131%	-18.607***	-19.361***	-19.934***	-5.470%	-23.667***	-23.617***	-26.430***
23-09-2020	1,326	-2.560%	-39.853***	-29.202***	-40.915***	-1.706%	-13.677***	-13.800***	-12.582***	-1.823%	-7.844***	-7.702***	-7.726***
05-10-2020	1,326	2.523%	36.688***	28.606***	40.943***	3.696%	27.767***	23.849***	27.954***	9.859%	40.747***	29.090***	43.453***
09-10-2020	1,326	-0.780%	-13.437***	-13.966***	-12.033***	-0.398%	-3.219***	-2.435**	-0.926	-4.641%	-21.768***	-20.807***	-24.059***
30-11-2020	1,326	-2.535%	-30.052***	-25.164***	-27.833***	-2.501%	-16.682***	-16.278***	-11.755***	-2.341%	-10.329***	-9.847***	-6.384***
05-02-2021	1,326	1.161%	16.317***	19.433***	19.758***	5.269%	28.319***	27.566***	40.759***	8.205%	20.464***	25.913***	37.535***

11-02-2021	1,326	-0.089%	-1.189	-1.980*	-1.003	-0.362%	-2.808**	-3.196***	-1.962*	0.251%	1.105	2.079**	2.167**
16-02-2021	1,326	-0.743%	-10.439***	-11.677***	-12.820***	-2.300%	-17.079***	-18.078***	-19.791***	-4.875%	-19.484***	-20.268***	-23.148***
17-02-2021	1,326	-1.364%	-21.185***	-21.087***	-20.243***	-4.473%	-33.018***	-27.062***	-33.255***	-6.148%	-24.009***	-23.974***	-29.073***
28-01-2022	1,326	2.378%	36.370***	27.947***	34.028***	4.441%	35.179***	27.754***	35.283***	5.702%	27.146***	24.067***	28.227***
02-02-2022	1,326	1.022%	16.672***	18.288***	18.271***	2.576%	22.342***	21.568***	21.857***	11.026%	46.556***	30.254***	48.004***
18-07-2022	1,326	-0.153%	-2.642**	-5.825***	-9.013***	5.347%	43.678***	29.473***	44.053***	5.532%	28.045***	23.991***	27.233***
06-10-2022	1,326	0.010%	0.200	0.553	-2.069**	-1.276%	-11.963***	-13.866***	-15.312***	8.873%	38.562***	28.748***	36.482***
Negative													
04-09-2020	1,326	-0.205%	-3.383***	-3.944***	-7.960***	-4.936%	-36.020***	-27.834***	-33.986***	-3.348%	-16.116***	-18.271***	-18.648***
17-09-2020	1,326	-0.204%	-2.981***	-3.804***	-3.448***	0.574%	3.941***	2.124**	2.563**	1.483%	5.708***	4.794***	3.747***
08-10-2020	1,326	1.233%	15.466***	21.127***	20.697***	2.426%	18.905***	20.204***	23.103***	2.162%	9.995***	11.006***	13.601***
18-02-2021	1,326	-1.910%	-25.800***	-24.430***	-24.708***	-2.469%	-19.725***	-19.498***	-21.094***	-4.867%	-18.432***	-18.883***	-21.402***
19-02-2021	1,326	0.689%	10.135***	10.798***	7.595***	-1.403%	-9.357***	-9.131***	-9.117***	-2.353%	-8.390***	-8.661***	-9.207***
22-02-2021	1,326	-0.235%	-2.473**	-1.619	-1.709	-0.150%	-0.933	0.274	-0.111	-4.824%	-17.044***	-18.469***	-19.521***
07-02-2022	1,326	0.047%	0.830	0.699	2.043**	1.457%	12.147***	12.489***	11.396***	-0.791%	-4.133***	-4.657***	-3.899***
10-05-2022	1,326	-0.499%	-5.314***	-7.792***	-6.040***	-5.423%	-34.542***	-27.631***	-35.244***	-6.883%	-28.833***	-24.241***	-29.123***

Extreme changes in coal prices

Event date	**Obs.**	$\mathbf{AAR_0}$	**t-value**	**Z-value**	**BMP**	$\mathbf{CAAR_{(-1.1)}}$	**t-value**	**Z-value**	**BMP**	$\mathbf{CAAR_{(-3.3)}}$	**t-value**	**Z-value**	**BMP**
Positive													
01-06-2020	1,326	-0.461%	-6.062***	-9.960***	-6.622***	-3.583%	-24.093***	-21.911***	-19.063***	-4.735%	-18.756***	-18.788***	-15.425***
27-09-2021	1,326	1.549%	22.831***	20.637***	18.977***	0.730%	6.550***	7.152***	3.905***	3.836%	20.131***	19.152***	21.068***
28-02-2022	1,326	0.414%	5.130***	4.519***	4.020***	1.986%	12.448***	13.892***	14.363***	6.127%	23.234***	22.134***	24.114***
01-03-2022	1,326	-1.407%	-17.327***	-17.706***	-17.205***	2.285%	16.367***	17.593***	16.333***	6.625%	23.889***	22.567***	24.490***
02-03-2022	1,326	2.965%	40.309***	29.409***	45.293***	0.908%	7.034***	8.865***	11.837***	0.066%	0.218	1.007	5.578***
04-03-2022	1,326	-1.076%	-14.432***	-14.275***	-11.464***	-4.296%	-22.998***	-21.214***	-21.875***	-0.248%	-1.091	-2.702**	-1.237
Negative													
01-11-2021	1,326	1.812%	23.005***	22.843***	22.558***	1.349%	9.191***	10.035***	9.225***	1.792%	7.371***	6.232***	5.985***
03-03-2022	1,326	-0.723%	-10.91***	-10.632***	-7.190***	0.511%	3.640***	5.234***	8.163***	-4.769%	-16.748***	-17.977***	-17.882***
28-03-2022	1,326	-0.603%	-11.119***	-13.215***	-12.3001***	1.223%	12.183***	13.935***	16.089***	-4.173%	-20.663***	-19.868***	-19.408***
02-05-2022	1,326	1.265%	17.371***	16.628***	12.575***	0.540%	4.209***	3.221***	-1.184	4.034%	17.278***	16.342***	14.431***
31-10-2022	1,326	-0.767%	-14.071***	-16.132***	-15.302***	0.667%	5.231***	6.711***	4.874***	-4.817%	-18.825***	-18.590***	-19.509***

Table 18: The (cumulative) average abnormal returns with additional event windows

This Table reports the event study results of AAR_0, $\mathrm{CAAR}_{(-3,0)}$, $\mathrm{CAAR}_{(0,3)}$, $\mathrm{CAAR}_{(-1,0)}$, and $\mathrm{CAAR}_{(0,1)}$ indicating the (cumulative) average abnormal returns on the event day and over additional event windows of [-3,0], [0,3], [-1,0], and [0,1], respectively. The (C)AARs are calculated for 1,326 firms using a constant mean return model with an 8-day estimation window during a sample period from March 2020 to October 2022. An extreme energy price change is referred to as an event if the daily energy price is at least 15% higher than the previous day, resulting in a total of 47 events, of which 29 energy price increases and 18 energy price decreases. Afterwards, these AARs are aggregated across all firms and all positive and negative events categorized by energy commodity.

Extreme changes in oil price						
Event direction	**Obs.**	$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0,,3)}$	$\mathbf{AAR}_0$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0,.1)}$
Positive	10,608	-0.904%	2.215%	1.478%	-0.811%	-0.537%
Negative	6,630	-2.422%	-3.77%	-3.912%	-2.234%	-1.240%
Extreme changes in gas prices						
Event direction	**Obs.**	$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0,,3)}$	$\mathbf{AAR}_0$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0,.1)}$
Positive	19,890	0.393%	1.058%	0.047%	0.174%	0.367%
Negative	10,608	-1.620%	-0.943%	-0.135%	-0.781%	-0.595%
Extreme changes in coal prices						
Event direction	**Obs.**	$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0,,3)}$	$\mathbf{AAR}_0$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0,.1)}$
Positive	7,956	2.095%	0.181%	0.331%	0.168%	-0.166%
Negative	6,630	0.123%	-1.513%	0.197%	0.578%	0.477%
Extreme changes in energy prices						
Event direction	**Obs.**	$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0,,3)}$	$\mathbf{AAR}_0$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0,.1)}$
Positive	38,454	0.387%	1.196%	0.501%	-0.099%	0.007%
Negative	23,868	-1.359%	-1.888%	-1.092%	-0.807%	-0.476%

Table 19: The (cumulative) average abnormal returns with additional event windows divided over four subperiods

This Table reports the event study results of AAR_0, $\mathrm{CAAR}_{(-3,0)}$, $\mathrm{CAAR}_{(0,3)}$, $\mathrm{CAAR}_{(-1,0)}$, and $\mathrm{CAAR}_{(0,1)}$ indicating the (cumulative) average abnormal returns on the event day and over additional event windows of [-3,0], [0,3], [-1,0], and [0,1], respectively, divided into four different subperiods. The (C)AARs are calculated for 1,326 firms using a constant mean return model with an 8-day estimation window during a sample period from March 2020 to October 2022. An extreme energy price change is referred to as an event if the daily energy price is at least 15% higher than the previous day, resulting in a total of 47 events, of which 29 energy price increases and 18 energy price decreases. Afterwards, these AARs are aggregated across all firms and all positive and negative events categorized by energy commodity. The first subperiods is the Covid-19 outbreak phase from March 2020 to June 2020. The second subperiod represents the Covid-19 follow-up phase from July 2020 until June 2021, while the third subperiod covers the recovery phase of Covid-19 from July 2021 to February 21, 2022. Finally, the last subperiods represents the period around the Russia-Ukraine war from February 21, 2022, to October 2022.

Positive events							
Covid-19 outbreak phase				**Covid-19 follow-up phase**			
Oil prices (10,608)				*Oil prices (0)*			
$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$	$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$
-0.904%	2.215%	-0.811%	-0.537%	N/A	N/A	N/A	N/A
Gas prices (2,652)				*Gas prices (11,934)*			
$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$	$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$
-2.724%	3.372%	0.445%	2.358%	-0.877%	-0.670%	-0.576%	-0.740%
Coal prices (1,326)				*Coal prices (0)*			
$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$	$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$
-5.243%	0.047%	-3.054%	-0.990%	N/A	N/A	N/A	N/A
Total energy prices (14,586)				*Total energy prices (11,934)*			
$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$	$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$
-1.630%	2.228%	-0.787%	-0.052%	-0.877%	-0.670%	-0.576%	-0.740%

Negative events

Covid-19 outbreak phase				**Covid-19 follow-up phase**			
Oil prices (6,630)				*Oil prices (0)*			
$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$	$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$
-2.422%	-3.776%	-2.234%	-1.240%	N/A	N/A	N/A	N/A
Gas prices (0)				*Gas prices (7,956)*			
$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$	$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$
N/A	N/A	N/A	N/A	-0.421%	-1.643%	-0.430%	-0.669%
Coal prices (0)				*Coal prices (0)*			
$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$	$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$
N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Total energy prices (6,630)				*Total energy prices (7,956)*			
$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$	$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$
-2.422%	-3.776%	-2.234%	-1.240%	-0.421%	-1.643%	-0.430%	-0.669%

Positive events

Covid-19 recovery phase				**Russia-Ukraine war**			
Oil prices (10,608)				*Oil prices (0)*			
$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$	$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$
N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Gas prices (2,652)				*Gas prices (11,934)*			
$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$	$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$
4.859%	5.205%	2.314%	2.895%	4.756%	2.376%	1.135%	0.829%
Coal prices (1,326)				*Coal prices (0)*			
$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$	$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$
5.638%	-0.253%	1.885%	0.394%	3.043%	0.323%	0.545%	-0.100%
Total energy prices (14,586)				*Total energy prices (11,934)*			
$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$	$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$
5.119%	3.386%	2.171%	2.061%	3.614%	1.007%	0.742%	0.210%

Negative events

Covid-19 recovery phase				**Russia-Ukraine war**			
Oil prices (6,630)				*Oil prices (0)*			
$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$	$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$
N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Gas prices (0)				*Gas prices (7,956)*			
$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$	$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$
-1.906%	1.163%	-0.003	1.536%	-8.531%	1.150%	-3.640%	-2.281%
Coal prices (0)				*Coal prices (0)*			
$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$	$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$
1.062%	2.542%	1.554%	1.607%	-0.112%	-2.57%	0.334%	0.194%
Total energy prices (6,630)				*Total energy prices (7,956)*			
$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$	$\mathbf{CAAR}_{(-3,0)}$	$\mathbf{CAAR}_{(0.3)}$	$\mathbf{CAAR}_{(-1.0)}$	$\mathbf{CAAR}_{(0.1)}$
-0.422%	1.852%	0.761%	1.571%	-1.796%	-1.791%	-0.461%	-0.301%

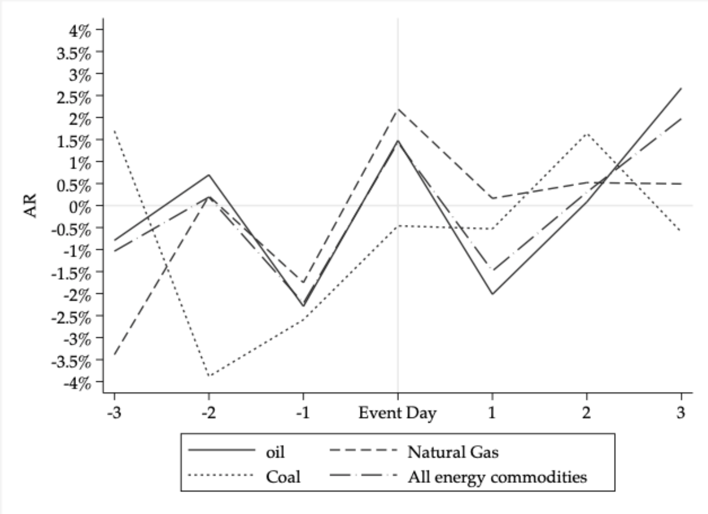

Figure 7: the daily average abnormal returns before and after positive events during the Covid-19 outbreak phase
This figure shows the trend of the average abnormal returns in percentage (%) on the Y-axis over the seven days consisting of three days before and three days after an extreme energy price increase, denoted as the event day on the X-axis. This figure displays the results for the Covid-19 outbreak phase from March 2020 to June 2020. The AARs are calculated for 1,326 firms using the constant mean return model with an 8-day estimation window during a sample period from March 2020 to October 2022. Afterwards, these AARs are aggregated across all firms and all positive and negative events categorized by energy commodity. This study focuses on the cumulative average abnormal returns consisting of [-1,1] and [-3,3] whose trend around positive events can be derived from this figure.

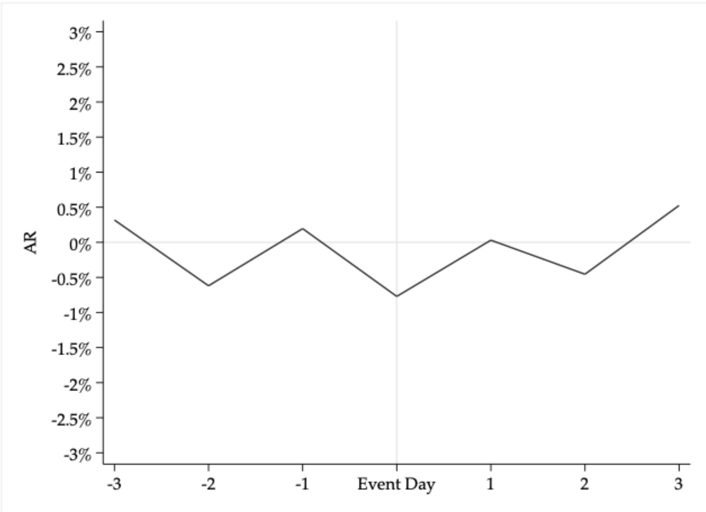

Figure 8: the daily average abnormal returns before and after positive events during the Covid-19 follow-up phase
This figure shows the trend of the average abnormal returns in percentage (%) on the Y-axis over the seven days consisting of three days before and three days after an extreme energy price increase, denoted as the event day on the X-axis. This figure displays the results for the Covid-19 follow-up phase from March 2020 to June 2020. Only events caused by natural gas price changes occurred, represented by the black line. The AARs are calculated for 1,326 firms using the constant mean return model with an 8-day estimation window during a sample period from March 2020 to October 2022. Afterwards, these AARs are aggregated across all firms and all positive and negative events categorized by energy commodity. This study focuses on the cumulative average abnormal returns consisting of [-1,1] and [-3,3] whose trend around positive events can be derived from this figure.

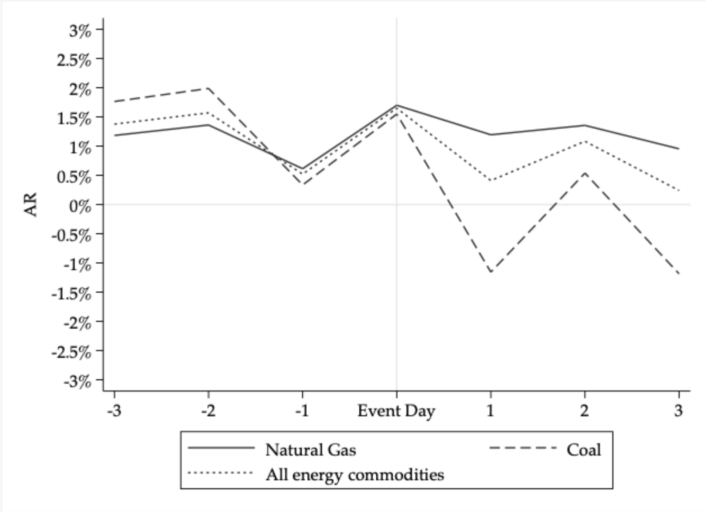

Figure 9: the daily average abnormal returns before and after positive events during the Covid-19 recovery phase
This figure shows the trend of the average abnormal returns in percentage (%) on the Y-axis over the seven days consisting of three days before and three days after an extreme energy price increase, denoted as the event day on the X-axis. This figure displays the results for the Covid-19 recovery phase from July 2021 to February 21, 2022. The AARs are calculated for 1,326 firms using the constant mean return model with an 8-day estimation window during a sample period from March 2020 to October 2022. Afterwards, these AARs are aggregated across all firms and all positive and negative events categorized by energy commodity. This study focuses on the cumulative average abnormal returns consisting of [-1,1] and [-3,3] whose trend around positive events can be derived from this figure.

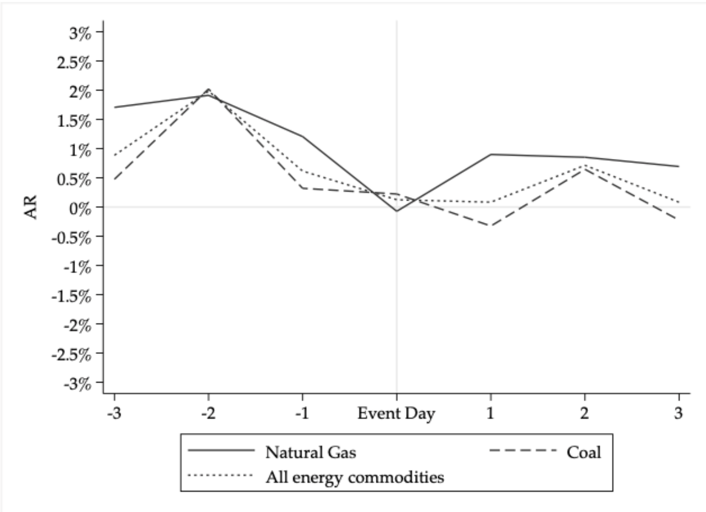

Figure 10: the daily average abnormal returns before and after positive events during the Russia-Ukraine war
This figure shows the trend of the average abnormal returns in percentage (%) on the Y-axis over the seven days consisting of three days before and three days after an extreme energy price increase, denoted as the event day on the X-axis. This figure displays the results for the period around the Russia-Ukraine war from February 21, 2022, to October 2022. The AARs are calculated for 1,326 firms using the constant mean return model with an 8-day estimation window a sample period from March 2020 to October 2022. Afterwards, these AARs are aggregated across all firms and all positive and negative events categorized by energy commodity. This study focuses on the cumulative average abnormal returns consisting of [-1,1] and [-3,3] whose trend around positive events can be derived from this figure.

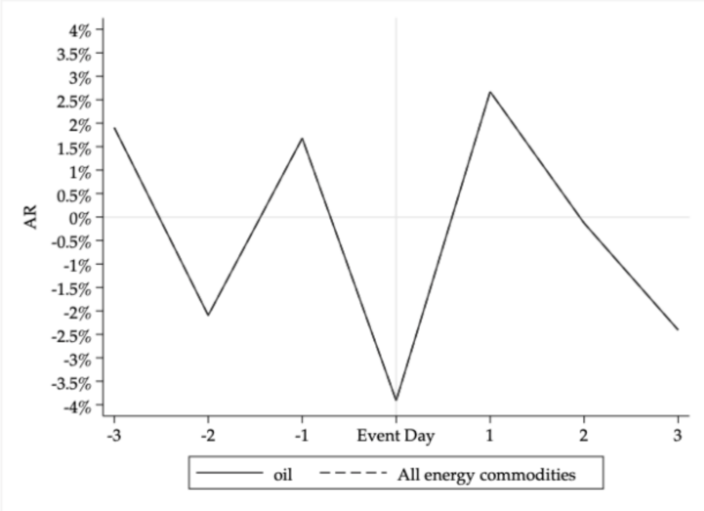

Figure 11: the daily average abnormal returns before and after negative events during the Covid-19 outbreak phase
This figure shows the trend of the average abnormal returns in percentage (%) on the Y-axis over the seven days consisting of three days before and three days after an extreme energy price decreases, denoted as the event day on the X-axis. This figure displays the results for the Covid-19 outbreak phase from March 2020 to June 2020. The AARs are calculated for 1,326 firms using the constant mean return model with an 8-day estimation window during a sample period from March 2020 to October 2022. Afterwards, these AARs are aggregated across all firms and all positive and negative events categorized by energy commodity. This study focuses on the cumulative average abnormal returns consisting of [-1,1] and [-3,3] whose trend around positive events can be derived from this figure.

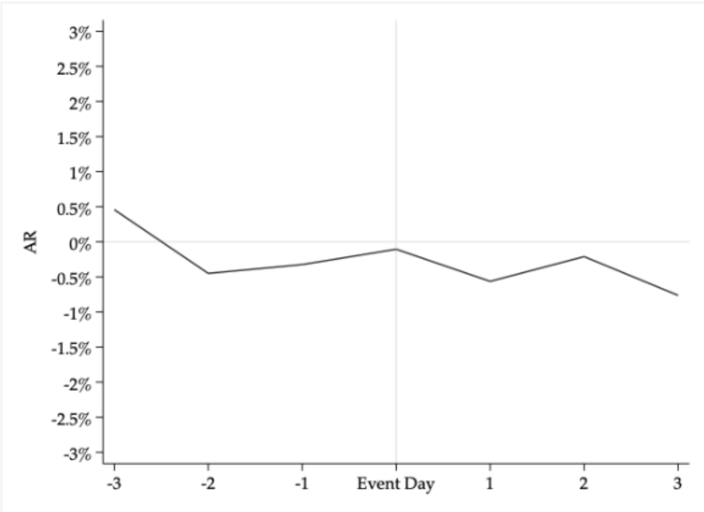

Figure 12: the daily average abnormal returns before and after negative events during the Covid-19 follow-up phase
This figure shows the trend of the average abnormal returns in percentage (%) on the Y-axis over the seven days consisting of three days before and three days after an extreme energy price decreases, denoted as the event day on the X-axis. This figure displays the results for the Covid-19 follow-up phase from March 2020 to June 2020. Only events caused by natural gas price changes occurred, represented by the black line. The AARs are calculated for 1,326 firms using the constant mean return model with an 8-day estimation window during a sample period from March 2020 to October 2022. Afterwards, these AARs are aggregated across all firms and all positive and negative events categorized by energy commodity. This study focuses on the cumulative average abnormal returns consisting of [-1,1] and [-3,3] whose trend around positive events can be derived from this figure.

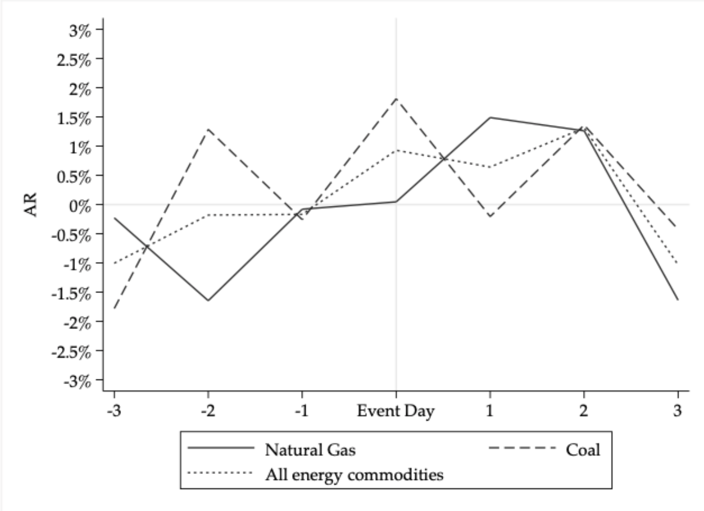

Figure 13: the daily average abnormal returns before and after negative events during the Covid-19 recovery phase
This figure shows the trend of the average abnormal returns in percentage (%) on the Y-axis over the seven days consisting of three days before and three days after an extreme energy price decreases, denoted as the event day on the X-axis. This figure displays the results for the Covid-19 recovery phase from July 2021 to February 21, 2022. The AARs are calculated for 1,326 firms using the constant mean return model with an 8-day estimation window during a sample period from March 2020 to October 2022. Afterwards, these AARs are aggregated across all firms and all positive and negative events categorized by energy commodity. This study focuses on the cumulative average abnormal returns consisting of [-1,1] and [-3,3] whose trend around positive events can be derived from this figure.

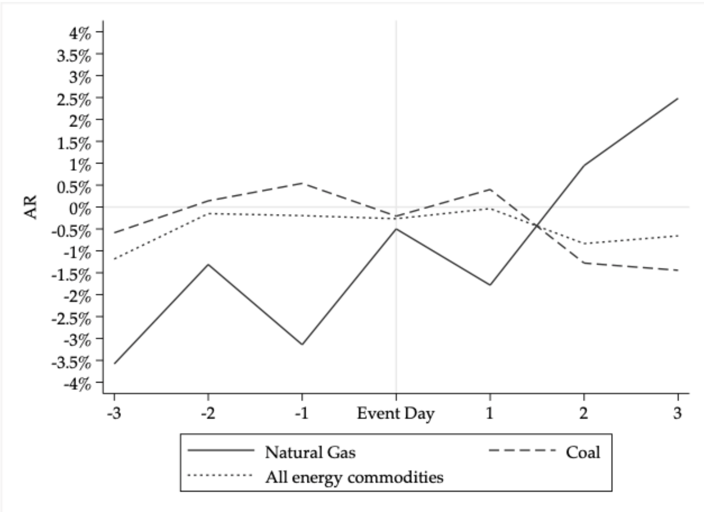

Figure 14: the daily average abnormal returns before and after negative events during the Russia-Ukraine war
This figure shows the trend of the average abnormal returns in percentage (%) on the Y-axis over the seven days consisting of three days before and three days after an extreme energy price decreases, denoted as the event day on the X-axis. This figure displays the results for the period around the Russia-Ukraine war from February 21, 2022, to October 2022. The AARs are calculated for 1,326 firms using the constant mean return model with an 8-day estimation window a sample period from March 2020 to October 2022. Afterwards, these AARs are aggregated across all firms and all positive and negative events categorized by energy commodity. This study focuses on the cumulative average abnormal returns consisting of [-1,1] and [-3,3] whose trend around positive events can be derived from this figure.

Table 20: Significance of the (cumulative) average abnormal returns for firms with low and high environmental scores

This Table reports the event study results of AAR_0, $\text{CAAR}_{(-1,1)}$, and $\text{CAAR}_{(-3,3)}$ indicating the (cumulative) average abnormal returns on the event day and over a 3- and 7-day event window, respectively, divided into two different portfolios. The (C)AARs are calculated for 1,326 firms using a constant mean return model with an 8-day estimation window during a sample period from March 2020 to October 2022. An extreme energy price change is referred to as an event if the daily energy price is at least 15% higher than the previous day, resulting in a total of 47 events, of which 29 energy price increases and 18 energy price decreases. Afterwards, these AARs are aggregated across all firms and all positive and negative events categorized by energy commodity. The (C)AARs are divided into two different portfolios of firms. The first portfolio consists of firms with an average environmental score below the overall median score, representing low-environmental scoring firms. The second portfolio consists of firms with an average environmental score above the overall median score, representing high-environmental scoring firms. To test whether the (C)AARs of the two portfolios are significantly different from each other, a two-sample t-test is performed. The statistical significance is indicated by ***, **, and * at the 1%, 5% and 10% level.

Extreme changes in oil prices		**Panel A [0]**			**Panel B [-1,1]**			**Panel C [-3,3]**		
Event direction	**Obs.**	$\textbf{AAR}_{low}$	$\textbf{AAR}_{high}$	**Difference**	$\textbf{CAAR}_{low}$	$\textbf{CAAR}_{high}$	**Difference**	$\textbf{CAAR}_{low}$	$\textbf{CAAR}_{high}$	**Difference**
Positive	5,304	1.693%	1.264%	0.430%***	-2.929%	-2.725%	-0.203%	-0.248%	-0.088%	-0.160%
Negative	3,315	-3.921%	-3.901%	-0.018%	0.918%	-0.041%	0.960%***	-1.605%	-2.968%	1.363%**
Extreme changes in gas prices		**Panel A [0]**			**Panel B [-1,1]**			**Panel C [-3,3]**		
Event direction	**Obs.**	$\textbf{AAR}_{low}$	$\textbf{AAR}_{high}$	**Difference**	$\textbf{CAAR}_{low}$	$\textbf{CAAR}_{high}$	**Difference**	$\textbf{CAAR}_{low}$	$\textbf{CAAR}_{high}$	**Difference**
Positive	9,945	-0.013%	0.108%	-0.121%**	0.303%	0.684%	-0.381%***	1.008%	1.800%	-0.792%***
Negative	5,304	-0.167%	-0.103%	-0.064%	-1.261%	-1.220%	-0.041%	-2.655%	-2.200%	-0.455%**
Extreme changes in coal prices		**Panel A [0]**			**Panel B [-1,1]**			**Panel C [-3,3]**		
Event direction	**Obs.**	$\textbf{AAR}_{low}$	$\textbf{AAR}_{high}$	**Difference**	$\textbf{CAAR}_{low}$	$\textbf{CAAR}_{high}$	**Difference**	$\textbf{CAAR}_{low}$	$\textbf{CAAR}_{high}$	**Difference**
Positive	3,978	0.314%	0.348%	-0.034%	-0.605%	-0.052%	-0.553%***	1.547%	2.343%	-0.796%***
Negative	3,315	0.338%	0.056%	0.282%***	1.053%	0.662%	0.392%***	-1.395%	-1.778%	0.382%
Total changes in energy prices		**Panel A [0]**			**Panel B [-1,1]**			**Panel C [-3,3]**		
Event direction	**Obs.**	$\textbf{AAR}_{low}$	$\textbf{AAR}_{high}$	**Difference**	$\textbf{CAAR}_{low}$	$\textbf{CAAR}_{high}$	**Difference**	$\textbf{CAAR}_{low}$	$\textbf{CAAR}_{high}$	**Difference**
Positive	19,277	0.525%	0.476%	0.049%	-0.776%	-0.409%	-0.368%***	0.773%	1.391%	-0.618%***
Negative	11,934	-1.070%	-1.115%	0.045%	-0.013%	-0.370%	0.357%***	-2.013%	-2.296%	0.283%

APPENDIX E Robustness tests

Table 21: Significance of the (cumulative) average abnormal returns

This Table reports per event the results of AAR_0, $\mathrm{CAAR}_{(-1,1)}$, and $\mathrm{CAAR}_{(-3,3)}$ indicating the (cumulative) average abnormal returns on the event day and over a 3- and 7-day event window, respectively. The (C)AARs are calculated for 1,326 firms using a market-adjusted model without an estimation window during a sample period from March 2020 to October 2022. An extreme energy price change is referred to as an event if the daily energy price is at least 15% higher than the previous day, resulting in a total of 47 events, of which 29 energy price increases and 18 energy price decreases. Afterwards, these AARs are aggregated across all firms and all positive and negative events categorized by energy commodity. To test whether the (C)AARs are significantly different from zero a two-sided t-test (MacKinlay, 1997) and a generalized sign test (Kolari & Pynnonen, 2011) are used. The statistical significance is indicated by ***, **, and * at the 1%, 5% and 10% level.

Extreme change in oil prices										
Event date	**Obs.**	**AAR_0**	**t-value**	**Z-value**	**$\mathrm{CAAR}_{(-1.1)}$**	**t-value**	**Z-value**	**$\mathrm{CAAR}_{(-3.3)}$**	**t-value**	**Z-value**
Positive										
19-03-2020	1,326	5.483%	15.820***	15.286***	0.516%	1.502	-0.441	0.217%	0.479	1.738*
30-03-2020	1,326	-1.439%	-9.601***	-8.492***	-1.510%	-6.900***	-5.155***	-2.380%	-6.789***	-6.036***
02-04-2020	1,326	-1.003%	-7.915***	-8.620***	-4.137%	-16.564***	-16.466***	-1.469%	-5.360***	-5.374***
22-04-2020	1,326	-0.932%	-10.528***	-12.634***	0.930%	5.959***	4.875***	4.677%	19.668***	18.128***
23-04-2020	1,326	1.196%	11.545***	12.711***	0.241%	1.558	0.080	5.259%	23.465***	21.191***
29-04-2020	1,326	2.380%	14.688***	14.681***	3.014%	12.869***	11.612***	3.748%	14.707***	13.134***
30-04-2020	1,326	-1.873%	-18.313***	-20.731***	-0.477%	-2.764**	-7.900***	3.070%	12.993***	11.898***
05-05-2020	1,326	-0.701%	-7.644***	-8.377***	-2.225%	-13.106***	-14.013***	-2.397%	-11.185***	-12.667***
Negative										
09-03-2020	1,326	-2.033%	-10.211***	-8.784***	-3.168%	-11.670***	-12.220***	-7.036%	-16.540***	-15.268***
18-03-2020	1,326	-5.141%	-19.068***	-16.830***	-0.759%	-2.055**	-1.934*	-1.897%	-3.9607***	-3.228***
20-04-2020	1,326	-0.530%	-5.615***	-7.375***	2.062%	13.076***	12.671***	-1.056%	-4.345***	-6.558***
21-04-2020	1,326	0.666%	8.505***	8.197***	-0.796%	-5.268***	-6.806***	0.910%	3.845***	3.432***
27-04-2020	1,326	2.373%	24.552***	22.095***	4.858%	27.095***	23.132***	5.629%	17.450***	16.385***

Extreme changes in gas prices										
Event date	**Obs.**	**AAR_0**	**t-value**	**Z-value**	**$\mathrm{CAAR}_{(-1.1)}$**	**t-value**	**Z-value**	**$\mathrm{CAAR}_{(-3.3)}$**	**t-value**	**Z-value**
Positive										
03-06-2020	1,326	1.940%	18.144***	17.731***	3.917%	19.370***	18.185***	6.507%	17.553***	17.137***
29-06-2020	1,326	1.687%	21.385***	19.265***	1.401%	15.115***	15.916***	-0.860%	-5.917***	-6.331***
08-09-2020	1,326	0.509%	7.363***	9.283***	-0.472%	-4.913***	-4.754***	1.565%	9.926***	11.768***
23-09-2020	1,326	-0.185%	-3.134***	-1.638	-0.668%	-6.688***	-6.500***	-2.263%	-14.719***	-15.532***
05-10-2020	1,326	0.277%	4.175***	3.196***	2.740%	25.011***	23.064***	3.257%	20.294***	19.185***
09-10-2020	1,326	-0.681%	-12.917***	-14.440***	-0.695%	-7.294***	-9.442***	-0.497%	-3.543***	-4.545***
30-11-2020	1,326	-1.347%	-19.111***	-18.580***	-1.470%	-14.023***	-15.820***	-1.388%	-9.977***	-13.303***
05-02-2020	1,326	0.329%	4.839***	3.003***	1.779%	13.994***	15.185***	2.099%	10.681***	12.425***
11-02-2021	1,326	0.022%	0.305	-1.212***	-0.013%	-0.120	-1.480	1.489%	9.340***	8.741***
16-02-2021	1,326	0.202%	2.997***	1.892*	0.057%	0.621	-0.411	0.713%	4.585***	4.518***
17-02-2021	1,326	-0.145%	-2.506**	-3.538***	-0.451%	-4.165***	-4.170***	2.083%	11.138***	12.251***

28-01-2022	1,326	-0.763%	-13.011***	-15.10***	-1.554%	-16.330***	-17.444***	-2.808%	-20.11***	-19.723***
02-02-2022	1,326	-0.705%	-11.815**	-13.225***	0.310%	2.931***	4.302***	-0.713%	-4.843***	-6.214***
18-07-2022	1,326	0.582%	11.548***	10.583***	1.310%	13.012***	12.544***	0.627%	4.110***	3.958***
06-10-2022	1,326	0.031%	0.589	1.633	-0.006%	-0.061	1.574	2.008%	11.054***	13.276***
Negative										
04-09-2020	1,326	0.688%	11.670***	12.415***	1.950%	17.642***	16.910***	1.474%	8.809***	11.051***
17-09-2020	1,326	0.254%	4.056***	5.600***	1.532%	12.920***	13.018***	-1.030%	-5.835***	-8.231***
08-10-2020	1,326	0.763%	10.374***	14.627***	0.041%	0.392	-1.547	-0.383%	-2.489**	-3.727***
18-02-2021	1,326	-0.508%	-7.508***	-7.839***	0.605%	5.917***	8.308***	2.242%	11.013***	12.721***
19-02-2021	1,326	1.258%	18.347***	17.820***	2.142%	15.797***	17.354***	3.269%	13.101***	14.775***
22-02-2021	1,326	1.392%	14.789***	16.464***	2.693%	17.255***	17.903***	2.997%	13.554***	15.193***
07-02-2022	1,326	0.446%	8.253***	10.755***	0.526%	4.723***	3.735***	0.830%	5.308***	5.466***
10-05-2022	1,326	-0.569%	-6.326***	-9.251***	-0.003%	-0.026	3.005***	0.692%	3.827***	6.311***

Extreme changes in coal prices

Event date	Obs.	$\mathbf{AAR_0}$	t-value	Z-value	$\mathbf{CAAR_{(-1.1)}}$	t-value	Z-value	$\mathbf{CAAR_{(-3.3)}}$	t-value	Z-value
Positive										
01-06-2020	1,326	0.813%	10.133***	8.636***	-0.015%	-0.132	-2.304**	3.672%	15.878***	15.250***
27-09-2021	1,326	1.360%	20.523***	19.239***	1.900%	18.566***	17.937***	2.365%	14.776***	13.792***
28-02-2022	1,326	0.003%	0.043	-3.067***	-0.158%	-1.058	-3.159***	0.901%	4.237***	3.566***
01-03-2022	1,326	-0.379%	-4.752***	-5.115***	0.448%	3.608***	2.009*	0.387%	1.629	1.133
02-03-2022	1,326	0.824%	11.887***	12.768***	0.611%	5.282***	6.593***	0.713%	2.592**	3.273***
04-03-2022	1,326	-0.236%	-3.007***	-2.690**	0.047%	0.241	1.454	0.981%	5.386***	5.154***
Negative										
01-11-2021	1,326	1.502%	20.279***	21.326***	0.891%	6.428***	6.805***	0.542%	2.559**	0.253
03-03-2022	1,326	0.166%	2.580**	4.871***	0.754%	5.874***	7.462***	1.265%	5.134***	5.030***
28-03-2022	1,326	-0.793%	-14.508***	-17.429***	0.191%	2.285**	3.095***	-0.969%	-6.608**	-6.637***
02-05-2022	1,326	-0.020%	-0.298	-1.642	1.097%	10.122***	11.482***	0.336%	1.760*	1.959*
31-10-2022	1,326	0.471%	9.259***	10.411***	0.976%	-1.803*	12.230***	2.494%	-4.402***	14.446***

Table 22: Significance of the (cumulative) average abnormal returns

This Table reports the event study results of AAR_0, $CAAR_{(-1,1)}$, and $CAAR_{(-3,3)}$ indicating the (cumulative) average abnormal returns on the event day and over a 3- and 7-day event window, respectively. The (C)AARs are calculated for 1,326 firms using a market-adjusted model without an estimation window during a sample period from March 2020 to October 2022. An extreme energy price change is referred to as an event if the daily energy price is at least 15% higher than the previous day, resulting in a total of 47 events, of which 29 energy price increases and 18 energy price decreases. Afterwards, these AARs are aggregated across all firms and all positive and negative events categorized by energy commodity. To test whether the (C)AARs are significantly different from zero a two-sided t-test (MacKinlay, 1997) and a generalized sign test (Kolari & Pynnonen, 2011) are used. The statistical significance is indicated by ***, **, and * at the 1%, 5% and 10% level.

Extreme changes in oil prices										
Event direction	**Obs.**	**AAR_0**	**t-value**	**Z-value**	**$CAAR_{(-1.1)}$**	**t-value**	**Z-value**	**$CAAR_{(-1.1)}$**	**t-value**	**Z-value**
Positive	10,608	0.389%	6.165***	-3.597***	-0.456%	-5.662***	-10.198***	1.341%	12.542***	14.881***
Negative	6,630	-0.933%	-11.617***	-3.361***	0.440%	3.897***	7.146***	-0.690%	-4.145***	-2.785**
Extreme changes in gas prices										
Event direction	**Obs.**	**AAR_0**	**t-value**	**Z-value**	**$CAAR_{(-1.1)}$**	**t-value**	**Z-value**	**$CAAR_{(-1.1)}$**	**t-value**	**Z-value**
Positive	19,890	0.117%	6.367***	1.145	0.412%	13.335***	10.007***	0.788%	15.920***	11.411***
Negative	10,608	0.466%	17.610***	21.627***	1.186%	26.654***	29.572***	1.261%	18.536***	20.274***
Extreme changes in coal prices										
Event direction	**Obs.**	**AAR_0**	**t-value**	**Z-value**	**$CAAR_{(-1.1)}$**	**t-value**	**Z-value**	**$CAAR_{(-1.1)}$**	**t-value**	**Z-value**
Positive	7,956	0.398%	12.562***	12.403***	0.473%	8.353***	9.547***	1.503%	16.592***	17.035***
Negative	6,630	0.266%	9.0123***	8.778***	0.782%	15.046***	18.723***	0.734%	7.857***	8.064***
Total changes in energy prices										
Event direction	**Obs.**	**AAR_0**	**t-value**	**Z-value**	**$CAAR_{(-1.1)}$**	**t-value**	**Z-value**	**$CAAR_{(-1.1)}$**	**t-value**	**Z-value**
Positive	38,454	0.250%	11.968***	3.461***	0.185%	6.209***	4.717***	1.088%	25.110***	24.378***
Negative	23,868	0.022%	0.805	16.401***	0.866%	21.754***	31.739***	0.573%	9.350***	14.998***

Table 23: Significance of the (cumulative) average abnormal returns distributed over four subperiods

This Table reports the event study results of AAR_0, $\mathrm{CAAR}_{(-1,1)}$, and $\mathrm{CAAR}_{(-3,3)}$ indicating the (cumulative) average abnormal returns on the event day and over a 3- and 7-day event window, respectively, divided into four different subperiods. The (C)AARs are calculated for 1,326 firms using a market-adjusted model without an estimation window during a sample period from March 2020 to October 2022. An extreme energy price change is referred to as an event if the daily energy price is at least 15% higher than the previous day, resulting in a total of 47 events, of which 29 energy price increases and 18 energy price decreases. Afterwards, these AARs are aggregated across all firms and all positive and negative events categorized by energy commodity. The first subperiods is the Covid-19 outbreak phase from March 2020 to June 2020. The second subperiod represents the Covid-19 follow-up phase from July 2020 until June 2021, while the third subperiod covers the recovery phase of Covid-19 from July 2021 to February 21, 2022. Finally, the last subperiods represents the period around the Russia-Ukraine war from February 21, 2022, to October 2022. To test whether the (C)AARs are significantly different from zero a two-sided t-test (MacKinlay, 1997) and a generalized sign test (Kolari & Pynnonen, 2011) are used. In this table, statistical significance is shown only for the two-sided t-test, with significance indicated by ***, **, and * at the 1%, 5% and 10% level. No significant differences were found with the other statistical tests.

Positive events											
Covid-19 outbreak phase			**Covid-19 follow-up phase**			**Covid-19 recovery phase**			**Russia/Ukraine war**		
Oil prices (10,608)			*Oil prices (0)*			*Oil prices (0)*			*Oil prices (0)*		
$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$
0.389%***	-0.456%***	1.341%***	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Gas prices (2,652)			*Gas prices (11,934)*			*Gas prices (2,652)*			*Gas prices (2,652)*		
$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$
1.814%***	2.659%***	2.824%***	-0.113%***	0.090**	0.784***	-0.734%***	-0.622%***	-1.760%***	0.307%***	0.652%***	1.317%***
Coal prices (1,326)			*Coal prices (0)*			*Coal prices (1,326)*			*Coal prices (5,304)*		
$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$
0.813%***	-0.015%	3.672%***	N/A	N/A	N/A	1.360%***	1.902%***	2.365%***	0.053%	0.237%***	0.746%***
Total energy prices (14,586)			*Total energy prices (11,934)*			*Total energy prices (3,978)*			*Total energy prices (7,956)*		
$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$
0.687%***	0.151%**	1.822%***	-0.113%***	0.090%**	0.784%***	-0.036%	0.219%***	-0.385%***	0.138%***	0.375%***	0.936%***
Negative events											
Covid-19 outbreak phase			**Covid-19 follow-up phase**			**Covid-19 recovery phase**			**Russia/Ukraine war**		
Oil prices (6,630)			*Oil prices (0)*			*Oil prices (0)*			*Oil prices (0)*		
$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$
-0.933%***	0.440%***	-0.690%***	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Gas prices (0)			*Gas prices (7,956)*			*Gas prices (1,326)*			*Gas prices (1,326)*		
$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$	$\mathbf{AAR_0}$	$\mathbf{CAAR_{(-1.1)}}$	$\mathbf{CAAR_{(-3.3)}}$

N/A	N/A	N/A	0.641%***	1.494%***	1.428%***	0.446%***	0.526%***	0.830%***	-0.569%***	-0.003%	0.692%***
Coal prices (0)			*Coal prices (0)*			*Coal prices (1,326)*			*Coal prices (5,304)*		
$\mathbf{AAR_0}$	$\mathbf{CAAR}_{(-1.1)}$	$\mathbf{CAAR}_{(-3.3)}$	$\mathbf{AAR_0}$	$\mathbf{CAAR}_{(-1.1)}$	$\mathbf{CAAR}_{(-3.3)}$	$\mathbf{AAR_0}$	$\mathbf{CAAR}_{(-1.1)}$	$\mathbf{CAAR}_{(-3.3)}$	$\mathbf{AAR_0}$	$\mathbf{CAAR}_{(-1.1)}$	$\mathbf{CAAR}_{(-3.3)}$
N/A	N/A	N/A	N/A	N/A	N/A	1.504%***	0.891%***	0.542%**	-0.044%	0.755%***	0.781%***
Total energy prices (6,630)			*Total energy prices (7,956)*			*Total energy prices (2,652)*			*Total energy prices (6,630)*		
$\mathbf{AAR_0}$	$\mathbf{CAAR}_{(-1.1)}$	$\mathbf{CAAR}_{(-3.3)}$	$\mathbf{AAR_0}$	$\mathbf{CAAR}_{(-1.1)}$	$\mathbf{CAAR}_{(-3.3)}$	$\mathbf{AAR_0}$	$\mathbf{CAAR}_{(-1.1)}$	$\mathbf{CAAR}_{(-3.3)}$	$\mathbf{AAR_0}$	$\mathbf{CAAR}_{(-1.1)}$	$\mathbf{CAAR}_{(-3.3)}$
-0.933%***	0.440%***	-0.690%***	0.641%***	1.494%***	1.428%***	0.975%***	0.709%***	0.686%***	-0.149%***	0.603%***	0.763%***

Table 24: Regression model results measuring the influence of ESG performance on abnormal returns

This Table presents the results of the pooled OLS regressions in which a firm's ESG performance is regressed on the (C)ARs of all 1,326 individual firms. The dependent variable consists of a firm's AR_0, $\mathrm{CAR}_{(-1,1)}$, or $\mathrm{CAR}_{(-3,3)}$ indicating the (cumulative) abnormal returns on the event day and over a 3- and 7-day event window, respectively. The (C)ARs are calculated for all 1,326 firms using a constant mean return model with an 8-day estimation window during a sample period from March 2020 to October 2022. An extreme energy price change is referred to as an event if the daily energy price is at least 15% higher than the previous day, resulting in a total of 47 events, of which 29 energy price increases and 18 energy price decreases. Columns 1 shows the regression results with the total ESG score as main independent variable, while columns 2 presents the influence of having a total ESG score higher than the median score of the whole sample. Columns 3 show the results of the models using only the individual environmental pillar of the total ESG score as the main independent variable. Columns 4 present the results of the models including all three individual pillars of the total ESG score: environmental, social, and corporate governance. All regression models include a set of control variables including firm size calculated as the natural logarithm of a firm's total assets, leverage as the ratio of a firm's total debt to total assets, total cash holdings, and returns on assets (ROA) a firm's total net income relative to its total assets. Additional variables are added as a robustness test. First, P/E ratio is calculated by dividing the closing price of a common share by their earnings per share. Second, EXP reflects the percentage change in decrease or increase in daily oil, natural gas, or coal prices. All regression models include industry and year fixed effects and control for autocorrelation and heteroskedasticity by using robust standard errors, clustered by events. The p-values are reported in parentheses and the statistical significance is indicated by ***, **, and * at the 1%, 5% and 10% level, respectively.

	$\boldsymbol{AR_0}$				$\boldsymbol{CAR_{(-1,1)}}$				$\boldsymbol{CAR_{(-3,3)}}$			
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
ESG	0.001				0.003				0.006			
	(0.002)				(0.003)				(0.006)			
High_ESG		-0.000				0.000				0.002		
		(0.000)				(0.001)				(0.001)		
Environmental			0.000	-0.000			0.002	0.002			0.005	0.005
			(0.001)	(0.001)			(0.002)	(0.002)			(0.004)	(0.004)
Social				0.000				0.000				-0.002
				(0.002)				(0.003)				(0.004)
Governance				0.001				0.002				0.003*
				(0.001)				(0.002)				(0.002)
Leverage	-0.002	-0.002	-0.002	-0.002	-0.005	-0.005	-0.005	-0.005	-0.009	-0.009	-0.010	-0.010
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)
Cash	0.001	0.001	0.001	0.002	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005	-0.004
	(0.004)	(0.004)	(0.004)	(0.003)	(0.007)	(0.007)	(0.007)	(0.007)	(0.011)	(0.011)	(0.011)	(0.011)
ROA	-0.005	-0.005	-0.005	-0.005	-0.009	-0.008	-0.009	-0.009	-0.033*	-0.032*	-0.033*	-0.033*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.010)	(0.010)	(0.010)	(0.010)	(0.018)	(0.018)	(0.018)	0.018)

Firm size	-0.000	-0.000	-0.000	-0.000	-0.000	0.000	-0.000	-0.000	0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
P/E	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EXP	0.013***	0.013***	0.013***	0.013***	0.011	0.011	0.011	0.011	0.039***	0.039***	0.039***	0.039***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.008)	(0.008)	(0.008)	(0.008)	(0.012)	(0.012)	(0.012)	(0.012)
Constant	-0.001	-0.001	-0.001	-0.001	-0.006	-0.007	-0.005	-0.006	-0.001	-0.001	-0.002	0.000
	(-0.010)	(0.010)	(0.010)	(0.010)	(0.014)	(0.014)	(0.014)	(0.014)	(0.024)	(0.024)	(0.023)	(0.023)
Observations	56,989	56,989	56,989	56,989	56,989	56,989	56,989	56,989	56,989	56.989	56,989	56,989
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0463	0.0463	0.0463	0.0463	0.0283	0.0282	0.0283	0.0284	0.0548	0.0548	0.0548	0.0549
Adjusted R^2	0.0460	0.0460	0.0460	0.0460	0.0281	0.0280	0.0280	0.0281	0.0545	0.0545	0.0546	0.0546

Table 25: Regression model results measuring the influence of several proxies of a firm's environmental performance on abnormal returns

This Table presents the results of the pooled OLS regressions in which a several proxies for a firm's environmental performance is regressed on the (C)ARs of all 1,326 individual firms. The dependent variable consists of a firm's AR_0, $\mathrm{CAR}_{(-1,1)}$, or $\mathrm{CAR}_{(-3,3)}$ indicating the (cumulative) abnormal returns on the event day and over a 3- and 7-day event window, respectively. The (C)ARs are calculated for all 1,326 firms using a constant mean return model with an 8-day estimation window during a sample period from March 2020 to October 2022. An extreme energy price change is referred to as an event if the daily energy price is at least 15% higher than the previous day, resulting in a total of 47 events, of which 29 energy price increases and 18 energy price decreases. Columns 1 shows the regression results with CO_2 intensity as main independent variable, where CO_2 intensity is a firm's total CO_2 and CO_2 equivalent emissions in tonnes, divided by its total assets. Columns 2 show the results of the models using a firm's political affiliation as independent variable of interest, which is denoted as a dummy variable that takes a value of one if the firm's headquarter is located in a state where a Democrat won, and zero otherwise. Columns 3 presents the results of the models that proxied a firm's political affiliation with the help of the variable presidential votes that reflect the percentage of votes that is received by the Democratic candidate Biden in the 2020 presidential election in the state where the firm's headquarter is located. Finally, columns 4 demonstrate the results of the models that combines two independent variables: CO_2 intensity and political affiliation. All regression models include a set of control variables including firm size calculated as the natural logarithm of a firm's total assets, leverage as the ratio of a firm's total debt to total assets, total cash holdings, and returns on assets (ROA) a firm's total net income relative to its total assets. Additional variables are added as a robustness test. First, P/E ratio is calculated by dividing the closing price of a common share by their earnings per share. Second, EXP reflects the percentage change in decrease or increase in daily oil, natural gas, or coal prices. All regression models include industry and year fixed effects and control for autocorrelation and heteroskedasticity by using robust standard errors, clustered by events. The p-values are reported in parentheses and the statistical significance is indicated by ***, **, and * at the 1%, 5% and 10% level, respectively.

	$\boldsymbol{AR_0}$				$\boldsymbol{CAR_{(-1,1)}}$				$\boldsymbol{CAR_{(-3,3)}}$			
	1	**2**	**3**	**4**	**1**	**2**	**3**	**4**	**1**	**2**	**3**	**4**
CO2 intensity	0.000			0.000	0.000**			0.000*	0.001**			0.001
	(0.000)			(0.000)	(0.000)			(0.000)	(0.000)			(0.000)
Democratic dummy		-0.000		-0.001		-0.002		-0.004**		-0.004**		-0.007
		(0.001)		(0.001)		(0.001)		(0.002)		(0.002)		(0.003)
Democratic percentage			-0.002				-0.006				-0.015	
			(0.004)				(0.006)				(0.009)	
Leverage	-0.001	-0.002	-0.002	-0.001	-0.004	-0.005*	-0.005	-0.005*	-0.005	-0.010	-0.009	-0.007

	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.006)	(0.006)	(0.005)
Cash	0.003	0.002	0.002	0.004	-0.004	-0.005	-0.005	-0.001	0.004	-0.004	-0.003	0.008
	(0.004)	(0.003)	(0.003)	(0.004)	(0.009)	(0.007)	(0.007)	(0.009)	(0.015)	(0.011)	(0.010)	(0.015)
ROA	-0.007	-0.005	-0.005	-0.007	-0.014	-0.008	-0.008	-0.013	-0.043	-0.031*	-0.032*	-0.042
	(0.011)	(0.007)	(0.007)	(0.011)	(0.017)	(0.010)	(0.010)	(0.016)	(0.029)	(0.018)	(0.018)	(0.029)
Firm size	-0.000	-0.000	-0.000	-0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
P/E	-0.000	0.000	0.000	-0.000	-0.000	0.000	0.000	-0.000	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EXP	0.014***	0.013***	0.013***	0.014***	0.013*	0.011	0.011	0.013*	0.041***	0.039***	0.039***	0.042***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.008)	(0.008)	(0.007)	(0.011)	(0.012)	(0.012)	(0.011)
Constant	-0.003	-0.001	-0.000	-0.003	-0.014	-0.007	-0.006	-0.012	-0.017	-0.003	0.003	-0.013
	(0.011)	(0.011)	(0.012)	(0.012)	(0.016)	(0.015)	(0.017)	(0.016)	(0.025)	(0.026)	(0.028)	(0.026)
Observations	27,838	56,989	56,989	27,838	27,838	56,989	56,989	27,838	27,838	56,989	56,989	27,838
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0552	0.0463	0.0463	0.0553	0.0358	0.0284	0.0283	0.0364	0.0665	0.0549	0.0549	0.0671
Adjusted R^2	0.0546	0.0460	0.0460	0.0547	0.0352	0.0281	0.0281	0.0358	0.0659	0.0547	0.0546	0.0665