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Shifting E-ttention During the Russian Invasion

Insights from the Energy Sector

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PREFACE & ACKNOWLEDGEMENT

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ABSTRACT

This study examines whether investor's preferences toward environmental concerns have changed throughout the course of the Russian invasion. In doing so, this thesis contributes to existing literature by extending prior findings from Deng et al. (2022), who reveal investors to expect a slowdown in the climate transition. Specifically, it concentrates on changing dynamics within the energy sector. Focusing on Environmental scores, this thesis finds an increasing abnormal return for companies suffering from high environmental risks. At company-level, this effect is amplified whenever subject to high levels of investor attention, proxied by Google search volume. Concentrating on investor's economy-wide concerns, this research shows the effect of investor attention to be dependent upon the public sentiment and behave differently for high-/low environmental risk companies. Overall, this thesis demonstrates investors' renewed perspective on environmental concerns within the energy sector over the course of the invasion.

Keywords:
ESG performance, Investor attention, Social sentiment, Russian war, Energy sector

JEL Classification: G1, G10, G14, Q51

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1 INTRODUCTION

"We think we're near energy independence – nothing could be further from the truth."

Since its inception, the concept of Socially Responsible Investing (SRI) has gradually matured and become one of the most debated in finance. Though topics of interest have changed dramatically over the course of its existence, SRI has always been characterized by envisioning a social objective in addition to achieving returns. As of the last decade, this concept has become standard in financial analysis, reflected in the emerging Environmental, Social and Governance (ESG) standards. Accordingly, this has led to a vast body of academic literature justifying both asymmetric and symmetric views on the relationship between ESG characteristics and financial performance. Recently, studies primarily favor the latter and point to the outperformance of strong ESG companies, attributed to their risk-mitigating nature in times of high uncertainty. Using the Covid-19 pandemic as a laboratory, investors are demonstrated to primarily focus on the Environmental component, centering on risks arising from the transition to a low-carbon economy. Following Albuquerque et al. (2021), these concerns translate into better resilience for companies with high Environmental scores.

With the outbreak of the Russian invasion, yet another exogenous shock accompanied by great uncertainty has emerged. Apart from the unprecedented direct impact on humanity, this invasion is predominantly characterized by its role as initiator of a revision on conventional ESG perspectives. That is to say, findings show a renewed appetite for companies suffering from risks related to the transition to a low-carbon economy, with a recalibration of investor attention towards the energy sector. The seamlessness of these company-level and industry-wide observations, culminated in this studies research objective. Accordingly, this thesis aims to investigate whether this changing Environmental narrative is persistent within the energy sector. To maximize the added value of this thesis, the following research question examines both effects of company-level and economy-wide concerns.

Have investor preferences regarding the Energy Sector changed during the Russian Invasion?

Since this research aims to demonstrate differences throughout the course of the Russian invasion, a framework consisting of three distinct phases is constructed. Essentially, the main objective is to capture the effect of explanatory variables before, during and in the lag of the Russian invasion to compare disparities in abnormal return effects.

First of all, the thesis focuses on company-level environmental concerns for the firms included in the MSCI World Energy Index. In doing so, the company's Environmental score is obtained from Thomson Reuters' ASSET4 database to proxy for the level of environmental risk. Accordingly, Google search volume data is gathered from Google Trends, to capture effects of investor's attention. By means of extension, the interaction between both terms is considered to demonstrate the effects of environmental scrutiny.

Subsequently, the thesis shifts focus to investors' economy-wide environmental concerns. The intention of this broad view is to examine the effect of investor attention and social sentiment on abnormal return for the words 'Emission', 'Low-carbon' and 'Pollution'. To capture the latter, this thesis follows Polyzos (2022) and uses Twitter data to proxy for movements in the public perception. In particular, this part explores whether the effect of investor attention on abnormal returns is dependent upon the state of the public opinion and differs among high- and low Environmental score companies.

Evidence from company-level analysis presents findings that point to an outperformance of low Environmental score companies, with an amplifying magnitude over the course of the Russian invasion. Different from prior research of El Ouadghiri et al. (2021), results prove investor attention for Environmental risks to be negatively related with abnormal stock return during the full course of the sample period. This effect is the most pronounced in the continuum of the Russian invasion.

Focusing on economy-wide evidence, this negative relationship is persistent in the continuation period when considering the interaction between public concerns and investor attention. In fact, this persistence is founded to be particularly relevant for the companies at the forefront of the transition to a low-carbon economy. This finding contradicts existing ESG literature that indicates an outperformance of low-carbon transition leaders during times of uncertainty.

The remaining study is organized as follows: Chapter 2 covers the literature review and explores in greater depth the effect of ESG scores, investor attention and social sentiment on stock performance. After this stand-alone consideration, section 2.4 defines the exact scope of this research question, adding the proper context to the framework. Chapter 3 then explains the collection of data, consisting of Environmental scores and the proxies for investor attention and social sentiment. Chapter 4 examines the methodology used to answer the research question, whereas Chapter 5 contains the analysis of the results from the constructed hypotheses. Chapter 6 discusses the limitations of the findings and provides recommendations for further research. Ultimately, Chapter 7 summarizes the outcomes and provide some concluding remarks.

2 LITERATURE REVIEW

This review describes the different theories and frameworks underlying this master thesis. The first subpart discusses the emergence of ESG investing and its role as a quantifier of companies' climate transition positioning. In this, the main focus is on the relationship with stock performance in times of uncertainty. The second part introduces a behavioral view on stock performance in which investor attention and social sentiment will be dealt with. Third, the section continuous with an overview of related literature that originated during the Russian invasion. Together, these parts will form the basis of the Russian invasion's-oriented hypotheses formulated within the final section.

2.1 ESG and stock performance

Whereas the practice of socially responsible investing (SRI) already started in the 1960s (MSCI, 2022), the introduction of a first index that focused on 'social conscious investors' only took place in 1990. Since then, the market observed a quest for socially responsible investment opportunities that has gradually spilled over to a vast majority of people[1]. Not surprisingly, dominant issues and trends of 'socially conscious investors' have evolved during this period of time. Today, this type of investments is referred to as ESG conform and concerned with the presence of global challenges such as climate change, carbon neutrality and human rights. Essentially, taking into consideration environmental, social and governance issues on top of traditional financial analysis.

As the rise of ESG investing had clearly spread sustainability concerns into financial markets, European regulators anticipated and introduced the Sustainable Finance Disclosure Regulation (SFDR). The directive was documented with the purpose of steering companies and investors towards more sustainable solutions, nudged by exclusion. As a result of these ESG concerns, a whole new sector emerged that was concerned with quantifying this non-financial information. By the start of 2020, Li & Polychronopoulos (2020) identified at least 70 different firms in the business of ESG score evaluation. Gradually, the importance of these rating agency's scores grew, fueled by the broader topic of climate transition. Hence, a considerable amount of academic research on the link between financial performance and ESG characteristics followed.

Statman & Glushkov (2009) were one of the first researchers who compared returns of 'tilted' portfolios with returns of conventional investors' portfolios during the period of 1992-2007. They distinguish between two types of socially responsible investing, 'tilting' and 'shunning'. The first manner focuses on investors tilting towards socially responsible companies and resulted in better than

[1] Bloomberg expects the amount of global ESG investments to represent a third of the total worldwide AUM in 2025. https://www.bloomberg.com/professional/blog/esg-assets-may-hit-53-trillion-by-2025-a-third-of-global-aum/

conventional stock performance. The latter, that shuns typical non-ESG industries, led to below average stock performance. Intuitively, this 'shunning' result makes sense, especially considering Markowitz (1991) portfolio theory. The exclusion of non-ESG stocks lowers the feasible set of investment options, hence worsens the risk – return trade-off. Moreover, the effect of exclusion reduces the potential number of investors in non-ESG stocks, leaving room for outperformance when investing in 'sin companies'[2]. Hong & Kacperczyk (2009) and more recently Richey (2020) found evidence in favor of a 'sin company' outperformance compared to a regular portfolio. Implicitly establishing that a portfolio without 'sin stocks' performed worse. Benske & Kristiansen (2020) investigated the impact of ESG score changes and identified results in line with this 'tilting' principle. They found a positive relationship between changes in ESG score and stock movements.

On the other hand, investing in a portfolio with high ESG scores essentially lowers the factor of risk. Since higher ESG scores imply a better potential risk mitigation, the risk – return relationship would instead predict lower returns. A recent paper by Pederson et al. (2021) describes the risk – return relationship for different types of investors. The authors create a second 'ESG-efficient' mean – variance frontier to show differences in preferences. This second frontier namely corresponds with slightly more risk-averse investors that prefer doing good above a small extra percentage of return. In essence, this corresponds to ESG investors who mitigate ESG related risk. Pastor et al. (2021) extend these findings and demonstrate that green assets have a lower expected return in equilibrium because investors enjoy holding these assets and mitigate ESG risk.

Theory thus justifies both ways. Nonetheless, in recent times we have seen especially the latter as a result of research. As the COVID-19 pandemic triggered a worldwide financial crisis, high ESG performers have shown to be better resistant against financial downturns (Broadstock et al. 2021). Financial risks for these companies are in general lower, which resulted in an outperformance of high- compared to low ESG portfolios. More specifically, the authors showed that high E and G scores in particular ensured that companies were better prepared for negative impacts emerging during the pandemic. Similarly, Albuquerque et al. (2020) find stocks with high ratings to have significantly higher returns, lower return volatilities and higher trading volumes compared to other stocks. In addition, they solve for the causality problem by portraying the pandemic as an unexpected shock[3]. Along with its exogenous nature, the shock does not allow companies to adequately act. Hence, the authors argue that stock market responses are judged based upon companies' preexisting conditions. That has to say, any abnormal stock response is due to its ESG score controlled for all other variables. Moreover, the paper especially highlights the importance of Environmental and Social scores in

[2] Stocks of companies within industries which are usually exempted from ESG indices.
[3] Causality problem: Does strong firm performance enables ESG activity, or does ESG activity add value to the firm?

making companies resilient in times of uncertainty. In line with the foregoing, Ferriani & Natoli (2021) decompose the risk factors in separate pillars when identifying investor preferences. They demonstrate investors to prefer low-risk ESG stocks during the outbreak and recovery period of the pandemic, with environmental risks as their primary concern. Garel & Petit-Romec (2021) in their turn show that companies embracing responsibilities regarding environmental issues, experience better stock returns. This effect is mainly driven by factors addressing climate change, such as 'resource use' and 'emission'.

Taking the above results for granted, climate responsibility is rewarded during the pandemic and following crisis. The nature of the financial crisis (Covid-19 pandemic) created acceptance from investors to prioritize human's role in climate change. Firms already at the forefront of the climate transition were found to benefit. Today, we experience another rare event now that a war is taking place on European soil. This war may shine a very different light on investors' previous climate transition perception, as there are growing concerns on energy supply[4]. For that reason, this thesis studies the relationship between environmental scores and stock performance during the run-up and course of the Russian invasion.

Table 1 – Overview of ESG studies

Table 1 provides an overview of the ESG studies considered within this research.

Author(s) (Publication year)	**Time period**	**Method**	**ESG & Stock data**	**Results**
Statman & Glushkov (2009)	1992 – 2007	Asset pricing model, 3- & 4-factor model	S&P500, KLD DS400 (Index social responsibility)	Outperformance of SRI portfolios compared to conventional
Hong & Kacperczyk (2009)	1962 – 2007	Asset pricing model, CAPM, 4-factor model	CRSP data on NYSE & Nasdaq, Fama & French industry group 4 & 5	Sin stocks have higher expected returns, due to underpricing
Richey (2020)	1980 – 2019	EGARCH model, Factor portfolio construction	S&P500 benchmark, 106 Alcohol, Tabacco, Defense & gambling stocks	Sin funds mean return equals 1.29 and is 0.2 higher than S&P500, while enjoying a beta of 0.79
Benske & Kristiansen (2020)	2011 – 2020	Event study calculation of abnormal stock price reaction	Thomson Reuters' ASSET4, 1278 unique ESG events	Positive events have 10.61% yoy change, while negative events have < -2.77%

[4] A more extensive discussion follows in subsection 2.4 of this literature overview

Pederson et al. (2021)	1963 – 2019	Efficiency frontier, CAPM, 5-factor model	MSCI ESG scores, XpressFeed, Compustat, Barra US Equity	Sin premium up to 4% a year with value-weighted returns Removing low-ESG score firms from portfolios reduces sharp ratio
Pastor et al. (2021)	Multiple timespans coming from other papers	CAPM, ESG factor portfolio, Equilibrium model	Datasets used in several papers that are covered in this analysis	Negative alpha for 'green stocks' due to preference, Positive alpha for 'brown stocks'
Broadstock et al. (2021)	2015 – 2020	Event study calculating abnormal return, ESG factor portfolio	China's CSI300, wind database, SynTao Green finance ESG data	Stock price reactions of High-ESG firms are more resilient given a 1% less decline
Albuquerque et al. (2020)	1st quarter 2020	Regressing quarterly log returns, Difference-in-difference	Thomson Reuters' ASSET4, 13F equity holdings, Capital IG, Compustat	A one-standard deviation increase in ES ratings leads to a higher average stock return of 2.1%
Ferriani & Natoli (2021)	January 20th – May 1st 2020	Pooled regression on Cumulative Abnormal Return, ESG factor portfolio	Sustainalytics risk factor, Morningstar 'globes', MSCI World equity index	Beta coefficients of low E risk portfolios more than doubled during crash & recovery, showing increasing inflow
Garel & Petit-Romec (2021)	February 20th – March 20th 2020	Cross-sectional regression	Thomson Reuters' ASSET 4, U.S headquartered stock data using Eikon	A one-standard deviation higher E score is associated with 1.41% higher stock returns in COVID-19 crisis

2.2 Limited Attention

In 1973, Kahneman (1973) introduces the so-called 'limited attention' bias. This theory describes the situation of people suffering from a limited ability to observe and process all available information. Abruptly, Kahneman becomes one of the first psychologists to infer with economic theory. According to his findings, information efficiency as assumed in traditional efficient markets seemed counterintuitive. Not long afterwards, it became the foundation of many financial studies focusing on stock performance and investor attention.

Among the first, Merton (1987) demonstrates a situation in which the market is in equilibrium with incomplete information. He finds a market anomaly that requires low attention firms to compensate investors by offering higher returns based on Kahneman's theory. Today, the basis of this anomaly still exists in the form of an information gap between small companies with less information scrutiny and large companies that ought to have more efficient information disclosure. In the field of accounting, Hirshleifer et al. (2003) focus on the relation between financial reporting and limited attention. They find the presentation form to influence investor's perception for both equivalent and non-equivalent disclosures. They argue that people easily absorb information that is presented in a salient way, while struggling to adjust interpretations that are based on more complicated types of disclosure.

Barber and Odean (2008) build on this irrationality of individuals in financial markets and relate it to investors' buying behavior. They decompose the process of human decision making and find that an individual investor divides the process into two parts. First, an investor selects a limited number of stocks to consider. Then, a more in-depth analysis of this limited set of options follows. This division emanates from Kahneman's limited attention bias. They hypothesize that attention-grabbing stocks are more likely to be considered since attention is prone to be a scarce resource. After all, these stocks are more often within the first set of potential buy options. The number of news articles, abnormal trading volume and unusual return act as indirect proxies for attention-grabbing and provide evidence in line with what has been hypothesized. Although Barber & Odean's (2008) theory has been widely recognized, it wasn't long before academics criticized the proxies used. Engle & Rangle (2008) question the incremental value of abnormal trading volume and unusual return as they find unrelated macroenvironmental events to be of influence. Gurun & Butler (2012) investigate media coverage and find investor's home bias to be related with that term. Moreover, it is not guaranteed that media coverage, proxied by news articles, reflects an investor's genuine attention. After all, a published news article must be read before information reaches the investor.

Today, digitalization provides us with an interesting set of potential measures of social behavior and attention. Instead of indirect proxies, search engines like Google and Yahoo reflect the interests of individuals by recording worldwide search queries. According to Batelle (2005), the combined set of queries reveals patterns and potentially represents our collective thinking. Accordingly, Mishne (2006) used online Internet Movie Database (IMDB) reviews in order to predict movie success in terms of sales earnings. Ginsberg et al. (2009) used Google searches to present a method that tracks influenza-like symptoms to predict weekly influenza activity. Van Dijk & Francke (2015) investigate internet search behavior in relation to the Dutch housing market. Their results indicate that the number of internet clicks on listed properties proxies demand, while supply is proxied by the amount of online listed properties.

Within the field of stock performance, Da et al. (2011) support the attention-grabbing hypothesis of Barber and Odean (2008). Using company ticker queries, they demonstrate Google search volume to capture attention of less-sophisticated individual investors. As a method of separation, the type of market center is assumed to reveal an investor's level of sophistication. Subsequently, they provide evidence of an increase in investor attention to cause for positive price pressure within the first two weeks. In the same way, Zhang et al. (2013) reveal direct relationship between investor attention and search frequency of stock names in Baidu index.

More recently, researchers have begun to apply the concept of investor attention to several angles of the climate transition. Both in terms of financial implications and 'limited-attention' effects, interesting relationships have been demonstrated. A study of Choi et al. (2020) illustrates that investors' attention to climate change increases whenever local temperature reaches an abnormally high value. This works its way into financial markets given the observation that, during these days, stocks of carbon-intensive companies underperform vis-a-vis stocks of firms with low-carbon emission. Focusing on trading behavior, the same correlation is noticeable as retail investors have proven to sell carbon-intensive stocks during periods of abnormally high temperature. Essentially Choi et al. (2020) reveal the influence of personal experiences on peoples' collective belief on global warming. Similarly, a study of Liu et al. (2022) investigates potential relationships between air pollution, investor attention and stock performance. Firstly, they demonstrate heterogeneity between the direct effect of air pollution on high- and low polluting stocks[5]. Whereas air pollution could directly influence polluting companies' stock prices negatively, there is no direct effect on green company's stock price. As discussed later, the detection of heterogeneity holds a crucial role within this master thesis. Second, they show investor attention – proxied by the Baidu Index – to function as a mediator between air pollution and stock performance. Namely, all companies within the sample experience a higher level of investor attention on trading days with air pollution. Following Barber and Odean (2008), that higher level of attention could potentially be transposed into higher stock prices. Lastly, the authors find the relationship between investor attention, air pollution and stock prices to be dependent on overall stock market performance. In a way, this finding points towards the importance of contrasting market conditions that are often a result of rigorous policy changes or exogenous shocks.

Notwithstanding the above, studies of He et al. (2022) and El Ouadghiri et al. (2021) primarily indicate a positive relationship between investor attention and environmental issues. He et al. (2022)

[5] In their research, Liu et al. make use of two different groups referred to as 'polluting companies' and 'new energy companies'. In the guise of simplicity, these groups are considered to be high- and low polluting as they hold the same characteristics.

use non-financial, Chinese listed firms to investigate whether corporate green innovation is promoted by retail investor attention. They find evidence of a positive, significant impact of investor attention on corporate green innovation primarily guided by reducing information asymmetry. On top of that, the reduction of funding constraints as well as deterring agency costs both serve as conductor of impact.

Moreover, El Ouadghiri et al. (2021) assessed the effect of public attention for environmental issues through the words ‘climate change’ and ‘pollution’. They find robust evidence for a positive relationship between public attention to environmental issues and returns on US sustainability indices for both media attention as well as Google search volume[6]. In explaining the positive effect, the authors highlight three potential incentives for investor’s buying behavior. Most obviously, a rising public attention for environmental issues could enhance traditional investors’ move towards sustainable investing. This rising attention is likely to result in increasing prices driven by a higher demand. The other two potential explanations are linked with investor sentiment. Supplemental to investor attention, this behavioral concept considers investor’s sentiment and aims to define the level of attention as positive or negative. They argue a high level of positive, public attention for environmental issues to be likely accompanied by rewards for sustainable companies. Equally, this combination of a positive environmental sentiment and high level of awareness may trigger opportunistic investors into profit-seeking strategies. At least temporarily, investors would have the opportunity to make use of momentum and buy sustainable company stocks while divesting their conventional ones. Given this potential complementary effect, the following part further introduces the concept of social sentiment.

Table 2 – Overview of investor attention studies

Table 2 provides an overview of investor attention studies covered within this thesis

Author(s) (Publication year)	**Time period**	**Method**	**Data**	**Results**
Barber & Odean (2008)	1991 - 1996	Event study calculation of abnormal stock return / volume	Plexus Group (tracking professional money managers), CRSP (US stocks)	Attention grabbing hypothesis: Results show a positive buy-sell imbalance for stocks in the news and a negative for stocks out of news
Da et al. (2011)	2004 – 2008	Abnormal Google search volume, VAR model	Russel 3000 index, Google search volume index, SEC Rule 11Ac1-5 reports	Stocks undergoing search volume increases, weekly outperform stocks with decreasing levels by 0.11%

[6] Media coverage is reflected by the total number of published news articles on climate change and pollution in four major US papers.

Zhang et al. (2013)	2011 March 1st – 2012 March 30th	Abnormal return, Correlations, Granger causality	China stock market accounting research (CSMAR), Baidu index	Investor attention adds to explanatory power by at least 26%
Choi et al. (2020)	2001 – 2017 1983 – 2000 (placebo test)	Long-short portfolios, Asset pricing, Log changes	Google search volume index, National climate data center (daily temp.), CRDS stock data	A one-standard deviation increase in abnormal temp., corresponds to 38 bps decrease in return of emission - clean (EMC) portfolio.
Liu et al. (2022)	2016 – 2020	Mediating effect model	China's CSI300 (focusing on new energy & pollution), Baidu index	A 1% increase in Air quality index can lead to a 0.086 return increase for new energy stocks Realized via Baidu index, functioning as mediator given a 1% AGI increase is captured as well in search volume
He et al. (2022)	2011 – 2020	Univariate regression, Causality, Heckman 2 model	China's CSI300, China's Green patent statistics report, Baidu index	One unit increase in attention in t-1, increases number of patents applied for with 47.52% and results in extra 4.55% number of patents granted in t
El Ouadghiri et al. (2021)	2004 – 2018	Pooled linear panel model, Carhart 4-factor model, GARCH-M model	Google search volume index, FTSE4Good USA Index, FTSE USA Index	Interaction term of 0.029 at 1% level indicating return for sustainable index is positively correlated with Search volume index

2.3 Social sentiment

Closely related to the subject of investor attention, social sentiment captures the peoples' collective state of belief. Instead of quantifying the amount of attention, this concept is concerned with establishing society's general opinion. The nature of what the opinion is formed on can vary widely.

Social sentiment ranges from capturing political perceptions to exposing a community's views on a war to be fought. Moreover, since the advent of social media, the possibilities for capturing the collective state of belief have become countless. Hence, this subsection starts with a brief overview centered around the development of social sentiment research before highlighting topic related literature.

Prior to 2007, specifically chosen opinion panels gauged social sentiment through polls primarily. These opinion panels consisted of individuals who collectively matched the characteristics and demographics of the entire society. The aggregate results of these polls served to show what proportion of a population held a particular viewpoint. Yet, they did not explain why respondents answered in a certain way. Consequently, the analysis of the data obtained has always been in the hands of academics. One of the first academic studies on social sentiment – although the authors refer to it as affect analysis by that time – is performed by Abbasi & Chen (2008). Their study focuses on differences in propaganda postings by extremist groups. They measured the presence of hate and violence within extremist groups to show differences in propaganda dissemination across corresponding forums. Around the same time, companies started to use insights from social media to improve their customer satisfaction and overall performance (Zabin & Jefferies, 2008). Almost all leading companies cited in the report appeared to trust insights from social media, given that they acted on it. In this way, companies acknowledged the social media platforms to have become a meeting point for society. After all, these leading companies trusted the modest number of opinions extracted from social media to represent the views of all its customers.

Bollen et al. (2011) anticipated early stage and researched whether these social platforms indeed had potential to become predictors for the society at large. Convinced by the fact that anyone writing on, or searching for, certain topics is genuinely engaged, the authors argued the platforms to be a direct proxy. In their paper, they studied collective mood stages via twitter messages specifically, expecting it to proxy market wide sentiment and concern. Their results act as a confirmation and show an accuracy of 87% in predicting the direction of Dow Jones changes. Despite critics by Lachanski & Pav (2017), the high number of citations reflects the huge potential for further research in the area of social sentiment and limited attention. Among them were Sul et al. (2017) who researched the cumulative sentiment for individual S&P500 companies and related it with companies' corresponding stock return. They proved that using twitter sentiment was indeed valuable, showing tweet sentiment – either positive or negative – to have a significant impact on stock return during all investigated timespans.

Meanwhile, Laakkonen & Lanne (2009) studied the effect of macroeconomic news announcements on volatility during different phases of the economic business cycle. They demonstrate volatility to increase more in good times compared to bad times, especially when the news connotation is negative. Hence, findings demonstrate both the state of the economy and the type of news connotation to be of importance. However, their research design classifies news sentiment based on news announcement's direct impact on stock return. For that reason, their study suffers from endogeneity as the type of news label follows the stock return reaction. Drawing on this research, Shi et al. (2016) aim to solve the problem of endogeneity. Instead of market classification on the basis of immediate stock impact, they use linguistics-based sentiment scores as a classifier of news. Similar to Laakkonen & Lanne (2009) they relate social sentiment to market volatility, distinguishing between two different states of the economy. To be more precise, they differentiate between a 'calm' and 'turbulent' state that represent low- and high market volatility. Using the Markov Regime-Switching model, the hourly return volatility is demonstrated to behave differently per state of the economy. Namely, the stock return volatility appears more persistent in the calm- than in the turbulent state. In addition, the authors distinguish between the sign of the news sentiment and demonstrate the effect of 'bad news' to be more pronounced. As such, results are consistent with the claim that asymmetric news effects yield different results and are dependent upon the regime input.

Following evidence on regime dependency, Turkson (2021) studied the relationship between social sentiment – in terms of fear in the market – and ESG performance. Using the volatility index (VIX) designed by the Chicago Board Options Exchange, the author quantifies levels of fear and accordingly classifies a 'calm' and 'fearful' group. Turkson demonstrates that ESG score increases yield positive returns, whenever considerably higher levels of fear are of presence within the market. On the contrary, in times of lower levels of market fear, results point in the opposite direction and result in negative returns. The results of Turkson seem to indicate a link between ESG and stock performance, with the precise direction again depending on the connotation of social sentiment. By extension, Kvam et al. (2022) focus on short-term stock performance, economic uncertainty and ESG concerns based on real-time data from social platforms. Besides using the VIX to cover as a general measure of uncertainty, the authors distinguish two common approaches in social sentiment analysis to optimize the potential contribution of their findings. On the one hand, the authors incorporate company-level data to relate it with company ESG measures. Here the authors demonstrate high-quality ESG companies to have superior returns in periods characterized by a higher level of company scrutiny. This finding is more related to investor attention, since it is not directly linked to the public's perception. On the other hand, a different approach is employed to reveal heterogenic behavior in diverging stages of anxiety by monitoring the level of ESG concerns via Google Trends and Twitter. This was examined based on the expectation that investor preferences change whenever ESG related events happen. Results show that in times of rising ESG concerns, as measured by a low Twitter mood on ESG themes, high-quality ESG firms enjoyed higher short-term returns. Consequently, the heterogeneric effects of social sentiment on stock performance and ESG topics have been demonstrated in various ways. Hence, this study will incorporate the concept of heterogeneity with respect to social sentiment in the final research design.

Table 3 – Overview of social sentiment studies

Table 3 provides an overview of social sentiment studies addressed in the literature review section

Author(s) (Publication year)	**Time period**	**Method**	**Data**	**Results**
Bollen et al. (2011)	2008 Feb 28th – Dec 19th	Granger causality, Fuzzy neural network model	Dow Jones Industrial average, OpinionFinder (OF), Consumer Confidence Index, Sample of 9m tweets	Twitter mood to hold 87,6% accuracy in predicting Dow Jones Industrial average direction
Sul et al. (2017)	2011 – 2013	Cumulative abnormal return, Long-short portfolios	S&P500 data (CRSP), Sample of 3.5m tweets, Harvard-IV dictionary Institutional Brokers' estimate system (IBES)	Significant beta coefficients for all directions of sentiment, in all three time periods
Laakkonen & Lanne (2009)	1999 – 2004	(FFF) Flexible Fourier Form, (STR) Smooth Transition Regression (two-regimes)	5-min quote exchange rate USD/EUR, World Economic Calendar (WEC), ISM index[7]	News effects depend on the state of the business cycle (θ > 0) Asymmetric effects, volatility increases more in good than bad time
Shi et al. (2016)	2000 – 2010	Markov regime switching GARCH model	S&P100, CRSP, Thomson Reuters' thick history (TRTH), RavenPack Analytic News database	Modeling news variables induce stock return volatility persistence in calm states significantly in at least 82/85 estimates
Turkson (2021)	2011 – 2020	Asset pricing, 5-factor model, Time-fixed OLS	S&P500 Thomson Reuters' ASSET4, Volatility index (VIX)	In times of high VIX, a 10-point increase in ESG score corresponds with 0.04% higher weekly return

[7] Constructed from survey results completed by 300 people from 20 different manufacturing industries in order to comment on business cyclicity. These respondents are asked to classify the state of the economy as 'worse', 'equal' or 'better'. IFO Business sentiment serves as European equivalent.

Kvam et al. (2022)	2009 – 2019	Abnormal return, Multivariate regression: Panel analysis, 3-factor model	NYSE/Nasdaq (stock) Thomson Reuter's ASSET4, Google Trends, Twitter TextBloB, Volatility index (VIX)	The impact of the mood related to ESG topics shows high, asymmetric dependence on ESG scores

2.4 Investor preference in times of uncertainty

This part of the literature review explains the motivation behind the research question. For that reason, it focuses on the Russian invasion, which can be seen as driving force underlying this study. The tragic unfolding in Ukraine namely creates a unique environment for analyzing uncertainty. Further, this part functions as a synthesizer, given that it combines findings from the former, stand-alone literature sections to construct a foundation for this master thesis.

In the face of uncertainty

As demonstrated in the first subsection, the Covid-19 pandemic has proved a useful decor for economic analysis. Since the lockdowns were not anticipated for, originated from public health concerns and were followed by a stock market crash, the event satisfies the characteristics of a so-called exogenous shock (Christiano et al., 1999). Not surprisingly, given the nature and extent of the pandemic, studies predominantly focused on the uncertainty component. More precisely, most of the resulting studies were concerned with changing investor behavior and wondered if certain stock characteristics would entail different stock market reactions. Relevant to this master thesis, Broadstock et al. (2021) and Albuquerque et al. (2020) both performed such an analysis, while considering ESG-based investments. They find evidence in favor of the recalibration of investor' preferences. The former presents an outperformance of high- compared to low-ESG portfolios, while the latter finds higher returns for companies with high preexisting ESG rates. In fact, both studies in their own way demonstrate a small role of ESG performance in 'normal' times, while confirming its incremental importance during crises. In a similar way, Pastor et al. (2021) investigate return effects at times of climate shocks. They proxy for these shocks by the use of extreme weather events like heat waves and floods. Results show comparable effects, as high-quality ESG stocks outperform the lower ones whenever such a climate shock occurs. Strictly relying on the efficient market hypothesis, evidence should point in the direction of an immediate, correct stock price adjustment. However, the abovementioned studies arrive at a different conclusion. It is for that reason, that behavioral theories have been introduced to provide further clarification.

Just like the Covid-19 pandemic, the Russian invasion lent itself perfectly to broaden economic analysis focusing on uncertainty. As a matter of fact, a long-lasting period of peace within Europa has namely been interrupted. After several weeks of building up troops around the Ukraine border, the Russian's officially launched a special military invasion on the 24th of February 2022. According to EU Council president Charles Michel, this groundless attack is the worst on European soil ever since World War II[8]. Apart from the unparalleled direct consequences for humanity, the invasion also caused increasing geopolitical tensions between the Western world and Russia. Given that the Russian invasion of Ukraine originated from geopolitical concerns, had not been factored in by policymakers and was followed by a world-wide financial decline in stock markets, the event qualifies as an exogenous shock following Christiano et al. (1999)'s definition as well. This way, the unfolding of the Russian invasion transcends the boundaries of European soil and touches many different economic indicators that can be researched for.

Despite the fact that the invasion occurred only recently, there is already a fair amount of academic literature devoted to it. While this demonstrates the extraordinary nature of the event, it also allows for a brief extension of the literature review. One of the first researchers to use the Russian invasion as a laboratory are Clancey-Shang & Fu (2022). In their study, the authors test for the resiliency hypothesis that is concerned with corporate social responsibility figures and stock performance. They hypothesize a divergence between high- and low-ESG firms' stock market response at the time of the Russian invasion. After all, according to this theory, higher ESG scores should reflect higher stock quality in the form of a better risk resistance. Indeed, findings are in line with expectations as better ESG performance mitigates the deterioration of market quality. Berninger et al. (2022) examine companies' strategic decisions regarding potential divestment. After years of following globalization policies, companies' operations are widely distributed and often include Russian exposure. The authors choose to analyze companies' return movements on the basis of their decision to abandon or proceed Russian operations. After all, this has been a vivid topic throughout the invasion as companies were encouraged to make a statement on staying or leaving the invading country's soil[9]. They divide their sample into three parts of which the final group of interest consists of companies yet to be decided. Their results demonstrate that firms deciding to leave Russia performed less than the other two groups. Additionally, they find a divergence in industry wide reactions, indicating results to be industry dependent. Basnet et al. (2022) merge the methods of the previous two studies, motivated by ambiguous literature on ESG impact amidst the Russian invasion. Accordingly, they study companies' decision to stay or leave the Russian market using ESG scores. In doing so, they anticipate

[8] See https://europa.eu/!6F76mg

[9] During the first months, pulling back from Russia is a hot topic on news channels. In fact, researchers even dedicated a professional website to it: https://leave-russia.org/

stock market reactions to be either in line with Krüger's (2015) offsetting effect, or consistent with the resiliency hypothesis[10]. In line with the latter, the authors demonstrate a heterogeneous stock market effect where companies with higher scores experience better stock market reactions. Contrary, whenever in the possession of a low score, a companies' likelihood to preserve Russian operations increases. Hence, findings of Basnet et al. (2022) demonstrate high ESG scores to partly mitigate the negative cash flow impact related to its divestment decision.

Table 4 – Overview of uncertainty studies

Table 4 lists the uncertainty related studies covered within this thesis

Author(s) (Publication year)	Time period	Method	Data	Results
Broadstock et al. (2021)	2015 – 2020	Event study calculating abnormal return, ESG factor portfolio	China's CSI300, wind database, SynTao Green finance ESG data	Stock price reactions of High-ESG firms are more resilient given a 1% less decline
Albuquerque et al. (2020)	1st quarter 2020	Regressing quarterly log returns, Difference-in-difference	Thomson Reuters' ASSET4, 13F equity holdings, Capital IG, Compustat	A one-standard deviation increase in ES ratings leads to a higher average stock return of 2.1%
Pastor et al. (2022)	Multiple timespans coming from other papers	CAPM, ESG factor portfolio, Equilibrium model	Datasets used in several papers that are covered in this analysis	Outperformance of green stocks: Green-Brown (GMB) portfolio alpha ranges from 47 to 71 bps per month, controlled for all models
Clancey-Shang & Fu (2022)	2022 Jan 20th – March 31st	Event study, Pooled OLS, Propensity Score Matching method	CRSP US stock data, Bloomberg ESG data, Alternative Dispute Resolution II & III (foreign firms)	Better CSR scores experience on average 0.44-0.67 % less of price swings post- war outbreak
Berninger et al. (2022)	Event date: 24th Feb 2022 Timespan: 20- day 60-day	Event study on buy and hold abnormal returns (BHARs)	Sonnenfeld et al.'s list on firm's actions for Russian operations[11], Refinitiv DataStream stock data	Firms announcing to stay in Russia experience smaller decline than the ones announcing to stay during the 20-day window (-1.66 vs. -1.94 %)

[10] According to Krüger (2015), an offsetting effect reflects a situation in which positive ESG news results in a better stock market reaction for companies with low ESG scores.

[11] List of global companies with Russian exposure and their decision related the proceeding of their Russian operations. Berninger et al. only use the 806 publicly listed companies within their study

				Narrative revolves in 60-day window
Basnet et al. (2022)	Event date: 24th Feb 2022 Window: -1 +1 CAR -252 to -30	Cumulative Abnormal return (CAR),	Thomson Reuters' ASSET4, Yale SOM on firms' actions in Russia, MSCI World Index	A one-standard deviation increase in ESG score, decreases firm's probability to remain in Russia by 5.4%

Recalibration of investor preferences

The Russian invasion has also been examined from other perspectives. Rather than focusing on general theories describing investor behavior in times of uncertainty, Sing et al. (2022) consider the direct consequences of the invasion as an angle for their research. Since the conflict arose, energy independence has been at the top of global priority lists and is constant fuel for discussion. Especially following the Western announcements of financial- and trade sanctions imposed on Russia. Amidst this conflict, investors have to reconsider their conventional views on ESG requirements, given the changing narrative on energy production and domestic security. On top of that, countries' increasing spending in these areas leads to numerous new investment opportunities. For that reason, the authors expect a recalibration of investor preferences towards the Energy and Aerospace & Defense sector. Using the spillover effects framework as presented by Diebold & Yilmaz (2012), the authors find both Energy as well as Aerospace & Defense stocks to be the net pairwise receiver. These results suggest that investor preferences have increased for both sectors at the expense of the standard ESG indices[12].

Complimentary to the above, Deng et al. (2022) attempt to reveal investors' expectations regarding the climate transition as a response to the Russian invasion. More precise, the authors created a framework that is supposed to expose investors' expectations regarding the transition towards a low-carbon economy. To allow for that, the unfolding of the Russian invasion is divided into three separate parts, each subject to predefined characteristics. By examining the differences in effects during these periods, the authors expect a divergence as from the date of invasion[13]. Results demonstrate stocks more exposed to the regulatory risks of the transition to a low-carbon economy to perform better. Herein, these regulatory risks come primarily from threats centered around the persistent use of fossil fuels. Fundamentally, the results of Deng et al. (2022) are in line with research from Sing et al. (2022) and suggest other stocks to benefit at the expense of transition leaders.

[12] In their research design the authors proxy for sector and ESG focus, using the corresponding MSCI global indices
[13] The first period concerns the weeks before the date of invasion, the second period covers the circa two weeks of high uncertainty following the actual raid, while the third period examines the continuation in the weeks after

Essentially, results of both studies point in the direction of a changing investor perception. Whereas the results of the first study show a recalibration towards specific industries, the second study demonstrates stocks more exposed to the regulatory risks of a low-carbon transition to outperform. These outcomes provide scope for an examination of effects within a specific industry.

This thesis intends to fill that gap in academic literature and focuses on the effect of this climate risk characteristic within the oil and gas industry. In doing so, it draws on findings in the area of social sentiment. Just like Erhemjamts et al. (2022), climate risk exposure will be linked with ESG performance and social sentiment. However, instead of focusing on institutional bank's financial performance, this thesis rather visualizes the effects within the energy sector. In doing so, the already presented heterogeneric effects and social sentiment dependency are considered. A final look is taken on research of Polyzos (2022), who uses a comparable set of ingredients that are proposed for this thesis. Despite having a different purpose, his findings prove the significancy of Twitter sentiment as proxy for movements in the public's perception. In concrete terms, Polyzos (2022) finds real-time social media sentiment to function as a decision-making tool, demonstrating changing public perceptions to have a significant, asymmetric direct stock effect on European stock markets. This thesis draws Polyzos' timespan more broadly derived from Deng et al.'s (2022) concept for the classification of phases in the Russian invasion. A more thorough explanation of the rationale behind the chosen timespan follows in the methodology section.

Table 5 – Overview of recalibration of preferences studies

Table 5 lists the overview of recalibration of preferences studies, focusing on the Russian invasion

Author(s) (Publication year)	**Time period**	**Method**	**Data**	**Results**
Sing et al. (2022)	2019 April 1st – 2022 May 6th	Return spillover effects, Dickey Fuller, VAR model	MSCI World ESG, Energy, defense, Investment grade, High yield index (stock & bonds)	Return spillover reversal after 24th of February, from ESG index towards Energy & Defense sector
Deng et al. (2022)	2022 Jan 24th – 2022 April 29th	CAPM, 5-factor model, Cumulative return	Google trends, Compustat global, Thomson Reuter's ASSET4, Transition risk factor[14]	A one-standard deviation higher transition risk experiences 11% of a standard deviation higher return in outbreak
Erhemjamts et al. (2022)	2003 – 2018	Asset pricing, 3, 4- & 5-factor	MSCI ESG (KLD), Truvalue Labs (ESG sentiment),	Bank's climate risk exposure is negatively related

[14] Textual risk measure based on NLP provided by Sautner et al. (2022)

		Long-short portfolios	Urban Adaptation Assessment (risk for climate event)	to public sentiment around that bank's ESG issues
Polyzos (2022)	2022 15th of Feb – 2022 26th of Feb	Impulse response functions, Regime-switching	Twitter API (43mil), 5-minute closing prices (log return) Developed market stock data	Positive shocks (escalating) cause an immediate negative response on EU stocks

2.5 Hypotheses

The preceding sections have shed light on both separate and combined effects of environmental scores, investor attention and social sentiment in different periods of economic (un)certainty. This final subsection will list the key insights that have emerged during the literature review in order to properly formulate the thesis' research question. First, academic theory has justified both asymmetric and symmetric views on the link between financial performance and ESG characteristics. In recent years, accompanied by high levels of uncertainty, strong ESG performance has primarily been associated with risk aversion. Especially Environmental concerns stand out, as Ferriani & Natoli (2021) demonstrate it to be investors' main ESG concern. Accordingly, Albuquerque et al. (2020) find high E-score firms to be more resilient in uncertainty. Second, Zhang et al. (2013) reveal investor attention to add to explanatory power. This literature section shows a direct effect for which the direction depends on the state of the economy. The third part shows that social sentiment analysis has found its way into finance, culminating in Su et al. (2017) demonstrating significant beta coefficients based for all directions of sentiment. Moreover, Kvam et al. (2022) indicate that the impact of ESG sentiment – expressed by Twitter – is highly dependent on a companies' ESG score. Lastly, the overview shows the recalibration of investor attention towards the energy sector, focusing on emerging literature amidst the Russia-Ukraine conflict. In line with the amplifying results in times of uncertainty, the unfolding Russian invasion lends itself perfectly as a laboratory. With that in mind, the following main research question has been arrived at:

Have investor preferences regarding the Energy Sector changed during the Russian Invasion?

To answer the above research question, a framework comprising of three distinct phases of the research period is designed. These periods are referred to as build-up, outbreak and continuation phase and allow to capture investor preferences before, during and in the lag of the Russian invasion. Accordingly, this classification aims to reveal differences in the relationship of abnormal stock return and independent variables between three ambiguous phases of public sentiment and uncertainty.

Consistent with Kvam et al. (2022), this framework is structured to focus on both company-related and economy-wide Environmental concerns. In line with the literature review, the effect of Environmental scores on stock return is firstly discussed and is focused to uncover differences throughout the course of the invasion. From this, the first hypothesis was formed:

Hypothesis 1: *'The effect of Environmental scores on abnormal return is heterogeneous among different phases of the Russian Invasion.'*

In contrast with recent studies proving companies with high Environmental scores to outperform during periods of uncertainty (Garel & Petit-Romec 2021, Albuquerque 2020), this thesis expects lower score companies to experience higher returns from Ukraine's actual incursion. This unique situation is expected to reverse investor's perception on energy stocks, prioritizing energy supply. This expectation results in the following hypothesis based on the reverse resiliency effect.

Hypothesis 2: *'Firms with low Environmental scores experience higher abnormal return than firms with high Environmental scores starting from the outbreak phase.'*

Given that the literature points to the importance of two components underlying the Environmental score, the unique effect for these separate scores will be evaluated. Hence, the second hypothesis is divided into the three hypotheses below:

Hypothesis 2a: *'Firms with low Environmental scores experience higher abnormal return than firms with high Environmental scores starting from the outbreak phase.'*

Hypothesis 2b: *'Firms with low Emissions scores experience higher abnormal return than firms with high Emissions scores starting from the outbreak phase.'*

Hypothesis 2c: *'Firms with low Resource use scores experience higher abnormal return than firms with high Resource use scores starting from the outbreak phase.'*

Subsequently, Kahneman's limited attention theory is considered. Following Da et al. (2011), Google search volume is demonstrated to function as a proxy for investor attention. Combined with the results of Choi et al. (2020), a positive relationship between stock return and retail attention is expected. Hence, the third hypothesis states:

Hypothesis 3: *'Firms with high investor attention experience higher abnormal returns than firms with low investor attention.'*

By extension, the effect of investor attention is considered as an interaction term. This part of the thesis builds on findings from He et al. (2022) and El Ouadghiri et al. (2021) among others, who demonstrate a positive and significant interaction between Environmental concerns and attention. Since this thesis expects the invasion to have changed dynamics, the opposite is anticipated as from the outbreak phase. Hence, the hypothesis is further specified and reads as follows:

Hypothesis 4: *'The combination of investor attention and environmental scores has a significant, asymmetric effect on abnormal returns starting from the outbreak phase'*

Shifting the focus to economy-wide concerns, the public's perception is tested for within a panel regression. Following Sul et al. (2017), this thesis proxies for public sentiment by the use of Twitter data. Considering the literature overview to suggest a significant relationship, the direct explanatory power and direct effect of social sentiment is addressed:

Hypothesis 5: '*The interaction of social sentiment and investor attention has a significant effect on abnormal return during all phases of the Russian Invasion'.*

Finally, this thesis examines the different effects for economy-wide investor attention and sentiment for a split sample categorized by Environmental scores. Drawing on results of Kvam et al. (2022), a heterogeneous impact of public sentiment is expected for the different panels. The below stated hypothesis is formulized to test for this:

Hypothesis 6: '*The effect of social sentiment on abnormal returns given a certain level of investor attention is dependent upon a company's Environmental score'*

3 DATA

The following section sheds light on the necessary sources of data needed to answer the hypotheses formulated within this study. Since this thesis aims to expose differences in investor's behavior throughout the course of the invasion, data is presented per distinct phase. This part will mostly consider the collection of data and the choices made. It first elaborates on the collection of stock performance data. Second, the extraction of data related to environmental concerns is a subject of debate. Then, the use of Google trends as a measure of investor attention will be discussed. The final part considers the collection of Twitter data, gathered to perform the social sentiment analysis. Descriptive statistics of both explanatory and control variables will be presented at the end of each subsection.

3.1 Stock data

In this study, MSCI World Energy Index company data is used to assess stock performance. As discussed in the following methodology section, stock performance data during the period of Jan 24th until May 25th, 2022, is considered. Since the required data only covers less than a year of MSCI World Energy Index company data, a static portfolio composition is assumed. That has to say, the stocks included in the index as of the 1st of January 2022 are guiding. Daily data will be retrieved from Thomson Reuters Eikon and includes trading volume, market capitalization and stock prices. In total, the MSCI World Energy Index consists of 58 worldwide oil & gas companies within developed countries, divided into eight different categories. Tables 6A, 6B and 6C demonstrate the descriptive statistics of the extracted stock related and accounting data. The provided summary statistics aim for an intuitive demonstration, hence are generally shown as extracted prior to operationalization. Additionally, the data is further examined to provide a valid approximation of a normal distribution. Essentially this boils down to the standardization – and if necessary, transformation – of data to fit a regression that assumes normal distribution. The exact specifications have been excluded from text for the sake of brevity yet are listed in the concluding table of this section. Before that however, summary statistics on the stock related control variables are presented below.

Table 6A – Descriptive statistics Abnormal Return and Market Capitalization

Table 6A shows the descriptive statistics for a stock's daily abnormal return. The second column provides a summary of the corresponding market capitalization, calculated by the daily number of shares outstanding times the current stock price.

Table 6A – Descriptive statistics Abnormal Return and Market Capitalization

		Abnormal return			Market Cap (Millions of $)		
		Mean	Median	St. Dev	Mean	Median	St. Dev
	Buildup	0.005	0.004	0.025	44,556	27,596	60,094
	Outbreak	0.017	0.091	0.060	46,654	28,759	63,690
	Continuation	0.007	0.006	0.027	50,060	31,114	67,512
All		0.008	0.006	0.032	48,154	28,961	65,102
N	5,016						
Firms	57						

Table 6A demonstrates the outbreak period to exhibit the highest level of abnormal return. During this period, the average daily return was 1.7% higher than the expected return based on the risk level of the investment. Overall, the results show a daily positive abnormal return of 0.8%, indicating that the MSCI World Energy Index companies outperformed the market during this period[15]. As a consequence, the mean and median figures of the Market Cap variable show an upward trend throughout the course of the Russian invasion. Moving on to Table 6B, the control variable leverage shows a downward trend. Rather unsurprisingly, as it reflects the company's debt position relative to its Market Cap. The second column focuses on Abnormal trading Volume and demonstrates the outbreak period to exhibit positive Abnormal Volume. This indicates increasing market interest and/or activity compared to the full sample. Table 6C demonstrates the summary statistics for the control variables Cash and Return on Assets. Both variables represent a ratio that is based on a company's total assets held by the year end of 2021, implying that Cash and ROA are stable over the entire period.

[15] The FTSE All World index return is used to proxy for market-wide returns

Table 6B – Descriptive statistics control variables Leverage and Abnormal Volume

Table 6B shows the descriptive statistics for the control variables Leverage and Abnormal trading Volume. The first variable represents a company's end-of-year debt as a factor of the median periodic Market Cap. Abnormal trading volume reflects the company's level of activity relative to the period mean of all 57 companies.

Table 6B – Descriptive statistics control variables Leverage and Abnormal Volume

		Leverage			Abnormal Volume		
		Mean	Median	St. Dev	Mean	Median	St. Dev
	Buildup	0.457	0.378	0.373	-0.092	-0.080	0.555
	Outbreak	0.440	0.391	0.368	0.094	0.141	0.550
	Continuation	0.413	0.325	0.381	-0.013	-0.082	0.542
All		0.437	0.361	0.374			
N		171			5,016		
Firms		57			57		

Note: Daily Abnormal trading volume is aggregated per distinct phase to represent a period average

Table 6C – Descriptive statistics control variables Cash and ROA

Table 6C shows the descriptive statistics for the control variables Cash and Return on Assets. Both represent a financial ratio that is dependent upon the company's total assets held by the year end of 2021.

Table 6C – Descriptive statistics control variables Cash and ROA

		Cash			ROA		
		Mean	Median	St. Dev	Mean	Median	St. Dev
	Full sample	0.086	0.090	0.057	0.065	0.052	0.088
N	57						
Firms	57						

The subsections below elaborate on the independent variables of interest, directly addressing consequential elements needed to include a company in the data sample.

3.2 Environmental data

When it comes to climate risk quantification, this thesis follows a wide range of academic studies using ESG score frameworks. On top of the vast body of existing literature and research methodologies, the study of Hirshleifer et al. (2003) serves as a decisive factor for choosing ESG data as quantifier of climate risk. As shown in the literature review above, Hirshleifer et al. (2003) argue that people easily absorb information that is presented in a salient way. Over the past years, ESG data has peacefully increased in popularity, becoming normal practice when conducting financial analyses. In this regard, it has virtually the same function as conventional accounting principles. That has to say, independent agency firms assess the corporate social responsibility performance of businesses to provide the public with information. Given that these ESG scores are widely known and – due to their standardization – are easy to read, they properly fulfill Hirshleifer et al.'s definition. For that reason, investors should easily absorb this type of climate risk information, allowing for a quick reflection in financial markets.

For the purpose of this analysis, company scores for one of the most prominent ESG rating agencies, Thomson Reuters Eikon, have been chosen. This is in line with previous literature of Benske & Kristiansen (2020) and Basnet et al. (2022) among others, which rely upon the composed ASSET4 database. This database aggregates over 750 datapoints to arrive at company scores in the pillars of Environmental, Social and Governance matters[16]. These pillar scores are composed as the relative sum of the category weights, varying throughout the universe of industries. The scores for each of these components are normalized to percentages and range from 0 to 100. Collectively, these numbers provide a companies' overall ESG score, which reflects the level of corporate social responsibility.

Nonetheless, the meaning and value-added of this combined score differs, as it comprises a wide range of subjects (social, governance, environmental) into the aggregated score. It is for that, Ferriani & Natoli (2021) decomposed the overall ESG score to identify investor preferences during the pandemic. Similar to Broadstock et al. (2021), they demonstrate investors to favor low-ESG risk stocks during periods of uncertainty, with environmental risks of their primary concern. Undoubtedly, the nature of the current period of uncertainty causes investors to prioritize environmental concerns as well. Since the start of the Russian invasion, energy independence has been a hot topic, leading to renewed debates about fossil fuels and carbon emissions among others. Consequently, the focus of this thesis shifts towards the Environmental component. This pillar-specific approach ensures investor's primary climate concern to be considered, without further noise from Social and Governance matters.

The ASSET4 database divides the Environmental pillar into three distinct components, covering the use of resources, level of innovation and a company's emissions. Table 7 provides a categorized overview of the definitions used per specific measure[17].

[16] Specific information on the generation of all data points can be found in Asset4's professional guide provided by Thomson Reuters Refinitiv.
https://my.refinitiv.com/content/dam/myrefinitiv/productdoc/Asset4ESGProfessional_Guide.pdf
[17] Definitions are taken directly from Thomson Reuters Refinitiv's database

Table 7 – Definitions Environmental category scores

Table 7 shows the relevant Thomson Reuters Refinitiv definitions per component score

Table 7 – Definitions Environmental category scores	
Category score	**Definition**
Environmental Score E_{score}	Combined score of all three elements below
Emissions score $Tresgeners$	Emissions score measures a company's commitment to and effectiveness in reducing environmental emission in the production and operational processes
Innovation score $Tresgenpis$	Reflects a company's capacity to reduce the environmental costs and burdens for its customers, thereby creating new market opportunities through new environmental technologies and processes or eco-designed products
Resource use score $Tresgenrrs$	Resource use score reflects a company's performance and capacity to reduce the use of materials, energy or water, and to find more eco-efficient solutions by improving supply chain management

As a means of control, the qualification of climate risk within recently introduced papers using Natural Learning Program's (NLP) has been examined. Although all slightly different, the general methodology involves a climate risk score determination relying on a textual analysis of a predetermined set of words in company related material[18]. To single out a specific study, Sautner et al. (2022) reveal regulatory risks – arising from global shocks or political reforms – to be the most prominent in determining climate risk. According to Deng et al. (2022) this corresponds primarily to risks arising from a transition to a low-carbon economy, boiling down to company's persistence on sin operations. Extending this approach to ESG terminology, the take on climate risk factors corresponds mainly to the Environmental score. Deepening in on the environmental score, this machine learning way of qualifying climate risk seems to focus primarily on two underlying components, a company's emissions and fossil-fuel use. Garel & Petit-Romec (2021) arrive at the same conclusion, as they demonstrate factors addressing climate change to be more influential than the innovation component. However, their findings may also stem from the fact that innovation tends to involve a long-term focus.

Given the above, the use of Environmental scores seems well-founded. Nevertheless, combined with Ferriani & Natoli (2021) who demonstrate separate components to contain unique information, this thesis will shortly dive deeper into two underlying components. That has to say, the company's *Emissions score* and *Resource use score* will be analyzed independently in the second hypothesis. Hence, in addition to inclusion in the MSCI World Energy Index, it is necessary for a company to have an E_{score}, $Tresgeners$ and $Tresgenrrs$ score. Given that 2021 marks the last year of available year-

[18] For example, company filings, 10-Ks, annual reports

end data, this has been chosen as baseline. All in all, these requirements reduce the number of companies in the sample by only 1, leaving 57 companies spread across a total of 13 countries. Figure 1 shows most of these companies to be located in North America, with 39 companies in either Canada or the United States.

Table 8 – Descriptive statistics Environmental scores

Table 8 provides the summary statistics for the three Environmental related scores of interests. The figures presented cover the 2021 year-end score for a sample of 57 companies within the MSCI World Energy Index.

Table 8 – Descriptive statistics Environmental scores

	Measure						
	Mean	Median	Min	Max	St. Dev	Skewness	Kurtosis
Environmental score	65.57	71.28	6.64	94.60	19.70	-0.68	0.05
Emissions score	78.50	85.59	10.23	99.15	19.70	-1.31	1.62
Resource use score	73.22	78.62	3.57	99.71	19.94	-0.93	1.07

Note: The entire scope of scores ranges from 0 to 100.

Table 8 shows the descriptive statistics for the headline Environmental score and two of the three underlying components of additional interest. With respect to the headline pillar score, the values range from 6.64 to 94.60 resulting in a mean value of 65.57. Relative to both underlying components, the headline pillar mean is the lowest. Given this, it can be deduced that the *Environmental innovation score* – included in the headline score yet excluded as individual line in Table 8 – generally represents a company's lowest environmental component value. Further, all three scores are characterized by a higher median compared to the mean. This is also reflected in the skewness figures, where the negative signs indicate a greater number of higher scores. With respect to the distribution, especially the *Environmental*- and *Resource use* score perform excellent in terms of symmetricity. Yet, the Emissions score falls properly within the normality range[19]. Notwithstanding the differences within the kurtosis element, for all three scores, the values are acceptable.

[19] Skewness values beyond -2 and 2 are often qualified as substantial non-normal. For Kurtosis, the same range holds true, however focused on a too flat or too peaked distribution (George & Mallery, 2010)

3.3 Investor attention

Contrary to Environmental scores, the data collection of investor attention follows a completely different approach as it monitors news mentioning. Over the years, various methods have been emerged to attempt to capture the level of attention paid. Barber and Odean (2008) quantified attention through the number of news articles in major newspapers, while Zhang et al. (2021) incorporated the Baidu index to proxy for investor attention. Yet, this research chooses Google Trends data as the measure of investor attention for two reasons. First, internet users tend to gather and collect information by the use of search engines. This information is generally accepted by the public (Drake et al. 2012). Since Google has dominated the search engine market ever since its inception, it is most likely to capture the internet behavior of the general public[20]. Second, a Google query reveals an individual's direct interest in the topic of choice. Namely, an investor undoubtedly proves attention when searching for a particular stock on the internet. Using Google's worldwide search volume therefore directly measures investor attention in an unbiased way. It is this characteristic that favors the use of search engines over conventional means. An example of Huberman and Regeve (2001) on a potential cancer-curing breakthrough vividly visualizes the difference between news mentioning and investor attention through publicity. They demonstrate the stock impact on the company with licensing rights as from the moment the reports reached the 'new-news' section of the *New York Times*. That day, the stock price more or less tripled. However, already five months in advance, the same story reached the more obscure journal, *nature*. Despite revealing the same level of information then, barely any stock price movements were noticed at that point. Essentially, implying stock prices to move on the basis of investor attention instead of news mentioning. News coverage thus not necessarily guarantee investor attention.

In fact, this Google Search Volume (GSV) index holds information on the aggregated search volume data for a certain company name or ticker symbol for a specified region. This thesis collects the daily company search volume data for the predefined sample during the period of Jan 24th to May 25th. In this, it draws on two different web scraping interfaces known as 'TrendEcon' and 'Pytrends'. The first package directly interacts with the Google Trends API and oversees data inconsistencies during time. The open-source code namely eliminates the data inconsistency and random sampling problem, which were denounced by Eichenauer et al. (2021). For that reason, this R-package allows for daily analysis while maintaining explanatory power on trends on different points in time. The latter extracts Google Trends data via python and focuses on daily movements without controlling for longer-term trends. By doing so, investor attention is captured in two complementary ways.

[20] More specific; Google's share reflects about 85% of the worldwide search volume according to data measured by Statista. https://www.statista.com/statistics/216573/worldwide-market-share-of-search-engines/

Notwithstanding, reality reveals the data extracted via TrendEcon to be extremely adjusted for long-term trends. Considering this thesis actually benefits from daily differences due to its short-term event-like focus, Pytrends data is maintained.

Two forms of queries that are frequently used in academic literature are described by Da et al. (2011) as a means of capturing individual investor's attention to particular companies. Most obviously, they reveal company name searches to proxy for investor's attention. Though this measure seems straightforward, a name-based query potentially overestimates the search volume as it includes searches from people intending to buy a service or product. Additionally, some company names come with a name that has multiple meanings. Sample specific, this holds true for 'Williams' (racing team) or 'Santos' (Brazilian football club). It is for that, company name searches are an imperfect replicant for investor's company interest. The second proxy Da et al. (2011) highlight, relies upon company ticker symbols. These symbols are assigned whenever a company gets listed on the stock exchange. Contrary to the former, ticker symbols are likely to underestimate the level of search volume, considering not all retail investors to be aware of the unique symbol. Furthermore, ticker symbols frequently serve as abbreviations and as a result do not specifically identify a company as well. Within this specific data sample 'APA', 'KEY' or 'DINO' are examples of ticker symbols suffering from a likely other interpretation. Searching for this abbreviation probably has very different intentions than googling an MSCI World Energy Index company.

In general, this thesis assembles GSV data by searching for company names. Though, since the number of companies included within the MSCI World Energy Index is relatively small, an independent consideration per company is made. Adjustments are made in case the author believes a company name to represent multiple meanings or produces a frequently searched product. In the interest of space, the complete list of specific searches has been redirected to the appendix. In total, the search queries resulted in 6,954 valid daily observations for the 57 companies included in the sample. Table 9A shows the descriptive statistics of investor attention for the tailored company searches, as demonstrated in Table 19 in the appendix.

Table 9A – Descriptive statistics Google Search Volume

Table 9A provides the summary statistics for the Google Search Volume results. Using the Pytrends package, daily Google search volume for 57 companies is considered. The below figures demonstrate the sample wide statistics for average search volume in a certain period.

Table 9A –Descriptive statistics Google Search Volume

		Company query GSV				
		Mean	Median	St. Dev	Skewness	Kurtosis
	Buildup	36.10	36.00	15.77	0.45	-0.39
	Outbreak	47.47	49.00	16.22	0.02	-0.70
	Continuation	38.81	38.00	15.34	0.51	-0.46
All		39.04	38.00	15.15	0.47	-0.47
N	6,954					
Firms	57					

Table 9B in turn, demonstrates the descriptive statistics related to companies' daily Abnormal search volume. The periodic search volume is offset against the average full sample search volume to proxy for abnormality. As can be seen, the outbreak period is the only distinct period characterized by a positive abnormal mean, indicating increased level of investor attention.

Table 9B – Descriptive statistics Abnormal Google Search Volume

Table 9B provides the summary statistics for the standardized Google Search Volume results. Using Pytrends, the daily Abnormal Google search volume throughout the three periods of time is considered. The figures demonstrate the periodic results compared to the full sample.

Table 9B – Descriptive statistics Abnormal Google Search Volume

		Company query Abnormal Search Volume				
		Mean	Median	St. Dev	Skewness	Kurtosis
	Buildup	-0.272	-0.210	0.455	-0.583	0.353
	Outbreak	0.650	0.658	0.449	0.247	-0.654
	Continuation	-0.022	-0.021	0.166	0.382	0.218
N	6,954					
Firms	57					

As a second objective, this thesis aims to capture the effects of investors' economy-wide Environmental concerns. With this intention, Table 10 provides a descriptive overview of three words of interest related to the Environmental score. Following the literature overview, the words 'Pollution', 'Emission' and Low-carbon' closely relate to the underlying components of the Environmental score, thereby proxying for environmental concerns. Similar to investor attention at the company level, the search volume is extracted via the PyTrends API on a daily basis. The below results show an increasing level of search volume for all three words of interest during the outbreak period. At the same time, the standard deviation in that period is the smallest, indicating the days in the outbreak period to have little outliers compared to the other two phases.

Table 10 – Descriptive statistics GSV economy-wide concerns

Table 10 provides an overview of the Google search volume on the words 'Pollution', 'Emission' and 'Low-carbon'. These words have been chosen to proxy for economy wide concerns, tailored to a specific Environmental component score.

Table 10 – Descriptive statistics GSV economy-wide concerns

		Pollution			Emission			Low-Carbon		
		Mean	Median	St. Dev	Mean	Median	St. Dev	Mean	Median	St. Dev
	Buildup	72.81	71.00	12.35	84.58	85.00	7.61	52.94	55.00	11.89
	Outbreak	85.77	85.00	7.59	88.15	90.00	7.97	57.15	59.00	7.42
	Continuation	76.27	79.00	11.90	82.86	84.00	8.85	52.45	56.00	14.16
All		76.40	79.00	12.17	83.86	85.00	8.62	53.07	56.00	13.12
N	366									

3.4 Social sentiment

As stated in the literature overview, social sentiment captures the peoples' collective state of belief and is concerned with the public's general opinion. Since 2008, insights from social media have entered the domain of social sentiment analysis, proving to be of value. One of the first studies using insights from social media is conducted on the foundation of Twitter data (Bollen et al., 2011). Twitter allows people to communicate via short messages, called tweets. This type of communication is often referred to as microblogging, a combination of blogging and instant messaging[21]. In essence, Twitter offers an online platform where this form of blogging happens real-time. In this real-time environment, Twitter users post short messages in order to discuss relevant topics or share useful thoughts (Java et al. 2009). Users in turn benefit from the speed of communication and the sharing of information. Whereas Bollen et al. (2011) already demonstrated Twitter mood stages to correctly

[21] This concept is described in more detail by Java et al. 2009

predict the direction of Dow Jones changes, Rao and Srivastava (2012) are the first to expose a correlation between Twitter sentiment and stock market return. A few years later, Sul et al. (2017) demonstrated that an aggregation of all different opinions and thoughts on Twitter may serve as an interpretation of the complete market sentiment. They found sentiment, either positive or negative, to have explanatory value on individual S&P500 stocks.

Moreover, the Twitter platform provides researchers and developers with the opportunity to analyze platform content. For the purpose of this thesis, developer access on the level of academic research is granted. This type of access, allows academics to extract data from the full historical Twitter archive, essentially reaching back to 2006[22]. This archive will be used to extract relevant tweets related to the words 'Pollution', 'Emission', & 'Low-carbon'. Each word will be examined on a daily basis, after which it is assigned a sentiment score. A panel data regression is constructed for each of the three distinct phases, in which it observes daily data for each day included in the period. In this way, this part of the study also allows for comparison between coefficients over the course of the invasion.

To carry out the actual sentiment analysis, this thesis relies upon a library for processing textual data, called TextBlob. It allows computer communication, through a collection of definitions, between multiple layers of applications. Basically, it functions as an application programming interface (API), translating human language into sentiment. To be more precise, it acts as a bridge between the Twitter library and sentiment library to attach a deliberate score to a tweet. Existing academic literature has proved this score to reach an accuracy of about 70-80% (Hasan et al., 2018 and Bonta & Janardhan, 2019) allowing for a grounded reliance on this methodology.

The full sentiment data sample is restricted as the developer tool allows for a maximum of approximately 10 million tweets. Within this raw set of data, tweets need to be filtered and cleaned in order to perform a sentiment analysis based on the content. For that reason, Twitter usernames, URL's, text symbols, media content and text symbols like '#' or '!' are removed[23]. This involves an automated process programmed into the code. After controlling for these filters, another restriction came across. The full archive academic Twitter access is namely limited to 50 monthly queries, each extracting a maximum of 100 tweets. In the absence of a larger maximum data reach, it was chosen to work with a daily sample of 100 tweets per word of interest. As such, this thesis is left with a sample of 26,400 tweets.

Table 11 demonstrates the descriptive statistics of the tweets within the sample extracted via the Twitter API. The results show the differences between the number of positive tweets within three different time periods. As can be seen, the outbreak period holds the highest average for the words

[22] For further information on data options see the Twitter Developer webpages
[23] Retweets have not been accounted for

‘Pollution’ and ‘Emission’, whereas that same period contains the lowest positive percentage for the word ‘Low-Carbon’. The precise determination of these time periods is discussed in the subsequent methodology section.

Table 11 – Descriptive statistics Twitter Sentiment

Table 11 provides a visualization of the distribution of positive tweets related to the three words of interest ‘Pollution’, ‘Emission’ and ‘Low-Carbon’. Through academic access, a total of 26,400 tweets were extracted from the Twitter API, spread over 88 trading days during the full sample period.

Table 11 – Descriptive statistics Twitter Sentiment

		Pollution			Emission			Low-Carbon		
		Mean	Median	St. Dev	Mean	Median	St. Dev	Mean	Median	St. Dev
	Buildup	42.67	39.00	12.12	39.67	34.00	13.27	22.67	24.00	4.19
	Outbreak	46.33	46.00	6.94	48.33	50.00	8.65	13.00	6.00	9.90
	Continuation	37.00	36.00	10.23	39.67	39.00	13.89	15.00	17.00	5.10
All		42.56	39.00	12.83	42.00	39.00	10.71	16.89	17.00	8.03
N	26,400									

Note: The above visualization only shows the distribution of positive tweets, while neglecting the negative and neutral tweets

Finally, Table 12 provides a comprehensive overview of the complete set of explanatory and control variables used within the research. As mentioned in the first part of this section, data is standardized by default to ensure variables follow a more normally distributed pattern. The definitions column further provides for the precise choice of transformation.

Table 12 – Variable definitions

Table 12 provides the definitions and data type for each of the variables included within the regressions. The table comprises both independent and control variables. Most of the accounting variables within the analysis are set at 2021 year-end and for that reason predetermined to abnormal returns.

Variable	Definition	Data Source
$AbSVI_i$	The Abnormal Google Search volume, calculated as the logarithm of the company's period mean minus the logarithm of the periodic mean	Google Trends
$AbSVI_w$	The Abnormal Google Search volume, calculated as the logarithm of the daily search volume minus the logarithm of the periodic mean	Google Trends
$AbVolume_i$	The Abnormal trading volume, calculated as the logarithm of the company's period mean minus the logarithm of the periodic mean	DataStream
$Cash$	Cash & equivalents – investment <1 year – divided by total assets, calculated with end of year 2021 figures. Normalized following a Box-Cox transformation	DataStream
E_{score}	The Environmental pillar score retrieved from Thomson Reuter's ASSET4 database, ranging between 0 and 100. Reference data 31/12/2021	ASSET4 DataStream
ERS_{score}	The underlying emissions score retrieved from Thomson Reuter's ASSET4 database, ranging between 0 and 100. Reference data 31/12/2021	ASSET4 DataStream
EU_{ret}	The daily return on the European Emission Trade system, calculated via daily carbon price movements	Statista
$Leverage$	The natural logarithm of long-term debt divided by total assets, calculated with end of calendar year 2021 figures.	DataStream
MC	The natural logarithm of a company's mean market capitalization (in millions of $) for a given period. Estimated throughout daily calculations on shares outstanding & stock price	DataStream
ROA	The natural logarithm of return on assets – determined as Net income before Extra items divided by Total assets – calculated with end of year 2021 figures	DataStream
RRS_{score}	The underlying resource use score retrieved from Thomson Reuter's ASSET4 database, ranging between 0 and 100. Reference data 31/12/2021	ASSET4 DataStream
S_t	Sentiment per word, standardized given the sentiment index as the daily sentiment minus the full period mean divided by the periodic standard deviation	Twitter API
SVI_t	Square root of the Google Search volume, standardized as company period mean minus the periodic mean divided by the periodic standard deviation	Google Trends
$\mathbb{I}_{sentiment}$	Dummy variable indicating whether the public sentiment – proxied by Twitter data – is above- or below-average	Twitter API

Note: The variables 'AbVolume', 'Cash', 'ROA' serve as standard control variables throughout the full range of regressions. The control variables 'Leverage', 'MC' and 'EUret' are only included when explicitly mentioned.

4 METHODOLOGY

This section sheds light on the methodologies followed to obtain accurate answers to the formulated hypotheses. At first, the determination of the framework's distinct phases during the Russian invasion is elaborated on. This identification serves as the foundation in the designed research. Second, the structure for a cross-sectional regression focusing on company-related environmental concerns is examined. This part lays out descriptive evidence on stock performance across the sample. Finally, economy-wide concerns on the basis of social sentiment and investor attention are analyzed, using panel data.

4.1 Framework determination

This thesis builds upon research from Deng et al. (2022) on the impact of the Russian invasion on financial markets. Deng et al. (2022) are among the first to relate the Russian incursion with the broader issue of climate change. Specifically, their paper aims to expose investor's expectations regarding the continuation of the climate transition via the use of stock price reactions. These stock price reactions are monitored during three specific phases in the run-up and course of the war. Given that the identification of these three phases is crucial for this thesis, the following explains how these periods came about.

The first phase, labeled as *Build-up,* lasts from the 24th of January 2022 to February 23, 2022 and characterizes by close to 'normal' investor behavior. The start of this period is determined by NATO's decision of putting forces on standby, in response to Russia's continued military build-up around eastern Europe[24]. Together with the White House's declaration of the willingness of the US and its partners to impose sanctions with enormous consequences, this marked the beginning of rising tensions.

The *build-up* period ends with the actual Russian invasion of Ukraine on the 24th of February 2022, heralding the beginning of the outbreak phase. Though tensions have been rising in the weeks before, the actual invasion comes rather unexpectedly satisfying all the requirements of an exogenous shock. For that reason, this phase is characterized by the highest level of market uncertainty. This phase lasts until March 8, 2022, when the president of the United States sends a strong diplomatic message by pronouncing a complete ban on Russian gas and oil imports to the United States.

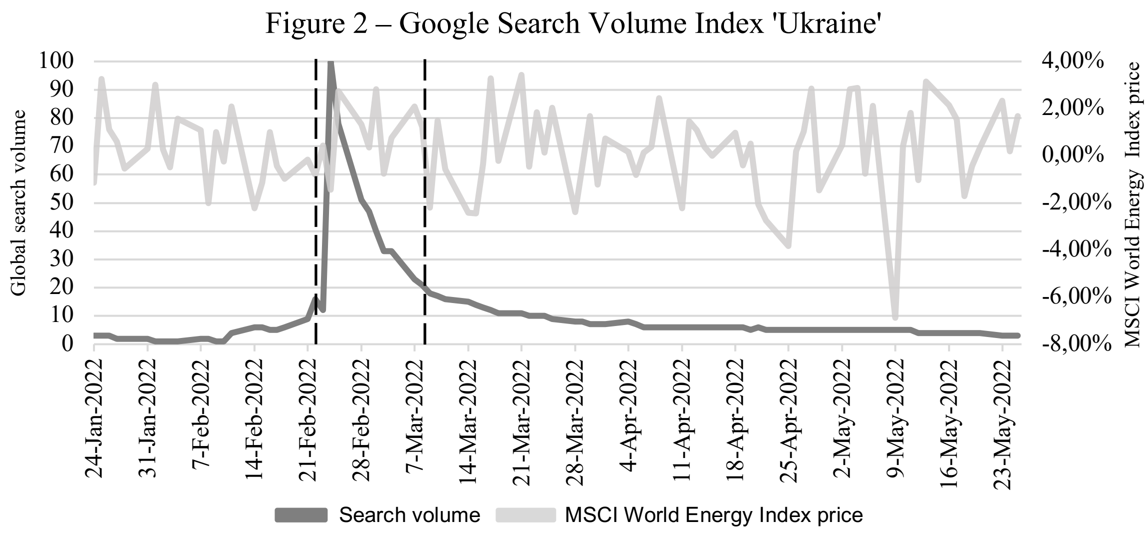
The last phase of the examined period runs until the 25th of May 2022 and is characterized by a renewed reality in which the Western world seeks to cut all ties with Russia. This phase is referred

[24] North Atlantic Treaty Organization, as published on their website on January 24th, 2022

to as *Continuation* period and involves a slightly adjusted end-date compared to the defined period in Deng et al. (2022). To be more precise, the period ends a week after implementation of the REPowerEU plan in which EU leaders denounce to rapidly reduce dependency on Russian energy imports. The decision to extend the period of interest stems from the aim of this research to capture all effects directly related to the Russian invasion. According to the EU Commission, the drafting of this regulation may have taken until May, but the intention was expressed right away as a direct response to the invasion. For that reason, the continuation period used in this research is extended to May 25, 2022, a week after the REPowerEU legislation became effective.

In addition to the above event-related outline of the course of the invasion, the classification of periods is also considered from an attention point of view. Retail investor attention, proxied by Google search volume as reasoned by Choi et al. (2020), is one of these measures. Figure 2 shows a similar sequence of phases based on individual's search behavior for the word 'Ukraine'[25], visualized by the dark grey line.

Figure 2 – Google Search Volume Index 'Ukraine'
Figure 2 demonstrates the relative development of global search queries for the word 'Ukraine'. The dot lines represent the start and/or end date of the defined build-up, outbreak and continuation period respectively. The dark grey line shows the worldwide search volume, whereas the light grey line demonstrates the price development of the MSCI World Energy index in percentages.



The first period is characterized by a small move upwards, representing individual's increasing awareness on growing tension over Russia. The *outbreak* period reveals an unprecedented increase in search volume arising directly at the day of invasion. During the days, a higher than usual search volume remains until quietly returning towards normal levels at the end of the *continuation*

[25] Google Search Volume Index inquiries for the words 'Russia', 'War' and 'Invasion' display overall similar patterns. When considering coverage on television, this blog https://blog.gdeltproject.org/ukraine-has-faded-from-the-news/ reveals that mentions of Ukraine decreased linearly and have been relatively stable since June 10th.

phase. Deng et al. (2022) demonstrate institutional attention to follow the same pattern, proxying for the keywords ‘War’, ‘Ukraine’ and ‘Russia’ within earnings conference call transcripts.

With the aim of performing a high-level analysis of joint movements, Figure 2 shows the MSCI World Energy index’ price changes during the period of interest. This movement is represented by the light grey line. Though the light grey line is slightly decreasing on the day of the outbreak – at the same time as the peak in search volume –, the further course of the MSCI World Energy index price changes indicate no joint movement. Hence, this high-level analysis implies search behavior for the word ‘Ukraine’ to have no direct predictive power on stock price movements of the MSCI World Energy Index.

4.2 Performance evaluation

As discussed in section 2.5, the remainder of this research merges the findings from Deng et al. (2022) and Sing et al. (2022) to analyze the changing dynamics within the Energy sector throughout the course of the Russian invasion. Rather unsurprisingly, it is complex to interpret the formation of these expectations, due to the broad impact of the conflict. For this reason, the thesis performs analyses on both company-level and economy-wide concerns.

4.2.1 Company-level concerns

As a first objective, this thesis aims to reveal abnormal stock effects related to company-level concerns. This part of the analysis is structured to first provide the single effect of Environmental scores. Second, company-specific investor attention is added as explanatory variable, after which the interaction with Environmental scores is considered. By means of extension, a split of data allows for analysis on heterogeneity. Conceptually, the company level estimations will analyze a form of:

$$CAR_{it} = f\ \{Escore_{it}, Investor\ attention_{it}, Interaction_{it}, Controls_{it}\} \qquad (1)$$

where CAR_{it} = Cumulative Abnormal Return for stock i during period t.

Accordingly, the cumulative abnormal return (CAR) per defined period will be used as dependent variable throughout the company-specific part of the analysis. This CAR is calculated on the basis of actual daily stock return numbers, compensated for expected return as calculated in the CAPM model. As such, the company βeta, market return and risk-free rate are included in the CAR calculation. This part conducts cross-sectional analyses, as all explanatory variables of interest are transformed to cover the full span of one of the three phases of interest. More precisely, three separate cross-sectional analyses are conducted for each hypothesis to compare the coefficients of interest throughout the course of the invasion. Ultimately, the differences in coefficients between the build-up, outbreak and continuation phase allow for an interpretation of the main research question. Since both the sign of the coefficient and its significance will be examined in this part, hypotheses tests are performed in a two-sided manner.

The first hypothesis attempts to reveal the standalone effect of Environmental scores on abnormal return during all three distinct periods of the Russian Invasion. This objective results in the below:

Hypothesis 1: *'The effect of Environmental scores on abnormal return is heterogeneous among different phases of the Russian Invasion.'*

Drawing on the following basic regression, the β_1 coefficient is expected to have different values and signs during the periods of interest within the framework. In here, CAR_{it} = Cumulative Abnormal Return for stock i during period t. The $E_{score,it}$ represents the Environmental score for the specific company during the given period of time. The rest of the expression consists of the three standard firm specific control variables C_{it} , as well as the robust standard error term[26].

$$CAR_{it} = \beta_0 + \beta_1 * E_{score,it} + C_{it} + \varepsilon_i \qquad (2)$$

In contrast with recent studies proving companies with high Environmental scores to outperform (Garel & Petit-Romec 2021, Albuquerque 2020), this thesis expects lower scores to experience higher returns as from the outbreak phase. This reversed resiliency hypothesis is underpinned by the academic results of Deng et al. (2022), showing an outperformance of high transition risk companies during the invasion. The below hypothesis is addressed to test for the above in the results section:

Hypothesis 2: *'Firms with low Environmental scores experience higher abnormal return than firms with high Environmental scores starting from the outbreak phase.'*

More specifically – given the composition of the Environmental score – the above hypothesis is divided into three parts and will be tested for accordingly to foresee in underlying component specific effects. In fact, the $E_{score,it}$ introduced in equation *(2)* will be adjusted to represent one of

[26] See table 1 for a description on all regression variables of interest

the three Environmental components, E_{score}, ERS_{score} and RRS_{score} reflected by E_{it} in the below equation. Since the rest of the equation remains unchanged, and the same set of control variables is included, the regression reads as follows:

$$CAR_{it} = \beta_0 + \beta_1 * E_{it} + C_{it} + \varepsilon_i \tag{3}$$

To foresee in biased estimates as a consequence of differences in scale, all Environmental (component) scores will be standardized to have zero mean and unit variance following the below equation:

$$Z_i = \frac{x_i - \mu}{\sigma} \tag{4}$$

with $Z_i =$ standardized i^{th} data, of the Environmental score value x. As all data will be dependent upon the $\mu = mean$ and $\sigma = St.dev$, uniformity is created throughout the framework. Accordingly, this allows for a more intuitive interpretation of coefficients in the below hypotheses:

> **Hypothesis 2a:** *'Firms with low Environmental scores experience higher abnormal return than firms with high Environmental scores starting from the outbreak phase.'*
>
> **Hypothesis 2b:** *'Firms with low Emissions scores experience higher abnormal return than firms with high Emissions scores starting from the outbreak phase.'*
>
> **Hypothesis 2c:** *'Firms with low Resource use scores experience higher abnormal return than firms with high Resource use scores starting from the outbreak phase.'*

The β_1 coefficient serves as matter of interest, since it determines the slope of the Environmental score. Given that we expect higher abnormal return for low Environmental score companies, for all above hypotheses a negative sign is expected. More extensively, the negative signal is expected as from the outbreak of the invasion and persists throughout the continuation phase. This difference serves as confirmation that investor expectations around Environmental interests have shifted.

Drawing on the above results, Environmental component scores will be regressed in panel form to serve as a means of verification. Different than usual, though in line with the methodology of Ferriani & Natoli (2022), this thesis selects two panels representing the best and worst performing companies in terms of score. Since Hartzmark & Sussman (2019) proved investors to primarily value extreme outcomes, a further specification in quantiles is excluded from consideration. For these portfolios, the same β_1 coefficient and corresponding abnormal return will be examined. Conceptually the same regression is performed twice, albeit tuned for the specified samples.

$$CAR_{it} = \beta_0 + \beta_1 * \mathbb{I}_{Escore}\ (E_{it} = 1)_i\ or\ (E_{it} = 0)_i + C_{it} + \varepsilon_{it} \tag{5}$$

here $\mathbb{I}_{Escore}$ is the dummy variable reflecting companies' categorization with respect to component score positioning. $E_{it} = 0$ represents the companies within the 1st quantile while $E_{it} = 1$ embodies the 5th quantile, reflecting the best and worst performing companies respectively.

Subsequently, the standalone effect of investor attention on abnormal stock return is considered. To account for this, it is common practice to extract longer-term Google Trends data in academic literature. This is because these longer time frames allow for the capturing of trends. However, the Russian invasion is characterized as 'shock' event instead. Therefore, it undoubtedly qualifies as a period of uncertainty. In times like these, investors' behavior changes, manifesting itself in more tendencies for rapid revision of attention (Eichenauer et al. 2021). As a means to counter this, the authors specifically point to the use of search volume because of its valuable, timely information during economic downturns. Hence, instead of following common practice, this thesis builds upon daily Google search volume data. The daily data extracted via PyTrends is transformed to follow a distribution closer to normal distribution using equation *(6)*, after which it is standardized for each phase as earlier presented in equation *(4)*.

$$SVI_{i,p} = \sqrt{\left(Mean\left(SVI_{i,t}, \dots SVI_{i,p}\right)\right)} \tag{6}$$

where $p =$ equal to the number of days within the timespan of the period of interest and i reflects the company of interest.

As a means of verification, this research follows Kvam et al. (2022) and composes an Abnormal search volume index. This index builds upon a logarithmic normalization of search volume figures to arrive at the company's periodic Abnormal Search volume. The realization of the index follows the below equation:

$$AbSVI_i = log\left(Mean\left(SVI_{i,p}\right)\right) - log\left(Mean\left(SVI_{t,}, \dots SVI_{t,n}\right)\right) \tag{7}$$

where the first term represents the logarithm of the mean of the full set of firm-specific search volumes during the timespan of one of the three phases of interest $SVI_{i,p}$. The second term takes the logarithm of the mean value of all daily search volumes SVI_t for the 57 companies in the period of interest.

The below hypothesis is the first to be tested for within this section and includes the standard set of control variables:

Hypothesis 3: *'Firms with high investor attention experience higher abnormal return than firms with low investor attention.'*

$$CAR_{it} = \beta_0 + \beta_1 * E_{it} + \beta_2 * SVI_{it} + C_{it} + \varepsilon_{it} \quad (8)$$

in here SVI_{it} stands for the level of investor attention – proxied by Google Trends data – for company i during the period of interest.

The β_2 coefficient serves as matter of interest, since it determines the slope of the investor attention measure. This beta is expected to have a positive sign, as it reflects the assumingly symmetric relation between high investor attention and higher abnormal return. Following Da et al. (2011), companies undergoing search volume increases weekly outperform companies suffering from decreasing levels. This result is expected to hold throughout different periods of the invasion, since it does not rely upon the underlying sentiment of the attention. For the sake of robustness, equation *(8)* is regressed using the $AbSVI_i$ variable as β_2 while holding the same expectations.

Hypothesis 4 examines the interaction between a company's Environmental score and investor attention to see if this holds additional explanatory value. From this the below hypothesis was formed:

Hypothesis 4: *'The combination of investor attention and environmental scores has a significant, asymmetric effect on abnormal return starting from the outbreak phase'*

More interestingly, the interaction between Environmental scores and investor attention is considered. Previous literature by He et al. (2022) namely point towards a positive, significant influence of investor attention on environmental concerns, attributed to reduced information asymmetry. During the analysis the Environmental component scores interact with the level of search volume. The main coefficient of interest for that reason corresponds with β_3 and is accordingly linked with the Environmental headline score. This hypothesis is examined with both measures of search volume, to assure a complete scope. Below a visualization of the corresponding regression with the $SVI_{i,t}$ measure is stated:

$$CAR_{it} = \beta_0 + \beta_1 * E_{it} + \beta_2 * SVI_{it} + \beta_3 * (E_{it} * SVI_{it}) + C_{it} + \varepsilon_{it} \qquad (9)$$

where C_{it} is extended with the control variables *'leverage', 'MC.*

Gradually, the regression gains complexity in form as well as in interpretation. In that way, for a complete interpretation the $\beta_1 and\ \beta_2$ coefficients should be examined as well. Nevertheless, the β_3 coefficient is of main interest. Contrary to existing findings, a negative relationship is expected to be observed indicating a change in investor's perception throughout the course of the invasion. This boils down to a weaker effect of Environmental scores for each unit of investor attention (or vice versa). Nonetheless, the exact sign of the coefficient is hard to determine, as search volume is a measure of attention rather than a measure of news sentiment.

4.2.2 Economy-wide concerns

As a second objective, the research aims to capture the impact of economy-wide concerns. This part of the analysis uses panel data, as the set-up of the hypotheses requires a daily approach to capture the effects during the three specific phases. Namely, abnormal return variation has to be explained by economy-wide factors that have the same value for each company. Since it remains crucial to capture the variations in impact between the three unique phases, a daily approach is introduced to allow for a regression within each distinct period. In other words, the daily impact of economy-wide concerns is compared on the back of the different characteristics for the framework's periods.

The social sentiment factor will be the first matter of subject and proxies for economy-wide environmental sentiment. In the same way as regressing company investor attention, the attention to environmental subjects will be used as second explanatory variable. Thirdly, the interaction between social sentiment and investor attention is examined to identify possible 'mood dependency'. Finally, the regression is compartmentalized to identify potential differences in economy-wide effects for companies dependent upon their environmental risk. Conceptually, this part follows the form below:

$$AR_{it} = f\ \{Investor\ attention_t, Social\ sentiment_t, Interaction_t, Controls_{it}\} \qquad (10)$$

where AR_{it} = Abnormal daily Return for stock i during period t.

The concept of social sentiment is often confused with investor attention. Nevertheless, literature has proven both to capture a different part of investor behavior. Specific to this study, social sentiment represents the overall market perception on environmental concerns. This concern is examined for three words of interest, identified based on the first part of the literature review. The word 'Pollution' is used in El Ouadghiri et al. (2021), 'Emission' stems from Garel & Petit-Romec (2021) and 'Low-carbon' is found to be of interest by Choi et al. (2021). Naturally, the words of interest 'Pollution', 'Emission' and 'Low-carbon' closely relate to the composition of the Environmental risk score. Similar to Polyzos (2022), Twitter data is used to proxy for social sentiment as he proves it to be of value during the Russian invasion.

Simultaneously, the concept of investor attention is added within the regression. Using equation *(11),* the daily Abnormal Google Search Volume for the above words – $AbSVI_w$ – is gathered in an attempt to capture the effect of investor attention for the public's environmental concern.

$$AbSVI_w = log\left(SVI_{w,p}\right) - log\left(Mean\left(SVI_{w,}, \ldots SVI_{w,n}\right)\right) \tag{11}$$

The normalization of this variable slightly differs compared to the company search volume – as in equation *(7)* – given the daily approach of this part of the thesis. More clearly, the periodic mean per word of interest is subtracted from the daily search volume figures instead of periodic ones. Importantly, the interaction between both behavior concepts is integrated in the regression as well, exploring their combined influence and resulting in the hypothesis below:

Hypothesis 5: '*The interaction of social sentiment and investor attention has a significant effect on abnormal return during all phases of the Russian Invasion'.*

The following regression is used to perform a two-sided t-test for in the result section:

$$AR_{it} = \beta_0 + \beta_1 * S_t + \beta_2 * AbSVI_w + \beta_3 * \mathbb{I}_{sentiment} + \beta_4 * (\mathbb{I}_{sentiment} * AbSVI_w) + \beta_5 * C_{it} + \varepsilon_{it} \tag{12}$$

where $S_t =$ the market wide social sentiment – on the word of input – during the given period of interest and $AbSVI_w =$ the standardized search volume for that word. The dummy variable $\mathbb{I}_{sentiment}$ categorizes the corresponding public sentiment (per word, per trading day) and equals 1 if above-average and 0 if below-average given that public sentiment is positive in the vast majority of the sample period. Lastly, C_{it} is extended with the control variables *'leverage', 'MC'* and EU_{ret} .

The sentiment score follows a set-up identified by Kvam et al. (2022), creating a single-word index that considers the different gradations within the public's daily sentiment by the below equation:

$$Sentiment_p = \left(\frac{TV_t{}^{+} - TV_t{}^{-}}{TV_t}\right) \quad (13)$$

where $t =$ daily, $TV =$ Total Volume of tweets and the plus and minus sign represent the positive or negative sentiment label. The sentiment score for that reason holds a number between -1 and 1 at all times. The final regression input follows the below standardization, designed to match a distinct period of interest:

$$S_t = \frac{Sentiment_p - Mean(Sentiment_p, \ldots Sentiment_{fp})}{\sigma Sentiment_{fp}} \quad (14)$$

where $\sigma Sentiment_{\text{fp}} =$ the standard deviation of the full span of daily sentiment score observations within the period of interest.

For an extensive understanding of this hypothesis, the first four betas are of interest in terms of interpretation. β_1 and $\beta_3$both relate to the social sentiment score. While β_1 captures the unique effect of a sentiment score following the compiled index, the β_3 coefficient is derivate from this score and is thus expected to show similar results. Reasoned from Turkson (2021)'s results, the link between stock performance and environmental concerns is expected to be dependent upon social sentiment. The classification of the Russian invasion into three phases was done so that they all characterize different market-wide conditions. Therefore, it is expected that the coefficient signals differ across the phases for each of the words. The β_2 coefficient captures effects of investor's abnormal attention towards one of the environmental related words. Results are expected to demonstrate opposite coefficient signals for the build-up and continuation phase for all words of interest, pointing towards the changing dynamics over the course of the invasion. This expectation stems from Kvam et al. (2022), who demonstrated asymmetric effects during different times of market uncertainty. Finally, the β_4 coefficient captures the interaction between the sentiment dummy and investor's abnormal search volume. Since this variable complement two unique angles of investor behavior, it is expected to be significant throughout the full sample period.

Hypothesis 6: '*The effect of social sentiment on abnormal return given a certain level of investor attention is dependent upon a company's Environmental score'*

As the above hypothesis reads, this thesis simultaneously researches whether there is a heterogeneous relationship for low- and high- Environmental score companies. For that reason, the dataset is split into two panels representing the above- and below-average Environmental scores. This is tested for following a two-sided t-test in the regression below:

$$AR_{it} = \beta_0 + \beta_1 * AbSVI_w + \beta_2 * S_t + \beta_3 * (AbSVI_w * S_t) + C_{it} + \varepsilon_{it} \quad (15)$$

for the different panels with $(E_{it} = 1)_i$ or $(E_{it} = 0)_i$ and where C_{it} is extended with the control variables *'leverage', 'MC'* and EU_{ret}.

As described in the literature review, El Ouadghiri et al. (2021) demonstrate a positive effect of public attention to environmental issues using the word 'pollution' among others. In explaining this effect, they link to investor sentiment and the obvious rewarding of sustainable companies in periods characterized by a high level of positive, public attention for Environmental issues. In the effort to expose changing investor expectations, this thesis expects to demonstrate contrary findings. Similar to Deng et al. (2022), it is expected that the panel with high environmental scores experiences the lowest level of abnormal returns. Hence, the β_3 coefficient is expected to be negative in the matching column during the continuation period.

4.2.3 Robustness

The main reason of adding control variables within this thesis is to minimize the effect of unobserved heterogeneity as best possible. Within all hypotheses, the study controls for two of the control variables of interest discovered by Fama & French (2016). First of all, the study implicitly controls for the risk-free rate as this is used within the abnormal return calculation following the CAPM model. For each period i of interest, the company's expected return is calculated using the risk-free rate, company beta, and realized market return. Finally, the actual realized stock return is subtracted from the expected return in order to determine the stock performance relative to its level of risk. The second control variable as established by Fama & French (2016) is concerned with the company's profitability. By adding Return on Assets into all underlying hypotheses' regressions, the study isolates the abnormal return effects resulting from differences in the companies' profitability on the returns. Further, this thesis controls for trading volume by including the Abnormal Volume control variable in all of the hypotheses. This variable provides information on the daily number of shares traded and allows to control for the effect of market activity on abnormal returns. Simultaneously it tackles literature on stock liquidity that hints toward an existing illiquidity premium. The last control variable included throughout the full thesis relates to the financial position of a company and measures its financial cash position. Cash has the potential to affect abnormal returns in both directions. Namely, higher levels of cash reduce the company risk as it provides a cushion during unexpected events like the Russian invasion. At the same time, large amounts of cash reduce the return potential given that this money is not invested within the company. Since it potentially influences the risk return relationship in two directions, the factor is controlled for.

Additionally, hypotheses 4,5 and 6 include two variables that are read by the terms leverage and firm size. The first variable measures the total level of debt as a percentage of its market capitalization and generally covers the chance of default. That has to say – from a certain point on – raising debt results in a higher probability of default. On the contrary, a high level of drawn debt also has the potential to boost equity returns. The inclusion of this variable is complementary to cash, though the variable has the same potential to affect abnormal return in both directions. The latter term is calculated by the market capitalization and is included to control for the level of riskiness. Larger firms are generally seen as less risky due to their established brand name and more stable cash flows, whereas smaller firms have more growth potential and a higher risk profile. The inclusion of the size factor therefore aims to control for these differences.

On top of the firm-specific control variables, the study includes a macro-economic variable in the last two hypotheses. This control variable is concerned with the European Emission Trading system as it measures daily return on the emission allowances that are traded between companies. Since its inception in 2005, companies have to hand in one piece of emission allowance when emitting 1,000kg of CO_2. Each year the total number of emission allowances slightly decreases and are traded for on the EU-ETS. Consequently, this market behaves like the stock market and accordingly moves based on supply and demand. In a way this mechanism is an essential driver underlying green innovation, as acknowledged by research of Wu et al. (2023) who demonstrate the EU-ETS to be essential in incentivizing low-carbon investment. To illustrate, an increasing carbon price would implicitly cost companies with a high carbon footprint a share of their future margin. For that reason, it could be a driver of green innovation, as such type of R&D could lower the footprint and such the dependence on these emissions. At the same time, a lower carbon price could reduce the need for green innovation, as the price of innovation is higher than the cost for these emission allowances. After all, there is a point where the price of carbon permits and green innovation break-even. For that reason, the price movements could be a factor of influence within the regression rather than just investor attention and environmental concerns. This angle is underpinned following the graphical visualization of the price movements as demonstrated in Figure 3 in the appendix.

5 RESULTS

The literature review revealed the Russia-Ukraine war to affect firm values in many dimensions. To provide a feel for the movements within the MSCI energy index, this section begins by laying out descriptive evidence on the average stock's performance across countries and subsectors during the distinct phases. This sets the basis for a proper understanding of further regression analysis, starting with an evaluation of company-level evidence.

Figure 1 presents the country spread and corresponding stock price movements. As can be seen, the return during alle three periods predominantly shows positive numbers. Especially during the continuation phase, where all individual countries reveal a positive abnormal stock return. For most of the countries, the abnormal return increases over time as moving one phase further. Figure 4 plots the stock market reactions in all three periods for different subsectors represented in the MSCI World Energy Index. In general, abnormal return patterns are similar to what observed in the country spread. Most striking is the result of the alternative fuel sector, which is the only sector displaying a negative abnormal return in the continuation phase. Though relying on a limited number of companies in this subsector, the high-over analysis sets a stage for further research into divergent behavior of clean energy and traditional subsectors in the index. Finally, the identification of abnormal return figures between the three distinct phases indicates the outbreak of the war to be a factor of acceleration for traditional energy sectors, demonstrated by the high positive cumulative abnormal return in the last two phases. This indicates a seeming shift in investor behavior towards high Environmental risk companies, to be investigated in more detail below.

5.1 Company-level evidence

The first section aims to isolate the effect of company-specific environmental concerns, hence focuses on environmental scores and investor's corresponding attention. The first hypothesis to be tested in the results section, is stated below:

Hypothesis 1: *'The effect of Environmental scores on abnormal return is heterogeneous among different phases of the Russian Invasion.'*

Table 13 demonstrates the results of the basic regression, with the explanatory variable E_{score} to be of interest. Considering model *(1)*, *(4)* and *(7)*, the β_1 coefficient proves to be significant during all three phases, though at different levels of significance. During all three periods of interest, the coefficient holds a minus, indicating a negative relationship between abnormal stock return and a company's environmental score. Given the nature of this Environmental score composition, companies at the forefront of the transition to a low-carbon economy performed worse during these periods. In other words, abnormal return tends to be higher for companies subject to higher environmental risk exposure. In line with findings of the high-over subsector split, the asymmetric effect amplifies in the continuation of the war, as a one standard deviation higher environmental score represents a 7.6% lower abnormal stock return. Noteworthy, this effect also turns out to be the most statistically significant following a t-statistic of -3.07. The basic regression finds no evidence of a heterogeneous effect across the three different phases, as the complete sample shows a negative relationship. Nonetheless, the effect of Environmental scores does intensify during the course of the Russian war.

Subsequently, the section deepens the evaluation of company-specific environmental effects by differentiating between high and low Environmental scores. Underpinned by the academic results of Deng et al. (2022), results from the below hypothesis are expected to reveal a reverse 'resiliency-effect' with low environmental scores to outperform their high score equivalents. If true, this indicates a reversal of the relationship found during the pandemic and financial crisis. The below hypothesis is formed accordingly:

> **Hypothesis 2:** *'Firms with low Environmental scores experience higher abnormal return than firms with high Environmental scores starting from the outbreak phase.'*

To accumulate insights on the dynamics of high- and low environmental scores, this research has chosen to construct quantiles additionally. In line with Ferriani & Natoli (2022), the highest and lowest quantile are examined as investors specifically value extreme outcomes (Hartzmark & Sussman, 2019). As the Environmental score metric allows for a more precise evaluation of underlying components, the above hypothesis is further divided into three hypotheses. In here, the separate effect for the underlying components of interest – E_{score}, ERS_{score} and RRS_{score} – is tested for. All component scores are calculated in a standardized way, to have zero mean and unit variance. In these analyses the basic specification includes the core set of control variables, being Cash, Return on Assets and Abnormal trading volume.

> **Hypothesis 2a:** *'Firms with low Environmental scores experience higher abnormal return than firms with high Environmental scores starting from the outbreak phase.'*

Hypothesis 2a is focused on the headline Environmental score, which characterizes as the most accessible for retail investors. The hypothesis showed the Environmental score to be negatively related with abnormal stock return during all three periods of time. Table 14 provides a deeper look into the relationship of environmental scores and abnormal return, focusing on the extreme quantiles. Panel A visualizes the dynamics of the twelve best performing companies, sorted on Environmental scores. Panel B in turn regresses the E_{score} and abnormal return for companies with the highest exposure to environmental risk. Considering model *(1)*, *(4)* and *(7)*, the differences in sign between Panel A and B are striking. Though most of the factors of interest are statistically unsignificant, all periods exhibit opposite signs, hinting to divergent investor expectations. With respect to the group of companies facing the highest level of environmental risk exposure, the strong positive relationship in the continuation period stands out. A one standard deviation higher exposure to environmental risk namely results in a 15.6% higher obtained abnormal return during the continuation period. Considering the findings during the periods before the Russian invasion, this indicates a changing narrative for traditional polluting companies. With respect to the companies at the forefront of the transition to a low-carbon economy, only the build-up period proves statistically significant at the 10% level. A higher score results in a negative abnormal return of 4.6%.

> **Hypothesis 2b:** *'Firms with low Emissions scores experience higher abnormal return than firms with high Emissions scores starting from the outbreak phase.'*

Table 13 provides the overview of the basic regression, in which model *(2)*, *(5)* and *(8)* relate to the company's ERS_{score}. Similar to the overall Environmental score, there is a pronounced negative relationship within all three distinct periods of interest. The degree of this effect increases over the course of the Russian invasion, judged by the coefficient. Consequently, a higher ERS_{score} score results in a negative abnormal stock return. During the outbreak and continuation period, the emissions scores are statistically significant at a 10% and 5% significance level respectively. Table 14 further evaluates dynamics by sorting both the top and bottom 20% of companies based on their emissions score.

Panel A shows the negative impact of an increase in emissions scores to intensify over the course of the Russian invasion. Where a one standard deviation higher score results in a 6.4% lower abnormal return in the build-up phase, this effect equals 15.4% in the continuation period. Noteworthy is the relationship in the outbreak period, as a one standard deviation increases causes a 7.2% lower abnormal return within a period of just 9 trading days. Panel B shows results which are in line with the findings extracted from the Environmental score regression, as the continuation period is the only statistically significant phase. Higher environmental risk exposure generates a 13.7% abnormal stock return within this period at a 10% significance level.

Hypothesis 2c: *'Firms with low Resource use scores experience higher abnormal return than firms with high Resource use scores starting from the outbreak phase.'*

As a final component of interest, model *(3)*, *(6)* and *(9)* in Table 13 and Table 14 focuses on the RRS_{score}. Just like the other component scores, Table 13 shows an increasingly negative β_1 coefficient. However, during all three periods of interest, the negative coefficient is statistically not significant. Moreover, it is noticeable that the coefficients for the RRS_{score} are considerably lower compared to the other two. Consequently, this score seems a bit out of tune. Looking at the R-squared, this assumption seems to gain strength due to the low proportion of the equation that is explained by the independent variable. Table 14 adds to this view, as Panel A's continuation period coefficient holds the smallest negative value compared with the other periods. Nevertheless, the negative relationship between abnormal return and scores is maintained. In fact, the RRS_{score} demonstrates the strongest statistical significance in the build-up period, where a one standard deviation increase in Resource use scores results in a 9.6% lower abnormal return. Results from Panel B are aligned with findings in the former hypotheses, as the coefficient in the continuation period (0.163) is positively related to the degree of climate risk exposure at a 5% significance level. Though the slightly negative coefficient during the outbreak period is remarkable, the t-statistic is by no means significant for which it is neglected.

In short, Table 13 shows the effect of all Environmental score components on abnormal return to be homogeneous among different phases of the Russian Invasion. However, the intensity differs between the distinct periods of interest. That has to say, the effect for all types of Environmental score components intensify during the course of the Russian Invasion. Especially the continuation period is characterized by a strong negative effect, yet the headline Environmental score is significant in all periods of time. Table 14 illustrates the abnormal stock return to be dependent upon the Environmental score of a company. Panel A endorses the negative relationship, relating a one-standard deviation better Environmental score to result in a negative abnormal return. Panel B provides an overview of the companies exposed to the highest level of environmental risk and finds it to be related with an abnormal return of ~15% during the continuation period. The other periods of interest show less pronounced results that lack statistical significance.

Table 13 – Explaining abnormal return with Environmental scores

This table presents the cross-sectional results on abnormal stock return covering the 'Buildup', 'Outbreak' and 'Continuation' period. The independent variables cover the company's measures for Environmental risk, defined by Thomson Reuters. Table 1 provides a more extensive overview of the complete set of included variables. Further, this table accounts for the robust standard errors and reports the t-statistics in parentheses below the estimates of the coefficient. Accordingly, the *, ** and *** signals provide information on the level of statistical significance at the 10%, 5% and 1% level.

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
Dependent variable:		$AR_{Buildup}$			$AR_{Outbreak}$			$AR_{Continution}$	
E_{score}	-0.026^{**}			-0.027^{*}			-0.076^{***}		
	(-2.10)			(-1.84)			(-3.07)		
ERS_{score}		-0.024			-0.027^{*}			-0.059^{**}	
		(-1.47)			(-1.73)			(-2.39)	
RRS_{score}			-0.011			-0.012			-0.034
			(-0.72)			(-0.88)			(-0.95)
$AbVolume_i$	0.067^{***}	0.059^{**}	0.055^{**}	0.065^{*}	0.060^{*}	0.054	0.058	0.029	0.023
	(2.99)	(2.62)	(2.03)	(1.83)	(1.79)	(1.49)	(1.40)	(0.65)	(0.52)
$Cash$	-0.002	-0.004	-0.003	-0.007	-0.010	-0.009	-0.013	-0.022	-0.018
	(-0.17)	(-0.44)	(-0.72)	(-0.55)	(-0.73)	(-0.63)	(-0.63)	(-0.98)	(-0.77)
ROA	0.005	0.003	0.010	0.011	0.009	0.016	-0.005	-0.007	0.010
	(0.47)	(0.24)	(0.85)	(1.07)	(0.81)	(1.62)	(-0.15)	(-0.30)	(0.31)
$Constant$	0.121^{***}	0.119^{***}	0.112^{***}	0.191^{***}	0.189^{***}	0.188^{***}	0.282^{***}	0.275^{***}	0.273^{***}
	(9.96)	(10.13)	(9.45)	(10.81)	(10.99)	(10.41)	(12.00)	(11.05)	(10.42)
R-squared	0.171	0.165	0.114	0.135	0.143	0.093	0.178	0.125	0.058

Table 14 – Robustness Environmental quantiles

This table presents the cross-sectional results on abnormal stock return covering the ‘Buildup’, ‘Outbreak’ and ‘Continuation’ period for a selected group of companies. Panel A summarizes the results for the top quantile, reflecting the 20% of companies with the highest Environmental scores. Panel B shows the bottom quantile, consisting of the companies with the lowest Environmental headline score. Further, this table accounts for the robust standard errors and reports the t-statistics in parentheses below the estimates of the coefficient. Accordingly, the *, ** and *** signals provide information on the level of statistical significance at the 10%, 5% and 1% level.

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
Dependent variable:		$AR_{Buildup}$			$AR_{Outbreak}$			$AR_{Continution}$	
				Panel A – Top quantile Environmental score					
E_{score}	-0.046^{*}			-0.42			-0.092		
	(-1.86)			(-1.13)			(-1.59)		
ERS_{score}		-0.064^{***}			-0.072^{**}			-0.154^{***}	
		(-2.87)			(-2.56)			(-3.19)	
RRS_{score}			-0.082^{*}			-0.096^{***}			-0.032
			(-1.77)			(-2.66)			(-0.61)
$AbVolume_i$	0.059^{**}	0.044^{**}	0.057^{**}	0.054	0.041	0.062^{**}	0.021	-0.011	-0.003
	(2.49)	(2.13)	(2.48)	(1.44)	(1.30)	(2.01)	(0.47)	(-0.29)	(-0.01)
$Cash$	-0.002	-0.004	0.003	-0.008	-0.009	0.003	-0.020	-0.024	-0.024
	(-0.22)	(-0.44)	(0.28)	(-0.63)	(-0.70)	(0.25)	(-0.85)	(-1.21)	(-0.92)
ROA	0.008	0.005	0.009	0.013	0.010	0.014	0.004	-0.003	0.007
	(0.66)	(0.44)	(0.76)	(1.39)	(1.08)	(1.53)	(0.12)	(-0.10)	(0.21)
$Constant$	0.128^{***}	0.128^{***}	0.130^{***}	0.191^{***}	0.200^{***}	0.210^{***}	0.292^{***}	0.297^{***}	0.274^{***}
	(8.80)	(10.16)	(9.41)	(9.06)	(11.13)	(11.27)	(8.76)	(10.96)	(8.89)
R-squared	0.142	0.195	0.163	0.107	0.167	0.201	0.068	0.161	0.033
				Panel B – 5th quantile Environmental score					
E_{score}	0.019			0.029			0.156^{**}		
	(0.67)			(1.01)			(2.08)		
ERS_{score}		0.042			0.031			0.137^{*}	
		(1.46)			(1.05)			(1.75)	
RRS_{score}			0.020			-0.005			0.163^{**}
			(0.76)			(-0.22)			(2.25)
$AbVolume_i$	0.050^{**}	0.055^{**}	0.051^{**}	0.050	0.050	0.041	0.033	0.025	0.043
	(2.12)	(2.28)	(2.06)	(1.49)	(1.45)	(1.20)	(0.85)	(0.62)	(1.05)
$Cash$	-0.005	-0.006	-0.005	-0.009	-0.012	-0.012	-0.012	-0.026	-0.018
	(-0.48)	(-0.60)	(-0.55)	(-0.68)	(-0.87)	(-0.90)	(-0.63)	(-1.38)	(-0.88)
ROA	0.008	0.005	0.010	0.013	0.012	0.015	-0.005	-0.007	0.012
	(0.63)	(0.36)	(0.80)	(1.44)	(1.27)	(1.58)	(-0.14)	(-0.20)	(0.44)
$Constant$	0.112^{***}	0.109^{***}	0.112^{***}	0.180^{***}	0.180^{***}	0.185^{***}	0.243^{***}	0.245^{***}	0.244^{***}
	(8.38)	(8.06)	(8.63)	(10.11)	(10.05)	(10.11)	(10.38)	(10.31)	(11.17)
R-squared	0.108	0.135	0.110	0.094	0.095	0.082	0.141	0.116	0.157

Additionally, this thesis evaluates the effect of the corresponding investor attention on abnormal stock return. This inclusion follows from Eichenauer et al. (2021), who demonstrate Google search volume to hold valuable, timely information in times of uncertainty. This objective is captured in the following hypothesis, tested for in this results section:

> **Hypothesis 3**: *'Firms with high investor attention experience higher abnormal return than firms with low investor attention.'*

As motivated in section 3.3, investor attention is proxied by Google Search Volume data and calculated for each firm separately on the basis of tailored company search queries. In general, the level of search volume is based on the company name yet is occasionally deviated from to ensure a better fit in terms of search query[27]. Building on findings from Eichenauer et al. (2021) regarding the rapid changing investor behavior in times of uncertainty, both SVI_i and $AbSVI_i$ uses daily search volume to timely capture valuable information.

Table 15 demonstrates the results for both measures of search volume on the abnormal return within the different periods of time. As can be seen, results show both measures' β_1 coefficient to be negatively related with abnormal return. Following column *(2)*, a one-standard deviation higher level of search volume is associated with a 2.4% lower abnormal return in the run-up to the war. Similar to the pattern seen earlier, the abnormal return reaction is increasingly negative during the course of the Russian Invasion with column *(6)* to almost show a twice as large effect in comparison with column *(1)*. The coefficients are proven statistically significant at the 5% or 1% level for all three periods.

Moving on to the Abnormal search volume, the effects are even more amplified. A one-standard deviation higher Abnormal volume in search queries is associated with a double digit lowered abnormal return during all periods. This relative measure shows the same pattern as seen using the SVI_i, with effects doubling in the outbreak and continuation period. Though this level of investor attention does not reveal the type of news – either good or bad – the negative relationship is persistent. Essentially, it demonstrates investor attention in times of uncertainty to be perceived as negative. Moreover, the results show the Google Search volume measure to be especially relevant during the moment characterized by the highest level of market uncertainty. During the outbreak period of the Russian war, both β_1 coefficients are significant at a 1% level, with the part of the regression to be explained by the independent variables – reflected by the R-squared – to be the highest. This finding is consistent with the reasoning of Eichenauer et al. (2021), who labels investor attention as a valuable tool during times with market shocks.

[27] A full overview of the used search queries can be found in Table 19 of the Appendix

Though outcomes do not confirm the hypothesis that higher level of attention transposes into higher stock prices as originally found by Barber and Odean (2008), it does fit the overall image of changing dynamics. Put differently, this finding aligns with the demonstrated pattern in hypothesis 1 and 2, where a reversal of effects compared to the pandemic and financial crisis is seen during the course of the invasion.

Moreover, building on research from Choi et al. (2020), the thesis dives deeper into the possible heterogenic dynamics of investor attention between high and low environmental scores. Where Choi et al. (2020) demonstrate carbon-intensive companies to underperform compared to low-carbon companies on days with abnormally high temperatures, this thesis studies the same pattern using the underlying characteristics of each of the phases. The following hypothesis was constructed from that:

> **Hypothesis 4**: *'The combination of investor attention and environmental scores has a significant, asymmetric effect on abnormal return starting from the outbreak phase'*

The objective of this hypothesis is to capture the interaction between investor attention and a company's headline Environmental score. Building on literature from He et al. (2022) and El Ouadghiri et al. (2021), reduced information asymmetry drives the positive effect of investor attention on environmental concerns. By then, researchers identified being at the forefront of the transition to a low-carbon economy to be perceived as beneficial. This was reflected in the positive impact of increasing levels of investor attention – essentially higher environmental scrutiny – on low-risk ESG companies. Rather unsurprisingly, this effect is expected to be reversed within this thesis as a result of the changing narrative on environmental concerns.

Table 16 shows the results for the interaction between search volume and Environmental scores. Panel A describes the situation where investor attention is measured on a relative basis and captures extraordinary levels of attention. Panel B focuses on the normalized returns from the Google Search volume index, extracted directly via Pytrends. Coefficients of interest in both panels includes β_{1-3} as the underlying main effects are of additional importance when interpreting the interaction term. In general Table 16 demonstrates the interaction term to hold explanatory power, as the coefficients are significant at a 5% level in all situations.

Zooming in on panel A, E_{score} has a negative effect on abnormal return in the build-up and continuation phase. This indicates higher Environmental scores to be associated with lower abnormal returns, statistically significant at the 5% level. During the outbreak period, the Environmental score variable displays a positive effect on cumulative abnormal return, though records no statistical significance with a p-value of only 0.09. Moving on to the individual $AbSVI_i$, the main effect appears only statistically significant in the outbreak phase, visualized by the p-value of -2.79 in column *(2)*. This implies abnormal high retail investor attention, proxied by the Google search volume, to be associated with lower abnormal returns at the 1% significance level. Given the insignificance of the coefficient in the build-up and continuation period, no further conclusions are drawn on these periods.

Now that both individual effects have been examined, the interpretation of the β_3 coefficient is matter of subject. During all three distinct phases, the interaction between the Environmental score and Abnormal search volume has a negative effect on cumulative abnormal return. The magnitude of this effect is increasing over the course of the war. Focusing on phase two and three, the negative effect of abnormal investor attention on abnormal return is more pronounced whenever a company has a higher Environmental score. Specifically, the β_3 coefficient of -0.323 in column *(3)* means that for a one-unit increase in Environmental score, the effect on cumulative abnormal return in the continuation phase is expected to be 0.323 unit smaller when abnormal search volume is high compared to low.

The analysis in Panel B is performed as a means of verification, to see whether a different approach of measuring retail investor attention produces the same results. Affirmative with this hypothesis, all β_{1-3} coefficients throughout the three phases show the same signal as found in Panel A. Particularly, the E_{score} in panel B is statistically significant in the build-up and continuation period, with negative coefficients. The individual SVI_i follows a same pattern as $AbSVI_i$, with negative values in the first two phases before turning positive in the continuation period. Similar to panel A, only the outbreak period coefficient is significant. Finally, the interaction term shows an equally pronounced negative relationship in all three periods, with only the magnitude of the interaction term differing due to another way of quantifying search volume.

All in all, this part of the thesis has shown the addition of Google search volume data to add to the explanatory power of the regression. From an individual perspective, retail investor attention influences the cumulative abnormal return for all three periods negatively. Table 15 has shown this negative impact to intensify throughout the course of the Russian invasion. Meanwhile, the table shows the outbreak coefficient to be the most significant, indicating the period characterized by the highest level of uncertainty to stand out. Table 16 introduced an interaction term between investor attention and environmental concerns, based on preliminary findings on the relation between return and increased environmental scrutiny. As opposed to findings from research during regular time periods, this study finds a decreasing cumulative return whenever the investor attention around companies with higher Environmental scores increases. During the continuation phase, the magnitude of this negative interaction effect is the highest. This finding seems to be complementary with the outperformance of high environmental risk companies as presented in the first section.

Table 15 – Abnormal return with company level investor attention

This table explains abnormal stock return using two different measures of Google Search volume. Thereby, it is differentiating between the 'Buildup', 'Outbreak' and 'Continuation' period. The $AbSVI_i$, represents the Abnormal Google search volume, calculated as the logarithm of the company period mean minus the logarithm of the periodic mean. The SVI_i represents the normalized search volume as extracted from PyTrends. Further, the standard control variables are added to the regression. Naturally, the table accounts for robust standard errors and reports the t-statistics in parentheses below the estimates of the coefficient. Accordingly, the *, ** and *** signals provide information on the level of statistical significance at the 10%, 5% and 1% level.

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Dependent variable:	$AR_{Buildup}$		$AR_{Outbreak}$		$AR_{Continuation}$	
$AbSVI_i$	-0.103^{**}		-0.231^{***}		-0.221^{*}	
	(-2.35)		(-2.98)		(-1.88)	
SVI_i		-0.024^{**}		-0.040^{***}		-0.043^{**}
		(-2.50)		(-3.07)		(-2.18)
$AbVolume_i$	0.055^{**}	0.058^{***}	0.066^{*}	0.050^{**}	0.014	0.017
	(2.56)	(2.66)	(1.93)	(2.00)	(0.36)	(0.3)
$Cash$	-0.002	-0.002	-0.003	-0.002	-0.020	-0.190
	(-0.21)	(-0.18)	(-0.25)	(-0.22)	(-0.96)	(-0.90)
ROA	0.011	0.011	0.015	0.014	0.007	0.006
	(0.99)	(0.98)	(1.45)	(1.40)	(0.19)	(0.18)
$Constant$	0.113^{***}	0.118^{***}	0.184^{***}	0.192^{***}	0.263^{***}	0.272^{***}
	(9.97)	(10.67)	(11.66)	(11.96)	(12.13)	(12.02)
R-squared	0.163	0.173	0.201	0.221	0.077	0.086

Table 16 – Abnormal return with Google Search volume & Environmental score

This table explains abnormal stock return using Google Search volume and a company's Environmental headline score. Thereby, it is differentiating between the 'Buildup', 'Outbreak' and 'Continuation' period. Panel A explains the abnormal periodic stock return using the Abnormal Search volume measure, $AbSVI_i$, E_{score}, as well as the interaction. Panel B in its turn uses the Search volume index as an explanation term. Besides the standard control variables, leverage and Market cap are added to the regression. Naturally, the table accounts for robust standard errors and reports the t-statistics in parentheses below the estimates of the coefficient. Accordingly, the *, ** and *** signals provide information on the level of statistical significance at the 10%, 5% and 1% level.

	(1)	*(2)*	*(3)*
Dependent variable:	$AR_{Buildup}$	$AR_{Outbreak}$	$AR_{Continuation}$
Panel A – Abnormal return with $AbSVI_i$			
E_{score}	-0.041^{**}	0.015	-0.108^{**}
	(-2.13)	(0.09)	(-2.64)
$AbSVI_i$	-0.048	-0.263^{***}	0.008
	(-0.86)	(-2.79)	(0.06)
$E_{score} * AbSVI_i$	-0.161^{***}	-0.166^{***}	-0.323^{**}
	(-3.70)	(-2.92)	(-2.40)
$AbVolume_i$	0.059^{***}	0.105^{***}	0.076
	(3.17)	(3.31)	(1.54)
$Cash$	-0.001	-0.007	-0.011
	(-0.13)	(-0.58)	(-0.47)
$Leverage$	-0.013	-0.052^{***}	-0.020
	(-0.96)	(-3.52)	(-0.71)
MC	0.008	-0.015	0.014
	(0.67)	(-1.04)	(0.54)
ROA	-0.005	-0.002	-0.019
	(-0.45)	(-0.34)	(-0.66)
$Constant$	0.143^{***}	0.212^{***}	0.322^{***}
	(10.15)	(12.15)	(10.65)
R-squared	0.321	0.395	0.276
Panel B – Abnormal return with SVI_i			
E_{score}	-0.034^{*}	0.007	-0.095^{**}
	(-1.81)	(0.45)	(-2.39)
SVI_i	-0.007	-0.041^{***}	0.001
	(-0.54)	(-2.69)	(0.04)
$E_{score} * SVI_t$	-0.031^{***}	-0.024^{**}	-0.056^{**}
	(-3.08)	(-2.52)	(-2.08)
$AbVolume_i$	0.081^{***}	0.106^{***}	0.077
	(3.11)	(3.30)	(1.53)
$Cash$	-0.001	-0.008	-0.011
	(-0.09)	(-0.60)	(-0.47)
$Leverage$	-0.012	-0.051^{***}	-0.020
	(-0.86)	(-3.45)	(-0.70)
MC	0.080	-0.015	0.015
	(0.69)	(-1.07)	(0.55)
ROA	-0.004	-0.002	-0.017
	(-0.36)	(-0.60)	(-0.59)
$Constant$	0.144^{***}	0.218^{***}	0.321^{***}
	(10.20)	(12.28)	(10.47)
R-squared	0.302	0.389	0.279

5.2 Economy-wide evidence

This final section draws the research broader and examines the impact of variables related to economy-wide concerns on daily abnormal stock return. Specifically, it aims to address the state dependency of return movements in response to overall environmental concerns. This part of the analysis is motivated by findings in the literature during recent times of economic uncertainty. These periods were characterized by strong resilience of high Environmental score companies. This part of the thesis tests whether those dynamics changed as a result of the Russian invasion, indicating a changing narrative on the use of traditional energy sources. To allow for this, the section considers both Abnormal search volume as well as the overall market perception regarding the words 'Pollution', Emission' and 'Low-carbon'. Moreover, the interaction between both explanatory variables is accounted for in hypothesis 5 and will be tested for as below:

Hypothesis 5: '*The interaction of social sentiment and investor attention has a significant effect on abnormal return during all phases of the Russian Invasion'*.

Contrary to the former hypotheses, the above regression studies the effect of economy-wide concerns. Consequently, the set-up of this part of the analysis requires a different approach, using panel data to capture the effects of the explanatory environmental variables within the three distinct phases. That is to say, the variation in abnormal return is examined from a general perspective for which daily data in a specific period is necessary to perform a regression. By regressing the daily effects on abnormal returns within each period, it remains possible to compare the different coefficients between the three identified periods of the Russian invasion. Accordingly, the dataset is transformed into panel form to allow for this examination of the same set of companies over different periods of time.

In a follow-up to the data transformation, the specific model for the panel data regression has to be specified. Using the Hausman test, the random effects model is deemed to be more appropriate. The obtained p-value *(0.8966)* from the Hausman test namely rejects the null hypothesis at all three significance levels maintained within this thesis. Rather than assuming no correlation between the unobserved heterogeneity and the dependent variables, the random effects model provides room for this. Given that many other macro-economic variables could influence the abnormal return movement, the random effects model best fits.

Table 17 contextualizes the impact of the investor attention and public sentiment proxies used to capture investors' economy-wide concerns. Using three pre-identified words related to environmental concerns, Panel A, B and C identify the relationships between daily abnormal return per different period. Within the regression, the $\beta_1 and\ \beta_3$ coefficient are both ways of identifying social sentiment, with β_1 grasping the precise sentiment factor and β_3 representing the derived dummy variable. Moreover, the regression incorporates the coefficient for the abnormal search volume of the word of interest represented by β_2. By means of extension, an interaction term between the sentiment dummy and abnormal search volume variable is examined. This interaction term follows from findings of El Ouadghiri et al. (2021), who demonstrate the likeliness of the type of investor attention – either positive or negative – to be the mediator in the ambiguous relationship of environmental attention on abnormal stock return.

Panel A represents the relationship for the word 'Emission'. This Panel shows the public sentiment variable, β_1, to be significant for the build-up and continuation phase. During the build-up phase, a one-unit increase in positive sentiment causes daily abnormal return to decrease by 0.026%. Essentially this increase in sentiment boils down to an increase in the number of positive tweets relative to the number of negative ones. The negative coefficient indicates an asymmetric relationship, pointing to higher abnormal returns when the market-wide sentiment is less positive. This effect is positive during the outbreak period, though lacks any statistical significance. During the continuation period, the relationship turns negative again, yet to a minimal degree. The coefficient of the derived dummy variable $\beta_{3,}$ demonstrates opposite signs. Focusing on the only significant score, an above-average positive public perception implies a 0.01% positive daily abnormal return during the continuation period.

In terms of investor attention, the β_2 coefficient shows a higher abnormal search volume for the word 'emission' to be related with a 0.302% lower daily abnormal return in the build-up phase. This effect remains in place – though to a lesser extent – in the third phase of the invasion. The interaction term suggests that the effect of the public's social sentiment on daily abnormal stock return for both the build-up and continuation period is moderated by the abnormal search volume. In the build-up period, the effect on abnormal stock return of a one-unit increase in abnormal search volume is 0.305% higher for days with an above-average public sentiment score compared to days whenever sentiment is below average. This effect reverses in the continuation phase, where investors increased abnormal search volume for the word 'emission' causes a decrease in abnormal return with an extra 0.072% in case of above-average public sentiment. This result indicates an increase in search volume to affect abnormal returns more negatively whenever the public sentiment on the word 'emission' is above-average positive.

Panel B conceptualizes the above for the word 'Low-carbon'. Similar to the word 'Emission', the public sentiment variable has a negative stand-alone effect on abnormal return in the build-up and continuation period, with the latter to be the only coefficient of significance. This β_1 coefficient shows abnormal return to be 0.155% higher for days characterized by a less positive sentiment for the word low-carbon. Again, the derived dummy variable shows opposite signs compared to the public sentiment component for all three periods of interest. Column *(3)* demonstrates a negative β_4 coefficient, implying the decreasing effect on abnormal return during the continuation phase for a one-unit increase in investor attention to be 0.068% less during days with below-average positive sentiment. The same effect, though of a lower magnitude, is seen in the build-up period. During the outbreak of the war, a reversal is seen as the coefficient is strongly positive (0.307) implying the effect of increased investor attention on abnormal return to be 0.307% higher abnormal return on days with high a strongly positive Twitter mood.

Results for the word 'pollution' – visualized in Panel C – demonstrate the interaction term in the continuation period to hold a positive sign instead. However, as demonstrated by column *(3)* in Panel C, this coefficient is proven to be insignificant. On the contrary, the β_4 coefficients during the build-up and outbreak period do provide significant positive numbers. These figures implicitly point to the positive effect of the interaction term.

To conclude, the measures capturing economy-wide investor concern seem to be of added value. Both abnormal search volume and social sentiment stand-alone add explanatory power to the regression. This is in line with findings from Polyzos (2022), who demonstrates Twitter data to hold predictive power during the Russian invasion. Especially within the build-up and continuation phase, the regression is proven solid based on the significance level of the independent variables included and the high F-statistic. In terms of the interaction term, results are complementary to Kvam et al. (2022) as findings indicate the effect on abnormal return to be dependent on the state of the prevailing public sentiment.

Finally, this thesis examines the interaction between social sentiment and abnormal return while compartmentalizing for high and low environmental score companies. As it extends the conducted research in hypothesis 5, it uses the identical panel regression framework. The following hypothesis is tested for in this section:

> **Hypothesis 6:** '*The effect of social sentiment on abnormal return given a certain level of investor attention is dependent upon a company's Environmental score'*

This hypothesis originates from findings of Deng et al. (2022) – who demonstrated a divergence in abnormal returns between companies with high-/low climate risks – and Liu et al. (2022) – who demonstrated a heterogeneous abnormal return effect for companies with high-/low pollution. Consistent with the set-up of the rest of this study, the effects for high and low Environmental scores are considered across different phases of the Russian invasion. The different phases of the Russian invasion are expected to show divergence in coefficients.

Table 18 visualizes the results per word of interest as portrayed in the previous hypothesis. All panels are categorized by the three distinct periods of interest, with a subclassification representing the part of the sample with companies holding *high* and *low* Environmental scores. This split is constructed based on the mean calculation. Addressing Panel A, results show the abnormal search volume coefficient, β_1, to have a negative individual effect on abnormal returns for basically all periods and Environmental scores. Yet, during the course of the invasion the relation seems to change. Whereas the strongest negative effect in the build-up period is found for the sample of companies with high Environmental scores, the continuation period demonstrates the group with lowest Environmental scores to hold the most pronounced negative relationship. The sentiment variable is negative for all Environmental scores during the first two periods of the Russian invasion, yet only statistically significant for the sample with high Environmental score companies in the outbreak phase. Essentially this number shows a strongly positive Twitter sentiment to correspond with a 0.04% decrease in daily abnormal return for companies at the forefront of the transition to a low-carbon economy during the two weeks of the outbreak. The continuation phase shows a reversed relation and demonstrates slightly positive coefficients for both high and low Environmental score companies, significant at least at a 5% level. More interestingly, the β_3 coefficient is founded to be statistically significant over all phases of the Russian invasion, irrespective of Environmental score. Throughout the course of the Russian invasion, the joint effect of investor attention and social sentiment reverses. Where the buildup period shows a more positive public sentiment to increase the effect of scrutinized investor attention on daily abnormal return (visualized by the 0.322 and 0.299 coefficient), the opposite is true for the continuation period. During the outbreak period, a divergence in the coefficient's sign is noticed. Focusing on differences between high and low Environmental score companies, the magnitude for the interaction term is higher for the companies within the sample of high scores. In all periods this points to a more pronounced effect for the companies that is characterized by low environmental risks.

Subsequently, the results from Panel B are examined. This table explains daily abnormal stock return using the economy-wide measures for the word 'Low-carbon'. This panel shows the β_1 coefficient to be solely significant during the outbreak phase. For both subsamples, investor's increased environmental scrutiny results in lower abnormal returns. Considering the β_2 coefficient, the public sentiment holds a significant negative value for the companies with high environmental risks during the build-up and continuation of the Russian invasion. The interaction term coefficient, β_3 holds a negative sign in the continuation period, demonstrating that whenever investors pay higher attention to the subject of low-carbon, the public sentiment has a weaker impact on abnormal return. However, this effect is only statistically significant for the sample of high Environmental score companies. Conversely, during the outbreak phase, the interaction term is statistically significant for the sample of low Environmental score companies and is accompanied by a highly positive coefficient. This finding indicates a more positive sentiment to increase the effect of investor attention on daily abnormal return by approximately 2.8% for companies with high environmental risk. Or, by the same token, the finding indicates a higher level of investor attention to increase the effect of a positive sentiment on daily abnormal return by approximately 2.8% for companies with high environmental risk. Apart from this, the findings in Panel B show the least statistical validity, as only the low column during the outbreak phase relies on three statistically significant independent variables.

Results from Panel C demonstrate a similar pattern as found in Panel A. Focusing on the word 'Pollution', the interaction term has a positive coefficient during the first two periods of the Russian invasion. As from the continuation period, the coefficients become negative, indicating a changing investor perception. With respect to the magnitude of the three β_3 coefficients, results show the companies in the *low* column to entail the most pronounced coefficients during all periods. Accordingly, this indicates the combined effect of investor attention and social sentiment to cause most variation in abnormal return for companies bearing the highest level of environmental risk.

Overall, the results demonstrate the regressions during the continuation period to hold the most statistical value. For all three words of interest the F-statistics for both *high* and *low* Environmental score samples are highest during the continuation phase followed by the build-up period regressions. The outbreak phase comes at a suitable distance. Zooming in on the continuation period, all three panels show negative coefficients that are statistically most significant for high Environmental score companies. Panel A and C demonstrate the interaction term coefficient to change from positive to negative throughout the course of the Russian invasion. During the outbreak phase, especially the *low* column shows statistical relevance having positive coefficient signs for the words 'Low-carbon' and 'Pollution' and a negative sign for 'Emission'. By contrast, two out of three panels with high Environmental score companies fail to show any statistical relevance. Focusing on the individual effects of the interaction term's underlying independent variables, a positive sentiment is accompanied by lower daily abnormal returns in the build-up and outbreak phase for low Environmental score companies. This effect changes after the actual outbreak of the Russian war, as the continuation period demonstrates positive coefficients for the sentiment score, statistically relevant for the words 'Emission' and 'Pollution'. For the words 'Low-carbon' and 'Pollution', the sentiment coefficient is statistically significant when centering on the low Environmental score companies during the first two phases of the war. In fact, the *low* columns represent coefficients with a higher magnitude compared to the statistically insignificant high Environmental score columns during these phases. The abnormal search volume variable shows a similar reflection, as the coefficients are of particular relevance for companies with high environmental risks during the outbreak period. Only Panel A illustrates broader relevance to the individual effect of investor attention during the other phases of the Russian war.

All in all, the results indicate the joint effect of public sentiment and retail investor attention to be dependent upon a companies’ Environmental score. This evidence points into the direction of changing investors perception, as hypothesized in forehand.

Table 17 – Daily abnormal return with economy-wide concerns

This table explains daily abnormal stock return on the basis of Google Search volume and public sentiment on related economy-wide words of interest. Thereby, it is differentiating between the 'Buildup', 'Outbreak' and 'Continuation' period. Using the Abnormal Search volume measure, $AbSVI_w$, the public mood, S_t, as well as the interaction term, effects are contextualized. Each panel represents results for a unique word related to economy-wide Environmental concerns. The table builds on a fixed effect panel regression and reports the t-statistics in parentheses below the estimates of the coefficient. Accordingly, the *, ** and *** signals provide information on the level of statistical significance at the 10%, 5% and 1% level.

Panel A – 'Emission'

	(1)	*(2)*	*(3)*
Dependent variable:	$AR_{Buildup}$	$AR_{Outbreak}$	$AR_{Continuation}$
Panel A – Daily abnormal return explained by 'Emission'			
S_t	-0.026^{***}	0.146	-0.009^{**}
	(-4.08)	(0.88)	(-1.96)
$AbSVI_w$	-0.324^{***}	0.110	-0.062^{**}
	(-3.73)	(1.49)	(-2.11)
$\mathbb{I}_{sentiment}$	0.006	-0.054	0.010^{***}
	(1.09)	(-1.04)	(2.75)
$\mathbb{I}_{sentiment} * AbSVI_w$	0.305^{***}	0.017	-0.072^{**}
	(3.36)	(0.10)	(-1.97)
$AbVolume_i$	-0.002	0.022^{***}	0.005^{*}
	(0.71)	(2.74)	(1.81)
$Cash$	-0.001	-0.001	-0.001
	(-0.29)	(-0.25)	(-0.16)
EU_{ret}	-0.044^{*}	-0.003	-0.154^{***}
	(-1.88)	(-0.14)	(-9.92)
$Leverage$	0.000	-0.007	-0.000
	(0.09)	(-1.43)	(-0.16)
MC	-0.002	-0.009^{**}	0.014
	(-0.52)	(-2.05)	(-0.93)
ROA	0.000	0.001	-0.000
	(0.02)	(0.13)	(-0.03)
$Constant$	0.011^{*}	0.011	0.001
	(1.88)	(0.79)	(0.33)
No. Observation	1,311	513	3,192
R-squared	0.072	0.044	0.054
R-squared between	0.003	0.007	0.000
F*	96.45^{***}	15.39	176.36^{***}

Panel B – 'Low-carbon'

Dependent variable:	(1) $AR_{Buildup}$	(2) $AR_{Outbreak}$	(3) $AR_{Continuation}$
Panel B – Daily abnormal return explained by 'Low-carbon'			
S_t	-0.228	0.065	-0.155^{***}
	(-1.51)	(0.48)	(-2.75)
$AbSVI_w$	-0.041^{**}	-0.141	0.014
	(-2.42)	(-1.26)	(0.74)
$\mathbb{I}_{sentiment}$	0.018	-0.022	0.017^{***}
	(1.30)	(-0.76)	(3.28)
$\mathbb{I}_{sentiment} * AbSVI_w$	-0.055^{**}	0.307^{**}	-0.068^{***}
	(-2.40)	(2.35)	(-3.46)
$AbVolume_i$	0.003	0.022^{***}	0.003
	(0.83)	(2.79)	(1.31)
$Cash$	-0.001	-0.001	-0.001
	(-0.28)	(-0.23)	(-0.19)
EU_{ret}	-0.040^{*}	0.015	-0.154^{***}
	(-1.64)	(0.52)	(-10.20)
$Leverage$	0.000	-0.006	-0.000
	(0.07)	(-1.40)	(-0.09)
MC	-0.002	-0.010^{**}	-0.003
	(-0.55)	(-2.08)	(-0.83)
ROA	0.000	0.001	-0.000
	(0.03)	(0.15)	(-0.04)
$Constant$	0.043^{**}	0.019^{**}	0.014^{***}
	(1.98)	(2.10)	(2.66)
No. Observation	1,311	513	3,192
R-squared	0.100	0.048	0.061
R-squared between	0.002	0.007	0.002
F*	138.73^{***}	17.80^{*}	201.23^{***}

Panel C – 'Pollution'

Dependent variable:	(1) $AR_{Buildup}$	(2) $AR_{Outbreak}$	(3) $AR_{Continuation}$
Panel C – Daily abnormal return explained by 'Pollution'			
S_t	-0.226^{***}	-0.216	0.056^{***}
	(-3.14)	(-1.56)	(3.50)
$AbSVI_w$	0.116^{***}	-0.287^{**}	-0.124^{***}
	(-7.16)	(-2.57)	(-5.62)
$\mathbb{I}_{sentiment}$	0.005	0.032	-0.010^{***}
	(1.06)	(1.34)	(-3.65)
$\mathbb{I}_{sentiment} * AbSVI_w$	0.100^{***}	0.208^{*}	0.028
	(2.67)	(1.66)	(1.11)
$AbVolume_i$	0.002	0.023^{***}	0.003
	(0.36)	(2.82)	(1.05)
$Cash$	-0.001	-0.001	-0.001
	(-0.31)	(-0.23)	(-0.21)
EU_{ret}	0.015	-0.007	-0.171^{***}
	(0.63)	(-0.41)	(-11.37)
$Leverage$	0.000	-0.007	-0.000
	(0.14)	(-1.42)	(-0.06)
MC	-0.002	-0.100^{**}	-0.003
	(-0.43)	(-2.09)	(-0.77)
ROA	0.000	0.001	-0.000
	(0.01)	(0.15)	(-0.05)
$Constant$	0.052^{***}	0.062^{**}	0.00
	(3.45)	(2.56)	(0.01)
No. Observation	1,311	513	3,192
R-squared	0.098	0.054	0.068
R-squared between	0.005	0.007	0.002
F*	135.73^{***}	20.85^{**}	228.73^{***}

Table 18 – Exploring economy-wide concerns and environmental scores

This table explains daily abnormal stock return using Google Search volume and public sentiment on related economy-wide words of interest. Thereby, it focuses on the distinction between low and high environmental scores for which the sample is split relative to the mean. Using the Abnormal Search volume measure $AbSVI_w$, the public mood, S_t, as well as the interaction term, effects are contextualized. Each panel represents results for a unique word related to economy-wide Environmental concerns. The table builds on a random effect panel regression and reports the t-statistics in parentheses below the estimates of the coefficient. Accordingly, the *, ** and *** signals provide information on the level of statistical significance at the 10%, 5% and 1% level.

Panel A – Emission

	High	*Low*	*High*	*Low*	*High*	*Low*
Dependent variable:	$AR_{Buildup}$		$AR_{Outbreak}$		$AR_{Continuation}$	
$AbSVI_w$	-0.183^{***}	-0.156^{***}	-0.172	0.394^{**}	-0.058^{***}	-0.098^{***}
	(-4.27)	(-2.90)	(-1.35)	(2.76)	(-2.95)	(-3.65)
St	-0.009	-0.001	-0.040^{**}	-0.009	0.004^{**}	0.005^{**}
	(-1.52)	(-0.15)	(-2.12)	(-0.45)	(2.28)	(2.06)
$St * AbSVI_w$	0.322^{**}	0.299^{*}	1.580^{***}	-1.324^{**}	-0.149^{**}	-0.114^{*}
	(2.36)	(1.73)	(2.77)	(-2.08)	(-2.91)	(-1.64)
$AbVolume_i$	0.000	0.005	0.066^{**}	0.031^{**}	0.003	0.007
	(0.00)	(1.02)	(2.00)	(2.06)	(0.81)	(1.56)
$Cash$	0.001	-0.001	-0.002	0.004	0.002	-0.000
	(0.36)	(-0.16)	(-0.51)	(0.50)	(0.52)	(-0.07)
EU_{ret}	0.001	-0.001^{***}	-0.006	0.024	-0.131^{***}	-0.194^{***}
	(1.29)	(-2.60)	(-0.25)	(0.91)	(-7.12)	(-7.74)
$Leverage$	0.002	0.002	-0.006	-0.004	0.001	0.001
	(0.37)	(0.28)	(-1.36)	(-0.36)	(0.32)	(0.16)
MC	0.002	0.002	-0.002	-0.010	-0.000	-0.001
	(0.38)	(0.21)	(-1.22)	(-0.94)	(-0.01)	(-0.18)
ROA	-0.003	0.001	-0.006	0.004	-0.001	-0.001
	(-0.54)	(0.11)	(-1.04)	(0.59)	(-0.09)	(-0.17)
$Constant$	-0.032	0.105^{***}	0.017^{**}	0.034^{***}	-0.001	0.015^{*}
	(-1.22)	(3.11)	(2.44)	(3.32)	(-0.11)	(1.90)
No. observation	736	0.173	288	225	1,792	1,400
R-squared	0.047	0.066	0.058	0.107	0.047	0.065
R-squared between	0.025	0.008	0.070	0.011	0.010	0.001
F*	35.03^{***}	38.32^{***}	16.66^{**}	17.25^{**}	86.06^{***}	94.12^{***}

Panel B – Low-carbon

Dependent variable:	*High*	*Low*	*High*	*Low*	*High*	*Low*
	$AR_{Buildup}$		$AR_{Outbreak}$		$AR_{Continuation}$	
$AbSVI_w$	0.005	0.046	−0.140***	−0.381**	0.037	−0.008
	(0.09)	(0.66)	(-2.98)	(-2.37)	(0.98)	(-0.15)
St	−0.019	−0.058**	−0.007	−0.073**	0.027	0.001
	(-0.84)	(-2.10)	(-0.20)	(-2.00)	(1.38)	(0.03)
$St * AbSVI_w$	−0.446*	−0.620*	0.341	2.882***	−0.598**	−0.373
	(-1.64)	(-1.79)	(0.45)	(3.48)	(-2.14)	(-0.98)
$AbVolume_i$	−0.001	0.006	0.021**	0.031**	0.001	0.005
	(-0.24)	(1.37)	(2.08)	(2.09)	(0.34)	(1.16)
$Cash$	0.002	−0.001	−0.002	0.004	0.002	−0.001
	(0.36)	(-0.14)	(-0.48)	(0.48)	(0.52)	(-0.10)
EU_{ret}	0.000	−0.001*	−0.006	0.061**	−0.127***	−0.183***
	(1.21)	(-1.66)	(-0.20)	(1.94)	(-6.86)	(-7.28)
$Leverage$	0.002	0.002	−0.006	−0.003	0.002	0.002
	(0.39)	(0.22)	(-1.35)	(-0.30)	(0.35)	(0.23)
MC	0.002	0.001	−0.007	−0.010	0.000	−0.001
	(0.45)	(0.15)	(-1.25)	(-0.93)	(0.08)	(-0.10)
ROA	−0.003	0.001	−0.005	0.004	−0.000	−0.001
	(-0.53)	(0.12)	(-1.05)	(0.62)	(-0.08)	(-0.18)
$Constant$	−0.023	0.077***	0.017**	0.034***	−0.003	0.16*
	(-1.05)	(2.80)	(2.48)	(3.39)	(-0.60)	(1.81)
No. observation	736	575	288	225	1,792	1,400
R-squared	0.095	0.120	0.029	0.131	0.049	0.0654
R-squared between	0.023	0.004	0.075	0.010	0.013	0.0034
F*	74.14***	73.67***	8.42	23.56***	91.40***	95.42***

Panel C – Pollution

Dependent variable:	*High*	*Low*	*High*	*Low*	*High*	*Low*
	$AR_{Buildup}$		$AR_{Outbreak}$		$AR_{Continuation}$	
$AbSVI_w$	−0.372**	−0.504**	−0.264	−0.904***	0.007	0.063
	(-2.19)	(-2.37)	(-0.83)	(-2.69)	(1.24)	(0.80)
S_t	−0.069	−0.144**	−0.019	−0.057**	0.023**	0.023*
	(-1.24)	(-2.08)	(-0.67)	(-1.87)	(2.39)	(1.73)
$St * AbSVI_w$	1.324*	1.904**	1.094	1.819*	−0.607***	−0.645**
	(1.68)	(1.94)	(1.45)	(1.66)	(-2.98)	(-2.32)
$AbVolume_i$	0.000	0.004	0.021**	0.034**	0.001	0.002
	(0.00)	(0.78)	(2.07)	(2.30)	(0.31)	(0.56)
$Cash$	0.001	−0.001	−0.002	0.004	0.002	−0.001
	(0.36)	(-0.18)	(-0.47)	(0.52)	(0.52)	(-0.15)
EU_{ret}	0.000	−0.001**	−0.031	0.034	−0.142***	−0.201***
	(1.29)	(-2.35)	(-1.32)	(1.39)	(-7.75)	(-8.04)
$Leverage$	0.002	0.003	−0.006	−0.004	0.002	0.003
	(0.37)	(0.33)	(-1.35)	(-0.45)	(0.36)	(0.33)
MC	0.002	0.002	−0.007	−0.011	0.000	0.000
	(0.38)	(0.26)	(-1.25)	(-1.04)	(0.09)	(0.02)
ROA	−0.03	0.001	−0.006	0.004	−0.000	−0.001
	(-0.54)	(0.10)	(-1.05)	(0.61)	(-0.08)	(-0.20)
$Constant$	−0.032	0.108***	0.019	0.049***	−0.005	0.010
	(-1.22)	(3.85)	(1.94)	(3.88)	(-0.95)	(1.17)
No. observation	736	575	288	225	1,792	1,400
R-squared	0.081	0.122	0.032	0.198	0.064	0.075
R-squared between	0.023	0.013	0.076	0.013	0.013	0.013
F*	62.08***	75.61***	9.30	41.10***	120.61***	110.27***

6 DISCUSSION

This thesis examines investor's perception regarding the energy sector by focusing on abnormal stock returns during the course of the Russian invasion. This chapter serves as discussion before interpretating the results gathered in section five. Specifically, this chapter aims to identify the main limitations of the research before providing concluding remarks in Chapter 7. Additionally, recommendations for further research are discussed within this section.

First of all, the use of Environmental scores as a measure of environmental concerns is debatable. Though Environmental scores are easily absorbed by retail investors, one could argue whether the use of this score quantifies climate risk in the most appropriate way. The main drawback is the current functioning of ESG scores. Due to a lack of general ESG rating standards, the more than 70 independent advisors have each developed a unique way of processing ESG data. Since ESG characteristics are generally qualitative, a large dependency on subjective indicators has emerged among these advisors (Li, 2020). The same input of data could be processed completely differently within an advisor's tailored evaluation framework. Yet, the Environmental scores are the foundation in this studies' attempt to relate companies' environmental concerns with stock performance. Accordingly, the findings of this research may be prone to noise. That has to say, the use of another ESG database as input for Environmental scores could significantly influence the findings of the research.

Moreover, the ASSET4 database provides academics with access to yearly ESG data. For that reason, this study uses the company's year-end 2021 scores. Especially with regard to the continuation period, consistency between findings in this study and reality may diverge due to outdated Environmental scores. Hence, further research on the effects with alternative climate risk quantification measures would be recommended to obtain more complete results. Especially Natural Learning Programs measures could be a valuable alternative, as demonstrated by Sautner et al. (2022) and Deng et al. (2022).

Second, this thesis is limited to Twitter's provided possibilities for academic research in their developer environment. Though access has been granted to extract 10 million tweets each month, the Twitter API only allows for 50 unique requests per month. Since each request in the full archive search mode in turn only covers 100 tweets, the maximum number of extracted tweets essentially boils down to 5,000 a month. As the thesis has been finalized over several months, and the use of multiple Twitter academic research accounts has been arranged, daily results for each word of interest has been covered for. However, the fact that only a small sample of the complete universe of tweets are incorporated is a serious limitation. In consequence, this study has not been able to validate Google Search volumes by the use of an identical abnormal tweet volume measure. Further research could be conducted in case Twitter eliminates the search query limitation. Additionally, the quantification of sentiment from the extracted tweets is imperfect and limited to the level of the Natural Learning Program technology. As far as the author considers, this limitation boils down to a lack of tracking subtle meanings such as sarcasm or semantic word groups that combine positive and negative words.

As a last important limitation, the sample size of this study has been relatively small. The MSCI World Energy Index mainly covers traditional energy stocks, for which this thesis draws conclusions on a one-sided perspective of the energy sector. In view of the increasing stream of clean energy companies, an incorporation of this type of company is recommended to broaden the scope of the thesis' context. Hence, while interpretating the results in the final section, it should be considered that differences in high and low environmental scores relate to companies active in traditional sin-industries.

7 CONCLUSION

This thesis is mainly designed to expose changing investor preferences throughout the course of the Russian invasion of Ukraine. Hereby, it focuses on the companies incorporated in the MSCI World Energy index and their accompanied environmental risk categorization determined by Thomson Reuters' ASSET4 database. This paper capitalizes on prior research regarding the Russian invasion, highlighting the recalibration of investor preferences towards companies suffering from higher climate risks. Specifically, this thesis aims to uncover whether a renewed perspective on environmental concerns results in similar changing dynamics within the Energy sector. In an effort to maximize this study's added-value, the below research question analyzes both company-level and economy-wide concerns:

Have investor preferences regarding the Energy Sector changed during the Russian Invasion?

To arrive at the answer to above research question, a framework comprising of three distinct phases of the research period is designed to capture investor preferences before, during and in the lag of the Russian invasion. Accordingly, differences in the explanatory variables' relationship with abnormal stock return are of key interest. At company-level, this entails effects of Environmental scores and investor attention. Conversely, for economy-wide concerns this entails capturing the public sentiment and level of attention relating to the words 'Emission', 'Low-carbon' and 'Pollution'. Together, the analysis of the below hypotheses allows for an interpretation of the changing preferences of investors.

The first hypothesis analyses company-specific environmental scores and expects a heterogenous effect on abnormal stock return during the different phases of the invasion. Contrary to expected, results demonstrate a negative sign during the course of the invasion, indicating a homogenous effect. Hence, Hypothesis 1 is rejected.

Hypothesis 2 expects a divergence in firms with high- and low Environmental scores, foreseeing higher abnormal return for the latter as from the outbreak phase. Since results show opposite effects for the top and bottom quantile – for each of the Environmental component score – all three underlying hypotheses are accepted. Findings further demonstrate an outperformance for the companies with the highest level of environmental risk during the continuation phase.

Adding investor attention to the company-level analysis, Hypothesis 3 states firms with high investor attention to experience higher abnormal return than firms with low investor attention. This hypothesis may be rejected, as investor attention has a significant, negative effect on abnormal return. This effect is most pronounced during the continuation period.

Hypothesis 4 combines investor attention and Environmental scores, testing for the interaction between both. Contrary to recent findings highlighting a positive effect for increased environmental scrutiny for low-risk companies, an asymmetric relationship is expected. Results show a negative coefficient, indicating decreasing abnormal return at moments investor attention for companies with high Environmental scores increases. Hence, hypothesis 4 is accepted.

In summary, company-level results demonstrate investor preferences regarding the Energy sector to have changed during the course of the Russian invasion. For all hypotheses of interest, coefficients have changed throughout the course of the invasion, or demonstrate opposite signs compared to literature on recent periods of uncertainty. Hypotheses 1 and 2 show soaring abnormal return for companies with low Environmental scores, proving the former. Hypotheses 3 and 4 demonstrate scrutinized investor attention to be negatively related with abnormal return, underwriting the latter.

Subsequently, research focus is shifted towards economy-wide concerns as it concentrates on social sentiment and public attention. Hypothesis 5 may be accepted, as results prove the interaction of sentiment and investor attention to have a significant effect on abnormal return during the course of the invasion. Hypothesis 6 follows Deng et al. (2022) and expects the joint effect of social sentiment and investor attention to be dependent upon the company's Environmental categorization. Generally speaking, results are affirmative, demonstrating the most statistically relevant outcomes for the group of high Environmental scores in the continuation period. From a broader perspective, results demonstrate a changing dynamic over the course of the Russian invasion, with a pronounced negative effect on abnormal return for all words of interest during the continuation of the war.

In essence, findings on economy-wide concerns reveal the effect of investor attention to be dependent upon the public's sentiment and behave differently for companies with high- or low Environmental scores. Though the joint effect of attention and sentiment follows a heterogeneous pattern as prior research of El Ouadghiri et al. (2021) demonstrated, the negative coefficient reveals contrary relationships to what have been found prior to the Russian invasion.

All in all, the changing dynamics hint towards a shift in investors' preferences concerning companies with high environmental risks. Their attention seems to be moving away from the traditional view on environmental concerns, proven by the changing coefficient signs over the course of the invasion in both the company-specific and economy-wide analysis. This observation confirms this studies' angle of research, proving the move towards high environmental risk companies to hold true even within the energy sector.

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APPENDIX

Table 19 – Overview search queries company related Google Search Volume
The below figure demonstrates the list of tailored search queries used during the investigation of investor attention via Search Volume data. The 57 companies included in the sample are predominantly searched on company names, alternated with some specified searches.

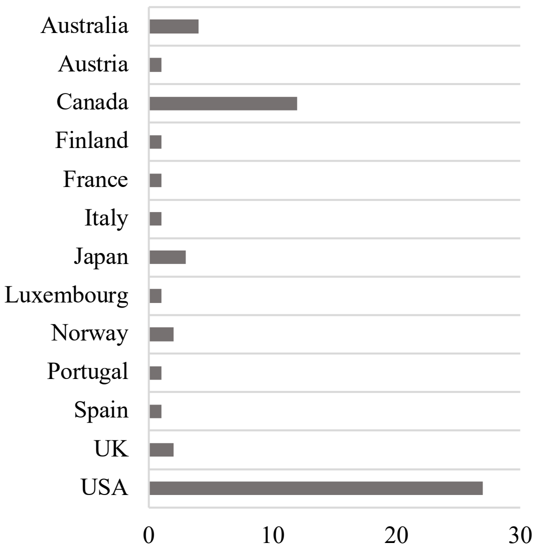
Table 19 – Overview search queries company related Google Search volume

Company name	Search query	Company name	Search query
Aker Bp	*Aker bp*	Inpex	*Inpex*
Ampol	*Ampol*	Keyera	*Keyera*
APA	*Apa corporation*	Kinder Morgan	*Kinder morgan*
Arc Resources	*Arc resources*	Marathon Oil	*Marathon oil*
Baker Hughes	*Baker hughes*	Marathon Petroleum	*Marathon petroleum*
BP	*BP*	Neste	*Neste*
Cameco	*Cameco*	Occidental Petroleum	*Occidental petroleum*
Canadian Natural Resources	*Canadian Natural*	OMV	*Omv*
Cenovus Energy	*Cenovus*	Oneok	*Oneok*
Cheniere Energy	*Cheniere*	Ovintiv	*Ovintiv*
Chesapeake Energy	*Chesapeake energy*	Pembina Pipeline	*Pembina*
Chevron	*Chevron*	Phillips 66	*Phillips 66*
Conocophillips	*Conocophillips*	Pioneer Natural Resources	*Pioneer natural resources*
Coterra Energy	*Coterra energy*	Repsol	*Repsol*
Devon Energy	*Devon energy*	Santos	*Santos energy*
Diamondback energy	*Diamondback energy*	Schlumberg	*Schlumberger*
Enbridge	*Enbridge*	Shell	*Shell*
Eneos Holdings	*Eneos*	Suncor Energy	*Suncor*
ENI	*Eni*	Targa Resources	*Trgp*
EOG Resources	*EOG resources*	TC Energy	*Tc energy*
EQT	*Eqt stock*	Tenaris	*Tenaris*
Equinor	*Equinor*	Texas Pacific Land Trust	*Texas Pacific*
Exxon Mobil	*Exxon*	TotalEnergies	*Totalenergies*
Galp Energia SGPS	*Galp*	Tourmaline Oil	*Tourmaline oil*
Halliburton	*Halliburton*	Valero Energy	*Valero energy*
Hess	*Hess stock*	Washinghton Soul Pattinson & Co	*Washington Pattinson*
HF Sinclair	*Hollyfrontier*	Williams	*Wmb stock*
Idemitsu Kosan	*Idemitsu*	Woodside Energy Group	*Woodside petroleum*
Imperial oil	*Imperial oil*		

Figure 1 – Country spread MSCI World Energy Index

The below figure demonstrates the composition of the MSCI World Energy Index in terms of country spread. The 57 companies included in the sample are divided over 13 different countries and are presented with corresponding cumulative abnormal stock return figures.

Country spread MSCI World Energy Index



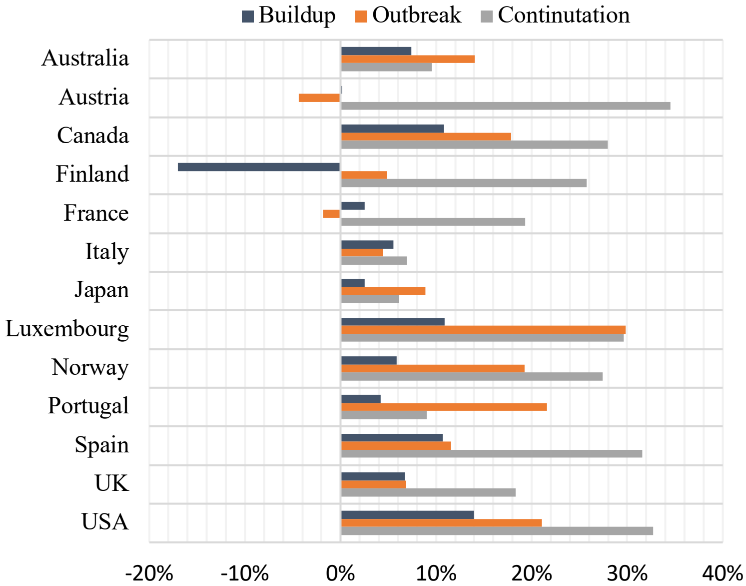
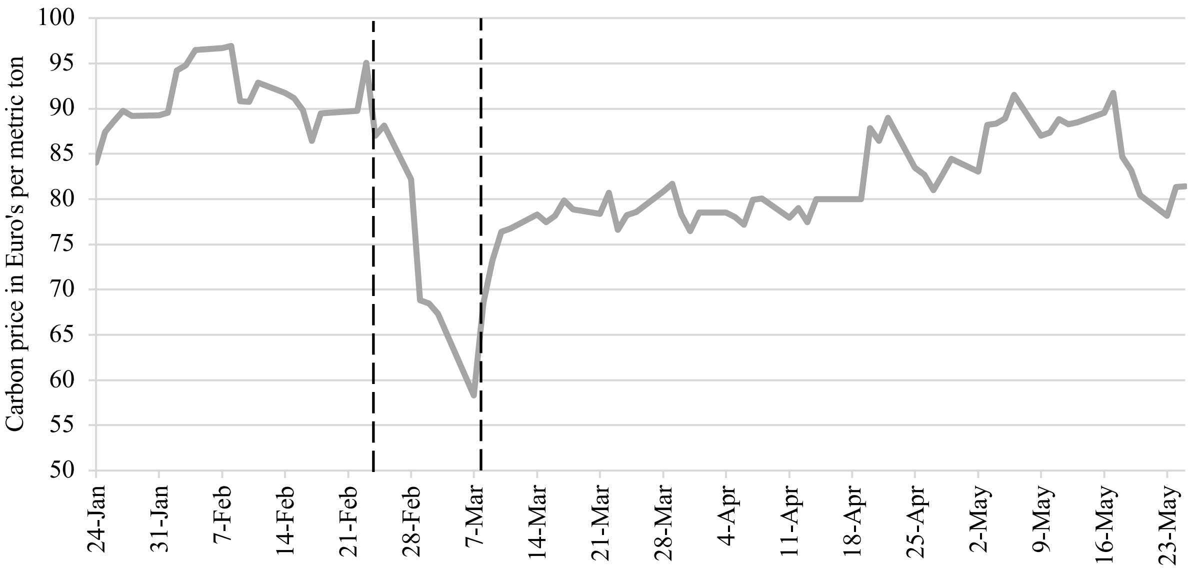


Figure 3 – European Emission Trading System Carbon price

Figure 3 demonstrates the development of the European Emission Trading System price in Euros per metric ton. The dot lines represent the start and/or end date of each period of interest respectively.

Figure 3 – EU ETS price development



Note: Data is extracted from Statista and holds daily price information in Euros specifically

Figure 4 – Subsector spread MSCI World Energy Index
The below figure demonstrates the composition of the MSCI World Energy Index in terms of subsector. The 57 companies included in the sample are divided over 8 different countries and presented with corresponding cumulative abnormal stock return figures.