German Energy-Intensive Firms and the Russia-Ukraine War: Evidence of Firm-Level Heterogeneity in Crisis Exposure

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Abstract

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This study examines the stock market response of German energy-intensive firms to the Russia-Ukraine war. The objective is to determine if energy intensity predicts a different crisis exposure and to identify factors explaining within-sector heterogeneity. An event study methodology is applied to measure abnormal returns around the February 24, 2022 invasion, using 16 energy-intensive firms and 39 control firms listed on German exchanges. The results show no significant average treatment effect, however substantial firm-level variation exists within the treatment group, spanning a 77-percentage-point range. Steel and metals producers achieved returns between +10.9% and +21.0%, while chemical producers suffered losses between -10.9% and -23.3%. This deviation reflects whether firms use natural gas as substitutable energy input or non-substitutable chemical feedstock, a distinction that sector classifications fail to capture. The findings indicate that binary treatment-control classifications obscure important dissimilarity. The results are specific to German firms during the immediate outbreak period. Regardless, the evidence shows that firm-level measures of gas consumption intensity are necessary for accurately identifying crisis vulnerability.

Keywords: energy-intensive firms, event study, Russia-Ukraine war, stock market response, energy intensity, natural gas, Germany, abnormal returns, crisis exposure

Empresas alemãs com elevado consumo energético e a guerra entre a Rússia e a Ucrânia: evidências da heterogeneidade ao nível das empresas na exposição à crise

Leonhard Peter Hirsch

Este estudo examina a resposta do mercado de ações das empresas alemãs com uso intensivo de energia à guerra entre a Rússia e a Ucrânia. O objetivo é determinar se a intensidade energética prevê uma exposição diferente à crise e identificar fatores que expliquem a heterogeneidade dentro do setor. A metodologia de estudo de eventos é aplicada para medir retornos anormais em torno da invasão de 24 de fevereiro de 2022, usando 16 empresas com uso intensivo de energia e 39 empresas de controle listadas nas bolsas alemãs. Os resultados não mostram nenhum efeito médio significativo do tratamento, porém existe uma variação substancial ao nível das empresas dentro do grupo de tratamento, abrangendo uma variação de

77 pontos percentuais. Os produtores de aço e metais alcançaram retornos entre +10,9% e +21,0%, enquanto os produtores químicos sofreram perdas entre -10,9% e -23,3%. Este desvio reflete se as empresas utilizam o gás natural como insumo energético substituível ou matéria-prima química não substituível, uma distinção que as classificações setoriais não conseguem captar. As conclusões indicam que as classificações binárias de tratamento-controlo obscurecem uma importante dissimilaridade. Os resultados são específicos para as empresas alemãs durante o período imediato do surto. Independentemente disso, as evidências mostram que as medidas da intensidade do consumo de gás ao nível das empresas são necessárias para identificar com precisão a vulnerabilidade à crise.

Palavras-chave: empresas com uso intensivo de energia, estudo de eventos, guerra entre a Rússia e a Ucrânia, resposta do mercado de ações, intensidade energética, gás natural, Alemanha, retornos anormais, exposição à crise

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1. Introduction

On February 24, 2022, Russia's invasion of Ukraine triggered an immediate energy crisis across Europe. Germany, which sourced approximately 55% of its natural gas imports from Russia prior to the war(Wettengel 2024) faced immediate exposure. Natural gas represents a critical input for energy-intensive industries such as chemicals, steel production, cement manufacturing, and glass production. This raises questions about how financial markets would price this supply shock. While prior research proves that energy supply shocks significantly affect stock market returns (Kilian 2009), the Russia-Ukraine war presents a more unique context, which is an abrupt and strong disruption to natural gas supply in a region with limited short-term alternatives and high dependence on the affected supplier.

Recent event studies examining stock market reactions to the Russia-Ukraine war provide important insights but focus primarily on cross-country differences or broad sectoral patterns. As exhibited by Federle, Meier et al. (2024), the geographic proximity to the conflict and trade linkages with Russia can explain a significant portion of the variation in stock market responses across European countries. Closeness accounts for around two-thirds of the observed effects. Ahmed, Hasan et al. (2022) document sectoral differences in European market reactions, finding that certain industries experienced more pronounced negative impacts. Rossi, Ni et al. (2025) categorise 1,770 European firms as "brown" (energy-intensive) versus "green" (energy-efficient) stocks and provide evidence that brown stocks underperformed during the outbreak period. Nerlinger and Utz (2022) verify that energy-producing firms experienced a net benefit from rising energy prices during the conflict, in contrast to energy-consuming firms.

However, these studies treat energy-intensive firms as a homogeneous category, which potentially overlooks within-sector variation. This aggregation may hide important heterogeneity, because energy-intensive firms differ substantially in how they use natural gas. For instance, chemical producers often use natural gas as both an energy input and a chemical feedstock in production. In contrast, steel producers primarily use gas as an energy source, which provides a greater flexibility to switch to coal or electricity. Recent evidence from the COVID-19 pandemic clearly shows that firm-level characteristics generate substantial discrepancy in crisis responses even within industries (Ramelli and Wagner 2020). The question whether similar firm-level variation exists among energy-intensive firms responding to energy supply shocks still remains an open empirical topic.

In this study two research questions will be addressed. First, what is the stock market response of German energy-intensive firms to the Russia-Ukraine war compared to less energy-intensive firms? This question will tell if energy intensity predicts a different crisis exposure in the direct aftermath of the Russian invasion. To answer this question I am testing if investors thought energy-intensive firms would be systematically more vulnerable to the gas supply disruption. Second, to what extent do energy-intensive firms show signs of heterogeneous responses to the natural gas supply shock, and what factors explain this variation? A key concern is if grouping firms as energy-intensive maybe overlooks meaningful variation across firms and subsectors in their actual exposure to gas supply disruptions. From a policy perspective, this insight helps distinguish between broad support for all "energy-intensive industries" and targeted measures based on actual gas use. From a theoretical perspective, it shows that industry labels often fail to capture firms' exposure to input shocks, making more detailed, firm-level indicators valuable.

To meet both questions, I employ an event study methodology, which examines 16 energy-intensive firms and 39 control firms listed on German exchanges. The event date is February 24, 2022, with an 11-day event window that spans across five days before through five days after the invasion. I estimate abnormal returns using the Market Model and consider multiple window specifications to ensure robustness. Germany provides an ideal setting for this analysis given its high dependence on Russian gas and the presence of major energy-intensive firms across multiple subsectors.

The work opens with a review of prior research on event studies, energy shocks, stock market effects, and firm-level heterogeneity in Section 2. The data is described in Section 3 with a sample selection, and the empirical methodology. Section 4 presents the empirical results, including average treatment effects and firm-level analysis. Afterwards, section 5 discusses the interpretation of findings, limitations, and implications for future research, while section 6 concludes.

2. Literature Review

2.1 Event Study Methodology

Event studies are a commonly used empirical tool in finance to measure the impact of specific events on firm value. The seminal methodological framework is provided by MacKinlay (1997), who defined an event study as using "financial market data to measure the impact of a specific event on the value of a firm." The efficient market hypothesis is essential for the methodology, which assumes that stock prices immediately reflect all publicly available information. Thus, abnormal returns observed around an event provide a measure of the event's economic impact. Kothari and Warner (2004) offer a full analysis of event study econometrics. In their work, they discuss methodological advances and potential difficulties in both short-horizon and long-horizon applications.

The standard event study procedure involves several steps. At the beginning, the event of interest and the event window must be defined. Typically, the event window includes the event day and surrounding days to capture anticipation effects and delayed reactions. Next, normal returns, which are the returns that would be expected absent the event, must be estimated using an estimation window earlier to the event. The most common approach is the market model, which regresses individual stock returns on a market index to obtain firm-specific parameters (alpha and beta). Further, abnormal returns are calculated as the difference between actual and predicted normal returns. Finally, abnormal returns are aggregated across firms and time to compute average abnormal returns (AAR) and cumulative abnormal returns (CAR), with statistical tests employed to assess significance.

Brown and Warner (1985) demonstrate that the market model performs well using daily data and that simple parametric tests are generally robust. This result still holds even when underlying statistical assumptions are violated. Empirical justification is provided by their findings for using daily returns in event studies. These findings are key for examining short-horizon market reactions to unexpected events.

Methodological refinements may be necessary for crisis events characterized by heightened volatility and cross-sectional correlation. A standardized cross-sectional test is proposed by Boehmer (1991) that adjusts for event-induced variance increases. Additionally, Kolari and Pynnönen (2010) developed corrections for cross-sectional correlation when events group in calendar time, which happens with market-wide shocks.

In the context of the Russia-Ukraine war, the event date (24 February 2022) is clearly defined and unanticipated, making it perfect for event study analysis. The market-wide nature of the shock possibly correlates in abnormal returns across firms, this justifies the use of robust standard errors and appropriate test statistics.

2.2 Energy Shocks and Stock Returns

Research demonstrates that the stock market impact of energy price movements depends critically on the underlying source and nature of the shock. Kilian (2009) decomposes crude oil price changes into supply-driven, demand-driven, and precautionary demand shocks. This shows that only uncertainty-driven shocks, such as increases in precautionary demand, lead to strongly negative stock market reactions. Energy price increases caused by rising global demand are likely to coincide with higher equity returns, while supply-driven shocks play a comparatively minor role. Importantly, their results highlight that energy shocks translate heterogeneously across industries, with energy-intensive sectors experiencing differential impacts.

Evidence that energy shocks influence stock returns by affecting firms' real cash flows is provided by Jones and Kaul (2012). For the United States and Canada, they demonstrate that stock market reactions to oil price shocks can be mainly explained by impacts on future real cash flows. However, for the United Kingdom and Japan, observed equity responses exceed what can be justified by cash flow changes alone. This proposes the existence of additional channels, such as heightened uncertainty or time-varying risk premia.

Sadorsky (1999) shows that oil price levels and volatility are both significant factors of stock returns, with volatility shocks having a particularly strong effect on equity markets. He shows that oil price shocks explain a solid share of stock return variation by using a VAR framework. The result is that oil price increases and volatility have a more adverse effect on energy-intensive industries than on less energy-dependent sectors.

While many studies focus on crude oil, natural gas markets behave differently and affect equity markets through their own specific channels. Natural gas is less fungible than oil due to pipeline infrastructure constraints and regional pricing. This makes supply disruptions potentially more severe for gas-dependent economies. Batten, Ciner et al. (2017) demonstrate that while oil and gas markets are linked, their dynamic relationships vary over time and across regions. One of those regions is the European market, which are more sensitive to gas supply shocks due to limited alternatives and high import dependence.

The impact of energy shocks is not uniform across different sectors. Even within energy-intensive industries, firms differ substantially in how they use energy inputs, their ability to substitute or pass on costs, and their exposure to supply troubles. As Griffin, Lont et al. (2017) demonstrate, empirical confirmation shows that the carbon footprints and energy efficiency of firms, as measured by greenhouse gas emissions relative to revenue, are significantly correlated with stock returns. This suggests that investors consider firm-level energy exposure beyond broad industry classifications when pricing. For instance, chemical producers often use natural gas as both energy input and chemical feedstock, that limits substitution possibilities. On the other hand, steel producers primarily use gas for energy, allowing greater flexibility. These firm-level differences hint that aggregate sector-based analyses may hide important variation in crisis exposure.

The Russia-Ukraine war represents a huge natural gas supply shock for Europe, due to Russia's dominant position as gas supplier prior to February 2022. This context combines a sharp, unanticipated supply disruption with limited short-term alternatives. Therefore, it provides an optimal situation to investigate how energy-intensive firms respond heterogeneously to energy shocks.

2.3 The Impact of the Russia-Ukraine War on Stock Markets

The relationship between military conflicts and stock markets has long interested financial economists. Hudson and Urquhart (2015) found that the British stock market exhibited resilience during the Second World War, with returns not significantly different to those seen in peacetime. This highlights the fact that market reactions depend on the nature and duration of the conflict, as well as on investors' evolving views.

The effects of the Russia-Ukraine war on global stock markets have been widely examined (Ahmed, Hasan et al. 2022, Boubaker, Goodell et al. 2022, Boungou and Yatié 2022). The data consistently shows a negative market reaction to the outbreak of the conflict, which can be seen across studies.

2.3.1 Geographical Differences in Market Reactions

Several studies highlight great regional variation, although the impact was global. Federle, Meier et al. (2024) identify a "proximity penalty" in the stock market response to the Russian invasion. They found that countries closer to Ukraine experienced lower equity returns in a four-week window around the invasion. Additionally, they demonstrate that trade linkages explain two-thirds of this proximity penalty, with the remainder attributed to military disaster risk. Boubaker, Goodell et al. (2022) found significant negative event-day returns for banks across 90 markets, while the strongest effects happened in Europe. Also, Yousaf, Patel et al. (2022) reported the most significant declines in European and Asian markets.

Economic dependence is also a key factor. Lo, Marcelin et al. (2022) demonstrate that countries with a greater reliance on Russian commodities experienced more serious stock market losses and increased volatility. Ahmed, Hasan et al. (2022) confirm that European markets, particularly those with close trade linkages to Russia, were among the worst affected.

2.3.2 Sector-Level Differences

Another finding on the stock market in response to the war is that market reactions varied extensively across sectors. Ahmed, Hasan et al. (2022) document negative abnormal returns for financials, telecommunications, consumer goods, industrials, and technology. Throughout the event window, the financial sector remained persistently affected. In contrast, the energy SECTOR, which consists of oil and gas producers such as Shell, BP, and TotalEnergies, faced positive abnormal returns as energy prices went up (Nerlinger and Utz 2022), (Ahmed, Hasan et al. 2022).

However, this positive energy sector response covers important heterogeneity, which was found by Rossi, Ni et al. (2025). In their work they distinguish between energy producers and energy-intensive firms (i.e., firms with high energy consumption such as manufacturers). When analysing 1,770 firms across 25 European countries, it was found that energy-intensive (brown) stocks underperformed energy-efficient (green) stocks during the outbreak period. These stocks demonstrated higher volatility and a negative energy risk premium. This suggests that the impact of energy supply shocks differs fundamentally between firms that produce energy (beneficiaries of higher prices) and firms that consume energy (victims of higher costs).

2.4 Firm-Level Heterogeneity and Research Gap

Recent studies of crises demonstrate that even when firms face the same macroeconomic shock, firm-level characteristics generate sizable heterogeneity in stock market responses. Ramelli and Wagner (2020) examine how firms reacted to the onset of the pandemic and found that corporate characteristics, including financial flexibility, international exposure and operational structure, determined differential stock price responses within industries. Similarly, Fahlenbrach, Rageth et al. (2020) demonstrate that firms with greater financial flexibility experienced significantly better stock performance during the pandemic. This underlines the fact that firm-specific elements can have a stronger impact on sectoral effects during periods of crisis.

While existing research on the Russia-Ukraine war has examined geographic variation(Federle, Meier et al. 2024), broad sectoral differences (Ahmed, Hasan et al. 2022), and aggregate energy-intensive versus energy-efficient classifications (Rossi, Ni et al. 2025), no study has examined heterogeneity at the firm level within energy-intensive firms in a single-country context. This discrepancy is significant because energy-intensive industries encompass a wide range of subsectors, including chemicals, steel, cement, and utilities. The fundamental differences between these subsectors are evident in their utilisation of natural gas, their capacity to substitute inputs or pass through costs, and their exposure to supply disruptions.

This study addresses this gap by assessing German-listed energy-intensive firms at the individual firm level. Germany provides an ideal setting, due to its high pre-war dependence on Russian gas and its position as Europe's largest economy. By analysing the heterogeneous responses within the energy-intensive category, I demonstrate that aggregate sector-based classifications can obscure important variation at the firm level. Our findings reveal that steel and metals producers benefited from the crisis while chemical producers suffered severe losses. This distinction would not be captured by a comparison of energy-intensive versus energy-efficient scenarios. This within-sector heterogeneity is important for understanding crisis exposure and the design of targeted policy responses.

3. Methodology

This section outlines the methodological approach of the thesis. Since the core analytical framework is an event study, a brief overview of event-study objectives, structure, and the normal-return estimation process is provided. The chosen return-estimation model is then introduced. Following the framework of an event-study, the statistical tests used to evaluate the hypotheses are described. Finally, this chapter also presents the cross-sectional regression methodology, which helps explain the sources of any discovered abnormal returns.

3.1 Event Study Method and Definition of Abnormal Returns

Event studies measure how financial markets react to new information by comparing observed returns to expected returns in the absence of an event. The method is based on the assumption that markets efficiently incorporate information into prices, meaning that price movements around events can be interpreted as the market's assessment of economic impact (MacKinlay (1997); Kothari and Warner (2004)).

The basic idea is to compare the observed return of a security at the time of the event with the return that would have been expected in the absence of the event. This requires specifying a model of normal performance, which is typically the market model, the CAPM, or a mean-adjusted benchmark, to estimate the return a stock would have earned had the event not occurred (Brown and Warner 1985). If there are significant deviations from this expected return, those are interpreted as abnormal returns, capturing the unanticipated impact of the event.

Formally, the abnormal return for firm i on day t is defined as the difference between the actual return $R_{it}$and the expected normal return K_{it}:

$$AR_{it} = R_{it} - K_{it}.$$

Abnormal returns represent the immediate market reaction to the event and are used for cumulative measures. As individual daily abnormal returns may be unreliable, event studies often aggregate them over a short event window surrounding the date of interest. The cumulative abnormal return (CAR) is a measure of the total effect of the event over this interval, calculated as follows:

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{it}$$

CARs capture the aggregated market response and allow researchers to evaluate if the event produced a statistically and economically meaningful valuation effect. Short-horizon measures such as one-day, three-day, or eleven-day CARs are widely deemed reliable and well specified, especially when daily data are used (Brown and Warner (1985); MacKinlay (1997)). As (Kothari and Warner 2004) show in their work, short-window event studies are relatively robust to model misspecification and are generally easier to interpret.

3.2 Event Definition and Event Windows

An Event Study typically follows the structure laid out by MacKinlay (1997) in his Paper: Event Studies in Economics and Finance. First, the event of interest and therefore the period over which the security prices of the firms involved in this event will be examined, must be defined. The time frame around the event of interest is known as the event window. This includes the event date itself and, typically, several days before or after the event to capture potential anticipatory or delayed market reactions. The model parameters used to estimate normal returns are derived from a separate estimation window. It is not expected to have any influence on stock prices, during this timeframe. To avoid contamination, the event window is excluded from the estimation window, to ensure that the estimated benchmark is not affected by the event. In this thesis, the estimation window begins twelve months before the event date and ends one and a half months prior to the start of the event window. Accordingly, the estimation window begins on 24 February 2021 and ends on 12 January 2022. The event window spans eleven days, capturing the 5 days before the invasion, the invasion day itself, and five days after (−5, 0, +5). As this paper examines the response of energy-specific German companies and non-energy-related German companies to the Russian invasion of Ukraine, the event day is defined as the day of the invasion, which is the 24th of February 2022. This is defined as $t = 0$.

The event window captures potential anticipatory reactions before February 24 and brief adjustments afterward, which is standard practice in geopolitical event studies (Brown and Warner (1985); MacKinlay (1997)).

3.3 Estimation of Normal Returns

With the event window established, the next step is to determine what returns would have been expected in the absence of the invasion. For this purpose, I employ the Market Model to estimate the normal returns. The Market Model assumes a linear relationship between the return of an individual security and the return of the overall market portfolio. This reflects the idea that part of a firm's return is driven by systematic market movements.

The model is expressed as:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}$$

where R_{it} denotes the return of firm *i* at time *t*, R_{mt} is the market return, and ε_{it} is a zero-mean disturbance term with constant variance. The parameters α_i and β_i capture the firm-specific intercept and its sensitivity to market fluctuations. In practice, a broad stock index is used to approximate the market portfolio; for European equities, this typically involves a regional or national benchmark index.

The Market Model offers an improvement over other and simpler methods such as the constant mean return model. By filtering out the component of returns explained by general market movements, it reduces the variance of abnormal returns and thereby increases the statistical power to detect effects related to events. The extent of this benefit depends on the explanatory strength (R^2) of the regression: the higher the R^2, the more precisely event impacts can be identified (MacKinlay 1997). The Market Model serves as the primary benchmark throughout the analysis. CAPM was not employed as it offers little advantage over the Market Model for short-horizon event studies (Brown and Warner 1985).

3.4 Calculation of Abnormal and Cumulative Abnormal Returns

After estimating expected returns using the Market Model, I calculate abnormal returns for each firm and aggregate them across groups for hypothesis testing. Furthermore, abnormal returns for each firm and each day in the event window were calculated, then the abnormal returns are averaged across all *N* firms in each group (treatment or control). This average abnormal return (AAR) is defined as:

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

The AAR reflects the group's average market reaction on each event-day. In order to assess the total effect over an event window, the AARs are then accumulated over time to get the cumulative average abnormal return (CAAR):

$$CAAR(t_1, t_2) = \sum_{t=t_1}^{t_2} AAR_t$$

The CAAR measures the combined impact of the event on a group of firms. It is the main statistic used to compare differences between the treatment and control groups. These group-level returns are used in the following statistical tests to see if the event caused important differences in reactions across classifications. For comparing different groups of firms, these aggregated returns form the basis. The key comparison in this study is between energy-intensive and non-energy-intensive companies.

3.5 Definition of Treatment and Control Groups

The sample is divided into a treatment and a control group, in order to examine if the market reacted differently to firms with varying levels of energy dependence. This classification reflects differences in exposure to natural gas as a production input and as feedstock, i.e. chemical companies and follows established regulatory definitions of energy-intensive industries.

Treatment Group

The treatment group consists of publicly listed German companies in energy-intensive sectors (chemicals, metals, utilities, basic materials) as defined by EU regulatory standards. These firms either rely heavily on natural gas as a production input or are directly involved in energy production and distribution, making them economically exposed to natural gas supply disruptions.

Control Group

The control group comprises publicly listed German companies from non-energy-intensive sectors (finance, technology, healthcare, consumer goods, real estate) with minimal exposure to natural gas prices, which serves as a benchmark

Regulatory Basis for Classification

The classification follows the definition of energy-intensive industries provided in the European Commission's *Annual Single Market Report 2021*. According to the report, energy-intensive industries are sectors in which energy inputs account for a significant share of total production costs and where firms depend heavily on electricity, natural gas, or high-temperature industrial processes. This includes chemicals and petrochemicals, iron and steel, non-ferrous metals, non-metallic mineral products (such as cement, glass, and ceramics), refineries, pulp and paper, and other basic materials industries. Firms in the treatment group operate in these sectors and are therefore naturally exposed to the energy-price and supply shocks triggered by the Russian invasion of Ukraine. Firms assigned to the control group, as expected, demonstrate a significantly lower energy intensity. Having defined the treatment and control groups based on energy exposure, I now describe the statistical tests used to evaluate whether these groups experienced significantly different market reactions.

To operationalize this classification framework, firms are assigned to treatment and control groups based on their primary business activity as defined by the Refinitiv Business Classification (TRBC) system. Table 1 presents the complete sector classification, listing each industry category with its corresponding TRBC code, group assignment, and the number of firms included in the sample. The TRBC codes provide standardized industry identifiers that enable precise classification and ensure consistency with international financial data standards.

Sector	**TRBC Code**	**Group**	**N Firms**
High Energy-Intensity Sectors (Treatment Group)			
Diversified Chemicals	51101090	Treatment	2
Specialty Chemicals	51101030	Treatment	2
Commodity Chemicals	51101010	Treatment	1
Agricultural Chemicals	51101020	Treatment	1
Iron & Steel	51201020	Treatment	2
Construction Materials	51202010	Treatment	1
Multiline Utilities	59104010	Treatment	3
Electric Utilities	59101010	Treatment	1

Oil & Gas Exploration and Production	50102020	Treatment	1
Oil Related Services and Equipment	50103020	Treatment	1
Construction & Engineering	52201020	Treatment	1
Total Treatment			**16**

Sector	**TRBC Code**	**Group**	**N Firms**
Low Energy-Intensity Sectors (Control Group)			
Banks	55101010	Control	8
Investment Banking & Brokerage Services	55102010	Control	3
Multiline Insurance & Brokers	55301010	Control	5
IT Services & Consulting	57201010	Control	4
Computer Hardware	57106010	Control	2
Pharmaceuticals	56201040	Control	3
Healthcare Facilities & Services	56102010	Control	2
Fishing & Farming	54102010	Control	3
Food Retail & Distribution	54301020	Control	4
Real Estate Rental, Development & Operations	55402010	Control	3
Integrated Telecommunications Services	58101010	Control	2
Total Control			**39**

Table 1

This table classifies firms into treatment (high energy-intensity) and control (low energy-intensity) groups based on sector membership. TRBC codes refer to Refinitiv Business Classification (Industry level, 8-digit codes). High energy-intensity sectors are defined following the European Commission's Annual Single Market Report 2021 as industries where energy costs represent a substantial share of production costs (>10%) or where natural gas serves as both energy input and chemical feedstock. Low energy-intensity sectors are service-based industries with minimal direct energy transformation requirements. Classification based on Refinitiv TRBC 2012 standard.

3.6 Statistical Tests for Abnormal Returns

3.6.1 t-tests and Wilcoxon tests

To evaluate if the event caused significant abnormal returns, this thesis employs a combination of hypothesis tests commonly used in event-study research. As first and basic test, the mean abnormal returns and cumulative abnormal returns are assessed using the t-test, which assumes normally distributed abnormal returns and has long been established as a standard tool in short-horizon event studies (Brown and Warner 1985), which builds on the original formulation by Student (1908). Given that return distributions around major market shocks can show signs of non-normality or event-induced variance, it is recommended that the analysis be complemented by the Wilcoxon rank-sum test, in order to compare the treatment and control groups (Wilcoxon 1945, Mann and Whitney 1947) . The legitimacy of these non-parametric procedures is maintained in the presence of heteroskedasticity and non-normal distributions (Corrado 1989). Collectively, these assessments ensure reliable inference without depending solely on parametric assumptions.

3.6.2 Cross-Sectional Regression Analysis

While the tests described above identify the presence of abnormal returns and differences between groups, they do not explain why some firms within these groups reacted more strongly than others. To address this question, I am adding a cross-sectional regression to the event-window analysis. The cross-sectional approach helps explain the reason why certain firms experience larger positive or negative CARs than others, while the event study just identifies whether abnormal returns occur. This follows the recommendation in (Kothari and Warner 2004), who emphasize that cross-sectional regressions provide important insights into the underlying economic channels.

The regression model links each firm's cumulative abnormal return (CAR) as energy-intensive or not (treatment dummy) and a set of firm-level characteristics often used in empirical finance:

$$CAR_i = \alpha + \beta_1 \text{Treatment}_i + \beta_2 \text{Size}_i + \beta_3 \text{Leverage}_i + \beta_4 \text{ROA}_i + \beta_5 \text{Beta}_i + \varepsilon_i.$$

Control Variables

- Size: Measured as the natural logarithm of total assets or market capitalization. Larger firms may exhibit lower event-induced volatility due to greater diversification and more stable earnings streams. So, Size is included to control for potential scale effects.

- Leverage: Calculated as total debt divided by total assets. Highly levered firms may be more sensitive to macroeconomic or geopolitical shocks because their equity values are higher exposed to financial risk.
- Return on Assets (ROA): Used as a representation for firm profitability and operational efficiency. More profitable firms may better absorb cost shocks or supply chain disruptions, making ROA important for capturing firm-specific resistance.
- Beta is estimated through a market model using pre-event data. It measures a firm's systematic risk and captures how strongly its returns co-move with the market. Including beta ensures that differences in risk exposure do not confound the interpretation of CARs.

By incorporating these variables, the regression isolates the effect of energy dependence (treatment status) on abnormal returns while controlling for firm size, leverage, profitability, and risk.

3.7 Alternative Event Windows

The methodological choices described above, which are the event window length and the Market Model specification, reflect standard practice but are of course debatable. To ensure the findings are not products of these specific choices, I analyse alternative event windows.

The [-5, +5] window captures the whole market reaction around the event date, whereas [-2, +2] allow for modest anticipatory or delayed adjustment. Additionally, I test asymmetric windows separating pre-event [-5, -1] from post-event [0, +5] periods to distinguish anticipatory effects from realized impacts. Consistent results across these alternative specifications strengthen the validity of inference by demonstrating that estimated market reactions are not sensitive to the specific event horizon chosen (Brown and Warner 1985).

4. Data

4.1 Overview of the Data

To calculate the market return model, I extracted the daily closing stock prices for each firm individually. Previously in the methodology part a clear definition for the treatment as well as the control firms was stated. Additionally, to be included in the study, the firm had to be listed in the German Stock Exchange. In total, the stocks of 16 publicly traded companies were specified as treatment group, and 39 for the control group. The complete data for both groups as well as the STOXX 600 index was collected from the LSEG Workspace database. In the following table the treatment group company names as well as their Sector is displayed. The same is done for the control firms, the table can be found in the appendix below.

Company	Sector	Stock Ticker
Aurubis AG	Oil & Gas Exploration and Production	NXIG.H
BASF SE	Diversified Chemicals	BASFn.DE
Bilfinger SE	Construction & Engineering	GBFG.DE
Covestro AG	Commodity Chemicals	1COVG.DE
E. ON SE / E. ON Ruhrgas	Multiline Utilities	EONGn.DE
EnBW AG	Electric Utilities	EBKG.DE
Evonik Industries AG	Specialty Chemicals	EVKn.DE
Heidelberg Materials	Construction Materials	HEIG.DE
K+S AG	Agricultural Chemicals	SDFGn.DE
Lanxess AG	Diversified Chemicals	LXSG.DE
RWE AG	Multiline Utilities	RWEG.DE
Salzgitter AG	Iron & Steel	SZGG.DE
Siemens Energy AG	Energy Equipment & Services	ENR1n.DE
Thyssenkrupp AG	Iron & Steel	TKAG.DE
Uniper SE	Multiline Utilities	UN0k.DE
Wacker Chemie AG	Specialty Chemicals	WCHG.DE

Table 2

This table lists the 16 energy-intensive firms comprising the treatment group. Firms are classified based on sector membership following the European Commission's definition of energy-intensive industries. All firms are listed on German exchanges. Stock tickers correspond to LSEG Workspace identifiers used for data collection.

The daily stock return for firm i on day t is calculated as the simple return, defined as:

$$R_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}}$$

where:

$R_{i,t}$ = the simple return of firm i on day t

$P_{i,t}$ = the closing price of firm i on day t

$P_{i,t-1}$ = the closing price of firm i on day $t-1$ (previous trading day)

The simple return represents the percentage change in stock price from one trading day to the next. This measure is widely used in event study methodology ((Brown and Warner 1985), MacKinlay (1997)) as it provides an intuitive interpretation of daily price movements and facilitates comparison across firms of different price levels.

Similarly, the market return on day t is calculated as:

$$R_{m,t} = \frac{I_{m,t} - I_{m,t-1}}{I_{m,t-1}}$$

where:

$R_{m,t}$ = the market return on day t

$I_{m,t}$ = the value of the market index (STOXX 600 Performance Index) on day t

$I_{m,t-1}$ = the value of the market index on day $t-1$ (previous trading day)

Please be advised that all returns are calculated using dividend-adjusted prices. This is to ensure that corporate actions such as dividend payments, stock splits and other capital structure changes are properly accounted for. The STOXX 600 Performance Index is widely regarded as the market benchmark, with the important caveat that it inherently accounts for dividend reinvestment. Furthermore, the STOXX Europe 600 Index is the recognised market benchmark, as opposed to the DAX, due to its comprehensive representation of the European market and the presence of multiple treatment group firms with international operations extending beyond Germany.

These returns are the dependent variable in the market model regression used to estimate expected returns during the event window, as explained in the Methodology section.

4.2 Data Sample Construction

The estimation window extends from 24th February 2021 to 12th January 2022 (11 months, approximately 200 trading days), concluding 30 days prior to the event to ensure parameter estimates are not influenced by event-related information.

The event window covers 17th of February 2022 to 3rd of March 2022 (11 trading days), centred around the Russian invasion of Ukraine on February 24, 2022.

The dataset for the treatment group involves 16 companies which are all highly exposed to the energy and gas prices. So, the Treatment group consists mostly of Chemicals (6 companies) and Utilities (4 companies), because they both use immense amounts of energy and more specifically gas or Russian gas.

The original data sample for the control group were all companies which were i; active during that time and data was available ii; German companies iii; not in a big percentage actively doing business with or in Russia iv; not benefitting or were in doubt of benefitting from the war e.g. renewables companies and v; not consuming a lot of energy or affected by enormous energy price fluctuations. So, the original dataset consisted of over 700 companies which were cut down to 39.

The Sector or Industry classification is based on Refinitiv's TRBC Industry Name for both groups. When some companies from the control group were in doubt of benefitting from the Energy price shock, a further analysis was done by analysing their annual reports.

Table 3 reports descriptive statistics for daily stock returns during the 11-month estimation window. The treatment group (energy-intensive firms, N = 3.696) and control group (less energy-intensive firms, N = 9.240) reveal similar mean returns (0,07%) and medians (0,03%), which indicates comparable average performance during the pre-event period. Volatility, as measured by variance, is also similar across groups (0,0356 vs. 0,0341). Notable differences emerge in distributional characteristics. The control group displays noticeably higher kurtosis (17,77 vs. 6,71), indicating heavier tails and more frequent extreme returns. This is further supported by the wider range of observed returns in the control group (minimum: -20,43%; maximum: 20,85%) compared to the treatment group (minimum: -11,34%; maximum: 13,08%). The control group also shows a slight negative skewness (-0,125), while the treatment group's distribution is almost symmetric (skewness = 0,006). The kurtosis values for both groups are excessively high (treatment: 3,71; control: 14,77), a common occurrence in financial return data, suggesting that the data may not adhere to a normal distribution. These baseline statistics provide the foundation for calculating expected and afterwards abnormal returns during the event window.

Estimation Window: 11 months								
Variables	μ	M	Min	Max	Skewness	Kurtosis	Var	N
Treatment	0,07	0,03	-11,34	13,08	0,00620	6,70735	0,0356	3696
Control	0,07	0,03	-20,43	20,85	-0,12496	17,77144	0,0341	9240
Total	0,07	0,03	-20,43	20,85	-0,085624	12,32604	0,0345	12936

Table 3

This table reports descriptive statistics for daily stock returns during the 11-month estimation window (February 24, 2021 to January 12, 2022). The treatment group comprises 16 energy-intensive firms (N=3,696 firm-day observations); the control group comprises 39 less energy-intensive firms (N=9,240 firm-day observations). Returns are calculated as simple percentage changes in dividend-adjusted closing prices. μ denotes mean, M median, Var variance, and N total observations.

Descriptive statistics for the 11-day event window surrounding the Russian invasion of Ukraine are reported in Table 4. Both groups experienced noticeably negative returns during the event window, in contrast to the estimation period. Importantly, the treatment groups' (energy-intensive firms) losses are more severe, with a mean daily return of -0,81% (median: -0,93%) compared to the control group's -0,72% (median: -0,81%). In addition to the difference in average returns, the treatment group reveals significantly higher volatility (variance: 0,001919 vs. 0,001028) and more extreme losses (minimum: -17,49% vs. -11,63%). The interpretation is that energy-intensive firms faced greater market uncertainty and downside risk during the crisis. Large negative returns dominated the distribution of the treatment group, which can be clearly shown by the treatment group's negative skewness (-0,34). On the other hand, the control group's distribution remained nearly symmetric (skewness: 0,05). The kurtosis statistics reveal contrasting patterns: the treatment group shows excess kurtosis (4,79). Fat tails and frequent extreme events are an indication for that, whereas the control group displays platykurtic behaviour (kurtosis: 0,45) with thinner tails. One can say that the energy-intensive firms experienced more volatile and unpredictable price movements during the event window. The findings imply that the gas supply shock had a differential impact on firms based on their energy intensity. Energy-intensive firms experienced both larger average losses and greater volatility. The subsequent abnormal return analysis will formally test the statistical significance of these differences.

Event Window: 11 days								
Variables	μ	M	Min	Max	Skewness	Kurtosis	Var	N
Treatment	-0,81	-0,93	-17,49	11,04	-0,34481	4,79486	0,001919	176
Control	-0,72	-0,81	-11,63	11,56	0,05151	0,45321	0,001028	440
Total	-0,75	-0,83	-17,49	11,56	-0,16424	5,18035	0,00128	616

Table 4

This table reports descriptive statistics for daily stock returns during the 11-day event window surrounding the Russian invasion of Ukraine (February 17, 2022 to March 3, 2022, with t=0 on February 24, 2022). The treatment group comprises 16 energy-intensive firms (N=176 firm-day observations); the control group comprises 39 less energy-intensive firms (N=440 firm-day observations). Returns are calculated as simple percentage changes in dividend-adjusted closing prices. μ denotes mean, M median, Var variance, and N total observations.

4.3 Data Cleaning and Sample Refinement

The final sample was constructed through systematic data screening procedures. From an initial sample of 20 treatment firms and 40 control firms, the analysis retains 16 treatment firms and 39 control firms after applying data quality filters.

Sample Exclusion Criteria

Firms were excluded because of the following criteria: (1) insufficient data availability, this occurred if more than 5% of trading days were missing during the estimation window (1 firm excluded); (2) low trading liquidity, if the stock price did not change for more than 5 days (1 firm excluded); and (3) if other data quality issues were identified by my manual verification (3 firms excluded). I decided that the observations from the return calculations should be omitted, rather than imputing values for non-trading days. In instances where a firm exceeded the 5% missing data threshold, the entire firm was excluded from the sample to avoid introducing bias through data imputation.

Data Adjustment and Verification

All stock prices were taken dividend-adjusted from the LSEG Workspace database, which accounts automatically for corporate actions including stock splits and dividend payments. Please note that no mechanical outlier filtering was applied. However, all extreme returns (exceeding ±10% in a single day) were manually inspected and cross-verified with market news to confirm their validity. Furthermore, the Data quality was verified by cross-checking a random sample of observations against Yahoo Finance, with no material differences found.

Special considerations apply to Uniper SE, which was later nationalized by the German government in September 2022 but was actively traded during the estimation and event windows. Uniper is retained in the treatment sample as its price reactions provide valuable information about market observations of energy-intensive firms' crisis exposure.

The final sample consists of 12.936 firm-day observations during the estimation window (treatment: 3.696; control: 9.240) and 616 observations during the event window (treatment: 176; control: 440), which is sufficient for robust statistical inference

5. Results

This section presents the empirical results of the event study examining the differential impact of the Russian invasion of Ukraine and subsequent gas supply shock on German publicly listed firms. The analysis is laid out in four stages. In the beginning, the average abnormal returns (AAR) are presented for both the treatment group (energy-intensive firms) and the control group (less energy-intensive firms) across the 11-day event window. These daily abnormal returns reveal the immediate market reaction to the advancing crisis and allow for the identification of anticipatory effects and delayed responses. Cumulative average abnormal returns (CAAR) are then calculated for various sub-periods within the event window to assess whether the impact materialized immediately or accumulated over time. Third, the treatment and control groups are directly compared through difference tests and a cross-sectional analysis. In order to respond to the second research question, it is necessary to display an additional firm-level analysis. This section details the winners and losers from both groups and provides information on the uniformity or heterogeneity of the results.

5.1 Daily Average Abnormal Returns

As illustrated in Table 5, the daily average abnormal returns (AAR) are divided into three columns: treatment, control and the difference between them. Contrary to expectations, the strongest market reactions occur before rather than on the invasion date. On February 21, 2022 (t = -3), both groups experienced highly significant negative AARs: -4,40% for treatment firms (t = -6,25) and -4,00% for control firms (t = -9,42). This was followed by a significant positive correction on t = -2 (+2,82% and +2,50%, respectively). The event day itself (February 24, 2022) shows no significant abnormal returns for either group (treatment: +0,71%, t = 0,65; control: +0,41%, t = 0,70). This suggests that markets had already incorporated expectations of the invasion into prices during the preceding days. The post-event period remains relatively calm until March 3 (t = +5), when negative abnormal returns reemerge (-2,52% for treatment, t = -2,14; -0,50% for control, t = -1,84). To note is the finding that the differential impact between treatment and control groups is not statistically significant on any individual day. One can imply that sector-specific effects may only emerge when examining cumulative abnormal returns over the full event window. These patterns show that geopolitical events may generate anticipatory market reactions, thereby complicating the identification of event-specific impacts in daily abnormal returns. Figure one and two illustrate the results in graphs.

day	date	Treatment_AAR	Control_AAR	Difference_AAR
-5	17,02,2022	0,217 (-0,47)	-0,496** (-2,10)	0,713 (-1,73)
-4	18,02,2022	-0,226 (-0,73)	-0,598** (-2,12)	0,371 (-0,89)
-3	21,02,2022	-4,403*** (-6,25)	-4,000*** (-9,42)	-0,403 (-0,49)
-2	22,02,2022	2,824*** (-3,5)	2,503*** (-4,44)	0,321 (-0,33)
-1	23,02,2022	-0,766 (-0,67)	-0,367 (-1,07)	-0,399 (-0,34)
0	24,02,2022	0,714 (-0,65)	0,406 (-0,7)	0,309 (-0,25)
1	25,02,2022	0,013 (-0,02)	-0,006 (-0,02)	0,020 (-0,02)
2	28,02,2022	1,373 (-1,04)	-0,367 (-0,83)	1,739 (-1,25)
3	01,03,2022	-0,825 (-0,93)	-0,203 (-0,49)	-0,622 (-0,63)
4	02,03,2022	0,503 (-0,68)	0,227 (-0,8)	0,276 (-0,35)
5	03,03,2022	-2,516** (-2,14)	-0,499* (-1,84)	-2,017 (-1,67)

Table 5

This table presents average abnormal returns (AAR) for treatment (energy-intensive firms, N=16) and control (less energy-intensive firms, N=39) groups across the 11-day event window surrounding the Russian invasion of Ukraine on February 24, 2022 (t=0). AARs are reported in percentage points. t-statistics in parentheses test the null hypothesis that AAR equals zero (one-sample t-test for Treatment and Control) or that the difference in AAR between groups equals zero (two-sample t-test for Difference). *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

5.2 Cumulative Average Abnormal Returns

While no single day showed significant abnormal returns, the cumulative effect over the complete event window may reveal large disparities. The daily evolution of cumulative average abnormal returns (CAAR) throughout the event window, can be seen in Table 6. The results do not support the hypothesis that energy-intensive firms experienced significantly greater cumulative losses than less energy-intensive firms during the gas supply shock.

At the end of the 11-day event window (March 03, 2022), both groups experienced nearly identical cumulative losses: treatment firms -3,09% (t = -0,65) and control firms -3,40% (t = -2,99). The difference of 0,31 percentage points (t = 0,06) is statistically insignificant. Throughout the entire event window, no single day reveals a significant differential impact, with t-statistics for the difference ranging from 0,06 to 1,43, which is well below conventional significance thresholds.

The cumulative losses begin accumulating on February 21 (t = -3), three days before the invasion, when both groups have highly significant negative returns. The control group's CAAR of -5,09% (t = -7,64) at this point exceeds the treatment group's -4,41% (t = -5,29). This is a pattern that remains consistent throughout much of the event window. This implicates that the crisis is a broad-based shock that affects all firms rather than a sector-specific energy disruption.

Another interesting finding is that the control group maintains highly significant CAARs (p < 0,01) throughout the event window, while the treatment group's CAARs fail to achieve significance after the initial February 21 shock. This is probably because there is less variation in abnormal returns among control firms, rather than differences in how exposed they are. This may reveal that market reactions within the less energy-intensive sector are more similar.

These findings clearly show that the immediate market response to the invasion did not differentiate between energy-intensive and less energy-intensive firms based on weakness to natural gas supply disruptions. The effects on specific sectors might have become clear over a longer time, after the 11-day event, as the full effects on European energy markets became apparent.

day	date	Treatment	Control	Difference
-5	17.02.2022	0,217 (0,47)	-0,496** (-2,10)	0,713 (1,37)
-4	18.02.2022	-0,009 (-0,01)	-1,094** (-2,71)	1,085 (1,43)
-3	21.02.2022	-4,412*** (-5,29)	-5,093*** (-7,64)	0,682 (0,64)
-2	22.02.2022	-1,588 (-1,69)	-2,590*** (-5,04)	1,002 (0,94)
-1	23.02.2022	-2,354 (-1,49)	-2,957*** (-5,07)	0,603 (0,36)
0	24.02.2022	-1,640 (-0,73)	-2,551*** (-4,60)	0,912 (0,39)
1	25.02.2022	-1,626 (-0,72)	-2,558*** (-4,37)	0,931 (0,40)
2	28.02.2022	-0,254 (-0,08)	-2,924*** (-3,41)	2,670 (0,79)
3	01.03.2022	-1,078 (-0,28)	-3,127*** (-2,88)	2,049 (0,51)
4	02.03.2022	-0,575 (-0,15)	-2,899*** (-2,79)	2,324 (0,57)
5	03.03.2022	-3,091 (-0,65)	-3,398*** (-2,99)	0,307 (0,06)

Table 6

Notes: This table presents the daily evolution of cumulative average abnormal returns (CAAR) for treatment (energy-intensive firms, N=16) and control (less energy-intensive firms, N=39) groups throughout the event window. CAARs represent the cumulative sum of average abnormal returns from day t=-5 to the current day. Day 0 represents February 24, 2022. Values are reported in percentage points with t-statistics in parentheses. t-statistics test whether CAARs differ significantly from zero (Treatment and Control columns) or whether treatment and control CAARs differ from each other (Difference column). *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed tests).

5.3 Event Window Specifications

In order to further consolidate the results obtained, the event window was divided into multiple sub-windows. In Table 7 the cumulative abnormal returns were aggregated across eight event window specifications to formally test if the treatment group was more affected than the control group. The results consistently fail to support the hypothesis that energy-intensive firms experienced significantly greater cumulative losses than less energy-intensive firms.

Over the full event window [-5,+5], both groups suffered nearly identical cumulative losses: treatment firms -3,09% (t = -0,65) and control firms -3,40% (t = -2,99). The differential impact of 0.31 percentage points (t = 0,06) is economically negligible and statistically insignificant, also this null result is robust across all window specifications.

The pre-event period [-5,-1] shows both groups experiencing negative CAARs (treatment: -2,35%; control: -2,96%), with an insignificant difference (t = 0,36). As previously described, the event day [0,0] reveals small positive abnormal returns for both groups (treatment: +0,71%; control: +0,41%), which implies that the invasion had been priced into asset values prior to the event date. The post-event period [+1,+5] shows modest negative CAARs for both groups, with an insignificant differential impact (t = -0,20).

These results further confirm that the initial market response to the invasion did not distinguish between energy-intensive and less energy-intensive firms in terms of their exposure to natural gas supply disruptions.

	Window	Treatment	Control	Difference
Pre-Event	[-5, -1]	-2,354 (-1,49)	-2,957*** (-5,07)	0,603 (0,36)
Event Day	[0, 0]	0,714 (0,65)	0,406 (0,70)	0,309 (0,25)
Post-Event	[+1, +5]	-1,451 (-0,50)	-0,847 (-1,01)	-0,604 (-0,20)
Short Window	[-2, +2]	4,158 (1,28)	2,169** (2,17)	1,989 (0,58)
Full Window	[-5, +5]	-3,091 (-0,65)	-3,398*** (-2,99)	0,307 (0,06)
Pre-Event Short	[-2, -1]	2,058	2,136***	-0,079

		(1,33)	(4,81)	(-0,05)
Post-Event Short	[0, +2]	2,100 (0,97)	0,033 (0,05)	2,067 (0,90)
Extended Post	[+1, +5]	-1,451 (-0,50)	-0,847 (-1,01)	-0,604 (-0,20)

Table 7

Notes: This table presents cumulative average abnormal returns (CAAR) for treatment (energy-intensive firms, N=16) and control (less energy-intensive firms, N=39) groups across eight event window specifications. CAARs represent the sum of average abnormal returns over the specified window. For each group, values are reported in percentage points with t-statistics in parentheses. t-statistics test whether CAARs differ significantly from zero (Treatment and Control columns) or whether treatment and control CAARs differ from each other (Difference column). Day 0 represents February 24, 2022, the date of the Russian invasion of Ukraine. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively (two-tailed tests). None of the differential impacts achieve statistical significance at conventional levels.

5.4 Cross-sectional Analysis

The previous analysis did not incorporate any firm specific metrics, which could influence the individual stock returns. As illustrated in Table 8, the study uses cross-sectional regressions to analyse how firm characteristics explain differences in cumulative abnormal returns during the event window. Model 1 confirms the null finding from the CAAR analysis: the treatment coefficient is economically small (0,31 percentage points) and statistically insignificant (t = 0,09).

Introducing control variables in Models 2-5 does not change this conclusion. The treatment effect remains consistently insignificant across all specifications, with coefficients ranging from -1,49 to +0,31 percentage points and t-statistics never exceeding |0,40|. This again shows that, after controlling for firm size, systematic risk, leverage, and profitability, energy-intensive firms did not experience significantly different cumulative returns than less energy-intensive firms.

Firm size emerges as the only marginally significant predictor (Models 3 and 5: $\beta \approx -2{,}3$, $t \approx -1{,}65$), suggesting that larger firms tended to experience somewhat more negative returns, though this effect is weak. Beta, leverage, and ROA show no significant relationship with event-period returns. The overall explanatory power of the models is very low, with R^2 reaching only 8.3% in the full specification and adjusted R^2 often negative, indicating that the included variables collectively explain very little of the cross-sectional variation in cumulative abnormal returns.

These results corroborate the CAAR findings: neither raw comparisons nor regression-adjusted comparisons reveal a significant impact of the gas supply shock on energy-intensive firms during the 11-day event window.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
(Intercept)	-3,3984* (1,8892)	-8,1395* (4,3041)	12,6289 (13,3104)	13,2267 (14,2470)	12,8274 (14,3697)
Treatment	0,3073 (3,5027)	-0,8400 (3,6100)	-1,3695 (3,5667)	-1,4870 (3,7195)	-1,1477 (3,8002)
Log Size			-2,2732 (1,3811)	-2,2944 (1,4047)	-2,3296 (1,4164)
Leverage				-1,4405 (11,3863)	0,0498 (11,8047)
ROA					0,0550 (0,1032)
Beta		6,5684 (5,3638)	7,0929 (5,2874)	7,0443 (5,3529)	6,7870 (5,4132)
R^2	0,0001	0,0282	0,0772	0,0775	0,0828
Adj. R^2	-0,0187	-0,0092	0,0229	0,0037	-0,0108
N	55	55	55	55	55

Table 8

Notes: This table presents cross-sectional regressions of cumulative abnormal returns (CAR, in percentage points) on firm characteristics. The dependent variable is CAR over the full event window [-5, +5]. Treatment is a dummy variable equal to 1 for energy-intensive firms. Log (Size) is the natural logarithm of market capitalization (in millions EUR). Leverage is debt-to-equity ratio. ROA is return on assets. Beta is systematic risk estimated from the market model over the estimation window. Robust standard errors in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels (two-tailed tests). N = 55 firms (16 treatment, 39 control)."

5.5 Wilcoxon rank-sum tests (Mann-Whitney U tests)

In order to ensure that the null findings are not driven by violations of parametric assumptions, I conduct Wilcoxon rank-sum tests (Mann-Whitney U tests) as non-parametric alternatives to the parametric t-tests. These results are reported in Table 9.

Consistent with the parametric analysis, the Wilcoxon rank-sum tests reveal no statistically significant differences between treatment and control groups in any event window specification. Over the full window [-5,+5], treatment firms display a median cumulative abnormal return of -2,16% compared to -0,91% for control firms, a difference of -1,24 percentage points (W = 341, p = 0,60). None of the other window specifications yield significant results either (all p > 0,10).

Notably, in several specifications, treatment firms show less negative or even positive median returns relative to control firms, especially on the event day itself (treatment: -0,49%; control:

-2,06%; p = 0,33) and in the short window [-2,+2] (treatment: +2,37%; control: -2,38%; p = 0,30). While these differences are not statistically significant, they disagree with the directional hypothesis that energy-intensive firms would underperform. The pattern signifies huge heterogeneity within groups rather than a systematic difference driven by energy intensity.

These non-parametric tests confirm that the absence of differential impact is not driven by distributional assumptions. In summary, the null finding holds under both parametric and non-parametric testing frameworks. This strengthens confidence in the conclusion that energy intensity did not determine firm-level stock market exposure during the 11-day event window surrounding the Russian invasion.

	Window	Treatment	Control	Difference	W	p
Full Window	[-5;+5]	-2,155	-0,912	-1,244	341	0,5974
Pre-Event	[-5;-1]	-1,773	-2,391	0,618	376	0,2393
Event Day	[0]	-0,489	-2,055	1,566	365	0,3306
Post-Event	[+1;+5]	-2,155	-0,912	-1,244	341	0,5974
Short Window	[-2;+2]	2,371	-2,380	4,751	368	0,3037

Table 9

Notes: This table presents non-parametric Wilcoxon rank-sum tests (Mann-Whitney U tests) comparing cumulative abnormal return distributions between treatment (energy-intensive firms, N=16) and control (less energy-intensive firms, N=39) groups. Median values reported in percentage points. W is the rank-sum statistic. The test does not assume normal distributions and is robust to outliers. None of the differences are statistically significant at conventional levels (all p > 0,10). *, **, *** would indicate significance at 10%, 5%, and 1% levels (two-tailed tests).

5.6 Firm level analysis

Finally, the CARs are analysed on a firm-level basis, to assess any occurring heterogeneity. Table 10 presents the five best and five worst performers in each group. The analysis reveals striking dissimilarity within the treatment group that explains the absence of significant average treatment effects.

All five top-performing treatment firms achieved strong positive returns ranging from +10,9% (Aurubis) to +20,9% (Salzgitter), which exceeds the best control firm performance of +7,4% (Carl Zeiss Meditec) by far. These energy-intensive firms appear to have benefited from expectations of rising commodity prices, domestic production advantages, or anticipated infrastructure investments following the crisis.

However, the bottom treatment performers experienced harsh losses. Uniper suffered an extraordinary -56,4% cumulative abnormal return, that is more than twice the loss of the next-worst treatment firm (Lanxess: -23,3%). Chemical producers BASF (-14,4%), Lanxess (-23,3%), and Covestro (-10.9%) are also among the bottom performers. This is due to their dependence on natural gas as both energy source and chemical feedstock.

The 77-percentage-point range in treatment group CARs (from +20,9% to -56,4%) is 2,6 times wider than the control group's 30-percentage-point range. This massive dispersion offsets large positive and negative returns in the group mean, producing a statistically insignificant average treatment effect despite generous firm-level impacts.

Among the bottom five performers, there can both treatment and control firms be found, with the two worst control firms being financial institutions (Deutsche Bank: -22,5%; Commerzbank: -19.0%). This mixing of treatment and control firms throughout the performance distribution shows that sector-based classification does not cleanly separate crisis winners from losers. Rather, firm-specific factors, which could be for example: subsector, gas procurement strategies, international exposure, and market expectations determine outcomes within the broad category of 'energy-intensive' firms."

Group	Category	Rank	Firm_label	CAR_pct
Treatment	Top 5	1	Salzgitter	20,85
Treatment	Top 5	2	K S N	16,63
Treatment	Top 5	3	Siemens Energy N	13,01
Treatment	Top 5	4	Thyssenkrupp	12,12
Treatment	Top 5	5	Aurubis	10,85
Control	Top 5	1	Carl Zeiss Meditec	7,44
Control	Top 5	2	Cancom	6,71
Control	Top 5	3	Hypoport Finance	6,11
Control	Top 5	4	Leg Immobilien	5,04
Control	Top 5	5	Nemetschek	4,30
Treatment	Bottom 5	12	Covestro	-10,87
Control	Bottom 5	38	Puma	-11,60
Treatment	Bottom 5	13	Heidelberg Materials	-12,79
Control	Bottom 5	39	United Internet	-14,12
Treatment	Bottom 5	14	Basf	-14,42
Control	Bottom 5	40	Prosiebensat 1 Media	-15,31
Control	Bottom 5	41	Commerzbank	-19,02
Control	Bottom 5	42	Deutsche Bank	-22,48
Treatment	Bottom 5	15	Lanxess	-23,34
Treatment	Bottom 5	16	Uniper K	-56,35

Table 10

Notes: This table presents the five best and five worst performing firms in each group based on cumulative abnormal returns (CAR) over the full event window [-5,+5]. Values reported in percentage points. Treatment group consists of 16 energy-intensive firms; control group consists of 39 less energy-intensive firms. The treatment group exhibits substantially higher dispersion (range: 77.2 pp) compared to the control group (range: 29.9 pp), with all five top treatment firms achieving positive returns that exceed the best control firm performance.

6. Discussion

6.1 Interpretation of Null Average Treatment Effects

The absence of significant average treatment effects in my event study could reflect three non-mutually exclusive explanations. One possible explanation is that energy intensity may genuinely not predict short-run stock market exposure to natural gas supply shocks. This suggests that investors either did not view energy-intensive firms as being particularly vulnerable, or they anticipated that factors such as government support or the ability to pass on higher costs to consumers would offset these costs. However, this interpretation appears not very consistent with the significant firm-level variation I observe within the treatment group, which says that energy exposure does matter but reveals dissimilarly.

The 11-day event window also may be too brief to capture sector-specific impacts that arrived over subsequent months. Federle, Meier et al. (2024) demonstrate that the full economic impact of the Russian invasion extended beyond the immediate invasion period. Trade linkages and military disaster risk affects stock returns over several weeks. In a similar fashion, policy responses, which included Germany's emergency energy procurement measures and EU sanctions, evolved gradually. This potentially delayed market recognition of differential firm-level weaknesses. Nevertheless, event studies are specifically designed to capture immediate market reactions under the efficient market hypothesis. Extending the event window may lead to the introduction of confounding factors, which may complicate the identification of causality.

Lastly, and most consistent with my firm-level analysis, considerable within-group heterogeneity hides average effects. The Russia-Ukraine conflict represents a severe supply-driven energy shock (Kilian 2009), with European markets particularly exposed, because of their high dependence on Russian gas (Batten, Ciner et al. 2017). Nonetheless, my treatment group encompasses firms with fundamentally different gas usage patterns, cost structures and market positions. On one side some energy-intensive firms suffered severe losses due to direct gas dependence or inflexible production processes. On the other side others benefited from rising commodity prices, domestic production advantages, or substitution possibilities. These opposing forces cancel in the group mean, producing insignificant average effects despite important firm-level impacts. This interpretation is further supported by the observation that the treatment group reveals significantly greater return dispersion than the control group. This finding signals that energy intensity amplifies rather than uniformly determines crisis exposure.

6.2 Firm-Level Heterogeneity as Key Explanation

The firm-level analysis reveals why average treatment effects are insignificant despite large impacts. While Rossi, Ni et al. (2025) document that energy-intensive (brown) stocks underperformed energy-efficient (green) stocks across Europe during the outbreak period, our analysis demonstrates sizable dissimilarity within the energy-intensive category itself. Treatment firms span a 77-percentage-point range from +20.9% (Salzgitter) to -56.4% (Uniper), compared to a 30-percentage-point range in the control group. This is also a result in Ramelli and Wagner (2020), who state that firm-level characteristics generate substantial heterogeneity in crisis responses even within industries.

Steel and metals producers achieved cumulative abnormal returns between +10.9% and +20.9%, benefiting from several supporting factors. One element is the expectations of rising commodity prices due to supply disruptions and increased demand for military production. Another aspect is Germany's announcement of a €100 billion special fund for the armed forces on 27 February 2022, which was just three days after the invasion. It signalled immense future infrastructure and defense spending, whose beneficiaries are steel and metals producers. This announcement coincides with a visible jump in cumulative abnormal returns on the second trading day following the invasion. Lastly, steel producers primarily use natural gas as an energy input, but they have some substitution flexibility through coal or electricity, as exemplified by Thyssenkrupp's diversified energy mix. This contrasts sharply with the energy sector itself, where oil and gas producers benefited from rising energy prices (Ahmed, Hasan et al. 2022, Nerlinger and Utz 2022).

Chemical producers suffered losses between -10.9% and -23.3%, reflecting fundamentally different gas dependencies. Unlike steel producers, chemical manufacturers use natural gas as both energy input and chemical feedstock in production processes, so they have limited substitution possibilities. Companies such as BASF, Lanxess, and Covestro face high gas intensity, with some reporting gas shares exceeding 60% of energy consumption and inflexible production technologies that prevent rapid input substitution. This distinction between gas as an energy source and gas as a feedstock is a critical firm-level characteristic that broader energy-intensive classifications fail to capture, consistent with Griffin, Lont et al. (2017) finding that firm-level energy exposure matters beyond industry membership.

Uniper's extreme loss of -56.4% reflects a distinct case of direct Russian gas supply exposure, that represents an existential threat which ultimately required government intervention. The group mean effectively neutralises these opposing forces, resulting in negligible average treatment effects despite notable firm-level impacts.

6.3 Classification and Measurement Issues

The way companies are grouped in this study does not adequately capture firm-level variation in actual natural gas usage. While sector membership provides an approximation of energy intensity, it hides important within-sector differences in gas procurement strategies, hedging positions, operational flexibility, and input substitution capabilities. Energy-intensive firms differ markedly in terms of whether they use gas as an energy input or a chemical feedstock, the extent of long-term supply contracts versus spot market exposure, and the availability of alternative energy sources. Some firms classified as energy-intensive have adopted hedging strategies for gas purchases through forward contracts, diversified their energy sources through investments in renewables or coal, or received implicit government support through regulated pricing mechanisms.

The huge variation among treatment firms, which ranges from gains over +20% to losses beyond -50%, shows that sector membership is an imperfect measure for crisis exposure This problem is not unique to my study. Rossi, Ni et al. (2025) find similar heterogeneity even within their broader classification of brown versus green stocks across Europe. Griffin, Lont et al. (2017) demonstrate that firm-specific measures like actual energy consumption or carbon emissions scaled by revenue, provide a higher degree of energy exposure than industry categories alone.

6.4 Limitations

One of the limitations is that the 11-day event window captures immediate market reactions but not medium- or long-term adjustment processes, which could be energy purchasing changes, government interventions, or gradual cost pass-through. Important sector-specific changing aspects may therefore remain unobserved, though short-horizon event studies are specifically designed to isolate immediate price impacts (Kothari and Warner 2004).

Another factor that limits statistical power and increases sensitivity to individual outliers, is the small size of the treatment group, which consists of only 16 firms. With such a small sample, cross-sectional interpretation becomes less robust, and group averages may be excessively influenced by extreme observations.

A third limitation concerns the classification method itself. Firms, in my thesis, are categorized based on sector membership rather than firm-specific natural gas intensity. Even though firms within the same sector differ substantially in gas reliance depending on technology, product mix, and operational flexibility. This measurement error may decrease the estimated treatment effects and obscures the granular variation that determines actual exposure (Griffin, Lont et al. 2017).

The analysis is also restricted to German-listed firms, which limits generalizability. Germany's unique industrial structure, high Russian gas dependence, and specific regulatory responses ensures that findings cannot automatically be extended to countries with different energy mixes or geopolitical positions.

Finally, several unobservable factors play crucial roles in determining economic exposure but remain unavailable in the data. Gas procurement contracts, hedging strategies, and input substitution capabilities vary markedly across firms, potentially leading to misclassification of firm-level vulnerability.

6.5 Implications and Future Research

Important methodological and policy implications are carried by these findings. Methodologically, they demonstrate that binary sector-based classifications may obscure heterogeneous treatment effects when the firms largely vary within-group. Researchers, who survey industry-level or sectoral responses to shocks should consider firm-level analyses to avoid an aggregation bias. This thesis lays out that not all energy-intensive firms react uniformly to an energy supply shock and rather subsector characteristics, i.e. the distinction between gas as energy input versus chemical feedstock reveal outcomes. Individual firm vulnerability can therefore not be determined by an aggregate sector study, like this one, because of this discrepancy.

For future research there are several directions, that could not be covered in this event study. In order to capture medium-term adjustment processes, which may include strategic responses such as input substitution, production relocation, or renegotiated supply contracts, the event window length must be extended. One aspect, that would enable a more precise measurement of exposure and reduce the classification error would be to find firm-level data on actual natural gas consumption and the associated procurement contracts, as well as hedging positions (Griffin, Lont et al. 2017). However, finding this kind of information will be difficult, since not all companies disclose this data. Another possible research topic is to clarify the mechanisms which drives the mixed responses by conducting subsector-specific analyses within energy-intensive industries. Lastly, cross-country comparisons could show to what extent the findings apply outside Germany or are limited by its high dependence on Russian gas.

7. Conclusion

This study examines the stock market response of German energy-intensive firms to the Russia-Ukraine war and the resulting natural gas supply shock. Using event study methodology on 16 energy-intensive firms and 39 control firms listed on German exchanges, I address two research questions: (1) whether energy-intensive firms exhibit differential stock market reactions compared to control firms, and (2) the extent of heterogeneity within the energy-intensive category and its determinants.

Regarding the first research question, I find no significant average treatment effect. Energy-intensive firms expose cumulative abnormal returns statistically indistinguishable from control firms across multiple event window specifications, with a full-window difference of +0.31 percentage points (t = 0.06). This null result is robust to non-parametric tests and alternative model specifications. I identified three explanations. First, investors may not have observed energy intensity as a central determinant of crisis exposure, possibly expecting government support or cost pass-on mechanisms. Also, the 11-day event window captures immediate reactions but not medium-term sector-specific adjustments that evolved over subsequent months. And to conclude the heterogeneity masks within-group average effects.

Regarding the second research question, I document a massive firm-level variation within the energy-intensive category. Treatment firms span a 77-percentage-point range from +20.9% (Salzgitter) to -56.4% (Uniper), compared to a 30-percentage-point range among control firms. This dissimilarity follows systematic subsector forms: steel and metals producers achieved returns between +10.9% and +20.9%, benefiting from expected commodity price increases, domestic production advantages, and Germany's €100 billion defence fund announcement. In contrast, chemical producers suffered losses between -10.9% and -23.3%, reflecting their dependence on natural gas as both energy input and chemical feedstock. Uniper's extreme loss reflects direct Russian gas supply exposure as Germany's largest gas importer. These opposing forces cancel in the group mean, which explains the null average effect despite huge individual firm impacts.

The Russia-Ukraine war demonstrated that energy intensity alone is an insufficient predictor of crisis exposure. As Europe continues its energy transition and navigates geopolitical risks, understanding firm-level heterogeneity in energy exposure becomes very important for both investors and policymakers.

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Appendix:

Company	**Sector / Type**	**Ticker**
adidas AG	Footwear	ADSGn.DE
Allianz SE	Multiline Insurance & Brokers	ALVG.DE
Aroundtown SA	Real Estate Rental, Development & Operations	AT1:DE
Bechtle AG	IT Services & Consulting	BC8G.DE
Beiersdorf AG	Personal Products	BEIG.DE
BioNTech SE	Biotechnology & Medical Research	BNTX.OQ
Cancom SE	IT Services & Consulting	COKG.DE
Carl Zeiss Meditec AG	Advanced Medical Equipment & Technology	AFXG.DE
Cewe Stiftung & Co KGaA	Commercial Printing Services	CWCG.DE
Commerzbank AG	Banks	CBKG.DE
Deutsche Bank AG	Banks	DBKGn.DE
Deutsche Boerse AG	Financial & Commodity Market Operators & Service Providers	DB1Gn.DE
Deutsche Telekom AG	Integrated Telecommunications Services	DTEGn.DE
DWS Group GmbH & Co KgaA	Investment Management & Fund Operators	DWSG.DE
Evotec SE	Biotechnology & Medical Research	EVTG.DE
Fielmann Group AG	Miscellaneous Specialty Retailers	FIEG.DE
Freenet AG	Integrated Telecommunications Services	FNTGn.DE
Fresenius Medical Care AG	Healthcare Facilities & Services	FMEG.DE
Grand City Properties SA	Real Estate Rental, Development & Operations	GYC:DE
Hannover Rueck SE	Reinsurance	HNRGn.DE
Henkel AG & Co KGaA	Specialty Chemicals	HNKG_p.DE
HORNBACH Holding AG & Co KgaA	Home Improvement Products & Services Retailers	HBH.DE
Hypoport SE	Financial Technology (Fintech)	HYQGn.DE
Infineon Technologies AG	Semiconductors	IFXGn.DE
Jenoptik AG	Semiconductors	JENGn.DE
LEG Immobilien SE	Real Estate Rental, Development & Operations	LEGn.DE
Merck KGaA	Pharmaceuticals	MRCG.DE
Nemetschek SE	Software	NEKG.DE
Prosiebensat 1 Media SE	Broadcasting	PSMGn.DE
Puma SE	Footwear	PUMG.DE
Qiagen N.V.	Real Estate Rental, Development & Operations	QIA:DE
Rational AG	Appliances, Tools & Housewares	RAAG.DE
SAP SE	Software	SAPG.DE
Sartorius AG	Advanced Medical Equipment & Technology	SATG.DE
Software AG (if still listed at event date)	Software	SOW:DE
Stroeer SE & Co KgaA	Advertising & Marketing	SAXG.DE
TAG Immobilien AG	Real Estate Rental, Development & Operations	TEGG.DE
United Internet AG	Integrated Telecommunications Services	UTDI.DE

Vonovia SE	Real Estate Rental, Development & Operations	VNAn.DE

Table 11

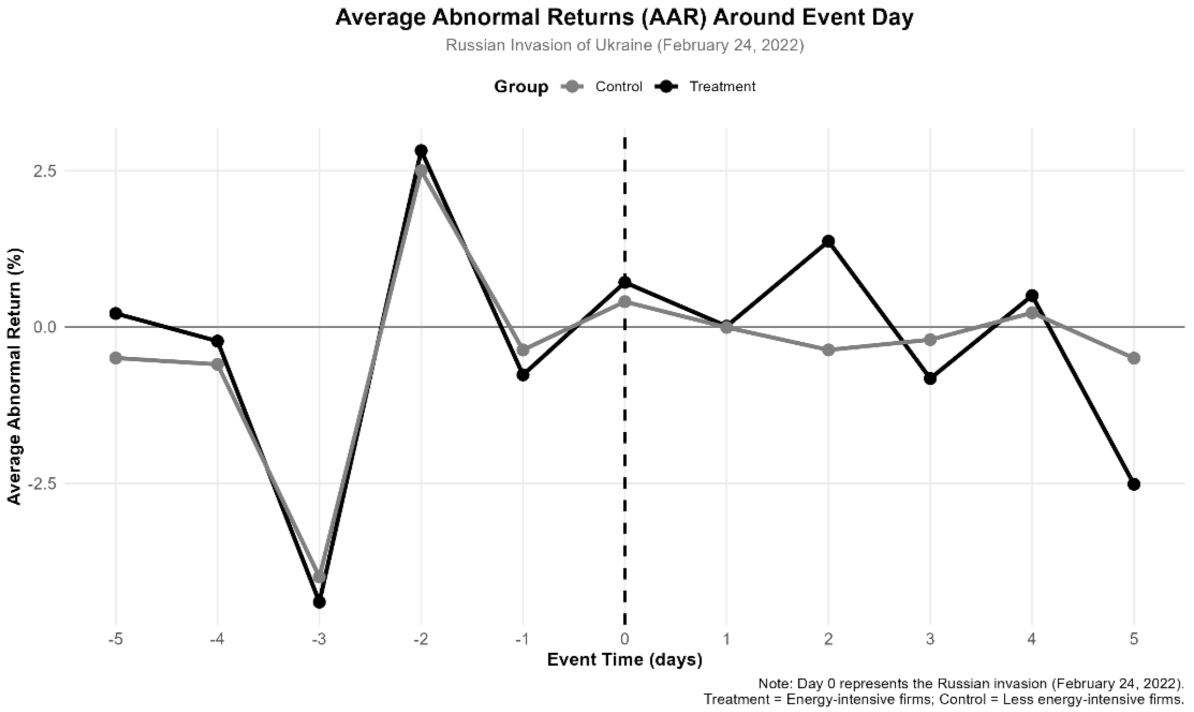

Figure 1

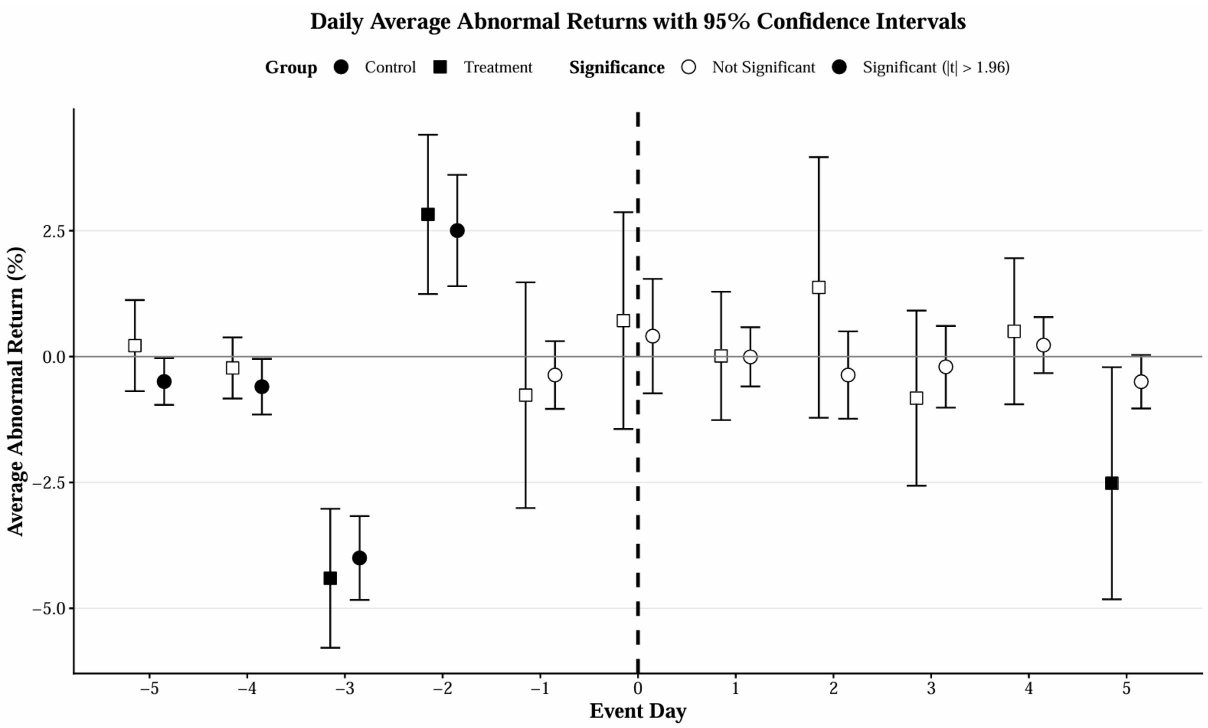

Figure 2

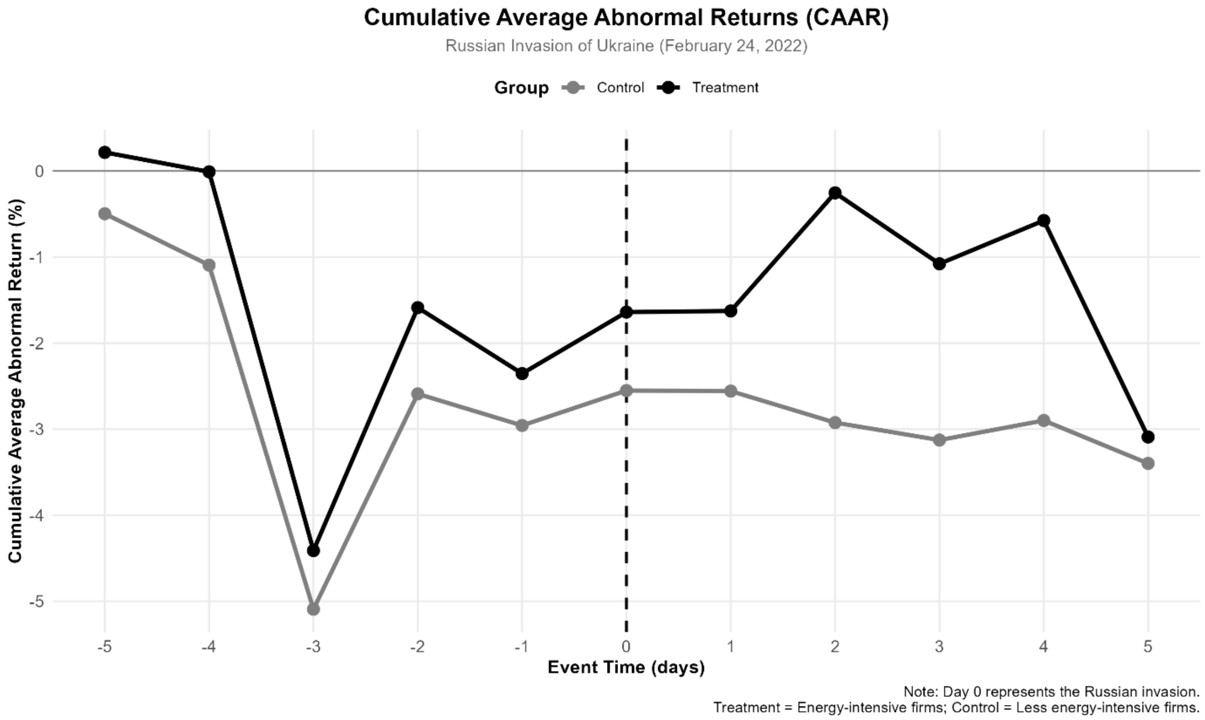
Cumulative Average Abnormal Returns (CAAR)
Russian Invasion of Ukraine (February 24, 2022)
Group Control Treatment
Cumulative Average Abnormal Return (%)
0
-1
-2
-3
-4
-5
-5 -4 -3 -2 -1 0 1 2 3 4 5
Event Time (days)
Note: Day 0 represents the Russian invasion.
Treatment = Energy-intensive firms; Control = Less energy-intensive firms.

Figure 3