Germany's Gas Price Brake: Firm-Level Evidence on Short-Term Financial Outcomes

LEVIN LINDENZWEIG* TINTIN WILSBY**

Master Thesis
Department of Finance
Stockholm School of Economics
Supervisor: Jan Starmans

December, 2025

Abstract

This thesis investigates how Germany's Gas Price Brake (GPB) affected market valuations and financial performance of German firms and whether leverage and ESG moderated these effects. An event study estimates cumulative abnormal returns around gas crisis and GPB policy dates. A difference-in-differences design exploits cross-industry variation in pre-crisis energy-intensity to quantify effects on return on assets (ROA) and interest-coverage ratios (ICR). The event study shows that high energy-intensive (HighEI) firms experienced more negative abnormal returns than low energy-intensive (LowEI) peers on crisis dates and relatively more positive abnormal returns on GPB policy dates, consistent with markets expecting larger crisis-related losses and subsequent policy support for these firms. However, accounting results show that HighEI firms experienced only a small relative profitability decline in 2022 and no detectable improvement in 2023, while no significant effect is observed for ICR. Within HighEI firms, leverage is associated with relatively higher ROA in both years, but not with stronger announcement-day returns. ESG performance does not systematically moderate valuation or accounting outcomes. Overall, the evidence indicates that while investors initially priced the GPB as a stabilising mechanism for highly exposed firms, this expectation did not translate into relative improvements in realised profitability or solvency within the annual reporting period. The thesis contributes to the literature by quantifying realised firm-level financial effects of the GPB and by offering new evidence on how leverage and ESG characteristics shape firms' responses to broad price-based fiscal stabilisation.

Keywords: Energy Crisis, Fiscal Policy, Germany, Energy-Intensive Firms, ESG

We would like to thank our supervisor Jan Starmans for his support and guidance throughout our thesis.

* 42667@student.hhs.se ** 25140@student.hhs.se

Contents

List of Abbreviations **3**

1 Introduction **1**

2 Background & Theoretical Framework **3**
2.1 The European Energy Crisis . . . 3
2.2 The German Economic and Policy Context . . . 4
2.3 Financial Transmission Channels of Input Price Shocks . . . 5

3 Literature Review **7**
3.1 Firm-Level Evidence from the European Energy Crisis . . . 7
3.2 Policy Interventions and Firm Financial Outcomes . . . 8
3.3 Financial Structure as a Determinant of Crisis Performance . . . 9
3.4 ESG as a Determinant of Crisis Performance . . . 10

4 Hypothesis Development **11**

5 Data Collection **12**
5.1 Market-Data Sample for Event Study . . . 12
5.2 Accounting Panel for Difference-in-Differences . . . 13
5.3 Shared Design and Variables . . . 14
5.3.1 Classification of Energy-Intensive Firms . . . 14
5.3.2 Treatment Timing . . . 14
5.3.3 Dependent Variables . . . 14
5.3.4 Moderators . . . 15
5.4 Descriptive Statistics . . . 15
5.4.1 Event Study Market Data . . . 15
5.4.2 Difference-in-Differences Panel Data . . . 16

6 Methodology **17**
6.1 Methodology I: Event Study . . . 18
6.1.1 Event Selection and Timeline Alignment . . . 18
6.1.2 Abnormal-Return Computation . . . 18
6.1.3 Cross-sectional Moderation Design . . . 19
6.2 Methodology II: Difference-in-Differences . . . 20
6.2.1 Identification & Regression Models . . . 20

6.2.2 Pre-Trends Diagnostics . . . 21
6.2.3 Standard Errors & Inference . . . 24
6.3 Research Limitations . . . 25

7 Results **26**
7.1 Event Study . . . 26
7.1.1 Hypothesis 1 and 2 . . . 26
7.1.2 Hypothesis 3a and 3b . . . 29
7.2 Difference-in-Differences . . . 32
7.2.1 Hypothesis 1 and 2 . . . 32
7.2.2 Hypothesis 3a and 3b . . . 34

8 Discussion **36**

9 Conclusion **38**

References **40**

A Appendix **45**
A.1 Event Study Details . . . 45
A.1.1 H1 and H2 Robustness . . . 45
A.1.2 H3a and H3b Robustness . . . 48
A.2 Difference-in-Differences Details . . . 51
A.2.1 Pre-trends Statistical Analysis . . . 51
A.2.2 H1 and H2 Robustness . . . 52
A.2.3 H3a and H3b Robustness . . . 54
A.3 AI . . . 60

List of Abbreviations

AAR = Average Abnormal Returns
AR = Abnormal Returns
BMP = Boehmer-Musumeci-Poulsen
CAAR = Cumulative Average Abnormal Returns
CAR = Cumulative Abnormal Returns
CDAX = Broad German stock market index (Composite DAX)
CI = Confidence Interval
DiD = Difference-in-Differences
D/A = Debt / Assets
EBIT = Earnings Before Interest and Taxes
ESG = Environmental, Social and Governance
EU = European Union
GPB = Gaspreisbremse, Gas Price Brake
HighEI = High energy-intensive
ICR = Interest Coverage Ratio
LowEI = Low energy-intensive
NACE = Statistical classification of economic activities in the European Union
ROA = Return on Assets
SE = Standard Error

1 Introduction

Russia's invasion of Ukraine in 2022 triggered an unprecedented energy-price shock in Europe as gas imports from Russia, previously 40% of the EU supply and over 50% of Germany's, collapsed (Ricci et al. 2024; Hornbach and Rammer 2024). The significant increase in gas prices hit Germany's industrial base especially hard, particularly in high energy-intensive industries such as chemicals, metals, and cement, where energy regularly constitutes more than 20% of production costs (Amaglobeli et al. 2024).

To prevent bankruptcies and production disruption caused by the cost pressures firms faced, EU governments intervened fiscally (Amaglobeli et al. 2024). The most extensive fiscal package was Germany's Gas Price Brake ("Gaspreisbremse", GPB) introduced in early 2023, which subsidised 70% of firms' 2021 (pre-crisis) gas consumption at a capped price, while leaving 30% exposed to market rates to maintain incentives for energy savings (Sgaravatti et al. 2023). Conceptually, by lowering expected input costs and stabilizing cash flows, the GPB should have directly affected firms' short-term financial outcomes, namely profitability, solvency, and market valuation, which constitute the focus of this thesis.

Existing research finds that European firms broadly maintained profitability and output throughout the crisis, aided by fiscal support (Amaglobeli et al. 2024; Archanskaia et al. 2024). However, empirical micro-level validation of how such policies affected firms' short-run financial outcomes remains scarce. While policy may have improved aggregate outcomes, it is important to understand firm-level heterogeneity, to identify which firms benefited most and whether the intended recipients transformed aid into positive financial outcomes. As such, Germany's GPB, the largest structural and most transparent intervention across Europe (Sgaravatti et al. 2023), provides a compelling case for studying how a fiscal policy transmitted to firm-level financial outcomes. Explicitly, this thesis asks: *How did Germany's Gas Price Brake affect the short-term financial position and market performance of energy-intensive firms, and how did this effect vary with firms' leverage and ESG performance?* The moderating characteristics are motivated by research linking balance-sheet strength (Eiling, Laeven, and Xu 2024) and sustainability capabilities (Ricci et al. 2024) to firms' ability to absorb external shocks.

The first research objective of this thesis therefore is to estimate the impact of the GPB on firms' short-term financial outcomes. To capture forward-looking market perceptions, we use an event study of cumulative abnormal returns (CARs) around key crisis and policy dates, comparing high energy-intensive (HighEI) and low energy-intensive (LowEI) firms. The results show that HighEI firms suffered larger valuation losses during crisis announcements but also saw greater positive abnormal returns on policy dates, with the gap between the two groups being statistically significant on two legislative dates. We complement this with a Difference-in-Differences (DiD) method with

a differential exposure design that exploits cross-industry variation in pre-crisis energy intensity, comparing HighEI and LowEI firms before and after the introduction of the GPB. The model identifies differential changes in profitability (return on assets, ROA) and solvency (interest-coverage ratio, ICR) between 2019-2024. The results indicate that HighEI firms experienced a small relative deterioration in profitability in 2022 compared with LowEI firms, while no statistically significant differential effect is detected for ICR. Following the implementation of the GPB, the DiD estimates remain negative for both ROA and ICR, with only ROA reaching statistical significance. These patterns indicate that, within the annual reporting window, we do not find evidence that the GPB improved realised financial outcomes for highly exposed firms relative to their less-exposed peers.

The second research objective is to assess whether leverage and ESG performance moderated the effects of the GPB. The findings show limited moderating effects. Leverage does not moderate announcement-day returns in the event study, but in the DiD specification high-leverage firms exhibit higher ROA in 2022-2023 relative to low-leverage firms, with a positive and significant ICR effect in 2022. ESG shows no consistent moderating role across either empirical approach; the event study only provides directional, non-significant evidence of superior returns among HighEI firms with high ESG scores.

This thesis contributes to the literature by quantifying the realised firm-level financial transmission of the GPB, a dimension not directly addressed in prior research. Archanskaia et al. (2024) analyze sectoral profitability and competitiveness using aggregated firm-level data but do not isolate the financial effects of the GPB itself, focusing instead on broader energy crisis outcomes. Amaglobeli et al. (2024) assess firms' resilience and the impact of fiscal incentives using survey data and economy-wide indicators, but their analysis does not examine the direct transfer of the GPB to firm financials, such as profitability or solvency, and instead emphasizes aggregate employment and output effects. Hornbach and Rammer (2024) study short-term operational reactions of German firms to energy price shocks, relying on sectoral and survey data, but do not quantify the direct financial transmission of the GPB to individual firms' financial statements or valuations. In contrast, this thesis isolates the effect of the GPB by employing firm-level accounting and market data, directly measuring its impact on profitability, solvency, and market valuation, thereby providing new evidence on the realised financial transmission of the policy to German firms.

Additionally, this thesis investigates how leverage and ESG performance condition firms' responses to policy support. Prior research shows that firms with stronger balance sheets and higher ESG scores absorb external shocks such as financial crises or energy price increases better (Lins, Servaes, and Tamayo 2017; Albuquerque et al. 2020; Eiling, Laeven, and Xu 2024; Ricci et al. 2024). However, these studies focus on how firm ESG characteristics moderate the direct impact of shocks, not how they shape the transmission of fiscal policy into firm-level financial outcomes. While research has examined how leverage moderates responses to monetary policy for example (Akarsu

et al. 2025; Ferrando, Lamboglia, and Offner 2025), no study to our knowledge investigates its role in the financial transmission of broad, price-based fiscal stabilization measures. By jointly analyzing policy exposure, balance-sheet strength, and ESG performance, this thesis offers new evidence on which firms benefit most from such interventions.

2 Background & Theoretical Framework

2.1 The European Energy Crisis

The 2022-23 Energy crisis, driven by reduced gas supply and increased prices, was caused by the progressive curtailment and later deliberate weaponisation of Russian gas exports to European economies (Archanskaia et al. 2024). First price increases were already seen in September 2021 due to Russia curtailing supply (Brookfield 2021). The invasion of Ukraine on 24.02.2022, with ensuing sanctions and the shutdown of Nord Stream 1 on 31.08.2022 (BBC 2022), exacerbated the crisis and drove significant increases in wholesale energy prices (European Commission 2025b).

Figure 1 shows the evolution of monthly average day-ahead natural gas prices across major European hubs. Between 2015 and 2020, TTF (the European Benchmark hub) prices fluctuated between €5-30/MWh, before rising sharply during 2021, reaching daily highs of €113/MWh by December 2021 and later peaking at a record daily high of €320/MWh on 26.08.2022 (European Commission 2025b).

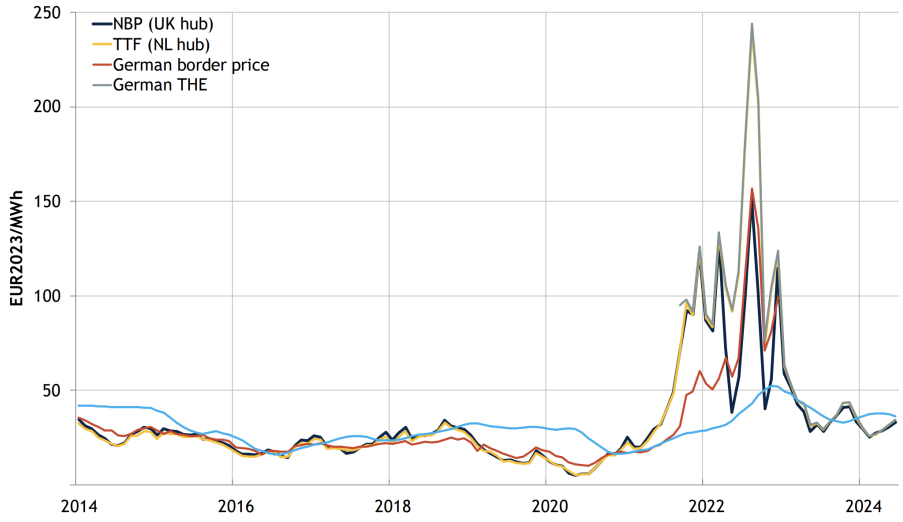


Figure 1: Monthly Average Day-Ahead Wholesale Natural Gas Prices at Key European Hubs

Note: The figure shows monthly average day-ahead natural gas prices at European hubs from 2014–2024. Prices are expressed in EUR2023/MWh, deflated using 2023 consumer price indices. Source: Trinomics (2024), based on S&P Platts and Enerdata EnerMonthly in 2022.

To shield households and firms from this significant input price shock, governments responded with fiscal measures such as tax reductions, transfer payments, price caps and direct subsidies totalling more than €650 Billion between September 2021 and June 2023, equivalent to 4.3% of EU GDP (Sgaravatti et al. 2023).

As Amaglobeli et al. (2024) highlight, this energy price shock quickly translated into broader inflation, which in turn increased input costs and cash-flow uncertainty for firms. While the aforementioned fiscal interventions alleviated immediate cost pressures, they also sparked debate over allocative efficiency, fiscal sustainability and risk of distorting long-term decarbonisation incentives (Sachverständigenrat 2022). This thesis contributes to the discussion by examining the allocative implications of the Gas Price Brake through micro-evidence on which firms benefitted most in terms of financial and market performance.

2.2 The German Economic and Policy Context

Among EU Member States, Germany was the most exposed to the crisis, with over 50% of its natural gas imports sourced from Russia before the war (Hornbach and Rammer 2024) and had the largest fiscal response with €158 Billion (Sgaravatti et al. 2023). Beyond its dependence on Russian gas imports, the country entered the energy crisis with an economic structure highly exposed to energy shocks. Industry represents 18% of GDP and 16% of employment - well above other advanced economies (Deutsche Bundesbank 2023). Energy costs account for 5% of total production costs for the median manufacturing firm but exceed 30% for the most energy-intensive ones, such as producers of chemicals, basic metals, paper and glass (Deutsche Bundesbank 2023).

The GPB was structured to relieve these exposed firms by capping 70% of 2021 gas consumption levels at €0.07 per kWh (Corbeau and Merz 2023), with the remaining volumes being settled at market prices to preserve incentives for conservation. Implementation began in March 2023 with retroactive settlement for January and February. Energy-intensity thus being both a determinant of the magnitude of exposure to the crisis and relief received under the GPB motivates its use as the treatment variable in this thesis.

In contrast to earlier, comparatively narrow relief measures, the GPB constitutes a structural intervention: a rule-based, universal measure that altered the price-formation mechanism itself rather than providing ad hoc transfers. This systemic design makes the GPB uniquely suitable for empirical analysis as its nationwide and rule-based implementation ensures a uniform policy environment, while the mechanical link between subsidy magnitude and firms' pre-crisis energy intensity introduces variation in treatment exposure. Table 1 below outlines the key crisis and policy dates.

Table 1: List of Crisis and Policy (Gas Price Brake) Events

Event date	Title	Type	Source
2022-02-24	Russia invasion of Ukraine	Crisis	UK Parliament
2022-06-14	Gazprom supply cut (to 40%)	Crisis	Reuters
2022-08-31	Nord Stream 1 gas supply suspended	Crisis	BBC
2022-09-29	GPB announced	Policy	Bruegel
2022-11-25	Cabinet approves GPB	Policy	BMWK
2022-12-15	Bundestag passes GPB law	Policy	Deutscher Bundestag
2022-12-19	Bundesrat approval and formal adoption of GPB	Policy	Bruegel
2023-03-01	GPB operational	Policy	European Commission

Note: The table lists the events studied in the thesis, the date they occurred, classification as crisis or policy event and the corresponding source. BMWK is short for Bundesministerium für Wirtschaft und Klimaschutz

2.3 Financial Transmission Channels of Input Price Shocks

Analysing how the GPB affected firm performance requires understanding the mechanisms through which energy-price shocks and consequently price caps transmit to corporate fundamentals and how investors adjust valuations in response. Building on the literature, two direct transmission channels can be distinguished, namely the operating-profit channel (Fontagné, Martin, and Orefice 2023; Alpino, Citino, and Frigo 2025) and the financing-friction channel (Eiling, Laeven, and Xu 2024). In addition, a valuation mechanism (Ricci et al. 2024) captures how investors update expectations about earnings and risk in response to these channels. Together, these elements form the conceptual link between the energy crisis, policy intervention, and later, how firm heterogeneity in leverage and ESG performance may moderate the policy effect on firm outcomes. This process is visually presented in Figure 2.

In the operating profit channel, a sudden rise in gas prices increases firms' cost of goods sold and compresses operating profit margins. Industrial-organization models of pricing (Hall 1988; De Loecker and Warzynski 2012) highlight that firms' ability to pass input-cost shocks to output prices depends on their market power and demand elasticity. Empirically, recent evidence from the energy crisis confirms that such pass-through was limited in energy-intensive intermediate-goods sectors due to inelastic gas demand and competitive pressures (Fontagné, Martin, and Orefice 2023), therefore profitability deteriorates. The GPB directly affects this channel by capping input prices, reducing variable cost volatility and stabilising cash flow. In principle, it should mitigate short-run financial pressure for energy-intensive firms. Whether it translated into differential improvements in realised performance, however, is an empirical question.

A second transmission mechanism operates through firms' financing conditions. When input costs increase and compress operating earnings, firms' interest-coverage ratios weaken, which tightens borrowing capacity and refinancing conditions, as lower earnings and collateral values

constrain the amount firms can pledge or refinance (Caglio, Darst, and Kalemli-Özcan 2021). Similarly, financing constraints amplify the real impact of shocks by limiting external funding and forcing firms to cut back investment and liquidity buffers (Campello, Graham, and Harvey 2010). By stabilising input costs and preserving EBIT, the GPB could in principle support short-run debt-servicing capacity.

A third mechanism operates indirectly through equity valuations. Rather than constituting a separate transmission channel, capital-market reactions reflect investors' updates to expected earnings and risk implied by the operating-profit and financing channels (Pástor and Veronesi 2012). If energy-intensive companies are expected to have lowered earnings and increased solvency risk, their stock prices should react negatively during the crisis. Conversely, the announcement and implementation of the GPB should trigger relatively stronger positive reactions among these firms, as the policy directly mitigates their perceived risk and earnings exposure.

These elements provide the conceptual backbone for the setup of the empirical strategy and ability to explain the short-run firm financial outcomes from the GPB. Energy intensity is the key determinant of both exposure to the shock and exposure to the intervention: high energy-intensive firms face disproportionately higher input-cost pass-through (increasing cost of goods sold, compressing margins and raising solvency risk), but also receive disproportionately larger relief because 70% of their baseline gas consumption is price-capped. Moreover, the channels and valuation mechanism motivate ROA, ICR and CAR as dependent variables. The DiD specification captures realised effects on profitability and solvency (the first two channels) between 2019 and 2024, while the event study framework measures market expectations (the third channel) around crisis and policy dates. Together, these designs quantify both fundamental and perceived short-term financial outcomes of German firms after the onset of the energy crisis and implementation of the GPB. Leverage and ESG performance are included as moderating firm characteristics, consistent with literature linking balance-sheet strength and sustainability capabilities to firms' ability to absorb external shocks.

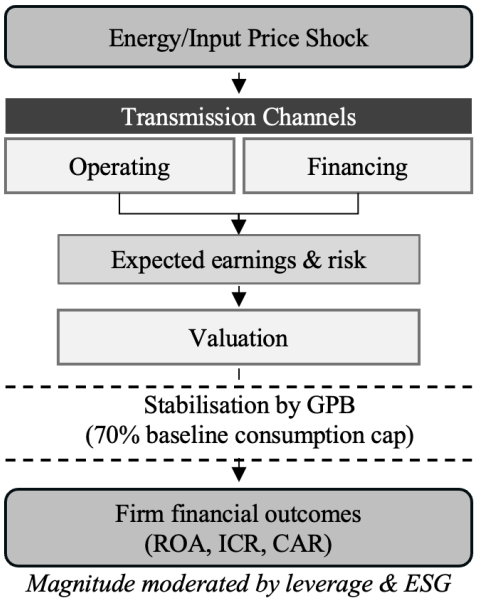


Figure 2: Conceptual Link Between Input-Price Shocks and Firm Financial Outcomes

Note: The figure summarises how the energy shock and the Gas Price Brake transmit to firm financial outcomes through the three transmission channels and how policy support may cushion these effects. Source: Authors' illustration.

3 Literature Review

3.1 Firm-Level Evidence from the European Energy Crisis

Firm-level analyses of the European energy crisis have primarily examined short-run operational and behavioural responses to rising energy costs, such as adjustments in production, pricing and investment, while evidence on firms' financial outcomes remains scarce (Fontagné, Martin, and Orefice 2023; Hornbach and Rammer 2024; Alpino, Citino, and Frigo 2025). In contrast, macroeconomic studies focus on aggregate output and inflation effects (Hutter and Weber 2023), offering little insight into firm-level heterogeneity.

Manufacturing energy cost shares varied across countries, ranging from about 3% of total expenses in France to over 8% in Germany, resulting in asymmetric impacts of the shock (Archanskaia et al. 2024). At the aggregate level, EU industrial output fell by 2-3% by late 2022, a figure that conceals cross-country and sectoral disparities in firm outcomes.

Empirical evidence highlights several short-term coping mechanisms on the firm-level, such as curtailing production or cost pass-through, reflecting attempts to absorb the shock within existing production and cost structures. In the Netherlands, for example, manufacturing gas use fell by nearly 40% relative to 2019 with output prices rising faster than input prices (Soederhuizen et al. 2023), indicating partial cost pass-through. Evidence from France and Italy, however, shows this

was not possible in these countries, as energy demand was largely inelastic and cost pass-through incomplete, leaving energy-intensive producers exposed to margin compression (Fontagné, Martin, and Orefice 2023; Alpino, Citino, and Frigo 2025). The coexistence of a sharp decline of gas use at the national level and a 2-3% fall in industrial output across Europe (Archanskaia et al. 2024) likely reflects cross-country differences in exposure and the use of price, efficiency and output adjustments as buffering margins (Hornbach and Rammer 2024).

The existing literature provides descriptive evidence of how firms adapted operationally to rising energy costs, but does not analyse the financial outcomes of these behaviours. Although some work, such as Archanskaia et al. (2024), includes profitability indicators at the aggregate level, firm-level analyses of solvency or investor-perceived performance are absent. This thesis complements these studies by moving beyond operational and pricing adjustments and examining how the GPB functioned as an additional stabilising force affecting firms' realised and investor-perceived performance.

3.2 Policy Interventions and Firm Financial Outcomes

Fiscal policy played a central role across Europe in cushioning firms and households from the 2022-23 energy shock. Faced with the collapse in gas supply and record wholesale prices, governments mobilised over €600 billion in support between late 2021 and early 2023 (Archanskaia et al. 2024). As many high energy-intensive firms faced limited short-term energy substitutability and high leverage, their financial fragility necessitated large-scale government intervention (Ari et al. 2023).

Evidence suggests that such support stabilised overall performance. Amaglobeli et al. (2024) show that fiscal measures helped preserve output and employment, especially in energy-intensive manufacturing. They also argue that these measures preserved solvency, citing the absence of a surge in bankruptcies or payment delays during 2022-23. Their analysis, however, relies on surveys and economy-wide insolvency indicators and evaluates support measures collectively rather than isolating specific interventions. These insights highlight the relevance of support measures in cushioning firms during extreme input-cost shocks, while leaving open how specific policies translated into firm-level financial outcomes.

This question is particularly relevant for broad price-based interventions, which accounted for 65% of support measures in Europe, including Germany's GPB (Ari et al. 2023). While aggregate assessments suggest such measures helped cushion profitability and liquidity, firm-level evidence is mixed. For example, Soederhuizen et al. (2023) show that even a tripling of energy prices in the Netherlands would have raised the share of loss-making firms by two to four percentage points, implying limited marginal benefits from price caps relative to their fiscal cost. Whether this conclusion generalises beyond the Dutch setting and to which firms, remains unclear.

The lack of firm-level evidence on broad, rule-based price caps motivates an examination of the

German GPB, specifically whether it measurably affected firms' profitability, solvency and market valuation, and which types of firms experienced greater stabilisation.

3.3 Financial Structure as a Determinant of Crisis Performance

Firm-level heterogeneity in financial structure critically shapes how shocks translate into differences in performance. While Section 2.3 outlined the operating and financing-friction channels and the valuation mechanism through which energy-price shocks affect firms, this section focuses on how leverage conditions firms' sensitivity to those channels and potentially their responsiveness to fiscal stabilisation policies such as the GPB.

In the crisis literature, leverage and liquidity are the main financial attributes influencing how shocks translate into liquidity stress or solvency risk (Eiling, Laeven, and Xu 2024; Fetzer, Palmou, and Schneebacher 2024). Empirically, Eiling, Laeven, and Xu (2024) find that a one-percentage-point increase in the debt-to-asset ratio reduces expected resilience, measured as the rise in conditional downside risk following an extreme loss relative to typical underperformance, by about 0.4 percentage points, indicating that highly leveraged firms are less capable of absorbing adverse earnings shocks. Similarly, Tascón, Castro, and Valdunciel (2024) measure financial resilience as firms' distance from bankruptcy using the Altman Z-score and find that indebted firms face elevated bankruptcy risk, whereas firms with moderate debt and high liquidity are more resilient. Leverage, in this sense, turns from a growth enabler in normal times into a crisis amplifier when credit conditions tighten.

Following the literature, leverage and liquidity are key financial characteristics that moderate the extent to which firms are affected by shocks and condition their ability to benefit from subsequent policy support. Leverage weakens firms' ability to maintain short-run financial performance, while liquidity buffers short-term distress. Within the energy crisis context, Fetzer, Palmou, and Schneebacher (2024) find that many energy-intensive SMEs accumulated precautionary cash reserves and drew new credit lines to stabilise operations, while less-constrained firms relied less on borrowing. Such evidence highlights how heterogeneity in financial structures likely shaped firms' crisis outcomes and motivates this thesis' focus on leverage as a key moderating factor determining firms' potential responsiveness to the GPB. While liquidity also plays a buffering role, it lies outside the scope of the empirical analysis due to data limitations.

What remains underexplored is how fiscal policy interacts with these financial channels. Broad support measures such as Germany's GPB explicitly aimed to stabilise margins and liquidity (Amaglobeli et al. 2024; Hornbach and Rammer 2024). By cushioning revenues and reducing cash-flow volatility, such intervention may weaken the usual penalty of high leverage, compressing differences in solvency and market reactions between high- and low-leveraged firms. Identifying whether financial structure moderates the stabilising effectiveness of broad price caps therefore

offers empirical insight into which firms benefit most from fiscal stabilisation.

3.4 ESG as a Determinant of Crisis Performance

A growing body of literature has found environmental, social and governance (ESG) capabilities to represent intangible capital, such as trust and operational foresight, that reduces firms' exposure to crises. The literature remains divided, however, over the persistence, mechanisms and conditionality of this superior crisis performance.

Lins, Servaes, and Tamayo (2017) first establish ESG as relational capital during the 2008-09 financial crisis, showing that firms with high pre-crisis corporate social responsibility (CSR) scores earned 4-7 percentage points higher during the crisis. They interpret this as being driven by greater investor trust and stakeholder loyalty, though these mechanisms are inferred rather than directly measured. Albuquerque et al. (2020) reinterpret this mechanism as financial capital: high-scoring ESG firms suffered smaller abnormal losses and exhibited lower systematic risk during COVID-19, attributing this protection to superior risk management and cash-flow stability rather than sentiment alone. Yahya (2023) extends this logic to accounting outcomes, finding that environmental and social performance preserved revenue and profitability among Nordic firms during lockdowns.

The Russia-Ukraine conflict and subsequent energy crisis shifted the ESG domain from trust and governance toward transition and input-cost risk. Ricci et al. (2024) find that among 2,000 European listed firms, those with stronger environmental disclosure experienced smaller cumulative abnormal return declines around gas-rationing announcements, implying that credible environmental commitments hedge transition risk, as these firms were perceived as better equipped to manage energy-price volatility. Zhou (2024) corroborates this for US firms, although the return premium faded within six months, implying that ESG stabilises expectations under uncertainty but does not translate into persistent outperformance once fundamentals dominate valuations.

Taken collectively, these findings suggest that ESG capabilities provide firms with a degree of downside protection during crises. However, the underlying mechanisms appear context specific: protection stems from social trust during financial crises Lins, Servaes, and Tamayo (2017) , but from transition-risk management during energy shocks Ricci et al. (2024) and Zhou (2024). The protective effect also seems more insurance-like rather than growth-generating, as it dampens immediate drawdowns but rarely produces lasting outperformance once normal conditions return.

Despite this breadth, two gaps remain. First, existing studies do not examine how government support interacts with ESG capabilities, even though fiscal stabilisation could alter the relevance of ESG in crisis performance. Broad support schemes may either neutralise cash-flow risk and thereby dilute ESG's differential benefits, or be amplified by high-scoring ESG firms if such capabilities enhance coordination or discipline in utilising public support. Second, with few exceptions Yahya (2023), the literature predominantly evaluates ESG performance through market-based outcomes,

leaving limited evidence on whether ESG also mitigates balance-sheet deterioration during crises.

Understanding whether ESG continues to differentiate firms under fiscal intervention therefore offers insight into whether ESG capabilities complement policy stabilisation, become redundant under universal support, or help firms capitalise on such support more effectively.

4 Hypothesis Development

H1. Exposure Penalty

Following the operating and financing-friction channel and valuation mechanism outlined in Section 2.3, firms with higher energy-intensity are more exposed to rising input costs than low-energy-intensive peers, as limited substitutability and pass-through compress margins and strain liquidity. Fontagné, Martin, and Orefice (2023) confirm this mechanism and firm-level evidence shows that energy-intensive producers experienced sharper profitability declines (Archanskaia et al. 2024; Hornbach and Rammer 2024; Alpino, Citino, and Frigo 2025; Fetzer, Palmou, and Schneebacher 2024). Therefore, H1 serves as a confirmatory baseline establishing the negative link between energy exposure and financial performance. Confirming this relationship is standard practice, as it provides the empirical foundation for analysing subsequent moderating effects.

H1 (Exposure penalty): In 2022, high energy-intensive firms exhibited larger declines in profitability, solvency and market valuation (ROA, ICR, CARs) than low energy-intensive firms.

H2. Policy Cushioning

The 2023 Gas Price Brake introduced price caps that partially decoupled input costs from wholesale markets. Through the operating-profit and financing channels described in Section 2.3, this should stabilise margins and solvency ratios. The European Commission's firm-level simulations indicate that energy-intensive firms in high-support countries preserved profit margins roughly three percentage points above peers in low-support countries (Archanskaia et al. 2024). Hence, once the GPB took effect, the performance gap in ROA, ICR, CARs between high and low energy-intensive firms should narrow.

H2 (Policy cushioning): In 2023, the relative performance gap in financial outcomes between high and low energy-intensive firms narrowed, consistent with the cushioning effect of the GPB.

H3. Moderators of Policy Effects: Financial Structure and ESG Performance

The GPB's impact should propagate through the same financial channels as the energy shock but in reverse: where the energy shock eroded profitability and solvency, the policy should restore

them by stabilising costs and cash flows. The strength of this transmission, however, likely depends on firm-specific characteristics that determine how policy support translates into improved financial outcomes. Two dimensions that come up as particularly relevant from the literature are leverage and ESG performance.

High leverage magnifies sensitivity to the financing-friction channel. When cost shocks compress cash flows, leveraged firms face greater liquidity stress and refinancing risk. Thus, fiscal cushioning should yield relatively larger gains for them, narrowing the performance gap between them and their low-leverage peers.

ESG performance, by contrast, relates primarily to the operating-profit channel and valuation mechanism. Firms with strong environmental and governance profiles tend to exhibit greater energy efficiency and investor trust, which can reduce exposure to input price volatility and sustain investor confidence. However, if the GPB neutralises most cost and risk heterogeneity, the advantage of ESG may fade as universal fiscal support substitutes for its protective effects.

H3a (Leverage moderation): Among high energy-intensive firms, the GPB's fiscal cushioning disproportionately benefits highly leveraged firms, narrowing their performance gap in ROA, ICR and CARs.

H3b (ESG moderation): Among high energy intensive-firms, the GPB attenuates the performance differential between high and low ESG-scoring firms across ROA, ICR and CARs, as universal fiscal support substitutes for ESG-related efficiency and trust effects.

5 Data Collection

We gather firm-level and market data to examine the impact of the energy crisis and the following policy responses on the short-term financial outcomes of German firms. The datasets combine daily returns (for an event study), annual accounting variables (for a Difference-in-Differences) and ESG metrics, matched by firm identifiers (ISIN code).

5.1 Market-Data Sample for Event Study

Market data for German listed firms were downloaded from LSEG Workspace (2025). The filter criteria were the following: firms had to be listed, be headquartered in Germany, have an IPO date before January 2019 and be active during the whole period. Furthermore, financial and real estate firms were excluded following standard practice given their non-comparable leverage/accounting metrics and distinct interest-rate/valuation channels (Fama and French 1992). These were identified using NACE sector classifications (K and L) (European Commission, n.d.). The final event study sample comprises 433 listed companies. Firm-level total-return data were retrieved using daily

closing prices adjusted for dividends, stock splits and other corporate actions. These were then computed to daily returns using the previous day lags:

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

All returns are denominated in euros and aligned to the official Xetra trading calendar. We de-string and coerce numeric fields, remove NULLs/NAs and prevent divide-by-zero in ratios.

The market benchmark is the CDAX, which represents all German stocks traded on the Frankfurt exchange and is thus appropriate for capturing market-wide shocks in a broad cross-section. To ensure data quality, firms with fewer than 250 trading-day observations prior to the earliest event date (24.02.2022) were excluded.

Accounting variables (total assets, debt, equity, market capitalisation) were obtained from LSEG Workspace, allowing computation of leverage (debt / total assets) and market-to-book ratios (market capitalisation / common equity).

5.2 Accounting Panel for Difference-in-Differences

To retrieve data on both listed and private firms in Germany, Orbis was utilised (Bureau van Dijk 2025). We include both listed and non-listed firms to ensure that the sample reflects the structure of the German economy. As Amaglobeli et al. (2024) note, energy-intensive firms in Germany are typically smaller than in economies such as the US, meaning that many of the most exposed firms are privately held. This is consistent with Germany's industrial landscape, where energy use and manufacturing output are concentrated in "Mittelstand" firms (SMEs). Limiting the sample to listed companies would therefore exclude much of the relevant exposure and bias results toward larger, capital-market-oriented firms.

When creating the DiD firm universe, firms had to be founded before 2019 and still be active to ensure full-period coverage. A total of 2.5 million firms were sourced. Then, all micro firms (revenue < EUR 2 million) and firms with NACE codes K and L were removed.

The resulting sample included ~ 70,000 firms and for each the following annual financial data was obtained: total assets, total debt, operating profit (EBIT), cash and cash equivalents and interest coverage ratio. Removing firms without full financial data dating from January 2019 to December 2024 meant 1,625 firms remained, of which 345 firms are listed. The listed were matched with ESG data from LSEG Workspace based on the firm's ISIN code.

5.3 Shared Design and Variables

5.3.1 Classification of Energy-Intensive Firms

Following Archanskaia et al. (2024), energy-intensive firms are identified based on NACE 2-digit industry codes manufacture of chemicals (C20), basic metals (C24), mineral products (C23), paper products (C17) and printing and reproduction of recorded media (C18) (European Commission, n.d.). In their analysis, which we will follow, industries whose average ratio of energy costs to gross value added exceeds the 75th percentile of the Eurostat "Quarterly Non-Financial Corporations Accounts" are designated as high energy-intensive (***HighEI***). All other industries form the low energy-intensive (***LowEI***) group.

5.3.2 Treatment Timing

In the event study, we include events from 2022-23, classifying each as either a crisis shock or a Gas Price Brake policy related announcement. In the DiD, outcomes are observed annually, so we treat 2022 as the crisis year and 2023 as the policy year, reflecting that the GPB affected 2023 financial statements. Policy announcements towards the end of 2022 may have triggered anticipation effects or partial implementation, which can attenuate annual contrasts. Accordingly, the event study captures intra-year market reactions around precise announcement dates, while the DiD estimates realised annual net effects.

5.3.3 Dependent Variables

To find the effect in the event study, Cumulative Abnormal Returns (CAR) is used as a dependent variable. In the DiD, Return on Assets (ROA) and Interest Coverage Ratio (ICR) are used.

- **CAR:** Defined as the sum of Abnormal Returns (AR) over the main event window. AR are market-model residuals estimated on a pre-event window. Equations, estimation steps and regression specifications are presented in the methodology section.
- **ROA:** Defined as EBIT divided by Total Assets. ROA as a measure of firm performance offers two key advantages. Firstly, it has strong predictive power for market performance, particularly in industries such as manufacturing where firms are heavily reliant on fixed assets. Secondly, ROA is less prone to short-term manipulation than measures such as Return on Investment, which can be manipulated in the short term to report higher returns.
- **ICR:** Defined as EBIT divided by Interest Expenses (Bureau van Dijk 2025). ICR indicates how many times a firm's operating profit can cover its interest costs, with higher values implying greater short-term debt-service capacity. It is also intuitive, comparable across firms and years and directly tied to default risk via the ability to service debt from operations.

5.3.4 Moderators

For both the event study and the DiD, dummy variables indicating leverage and ESG score are created. Both moderator dummies are time-invariant and based on pre-years (2019-2021) firm-median values compared to the sample median of firm-medians, following (Lins, Servaes, and Tamayo 2017) and (Eiling, Laeven, and Xu 2024). We use pre-treatment financial structure to ensure that leverage and ESG grouping is not influenced by post-policy outcomes.

A dummy variable called ***HighLeverage*** is created and takes the value of 1 if a firm's median Debt/Assets ≥ cutoff. The leverage moderator tests whether capital structure conditions amplify or reduce policy effects.

Firm-level ESG information was sourced from LSEG Workspace, providing annual ESG scores for listed firms and their Environmental, Social and Governance pillars from 2019 to 2024. A dummy variable called ***HighESG*** was created and equals 1 if a firm's median ESG score ≥ cutoff. In addition, a variable called ***HighEnv*** is defined analogously using the Environmental Pillar Score. The ESG moderator is analysed in the event study and in a listed subsample in the DiD.

5.4 Descriptive Statistics

5.4.1 Event Study Market Data

We study eight events in total, of which three are crisis events and five are policy events (see Table 1 for a full event calendar in the Background section 2.2). Our market data sample consist of 433 listed German firms, of which 23 are considered HighEI (see Table 2). After requiring sufficient trading-day coverage, 424 firms and 22 HighEI firms remain. The small share of HighEI firms matter for inference, thus we complement the per-event mean tests with median-based tests and report effect sizes with confidence intervals to show robustness.

Abnormal returns are estimated with a market model using the CDAX as the benchmark index and we require valid trading-day coverage around each announcement.

Table 2: Event Study Sample Overview

Observations	Firms	HighEI firms	% HighLeverage	% HighESG	% HighEnv
3,464(3392)	433(424)	23(22)	50.1	50.0	50.0

Note: The table shows the number of observations, firms, HighEI firms, and share of firms with high leverage, high ESG scores and high environmental pillar scores, calculated using pre-treatment medians.

5.4.2 Difference-in-Differences Panel Data

Table 3: DiD Sample Descriptive Statistics (2019–2024)

Variable	N	Mean	Median	SD	Skew	ExKurt	Min	Max
Overall								
Operating Profit/Loss (EBIT, EURm)	9750	100.09	3.18	1034.94	15.62	406.37	-21856	35005
Total Assets (EURm)	9750	2161.86	69.95	18577.44	21.21	556.82	0	632905
Interest Coverage Ratio	9750	24.11	5.12	74.97	6.28	47.97	-99	981
Total Debt (EURm)	9750	574.02	8.29	6366.50	21.72	524.87	0	205296
Cash & Equivalents (EURm)	1936	638.95	39.37	2645.64	9.63	116.08	0	43449
Return on Assets	9750	0.06	0.05	0.20	32.54	2456.17	-5	14
Debt-to-Assets	9750	0.22	0.15	0.48	33.04	1715.30	0	29
Treated (High EI = 1)								
Operating Profit/Loss (EBIT, EURm)	576	89.51	3.62	479.71	1.48	27.61	-4581	3077
Total Assets (EURm)	576	2299.79	104.02	6665.23	3.86	12.08	3	38589
Interest Coverage Ratio	576	9.05	3.36	35.12	8.06	96.26	-90	516
Total Debt (EURm)	576	338.90	8.30	1093.41	4.81	24.43	0	9772
Cash & Equivalents (EURm)	144	748.58	135.30	1660.59	4.11	16.30	0	11547
Return on Assets	576	0.04	0.04	0.15	-4.03	35.23	-2	0
Debt-to-Assets	576	0.20	0.12	0.26	3.44	22.81	0	3
Control (High EI = 0)								
Operating Profit/Loss (EBIT, EURm)	9174	100.75	3.16	1060.15	15.43	391.93	-21856	35005
Total Assets (EURm)	9174	2153.20	68.20	19078.95	20.80	531.75	0	632905
Interest Coverage Ratio	9174	25.05	5.25	76.69	6.16	45.84	-99	981
Total Debt (EURm)	9174	588.78	8.29	6557.35	21.12	495.16	0	205296
Cash & Equivalents (EURm)	1792	630.14	35.91	2709.42	9.62	113.81	0	43449
Return on Assets	9174	0.06	0.05	0.20	33.45	2484.44	-5	14
Debt-to-Assets	9174	0.23	0.15	0.49	32.91	1674.13	0	29

Note: The table shows observations, mean, median, standard deviation, skewness, excess kurtosis, and minimum and maximum for each variable in the panel data, first for the full sample and then separately for HighEI and LowEI groups.

Our final dataset for the DiD consist of 1,625 firms, of which 96 are HighEI (see Table 3). Within the listed subsample, there are 345 firms, of which 17 are HighEI. The distributions of firm size and financial performance are extremely right skewed (e.g., total assets mean is EUR 2.16bn vs median approximately EUR 70m, also skewness and excess kurtosis are very large), indicating that a small number of very large firms drive averages. In addition, several variables display extreme outliers and wide ranges (e.g., EBIT and ICR) and ratios such as ROA and debt/assets (D/A) exhibit heavy tails due to small denominators and special situations. To mitigate these issues, we (i) emphasise medians and percentile ranges in descriptives, (ii) use log/asinh transformations and winsorisation (1st/99th) where appropriate and (iii) confirm robustness with alternative clustering.

To determine potential multicollinearity issues, the correlations between the main financial variables are analysed in Figure 3. We find high correlations between EBIT, total assets and total debt, confirming that these size-related variables largely capture the same underlying dimension of firm scale. In contrast, the ratios ROA, ICR and D/A are less correlated and thus provide complementary information on profitability, interest burden and leverage. This supports our choice

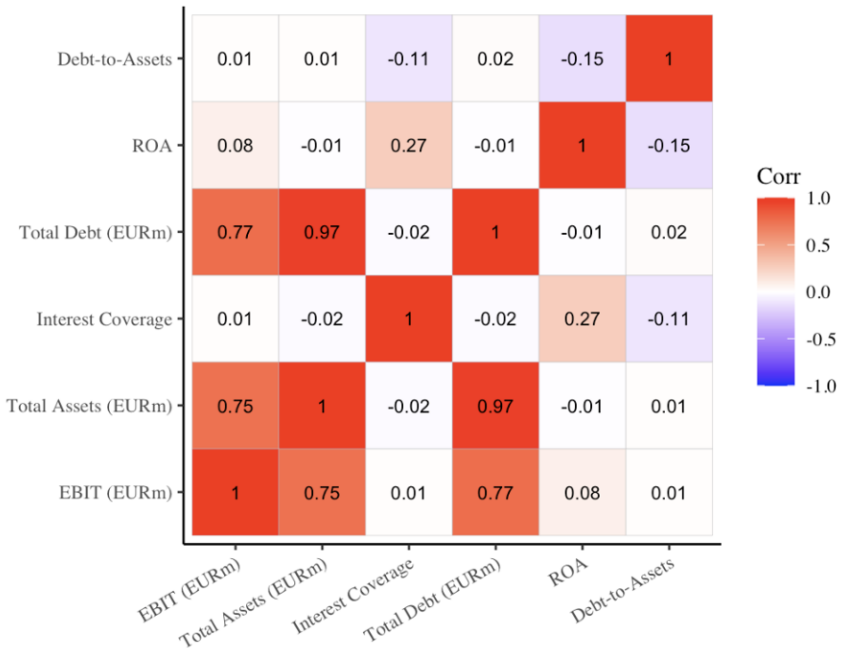


Figure 3: Correlation Heat Matrix

Note: The figure shows the correlations between the main firm-level variables in the DiD panel data, with darker shades indicating stronger positive or negative correlations.

of using these measures as dependent variables and controls in the DiD regressions, as they contain distinct information and mitigate collinearity problems in the estimation.

6 Methodology

Our empirical methodology combines two complementary approaches to analysing firm financial outcomes. First, an event study that estimates abnormal returns around crisis and Gas Price Brake policy dates, testing whether reactions differ by exposure to the crisis (HighEI vs. LowEI). Second, a Difference-in-Differences design that evaluates fundamental (accounting-based) outcomes during the period 2019-2024 and compares HighEI vs. LowEI before and after key GPB policy periods. Together, the event study reflects market expectations in real time, while the DiD traces realised profitability and solvency outcomes. Both frameworks also test how these effects are moderated by leverage and ESG performance.

6.1 Methodology I: Event Study

6.1.1 Event Selection and Timeline Alignment

The event set comprises major crisis and policy announcements between 2022-2023 that are directly related to the GPB. Events were compiled from verified sources and the full list of events and corresponding sources is reported in Table 1 in Section 2.2.

To ensure consistency with trading days, each calendar event date was aligned to the nearest Xetra trading day and all-time indices τ were mapped through a full market-calendar vector.

The estimation period for market parameters spans 250 trading days, ending 30 days before each event date to avoid contamination from anticipatory trading. For each firm i and event e, the event window for inferences is [-3, +3] trading days around the aligned event day ($\tau = 0$). For plots we also build paths over a wider horizon [-25, +25] that can be found in Appendix A.1.

6.1.2 Abnormal-Return Computation

Abnormal returns are estimated using the market model, following MacKinlay (1997) and Brown and Warner (1985). For each firm i, we estimate $R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t}$ by OLS over the estimation window (pre-event), where $R_{m,t}$ is the CDAX market return. Using the estimated parameters, expected (normal) returns in the event window are $\hat{R}_{i,t} = \hat{\alpha}_i + \hat{\beta}_i R_{m,t}$ and abnormal returns (AR) are $AR_{i,t} = R_{i,t} - \hat{R}_{i,t}$.

For each event window [-3, +3] cumulative abnormal returns (CAR) are obtained as:

$$\mathrm{CAR}_{i,e} = \sum_{\tau=-3}^{+3} AR_{i,\tau} \tag{2}$$

To plot dynamic event-level plots, we compute average abnormal returns (AAR) and cumulative AAR (CAAR) by event time τ and by group g (HighEI vs. LowEI):

$$\mathrm{AAR}_{\tau,g} = \frac{1}{N_{g,\tau}} \sum_{i \in g} AR_{i,\tau}, \quad \mathrm{CAAR}_{\tau,g} = \sum_{k \le \tau} \mathrm{AAR}_{k,g} \tag{3}$$

To limit tail influence and outliers, we winsorise at the 1st/99th percentiles: (i) in the estimation window (pre-event) on firm and market daily returns to stabilise $\hat{\beta}$ and (ii) cross-sectionally by event day in the event window before aggregating ARs into CARs.

We use three tests for statistical inference:

- **BMP** (Boehmer, Musumeci, and Poulsen 1991): $H_0 : \mu(CAR) = 0$. Cross-sectional t-test adjusted for increased variance under event-induced volatility.

- **Wilcoxon** (Wilcoxon 1945): $H_0 : \ median(CAR) = 0$. A non-parametric test, robust to non-normality and outliers.
- **Welch** (Welch 1947): $H_0 : \ \mu_{\text{HighEI}} = \mu_{\text{LowEI}}$. A t-test comparing the mean CARs of HighEI vs. LowEI firms, allowing for unequal variances across groups.

As robustness checks, equal-weighted, value-weighted (using static pre-crisis size weights) and median CAAR aggregations are also presented to ensure results are not driven by the sample being right-skewed.

6.1.3 Cross-sectional Moderation Design

To test whether leverage and ESG systematically moderate firms' announcement-day reactions, we follow MacKinlay (1997) and estimate a regression across event contexts (policy vs. crisis) with event fixed effects.

The dependent variable for all moderation tests is the firm-event $CAR_{i,e}$ over the main window [-3, +3] (see Equation 2). The rationale is to analyse heterogeneity within the HighEI industry sample, which is small because a limited number of firms operate in energy-intensive industries. We therefore also run moderation tests within a Manufacturing sample (firms with NACE 10-33, covers manufacturing industries) and the full sample (HighEI and LowEI).

Within the leverage and ESG moderator analysis, size (log market capitalisation) and market-to-book (market capitalisation to common equity) are included as control variables and are determined at pre-crisis levels.

Cross-sectional moderation regressions

$CAR_{i,e}$ is firm i's cumulative abnormal return around event e over [-3, +3]. $HighLeverage_i$ and $HighESG_i$ are firm-level dummies and $Policy_e$ is a dummy equalling 1 if it is a policy event and 0 if it is a crisis event. We estimate:

$$CAR_{i,e} = \beta \, (\mathrm{G}_i \times \mathrm{Policy}_e) + \theta' X_i + \gamma_e + \delta_{j(i)} + \varepsilon_{i,e}. \tag{4}$$

where G_i represent $HighLeverage_i$ and $HighESG_i$, X_i are pre-crisis controls (log of market cap and market-to-book), γ_e are event fixed effects (absorbing the average shock on each event date) and $\delta_{j(i)}$ are industry fixed effects. The coefficient of interest is β which captures how the G=1 and G=0 performance gap differs on policy events relative to crisis events:

$$\beta = \left[\overline{CAR}^{(G=1)} - \overline{CAR}^{(G=0)}\right]_{\text{Policy}} - \left[\overline{CAR}^{(G=1)} - \overline{CAR}^{(G=0)}\right]_{\text{Crisis}} \tag{5}$$

For interpretation, a positive β implies HighEI high-leverage/high-ESG firms perform relatively better on policy days than they do on crisis days, compared to their low-leverage/low-ESG peers.

Thus, it measures relative effects rather than absolute ones, showing how firm characteristics shape firm outcomes differently to favourable versus adverse shocks. The models use OLS with multi-way clustered standard errors (SE) at firm and event level to accommodate (i) repeated firms across events and (ii) within-event cross-firm correlation.

6.2 Methodology II: Difference-in-Differences

To complement the event study, we employ a DiD framework to identify the medium-term effect of the energy crisis and GPB on firm outcomes using accounting data for both listed and non-listed firms. Formally, in Germany, all firms were subject to the GPB, leaving no group that was not treated at all. However, firms with higher energy costs, thus HighEI firms, were more exposed and had a higher treatment intensity. Therefore, we follow Bertrand, Duflo, and Mullainathan (2004) and exploit *differential exposure* identification strategy to the 2022-23 German energy-price interventions.

6.2.1 Identification & Regression Models

Model 1 – Baseline DiD

$$Y_{i,t} = \alpha + \beta_1 \left(\text{HighEI}_i \times 2022_t\right) + \beta_2 \left(\text{HighEI}_i \times Post2023_t\right) + \gamma \log(\text{Assets}_{i,t}) + \mu_i + \tau_t + \varepsilon_{i,t} \quad (6)$$

Our first model that test H1 and H2 is a two-way fixed effects DiD model. $Y_{i,t}$ is the dependent variable, measured by either ROA (winsorised at 1st/99th percentiles) or the asinh-transformed ICR. To reduce the influence of outliers and stabilise variance, we transform ICR using the inverse hyperbolic sine, asinh(x), rather than a logarithm because ICR can be zero or negative (Bellemare and Wichman 2020).

The coefficient β_1 captures the 2022 (crisis-year) effect relative to pre-years (2019-21), while β_2 captures the post-2023 (GPB) effect. This structure with multiple pre-crisis years, a single crisis period and a post-crisis (policy) period is consistent with the identification strategy in Lins, Servaes, and Tamayo (2017). They similarly estimated a short crisis effect followed by a post-crisis using period interactions during the 2008–09 financial crisis.

Variables include the *HighEI* dummy, a *2022* indicator and a *Post2023* (2023 and 2024) indicator. These are not included in the regression as standalone variables because firm fixed effects (μ_i) absorb time-invariant firm characteristics (e.g., size, sector, business model) and time fixed effects (τ_t) absorb aggregate time shocks (e.g., demand conditions, monetary policy), thus identification relies on within-firm variation over time. The logarithmic value of total assets is included as a time-varying control variable (proxy for firm size).

We report two-way clustered SEs (firm and year). In addition, for clear hypothesis-driven interpretation, we run linear (Wald) tests of $\beta_1 = 0$, $\beta_2 = 0$ and $\beta_2 - \beta_1 = 0$ to assess changes in the HighEI-LowEI gap (2022 vs. Post2023). For robustness, we re-estimate the main regressions (i) with log1p(ICR) instead of asinh(ICR), (ii) within the manufacturing subsample, and (iii) with alternative clustering.

Model 2 – Leverage/ESG moderation

To test H3, we analyse whether, within energy-intensive firms' (HighEI), reactions to crisis and policy events vary with their leverage or ESG profiles. We estimate:

$$Y_{i,t} = \alpha + \delta_1 (\mathrm{G}_i \times 2022_t) + \delta_2 (\mathrm{G}_i \times \mathrm{Post2023}_t) + \gamma \log(\mathrm{Assets}_{i,t}) + \mu_i + \tau_t + \varepsilon_{i,t} \quad (7)$$

where G_i represent $HighLeverage_i$ and $HighESG_i$, μ_i are firm fixed effects and τ_t are year fixed effects. This model is reliant on the parallel trend's assumption of the two groups (high vs. low leverage and high vs. low ESG) which will be analysed. Regarding the ESG moderator, this is tested within a listed HighEI subsample as ESG data was only available for listed firms. As robustness, we re-estimate the regressions (i) with continuous moderators instead of dummies, (ii) within the manufacturing subsample and (iii) within the full sample (with triple interactions between *HighEI x Year x G*).

6.2.2 Pre-Trends Diagnostics

The causal interpretation of the estimates in a DiD regression relies on the assumption of parallel trends (Angrist and Pischke 2009). The parallel trends assumption requires that the two groups would have followed similar outcome trajectories in the absence of treatment. Only if this holds, any differences post-2022 can be attributed to the shock and policy intervention, rather than unrelated trend divergence.

To validate this assumption, we examine pre-treatment dynamics using (i) visual inspection of time series, (ii) placebo regressions and (iii) formal statistical tests based on Wald joint-significance tests. This multi-step approach follows best practices in DiD applications (Callaway and Sant'Anna 2021).

Visual analysis

The first dependent variable is ROA. The pre-2022 paths are not perfectly parallel; therefore, we present robustness checks using a placebo test. The HighEI group exhibits a steeper decline in 2020

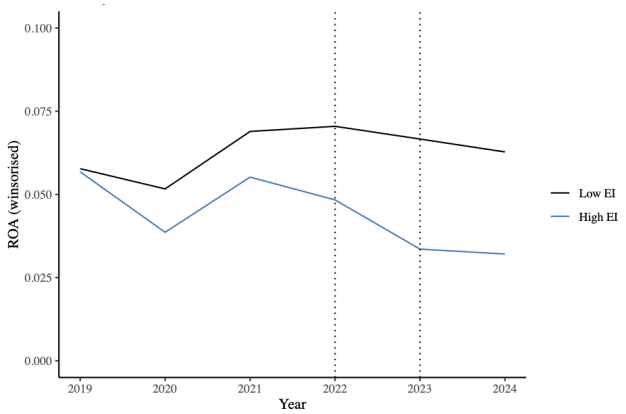
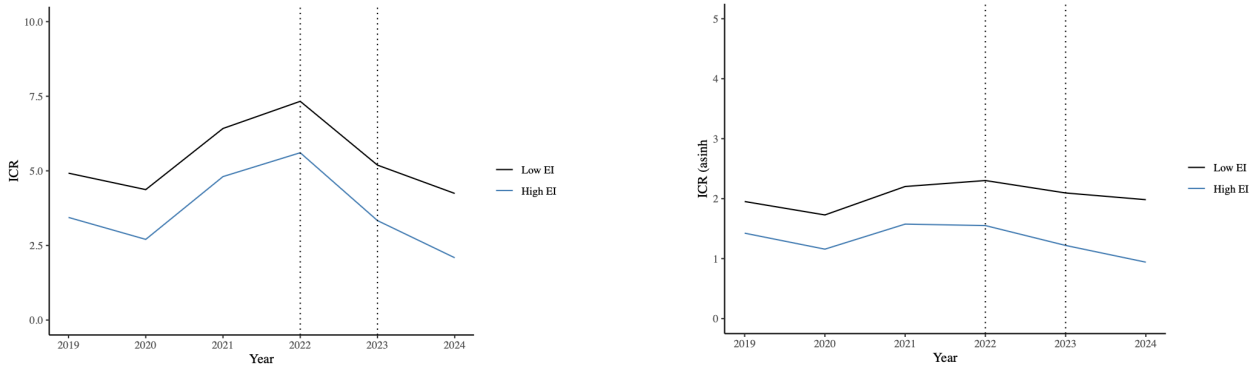


Figure 4: Parallel Trends: ROA (winsorised)

Note: The figure plots average ROA for HighEI and LowEI firms from 2019–2024, providing a visual analysis of whether profitability trends were similar across groups before the shock and GPB implementation.

than the control group, which may reflect that energy-intensive firms were more severely affected by the COVID-19 related shocks.



(a) Median ICR

(b) ICR (asinh)

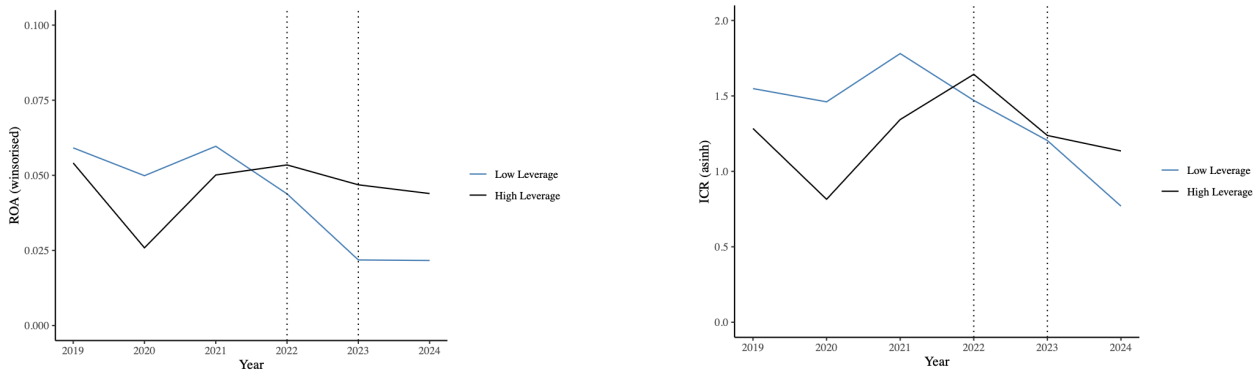
Figure 5: Parallel Trends: ICR

Note: These figures plot median and asinh transformed ICR for HighEI and LowEI firms from 2019–2024, providing a visual analysis of whether solvency trends were similar across groups before the shock and GPB implementation.

For interest coverage ratio, we plot both the median ICR and ICR using the inverse hyperbolic sine (asinh) transformation, which is used as the dependent variable in the regressions. The figure shows that both HighEI and LowEI firms followed similar pre-trends before 2022, which is consistent with the parallel trends assumption.

We also plot pre-trends within the HighEI sample to assess the parallel-trends requirement for the moderator DiD in Model 2.

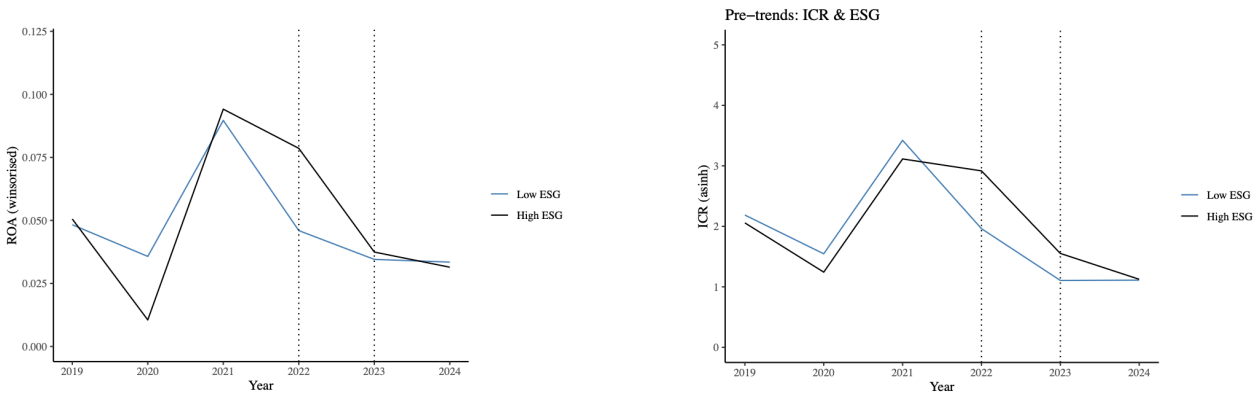
- For ***ROA x leverage***, high-leverage and low-leverage HighEI firms show roughly parallel



(a) ROA and Leverage (b) ICR and Leverage

Figure 6: Parallel Trends: Leverage DiD

Note: These figures plot average ROA and ICR for the high and low leverage HighEI groups to facilitate the visual analysis of the pre-trends.



(a) ROA and ESG (b) ICR and ESG

Figure 7: Parallel Trends: ESG DiD

Note: These figures plot average ROA and ICR for the high and low ESG HighEI groups to facilitate the visual analysis of the pre-trends.

trends pre-2022. However, the high-leverage firms show a deeper dip in 2020, followed by a stronger rebound.

- For ***ICR x leverage***, the high-leverage and low-leverage groups evolve in roughly similar patterns, both experience a decline in 2020 (Covid-19 shock) and recovery in 2021, followed by a gradual downturn through 2022–23. Their trajectories diverge in 2024, as low-leverage firms exhibit a sharper decline in ICR while high-leverage firms remain comparatively stable.
- For ***ROA x ESG***, high-ESG and low-ESG HighEI firms follow similar trajectories. ROA dips in 2020 and rebounds in 2021 for both groups.
- For ***ICR x ESG***, the pre-trends are similar across groups, reinforcing the parallel trend assumption.

Statistical pre-trend analysis

We formally test the pre-treatment trends for our regressions using placebo regressions and a Wald joint test. First, we estimate a placebo test where 2021 is pretended to be the treatment year. The placebo DiD for ROA and ICR both yield statistically insignificant coefficients, suggesting no systematic divergence between HighEI and LowEI firms in 2021, supporting the plausibility of the parallel trends assumption.

Second, we test whether the pre-treatment coefficients are jointly different from zero by including interaction terms between the treatment and the 2020-2021-year dummies (via a Wald test). We fail to reject, meaning the HighEI and LowEI groups did not exhibit significantly different pre-trends before 2022. Figure 21 in Appendix A.2.1 visualises the individual coefficients for 2020 and 2021 with a 95% confidence interval. The coefficients are close to zero and the confidence bands include zero, confirming pre-treatment dynamics were similar across groups. The same follows for the moderator DiD parallel trends also in Appendix A.2.1.

In conclusion, the combination of visual and statistical evidence supports the validity of the parallel trends assumption for our DiD regressions.

6.2.3 Standard Errors & Inference

In all DiD regressions, two-way clustered SEs at firm and year level are applied, following Cameron, Gelbach, and Miller (2011) and Bertrand, Duflo, and Mullainathan (2004). Two-way clustering accounts for potential serial correlation within firms, over time and cross-sectional dependence across firms, within the same year. Both issues can lead to downward-biased SE and misleading significance if ignored.

A Pesaran CD test is computed on the regression residuals to detect cross-sectional dependence across firms (Pesaran 2015). The test reveals high correlation across firm residuals within the same

year. To obtain a valid inference we cluster standard errors on the time dimension. Firm level clustering is also necessary since the dependent variables are financial indicators (ROA, ICR) and we see high differences between sectors and companies.

As a robustness check, we also re-estimate the models with different SE clustering (firm-only and industry), further elaborated in the results section.

6.3 Research Limitations

For the DiD, our estimates rest on the parallel-trends assumption and we only observe three pre-years (2019-2021). This short pre-period limits power to detect differences between HighEI and LowEI firms, so our visual and statistical pre-trend checks should be read as supportive, but not definitive. This limitation applies not only to the main treatment split, but also to our moderating interactions (leverage and ESG) where pre-trends show some deviations. The HighEI sample is also comparatively small in the moderating regressions, which makes some estimates imprecise and more sensitive to clustering choices. In addition, timing adds a constraint for the DiD. Parts of the energy shock were already visible in 2021, meaning firms may have anticipated relief measures in late-2022 or adjusted their contracts, production, or hedged against it. In addition, a few policy events occurred already in 2022, while the DiD treats 2022 as the crisis year and 2023 as the policy year (though the GPB was effective on 2023 accounts). These features can attenuate the measured effects in 2022-2023 and make treatment contrasts conservative.

The event study design faces similar limitations. The cross-sectional moderation tests are estimated within the HighEI sample, i.e., based on only eight events and 22 firms, which substantially reduces statistical power. This limits the precision of detecting leverage- and ESG-related heterogeneity and raises sensitivity to model specification and clustering choices.

For both the event study and DiD samples, we restrict the dataset to firms that were active throughout the full observation period. This allows us to track performance consistently over time, but introduces survivorship bias: firms that were delisted or became bankrupt during the crisis are excluded. If such exits were concentrated among HighEI firms, our estimates likely understate negative effects in 2022 and may overstate the recovery in 2023.

Finally, the Stable Unit Treatment Value Assumption (SUTVA) requires no interference between firms and a single, well-defined version of treatment and it underpins identification of potential outcomes and makes the treatment effects interpretable (Angrist and Pischke 2009). In our setting, SUTVA is unlikely to hold perfectly. Firms are linked through supply chains and energy markets, so one firm's exposure can affect others (violating no interference). Moreover, there may be multiple versions of treatment as firms differ in contracts, energy mix, or hedging. We mitigate these concerns with firm and time fixed effects, industry controls, and right-skew handling (winsorisation, log/asinh transforms). Some bias, most likely attenuation toward smaller effects, may remain.

7 Results

This section presents the empirical results. First, we report event study results on short-horizon CAR/CAAR around crisis vs. policy events, starting with the aggregate market reaction and the HighEI vs. LowEI gap and confirm significance with both mean-based (BMP) and median/sign tests. Thereafter, we show heterogeneity splits by leverage and ESG. Second, we report baseline DiD results testing the crisis and policy-cushioning hypotheses for ROA and ICR, followed by the heterogeneity analyses of ESG performance and leverage.

7.1 Event Study

7.1.1 Hypothesis 1 and 2

Visual analysis

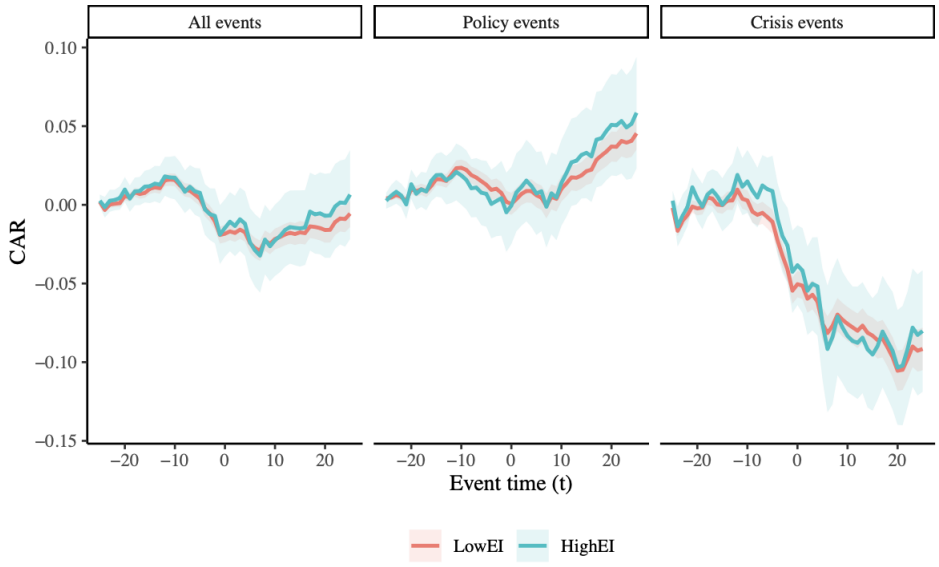


Figure 8: Average CAR Paths per Event Type and Group (long horizon [-25, +25]

Note: This figure shows cumulative average abnormal returns for HighEI and LowEI firms from 25 days before to 25 days after crisis events, GPB policy events and all events combined.

From Figure 8 we see that for policy events, CARs remain close to zero and show a mild positive drift after the event window, with HighEI firms displaying slightly stronger increases. In contrast, the crisis events produce a clear and persistent negative CAR trajectory around $\tau = 0$, with both groups declining and HighEI firms exhibiting somewhat sharper drops.

The per-event CAAR plots (Figure 16 in Appendix A.1.1) confirm this pattern. Crisis shocks trigger widespread negative market reactions, with HighEI firms experiencing larger drawdowns

than LowEI peers during both the Russian invasion and the Gazprom supply cut. This aligns with H1, which predicts a performance penalty for firms with greater energy-cost exposure.

For GPB events (initial announcement, cabinet approval, Bundestag passage, Bundesrat adoption and operationalisation), HighEI firms tend to exhibit more positive CAARs, with the HighEI series consistently above the LowEI series in the [0, +3] window. This is consistent with H2, suggesting that investors anticipated the GPB to cushion the shock for firms with higher energy intensity. However, these figures are descriptive; significance is assessed per event with BMP mean t-tests and Wilcoxon medians.

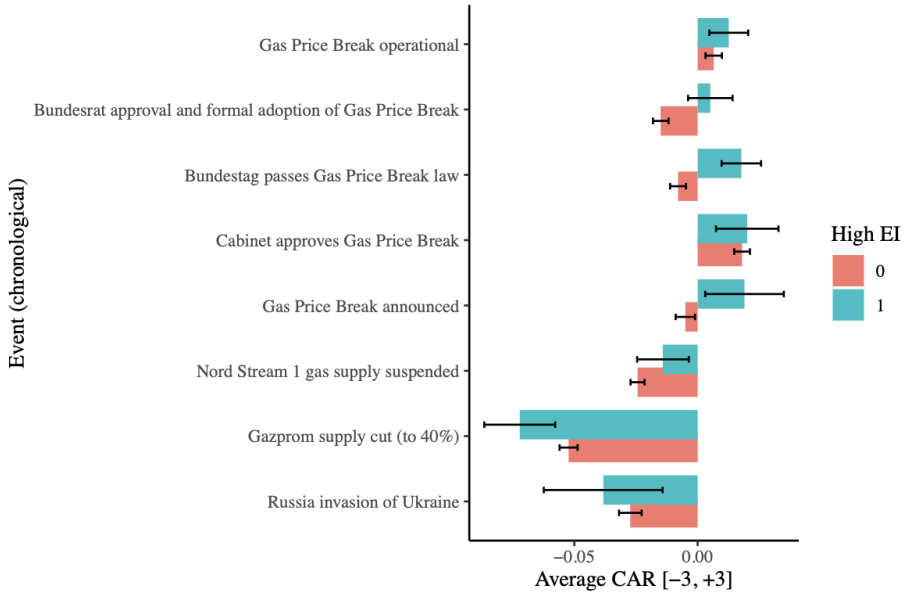


Figure 9: Average CAR by Group and Event [-3, +3]

Note: The figure summarises the short-window [-3, +3] average CARs for each event, split by HighEI and LowEI firms, providing a concise, event-by-event visualisation of the reversal in the HighEI-LowEI performance gap. Bars > 0 indicate positive abnormal returns and bars < 0 indicate negative returns. Given the large cross-sectional dispersion, these mean differences are descriptive and formal tests follow.

Figure 9 shows that HighEI firms experience greater negative abnormal returns than LowEI firms during crisis events, but comparatively stronger returns during the GPB announcements. This reversal is at the core of H1 and H2, so presenting the patterns side-by-side helps illustrate how market reactions switch sign across crisis and policy contexts.

The crisis-event CARs are negative with HighEI firms exhibiting larger declines (except for Nord Stream suspension), reflecting their greater exposure to rising input costs and supply disruptions. This pattern aligns with H1, indicating that firms with higher energy-cost exposure were penalised. In contrast, GPB-related announcements show modest positive reactions, with HighEI firms responding more strongly. This suggests that investors anticipated the GPB to reduce expected cost pressures precisely where exposure was highest, in line with H2.

As a size and outlier check for the pooled dynamics, Figure 12 in Appendix A.1 compares CAAR computed as equal-weighted, value-weighted (static 2019-2021) and median. The three tracks are similar, indicating they are not driven by mega-caps or outliers. Furthermore, the long-horizon of this plot (Figure 17 in Appendix A.1) confirms the short-window findings: signs and relative magnitudes are similar, suggesting limited influence of pre-trends.

For completeness, Figure 18 in Appendix A.1 plots the HighEI – LowEI abnormal-return gap (Welch differences) for each event. The patterns mirror those in Figure 9: crisis events yield negative gaps (except for NS1) and GPB events positive gaps.

Statistical analysis of policy events

Table 4: Event Study Summaries for Gas Price Brake Events

Panel A: Event counts and significance tests (BMP and Wilcoxon)

Date	Title	N_{HighEI}	N_{LowEI}	p (BMP)	p (Wilcoxon)	Direction
2022-09-29	GPB announced	22	401	0.329	0.445	neg
2022-11-25	Cabinet approves GPB	22	401	0.000	0.000	pos
2022-12-15	Bundestag passes GPB law	22	401	0.033	0.028	neg
2022-12-19	Bundesrat approval of GPB	22	401	0.000	0.000	neg
2023-03-01	GPB operational	22	400	0.033	0.000	pos

Panel B: CAR levels and group differences

Date	Title	$\text{CAR}_{\text{HighEI}}$	$\text{CAR}_{\text{LowEI}}$	Gap	p_{diff}	Sig.
2022-09-29	GPB announced	0.019	−0.005	0.024	0.157	no
2022-11-25	Cabinet approves GPB	0.020	0.018	0.002	0.874	no
2022-12-15	Bundestag passes GPB law	0.018	−0.008	0.026	0.006	**yes**
2022-12-19	Bundesrat approval of GPB	0.005	−0.015	0.020	0.045	**yes**
2023-03-01	GPB operational	0.013	0.007	0.006	0.480	no

Note: Panel A reports, for each GPB event date, the number of HighEI and LowEI firms and the p-values from the BMP mean test and Wilcoxon median test for whether average [-3, +3] CARs differ from zero, with the last column indicating the sign of the average CAR. Panel B reports mean [-3, +3] CARs for HighEI and LowEI firms, the HighEI–LowEI gap and the Welch test p-value (p_{diff}), with "Sig." marking whether the gap is significant.

Table 4 provides the event-level statistical tests for key policy dates. Across all GPB-related dates, HighEI firms exhibit positive mean CARs, whereas LowEI firms show mixed responses. The initial policy announcement shows no significant pooled reaction, with the rise in HighEI being netted out by negative LowEI, which is consistent with the bars in Figure 9 extending in opposite directions. The cabinet approval produces a strong positive pooled reaction, with both groups exhibiting positive abnormal returns, but no statistically significant difference between them. The Bundestag passage, however, shows a significant gap effect. HighEI firms display significantly positive CARs while low EI firms record negative CARs, yielding a statistically significant gap of

2.56 pp. Similarly, on the Bundesrat adoption, the pooled reaction is negative, but the HighEI-LowEI gap is significantly positive (2.01 pp), indicating that HighEI firms performed better despite the overall market decline. Finally, the operationalisation of the GPB produces a positive and significant pooled reaction, with both groups increasing and HighEI firms rising slightly more than LowEI (1.26 vs. 0.65 pp).

Overall, these results provide support for H2. HighEI firms react positively on all policy event dates and the gap to LowEI is significant on two events. This suggests that markets anticipated stronger benefits for firms with high energy-intensity as the GPB became more concrete and institutionally locked in. On these two legislative dates, the pooled mean and median CARs are negative despite HighEI gains, because LowEI firms exhibit larger declines. This suggests that while HighEI firms benefited from the GPB becoming legally binding, the broader market may have priced in associated fiscal implications, producing negative pooled reactions.

Together with the crisis-event visuals in the preceding sections, the evidence supports both H1 and H2. HighEI firms experience greater losses during crisis shocks, consistent with their higher exposure to rising input costs, while policy-related events generate comparatively stronger abnormal returns for HighEI firms, consistent with the GPB being perceived as targeted relief for the most exposed firms.

7.1.2 Hypothesis 3a and 3b

H3a (Leverage moderation)

Table 5: Cross-Event CAR Regression (Leverage)

	CAR
Variables	
Size (log mkt cap)	-0.002 (0.002)
Market-to-Book	0.004 (0.003)
HighLeverage × Policy	0.007 (0.009)
Fixed effects	
Event	Yes
Industry	Yes
S.E.: Clustered by	firm & event
Observations	168
R^2	0.219
Within R^2	0.016

Signif. codes: $^{\cdot}\,p < 0.10$, $^{*}\,p < 0.05$, $^{**}\,p < 0.01$, $^{***}\,p < 0.001$.

Note: The table shows cross-sectional regressions of [-3, +3] CAR on the HighLeverage x Policy interaction within the HighEI sample, controlling for size, market-to-book and event and industry fixed effects. Standard errors are clustered at firm and event level.

Table 5 reports the cross-sectional interaction regressions within the HighEI sample, testing whether leverage moderates firms' abnormal returns on policy days relative to crisis days. Within the HighEI group, the *HighLeverage x Policy* interaction is near zero (0.007, ns). Thus, on policy days, we do not find a statistically significant difference in performance between high-levered HighEI firms and their low-levered peers.

As a robustness check, we run the regression in two different samples (see Appendix A.1.2). In both the Manufacturing-only sample and the full sample, the interaction is near zero and insignificant, confirming that we cannot find support for a systematic difference between high- and low-leverage HighEI firms in CARs.

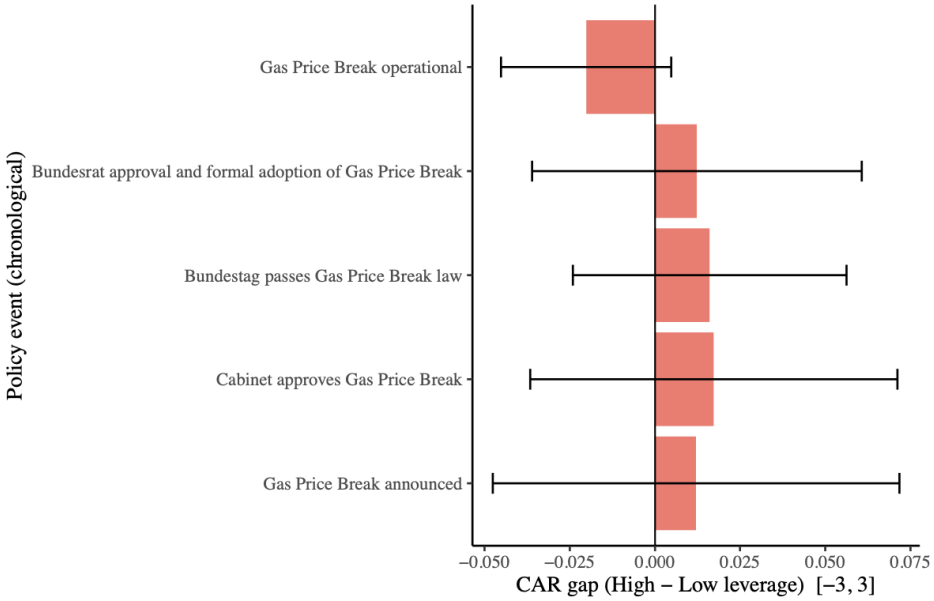


Figure 10: High - Low Leverage Gap (Welch) within HighEI for Policy Events

Note: The figure plots High - Low Leverage CAR gaps with 95% Welch confidence intervals for HighEI firms on GPB dates. Bars to the right (gap > 0) indicate that HighLeverage firms outperform LowLeverage peers, while bars to the left indicate underperformance.

To complement the regression, Figure 10 plots the event-level high – low leverage gaps within the HighEI group for each policy announcement. The gaps are generally positive but small in magnitude and all Welch 95% confidence intervals cross zero. This indicates no statistically reliable difference in short-window CARs between high- and low-leverage HighEI firms on any GPB event date. The same pattern holds in the full sample (see Appendix A.1.2). In sum, leverage's short-run moderating role is weak and inconsistent within HighEI firms in returns. Therefore, we cannot find evidence for H3a, that leverage moderates policy effectiveness on firm outcomes.

H3b (ESG moderation)

Table 6: Cross-Event CAR Regression (ESG)

	CAR	CAR
Variables		
Size (log mkt cap)	−0.007 (0.006)	−0.004 (0.004)
Market-to-book	0.005· (0.003)	0.005 (0.003)
HighESG × Policy	0.030 (0.019)	—
HighEnv × Policy	—	0.007 (0.024)
Fixed effects		
Event	Yes	Yes
Industry	Yes	Yes
S.E.: Clustered by	firm & event	firm & event
Observations	160	160
R^2	0.225	0.209
Within R^2	0.042	0.022

Signif. codes: · $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: The table shows cross-sectional regressions of [-3, +3] CAR on the HighESG x Policy and HighEnv x Policy interaction within the HighEI sample, controlling for size, market-to-book and event and industry fixed effects. Standard errors are clustered at firm and event level.

Table 6 reports the ESG-moderation regression within the HighEI sample, testing whether firms with stronger ESG profiles react differently to GPB event dates. The *HighESG x Policy* interaction is positive but statistically insignificant (0.030, ns), indicating no detectable difference in announcement-day CARs between high- and low-ESG HighEI firms. We run the same regression on the Environmental Pillar Score but again find no significant effect.

As robustness, we repeat the analysis in the Manufacturing subsample and the full sample (see Appendix A.1.2). In both cases, the ESG interaction terms remain insignificant, suggesting that neither overall ESG performance nor environmental pillar strength systematically moderates short-window abnormal returns around GPB events. Taken together, the evidence provides no support for H3b; there is no reliable ESG moderation in announcement returns, even when broadening the firm sample.

Figure 11 complements the regression by showing event-level HighESG – LowESG gaps within the HighEI sample. Most GPB events show positive HighESG – LowESG gaps, but 95% CIs are wide and include zero, so none are statistically different from zero. In Appendix A.1.2, we show the same plot for the full sample (incl. LowEI), where most events are positive and two are statistically significant (GPB announced and Bundestag passes GPB law). This suggests that investors sometimes reward higher ESG quality on GPB announcements, but the effect is not detectable within HighEI firms and appears on only two events.

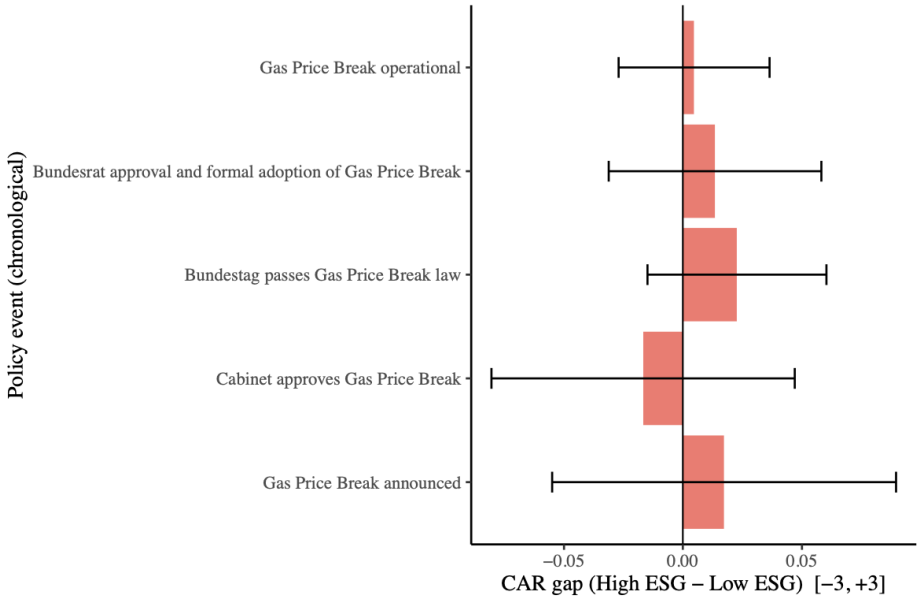


Figure 11: High - Low ESG Gap (Welch) within HighEI for Policy Events

Note: The figure plots High - Low ESG CAR gaps with 95% Welch confidence intervals for HighEI firms on GPB dates. Bars to the right (gap > 0) indicate that HighESG firms outperform LowESG peers, while bars to the left indicate underperformance of HighESG firms.

In sum, the evidence for HighESG firms outperforming LowESG firms on policy days is weak in the HighEI sample and only partially present when including LowEI firms. Overall, the event study evidence weakly support H3b at best: any ESG benefit seems small, occasional and not concentrated among HighEI firms.

7.2 Difference-in-Differences

7.2.1 Hypothesis 1 and 2

Table 7 presents the DiD estimates for profitability (ROA) and solvency (ICR), comparing HighEI and LowEI firms before and after the 2022 shock and the 2023 GPB implementation. Since identification relies on differential exposure, all coefficients reflect changes in the HighEI–LowEI gap (relative effects).

For ROA, the coefficient on *HighEI x 2022* is negative and marginally significant (-0.01, 10%), indicating that HighEI firms' profitability declined relative to LowEI firms in the crisis year. The *HighEI x Post2023* coefficient is also negative and marginally significant (-0.02, 10%), implying a further widening of the relative profitability gap in 2023. The 2023 gap corresponds to 2.04 p.p. lower ROA for HighEI firms, which is around 35-40% of the median firm's ROA in the sample (5-6%) suggesting a meaningful difference in operating performance. For ICR, both coefficients

Table 7: Difference-in-Differences Model 1 Results

	ROA	ICR (asinh)
Variables		
log(Assets)	0.016 (0.007)	0.558** (0.108)
HighEI × 2022	−0.012· (0.005)	−0.133 (0.117)
HighEI × Post2023	−0.020· (0.008)	−0.303 (0.188)
Fixed effects		
Firm	Yes	Yes
Year	Yes	Yes
S.E.: Clustered by	Firm & Year	Firm & Year
Observations	9,750	9,750
R^2	0.625	0.619
Within R^2	0.005	0.009

· $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: The table shows DiD estimates for ROA and asinh(ICR), comparing HighEI and LowEI firms in 2022 and Post2023 relative to pre-years, with firm and year fixed effects and standard errors clustered at firm and year level.

are negative, but statistically insignificant with large standard errors (SE).

A Wald test comparing Post2023 and 2022 finds no statistically significant change in the treatment effect for either ROA or ICR (see Table 12 Appendix A.2.2). Thus, although point estimates are more negative Post2023, we cannot conclude that the gap changed relative to 2022.

We assess robustness using alternative clustering (firm-only and industry), a manufacturing subsample and an alternative ICR transformation. For ROA, the HighEI–LowEI difference in 2023 remains statistically significant across specifications, while the 2022 relative deterioration of HighEI firms becomes statistically insignificant. For ICR, coefficients remain imprecisely estimated and transformation to log1p(ICR) do not alter the absence of differential solvency effects. Across robustness checks, the pattern holds that there is a deterioration in ROA for HighEI firms in 2023, whereas solvency effects remain weak and statistically inconsistent. All robustness tables can be found in Appendix A.2.2.

In conclusion, we find weak support for H1 (2022 exposure penalty) as ROA declines for HighEI firms in 2022 relative to LowEI, consistent with greater exposure to rising energy costs. Solvency effects are, however, not detected. We do not find support for H2 (2023 policy cushioning) in accounting outcomes. If anything, HighEI firms' relative profitability declines further in 2023, suggesting that the short-run market optimism observed in the event study did not translate into medium-term accounting gains.

7.2.2 Hypothesis 3a and 3b

Having established that the relative profitability gap widened during the crisis and the GPB, we now examine whether leverage and ESG performance influenced these effects.

H3a (Leverage moderation)

Table 8: DiD Model 2a Results (HighLeverage within HighEI Sample)

	ROA	**ICR (asinh)**
Variables		
log(Assets)	0.086 (0.040)	0.688 (0.554)
HighLeverage × 2022	0.023* (0.008)	0.624* (0.233)
HighLeverage × Post2023	0.037· (0.015)	0.656 (0.370)
Fixed effects		
Firm	Yes	Yes
Year	Yes	Yes
S.E.: Clustered by	Firm & Year	Firm & Year
Observations	576	576
R^2	0.536	0.529
Within R^2	0.044	0.014

$^{\cdot}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: The table reports DiD results for Model 2a, with HighLeverage x 2022 and HighLeverage x Post2023 interactions within the HighEI sample to test whether leverage moderates the impact of the crisis and GPB on ROA and ICR.

Table 8 reports leverage-moderation DiD estimates within the HighEI group, testing whether high leveraged firms experience different ROA and ICR outcomes than peers. While the main model showed that HighEI firms' ROA declined relative to LowEI in both years, the moderation regression indicates that within HighEI, highly leveraged firms performed better on average.

For ROA, *HighLeverage x 2022* is positive and statistically significant (0.023, 5%), implying that high-leverage HighEI firms experienced a roughly 2.27 pp higher change in ROA relative to low-leverage HighEI peers in 2022. The *HighLeverage x Post2023* coefficient is also positive (0.037, 10%), indicating a 3.74 pp relative improvement in 2023. Given that median ROA is around 5–6%, these effects are economically meaningful.

For ICR, leverage moderates outcomes within HighEI firms positively in 2022 (0.624, 5%), with the Post2023 coefficient remaining positive but statistically insignificant. Since 2022 precedes the GPB implementation, this result reflects differences in how financially constrained firms absorbed the crisis shock rather than an effect of the GPB. Given that ICR is measured using the asinh(ICR) transformation, the precise magnitude of the improvement in 2022 depends on the firm's baseline ICR, but the positive and significant coefficient indicates a relative strengthening of solvency among

high leverage HighEI firms in 2022 relative to peers. As our hypothesis pertains to whether leverage moderates the policy transmission of the GPB, this outcome is not interpreted as evidence on H3a, but may indicate that leverage acts as a proxy for financing access during the input-cost shock.

Robustness checks reinforce these results (see Appendix A.2.3). Replacing the dummy with a continuous, standardised leverage moderator yields the same pattern for ROA and ICR, with even tighter precision, indicating that the dummy did not drive the results. Re-estimating the model in the manufacturing-only sample and the full sample produces similarly positive moderation effects, confirming the result is not unique to the HighEI-only design.

Overall, the DiD evidence supports H3a: leverage positively moderates the HighEI ROA effect in 2022 and Post2023, with weaker evidence for ICR. Leverage appears to cushion HighEI firms rather than exacerbate the exposure penalty. This contrasts with the event study setting, where leverage showed no consistent moderating effect on announcement-day returns, suggesting that leverage matters more for medium-term adjustment dynamics than for short-run market reactions.

H3b (ESG moderation)

Table 9: DiD Model 2b Results (HighESG within HighEI Sample)

	ROA	**ICR (asinh)**
Variables		
log(Assets)	0.067 (0.048)	4.124 (2.549)
HighESG × 2022	0.040 (0.021)	1.285 (0.925)
HighESG × Post2023	0.011 (0.012)	0.734 (0.785)
Fixed effects		
Firm	Yes	Yes
Year	Yes	Yes
S.E.: Clustered by	Firm & Year	Firm & Year
Observations	102	102
R^2	0.471	0.613
Within R^2	0.034	0.108

$^{\cdot}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: The table reports DiD results for Model 2a, with HighESG x 2022 and HighESG x Post2023 interactions within the HighEI sample to test whether ESG score moderates the impact of the crisis and GPB on ROA and ICR.

Table 9 reports the ESG-moderation within the HighEI group, testing whether strong sustainability performance cushioned profitability and solvency during the crisis and GPB years. Across both outcomes, the *HighESG x 2022* and *HighESG x Post2023* interaction terms are positive but statistically insignificant. Thus, we cannot conclude that HighESG mitigated the decline in ROA and ICR from our Model 1.

We run four robustness checks (see Appendix A.2.3 for results). First, replacing the dummy with a continuous, standardised ESG score, produces the same insignificant estimates. Second, we replace the ESG score with the Environmental Pillar which again yields similar results. Finally, we run the regression in the manufacturing-only and the full sample. The triple interaction *HighEI x 2022 x HighESG* becomes marginally significant in the manufacturing sample for ROA, while the broader pattern remains insignificant.

Overall, the DiD results provide no support for H3b. Given the small listed-HighEI sample and wide CIs, we cannot conclude that ESG moderated the HighEI effect in 2022 or Post2023. This aligns with the event study evidence where ESG effects were weak rather than systematic.

8 Discussion

Across both empirical approaches, a consistent pattern emerges. Event study results show that markets priced an exposure penalty for HighEI firms during the 2022 crisis, reflected in larger negative abnormal returns for HighEI firms on crisis dates and an expected cushioning effect from the GPB, visible in relatively stronger positive abnormal returns on policy dates. Within the annual reporting window, however, realised accounting outcomes do not align with these expectations: HighEI firms experienced a small relative profitability decline in 2022 and no detectable improvement in 2023, while interest-coverage ratios remained negative but statistically insignificant. Taken together, these findings suggest that neither profitability nor solvency measures provide evidence of differential GPB relief for highly exposed firms during the period studied.

The divergence between forward-looking and realised outcomes aligns with adjustment mechanisms identified in recent firm-level evidence and context-specific factors. First, fixed-price contracts, multi-period procurement and hedging delay the pass-through of wholesale gas prices to firm-level costs (Fontagné, Martin, and Orefice 2023; Alpino, Citino, and Frigo 2025; Hornbach and Rammer 2024). Investors price exposure risk immediately, whereas realised balance-sheet effects tend to materialise more gradually. Second, wholesale prices had already fallen substantially from their 2022 peak by the time the GPB became operational (see Figure 1). Since only 30% of consumption remained exposed to spot prices, marginal costs were lower than anticipated. This likely reduced the scope for differential gains among HighEI firms, as falling wholesale prices ease input costs for all firms, compressing the crisis-induced component of the HighEI–LowEI profitability gap and leaving little differential relief for the DiD to identify. Annual reporting further compresses temporary convergence during 2022-23, making realised differences appear smaller than those anticipated at announcement. Taken together, the event study indicates that HighEI firms were expected to perform relatively better due to policy cushioning, yet accounting outcomes show no such relative improvements: the profitability gap between HighEI and LowEI firms persisted

throughout 2022-23.

Turning to heterogeneity, leverage does not moderate announcement-day returns, suggesting that investors initially priced energy-cost exposure rather than firms' capital structures. In contrast, the DiD results show that within HighEI firms, those with higher leverage exhibited relatively stronger realised outcomes than low leverage peers. As this comparison is internal to the HighEI group, the pattern more plausibly reflects differences in firms' financing capacity than differences in GPB-induced relief. In this setting, leverage may have proxied for access to external funding that helped firms stabilise operations despite input-cost pressure, consistent with evidence that credit access, rather than indebtedness per se, improves crisis performance under heightened uncertainty (European Investment Bank 2024; Yao, Feng, and Yang 2022). This interpretation does not contradict evidence that high leverage worsens crisis outcomes under tightening credit conditions (Eiling, Laeven, and Xu 2024; Tascón, Castro, and Valdunciel 2024), but rather highlights that the economic environment determines whether leverage functions as distress risk or as financing flexibility.

By contrast, ESG performance does not systematically moderate announcement-day reactions or realised accounting outcomes. Estimates are directionally positive but imprecise and statistically insignificant. This does not necessarily contradict prior evidence of ESG related downside protection during crisis phases (Lins, Servaes, and Tamayo 2017; Ricci et al. 2024; Yahya 2023) due to the context of our analysis. First, we evaluate ESG as a moderator of a fiscal intervention rather than as a buffer against the initial shock. By 2023, when the GPB took effect, much of the uncertainty that typically underpins ESG's downside protection had largely subsided, making ESG a less salient factor in shaping short-run financial outcomes. Second, ESG coverage in our panel is limited and concentrated among listed firms, reducing statistical power. Our null DiD results therefore do not contradict prior findings; rather, they imply that ESG's crisis-mitigating effects may be most pronounced during uncertainty spikes rather than in post-shock normalisation phases.

Several limitations affect the precision of our estimates, but do not invalidate the directional patterns observed. First, the number of HighEI firms in both the event study and DiD samples is small, resulting in wide confidence intervals and attenuation bias toward zero. Insignificant coefficients should thus not be interpreted as evidence of absent effects, but as conservative lower bounds. Second, identification relies on relative, not absolute, treatment variation. Since the GPB applied economy-wide, the DiD captures differential exposure rather than a clean treated-control contrast, reducing the variation available for identification. In addition, exposure is measured using industry-level energy intensities rather than firm-level cost shares due to data limitations, introducing measurement error that attenuates coefficients toward zero. Finally, the event-study sample of listed firms differs structurally from the broader DiD panel, which includes the wider German corporate sector. Listed firms tend to be larger, more international and have greater

hedging sophistication, whereas the DiD sample contains many SMEs with different adjustment capacities. These structural differences imply that market-based signals for listed firms may not fully reflect the adjustment dynamics of the broader firm population, limiting comparability between forward-looking valuations and realised outcomes.

9 Conclusion

This thesis examined how Germany's Gas Price Brake affected the short-run financial outcomes of German firms and whether leverage and ESG performance moderated these effects. The results show a divergence between market expectations and realised fundamentals. Markets priced exposure penalties for HighEI firms during the crisis and anticipated differential cushioning from the GPB, yet realised accounting outcomes show that the profitability gap between HighEI and LowEI firms persisted. We find no evidence that the GPB generated measurable relative improvements in ROA or ICR for the most exposed firms within the first two post-shock reporting periods.

These findings align with recent firm-level evidence showing that fixed-price contracts, staggered procurement and short-run operational adjustments can delay the cost shock pass-through to firms' operating cash flow (Fontagné, Martin, and Orefice 2023; Alpino, Citino, and Frigo 2025; Hornbach and Rammer 2024). They also relate to aggregate firm-survey and simulation evidence (Archanskaia et al. 2024; Amaglobeli et al. 2024), which indicates that broad fiscal support helped maintain overall corporate stability during the energy crisis but did not eliminate underlying exposure differences across sectors. Our analysis addresses the firm-level, differential dimension of this question: within the annual reporting window, we do not observe that the GPB narrowed the profitability gap between HighEI and LowEI firms or generated measurable improvements in ROA or ICR for highly exposed firms relative to their less-exposed peers.

The moderator analysis shows that leverage did not shape investor expectations but drove realised outcomes. Our interpretation is that, in this context, leverage may have proxied for financing flexibility rather than distress risk, allowing highly leveraged firms to smooth the input-cost shock better than low-leverage peers. ESG performance, by contrast, does not materially influence valuation or accounting outcomes in our setting. This divergence from crisis-phase studies (e.g., Lins, Servaes, and Tamayo (2017), Albuquerque et al. (2020), and Ricci et al. (2024)) likely reflects both limited ESG coverage in our dataset and the fact that ESG's benefits appear strongest during periods of acute uncertainty rather than during post-shock policy stabilisation.

These patterns have several implications for policymakers. The results suggest that the effectiveness of price-based fiscal support is closely linked to its timing and the degree of remaining exposure differences at implementation. As the GPB was introduced after wholesale prices had begun to normalise, the residual variation in spot-price exposure was limited, reducing the scope

for detectable relative gains among HighEI firms. This indicates that differential relief is more likely when support coincides with periods of elevated and heterogeneous exposure. In addition, the persistence of the profitability gap suggests that temporary price caps alone cannot address underlying exposure differences and may need to be complemented by structural measures such as tax incentives for energy-efficiency investments and process innovation. For firms, the findings imply that broad fiscal interventions do not substitute for internal risk-management capabilities: credit access, hedging strategies, and operational flexibility remain central for maintaining performance under input-cost shocks.

External validity is necessarily limited. Our identification relies on differential exposure rather than a treated-versus-untreated contrast and the results reflect Germany's institutional setting and the timing of the GPB relative to the crisis trajectory. Moreover, the GPB operated in an environment with unusually high wholesale price volatility and widespread forward-contract coverage, conditions that may differ in other crises. Listed firms and SMEs also differ in hedging sophistication, financial structure and international exposure, which may lead to heterogeneous responses in other contexts.

Future research could extend this analysis along three dimensions. First, it could examine whether the divergence between market expectations and realised firm-level outcomes documented here also arises under other stabilisation instruments, with a particular focus on policy timing and the extent to which support remains effective once market conditions have begun to normalise, or whether this pattern is specific to the Gas Price Brake context. Second, higher-frequency accounting or administrative data would capture short-lived effects that annual reporting smooths out, particularly during the transition between crisis and stabilisation phases. Third, access to firm-level data on hedging practices, contract structures and financing arrangements, such as credit-line drawdowns or refinancing activity, would allow more direct identification of the channels through which fiscal interventions translate into firm-level financial outcomes and help assess whether leverage proxies for financing flexibility or distress risk in different environments.

References

Akarsu, O., M. S. Çolak, H. Karahan, and H. Torun. 2025. "The heterogeneous impact of monetary policy announcements on firms' financial outcomes" [in en]. *Bank for International Settlements* 127:295–330.

Albuquerque, R., Y. Koskinen, S. Yang, and C. Zhang. 2020. "Resiliency of Environmental and Social Stocks: An Analysis of the Exogenous COVID-19 Market Crash" [in en]. Publisher: Oxford University Press (OUP), *The Review of Corporate Finance Studies* 9, no. 3 (November): 593–621. ISSN: 2046-9128, 2046-9136, accessed July 26, 2025. https://doi.org/10.1093/rcfs/cfaa011. https://academic.oup.com/rcfs/article/9/3/593/5868419.

Alpino, M., L. Citino, and A. Frigo. 2025. *Firms in the energy crisis: evidence from 2021-22* [in en]. Technical report SSRN Working Paper No. 5251730. Bank of Italy (via SSRN).

Amaglobeli, D., J. Guilhoto, S. Jahan, S. Khalid, R. Lam, G. Legoff, B. Meyer, et al. 2024. "Firms' Resilience to Energy Shocks and Response to Fiscal Incentives: Assessing the Impact of 2022 Energy Crisis" [in en]. Publisher: International Monetary Fund (IMF), *IMF Working Papers* 2024, no. 027 (February): 1. ISSN: 1018-5941, accessed July 29, 2025. https://doi.org/10.5089/9798400263149.001. https://elibrary.imf.org/openurl?genre=journal&issn=1018-5941&volume=2024&issue=027&cid=542428-com-dsp-crossref.

Angrist, J. D., and J.-S. Pischke. 2009. *Mostly Harmless Econometrics: An Empiricist's Companion.* Princeton, NJ: Princeton University Press. ISBN: 978-0-691-12035-5.

Archanskaia, L., P. Nikolov, S. Wouter, and V. Lukas. 2024. "Navigating Shocks: The Performance of the EU Corporate Sector from the Pandemic to the Energy Crisis" [in en], accessed July 30, 2025. https://doi.org/10.2765/1408701. https://data.europa.eu/doi/10.2765/1408701.

Ari, A., Philipp Engler, Gloria Li, Manasa Patnam, and Laura Valderrama. 2023. "Energy Support for Firms in Europe: Best Practice Considerations and Recent Experience" [in en]. *IMF Working Papers* 2023, no. 197 (September): 1. ISSN: 1018-5941, accessed July 30, 2025. https://doi.org/10.5089/9798400255007.001. https://elibrary.imf.org/openurl?genre=journal&issn=1018-5941&volume=2023&issue=197&cid=539372-com-dsp-crossref.

BBC. 2022. "Nord Stream 1: How Russia is cutting gas supplies to Europe" (September). Accessed November 25, 2025. https://www.bbc.com/news/world-europe-60131520.

Bellemare, M. F., and C. J. Wichman. 2020. "Elasticities and the Inverse Hyperbolic Sine Transformation." *Oxford Bulletin of Economics and Statistics* 82 (1 (Feb)): 50–61.

Bertrand, M., E. Duflo, and S. Mullainathan. 2004. "How Much Should We Trust Differences-in-Differences Estimates?" *The Quarterly Journal of Economics* 119 (1 (February)): 249–275.

Boehmer, E., J. Musumeci, and A. B. Poulsen. 1991. "Event-Study Methodology under Conditions of Event-Induced Variance." *Journal of Financial Economics* 30 (2 (December)): 253–272.

Brookfield. 2021. *Brookfield Energy Infrastructure September 2021 Industry Overview: Winter is Coming.* Technical report. Brookfield. Accessed November 25, 2025. https://publicsecurities.brookfield.com/sites/brookfield-psg-v3/files/brookfield-psg/insights/pdf/brookfield-energy-infrastructure-monthly-commentary-september-2021.pdf.

Brown, S. J., and J. B. Warner. 1985. "Using daily stock returns" [in en]. *Journal of Financial Economics* 14 (1): 3–31. ISSN: 0304405X, accessed November 12, 2025. https://doi.org/10.1016/0304-405X(85)90042-X. https://linkinghub.elsevier.com/retrieve/pii/0304405X8590042X.

Bureau van Dijk. 2025. *Orbis.* Accessed September 25, 2025. https://www.bvdinfo.com.

Caglio, C., R. M. Darst, and. Kalemli-Özcan. 2021. *Collateral Heterogeneity and Monetary Policy Transmission: Evidence from Loans to SMEs and Large Firms* [in en], April. Accessed November 11, 2025. https://doi.org/10.3386/w28685. http://www.nber.org/papers/w28685.pdf.

Callaway, B., and P. H. Sant'Anna. 2021. "Difference-in-Differences with multiple time periods" [in en]. *Journal of Econometrics* 225, no. 2 (December): 200–230. ISSN: 03044076, accessed September 6, 2025. https://doi.org/10.1016/j.jeconom.2020.12.001. https://linkinghub.elsevier.com/retrieve/pii/S0304407620303948.

Cameron, A. C., J. B. Gelbach, and D. L. Miller. 2011. "Robust Inference with Multiway Clustering." *Journal of Business & Economic Statistics* 29 (2 (Apr/Jun)): 238–249.

Campello, M., J. R. Graham, and C. R. Harvey. 2010. "The real effects of financial constraints Evidence from a financial crisis" [in en]. *Journal of Financial Economics* 97:470–487.

Corbeau, A.-S., and A.-K. Merz. 2023. *Understanding Germany's Gas Price Brake: Balancing Fast Relief and Complex Politics* [in en]. Center on Global Energy Policy at Columbia.

De Loecker, J., and F. Warzynski. 2012. "Markups and Firm-Level Export Status" [in en]. *American Economic Review* 102, no. 6 (October): 2437–2471. ISSN: 0002-8282, accessed November 25, 2025. https://doi.org/10.1257/aer.102.6.2437. https://pubs.aeaweb.org/doi/10.1257/aer.102.6.2437.

Deutsche Bundesbank. 2023. *Germany as a business location: selected aspects of current dependencies and medium-term challenges* [in en]. Monthly Report. Deutsche Bundesbank.

Eiling, E., R. J. A. Laeven, and D. Xu. 2024. *Coping with the Unexpected: A Forward-Looking Measure of Firm Resilience* [in en]. Accessed July 29, 2025. https://doi.org/10.2139/ssrn.4978453. https://www.ssrn.com/abstract=4978453.

European Commission. n.d. *NACE – all.* Technical report. European Commission. Accessed October 22, 2025. https://ec.europa.eu/competition/mergers/cases/index/nace_all.html.

———. 2025b. *Report on energy prices and costs in Europe.* Technical report. European Commission, February.

European Investment Bank. 2024. *Do financing conditions pose a threat to the performance and transformation of SMEs?* [In en]. LU. Accessed November 22, 2025. https://data.europa.eu/doi/10.2867/1358340.

Fama, E. F., and K. R. French. 1992. "The Cross-Section of Expected Stock Returns." *The Journal of Finance* 47 (2 (June)): 427–465.

Ferrando, A., S. Lamboglia, and E. Offner. 2025. "Monetary policy transmission to investment: evidence from a survey on enterprise finance" [in en]. *ECB Working Paper Series,* ECB Working Paper Series, 3150. Accessed December 3, 2025. https://data.europa.eu/doi/10.2866/3930066.

Fetzer, T., C. Palmou, and J. Schneebacher. 2024. "How Do Firms Cope with Economic Shocks in Real Time?" [In en]. *SSRN Electronic Journal,* ISSN: 1556-5068, accessed July 30, 2025. https://doi.org/10.2139/ssrn.4991915. https://www.ssrn.com/abstract=4991915.

Fontagné, L., P. Martin, and G. Orefice. 2023. "The Many Channels of Firm's Adjustment to Energy Shocks: Evidence from France" [in en]. *SSRN Electronic Journal,* ISSN: 2364-1428.

Hall, R. E. 1988. "The Relation between Price and Marginal Cost in U.S. Industry" [in en]. *Journal of Political Economy* 96 (5): 921–947. https://www.jstor.org/stable/1837241.

Hornbach, J., and C. Rammer. 2024. "Energy Price Shocks and Short-time Reactions of Firms: The Case of the German Energy Crisis in 2022" [in en]. *ZEW,* accessed July 30, 2025. https://doi.org/10.2139/ssrn.5045077. https://www.ssrn.com/abstract=5045077.

Hutter, C., and E. Weber. 2023. "Russia–Ukraine war: A note on short-run production and labour market effects of the energy crisis" [in en]. *Energy Policy* 183 (December): 113802. ISSN: 03014215, accessed October 19, 2025. https://doi.org/10.1016/j.enpol.2023.113802. https://linkinghub.elsevier.com/retrieve/pii/S0301421523003877.

Lins, K. V., H. Servaes, and A. Tamayo. 2017. "Social Capital, Trust, and Firm Performance: The Value of Corporate Social Responsibility during the Financial Crisis" [in en]. Publisher: Wiley, *The Journal of Finance* 72, no. 4 (August): 1785–1824. ISSN: 0022-1082, 1540-6261, accessed July 26, 2025. https://doi.org/10.1111/jofi.12505. https://onlinelibrary.wiley.com/doi/10.1111/jofi.12505.

LSEG Workspace. 2025. *LSEG Workspace.* London. Accessed September 26, 2025. https://www.lseg.com/en/data-analytics/refinitiv.

MacKinlay, A. C. 1997. "Event Studies in Economics and Finance." *Journal of Economic Literature* 35 (1): 13–39.

Pástor, L., and P. Veronesi. 2012. "Uncertainty about Government Policy and Stock Prices" [in en]. *The Journal of Finance* 67, no. 4 (August): 1219–1264. ISSN: 0022-1082, 1540-6261, accessed November 25, 2025. https://doi.org/10.1111/j.1540-6261.2012.01746.x. https://onlinelibrary.wiley.com/doi/10.1111/j.1540-6261.2012.01746.x.

Pesaran, M. H. 2015. "Testing Weak Cross-Sectional Dependence in Large Panels." *Econometric Reviews* 34 (6-10): 1089–1117.

Ricci, O., G. Santilli, G. Scardozzi, and F. S. Stentella Lopes. 2024. "ESG resilience in conflictual times" [in en]. Publisher: Elsevier BV, *Research in International Business and Finance* 71 (August): 102411. ISSN: 0275-5319, accessed July 29, 2025. https://doi.org/10.1016/j.ribaf.2024.102411. https://linkinghub.elsevier.com/retrieve/pii/S0275531924002046.

Sachverständigenrat. 2022. *Energiekrise und Strukturwandel: Perspektiven für die deutsche Industrie* [in DE]. Technical report. Sachverständigenrat zur Begutachtung der gesamtwirtschaftlichen Entwicklung. https://www.sachverstaendigenrat-wirtschaft.de/fileadmin/dateiablage/gutachten/jg202223/JG202223_Kapitel_5.pdf.

Sgaravatti, G., S. Tagliapietra, C. Trasi, and G. Zachmann. 2023. *National fiscal policy responses to the energy crisis.* Accessed November 25, 2025. https://www.bruegel.org/dataset/national-policies-shield-consumers-rising-energy-prices.

Soederhuizen, B., Adam Elbourne, Leon Bettendorf, Bert Kramer, Gerdien Meijerink, and Benjamin Wache. 2023. *A simulation of energy prices and corporate profits* [in en]. Technical report. CPB Netherlands Bureau for Economic Policy Analysis.

Tascón, M. T., P. Castro, and L. Valdunciel. 2024. "Effects of financial restrictions on firms' financial resilience against the COVID-19 pandemic: evidence from the European hospitality industry" [in en]. *Applied Economics* 56, no. 58 (December): 8226–8241. ISSN: 0003-6846, 1466-4283, accessed September 1, 2025. https://doi.org/10.1080/00036846.2023.2289951. https://www.tandfonline.com/doi/full/10.1080/00036846.2023.2289951.

Trinomics. 2024. *Study on energy prices and costs – evaluating impacts on households and industry's costs – 2024 edition.* Technical report. Trinomics, September. https://trinomics.eu/project/study-on-energy-prices-and-costs-evaluating-impacts-on-households-and-industrys-costs-2024-edition/.

Welch, B. L. 1947. "The generalization of "Student's" problem when several different population variances are involved." *Biometrika* 34 (1-2): 28–35.

Wilcoxon, F. 1945. "Individual Comparisons by Ranking Methods." *Biometrics Bulletin* 1 (6 (December)): 80–83.

Yahya, H. 2023. "The role of ESG performance in firms' resilience during the COVID-19 pandemic: Evidence from Nordic firms" [in en]. Publisher: Elsevier BV, *Global Finance Journal* 58 (November): 100905. ISSN: 1044-0283, accessed July 29, 2025. https://doi.org/10.1016/j.gfj.2023.100905. https://linkinghub.elsevier.com/retrieve/pii/S104402832300100X.

Yao, Y., J. Feng, and Q. Yang. 2022. "Impact of Financing Constraints on Firm Performance: Moderating Effect Based on Firm Size" [in en], edited by A. Bhardwaj. *Computational Intelligence and Neuroscience* 2022 (August): 1–8. ISSN: 1687-5273, 1687-5265, accessed November 22, 2025. https://doi.org/10.1155/2022/1954164. https://www.hindawi.com/journals/cin/2022/1954164/.

Zhou, Y. 2024. *ESG meets Geopolitics: Stock Returns during the Ukraine-Russia Conflict.* Technical report SSRN Working Paper No. 5122235. SSRN. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5122235.

A Appendix

A.1 Event Study Details

A.1.1 H1 and H2 Robustness

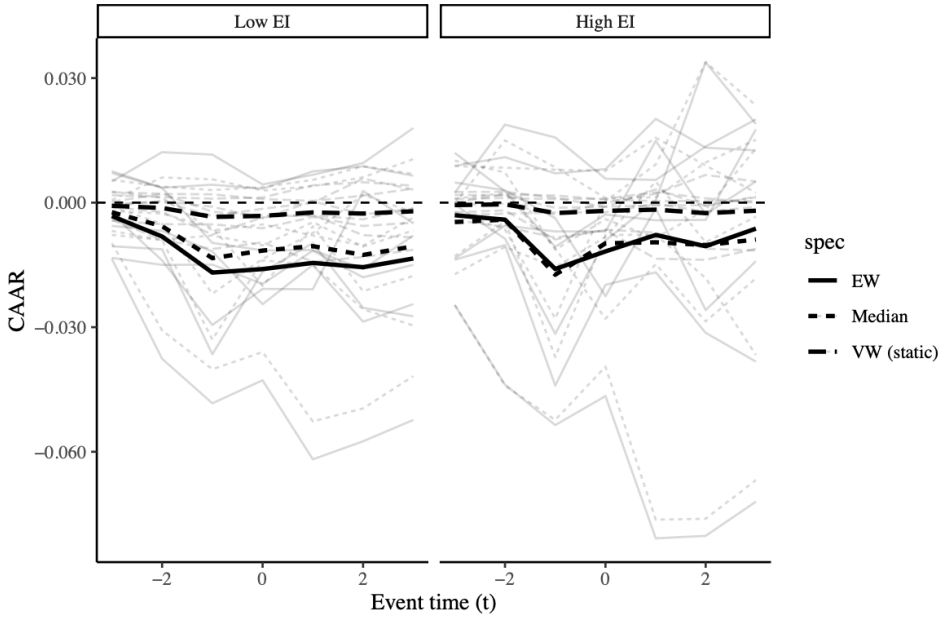
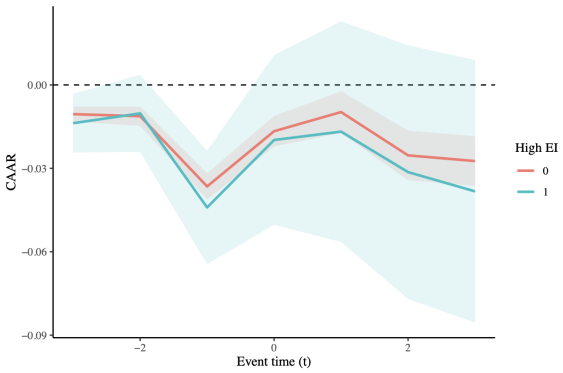
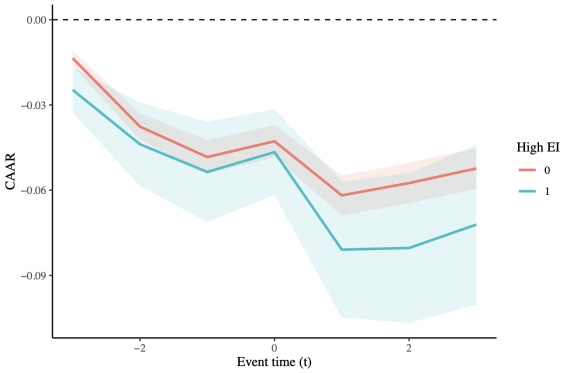


Figure 12: CAAR: Equal Weighted vs Value Weighted vs Median

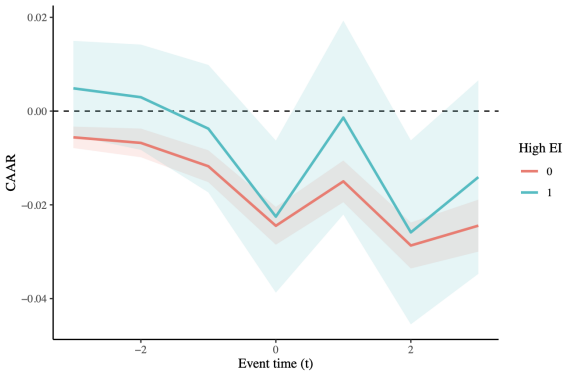
Note: The figure compares equal-weighted, value-weighted and median CAARs across the events for the HighEI and LowEI groups separately.



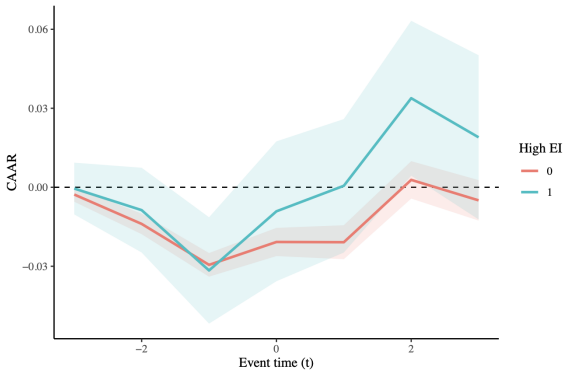
(a) Russia Invasion of Ukraine



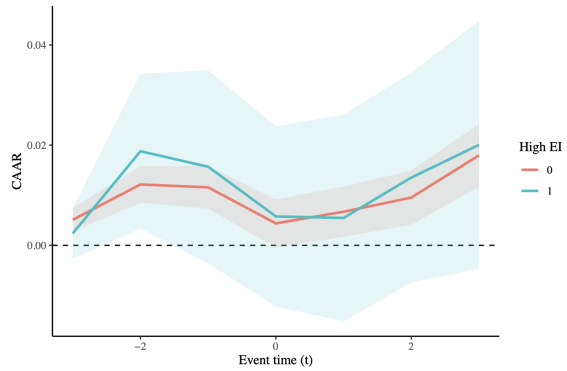
(b) Gazprom Supply Cut (to 40%)



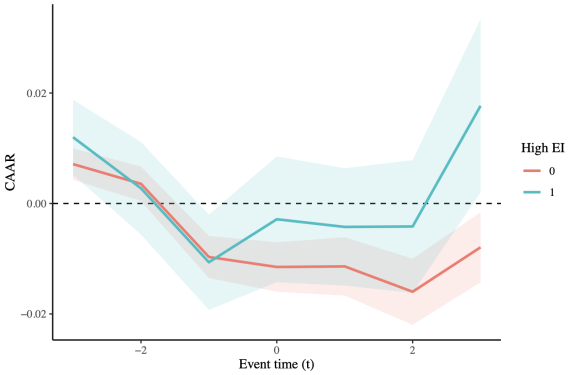
(a) Nord Stream 1 Gas Supply Suspended



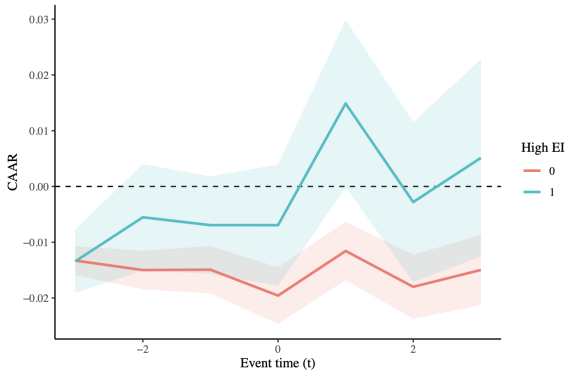
(b) Gas Price Brake Announced



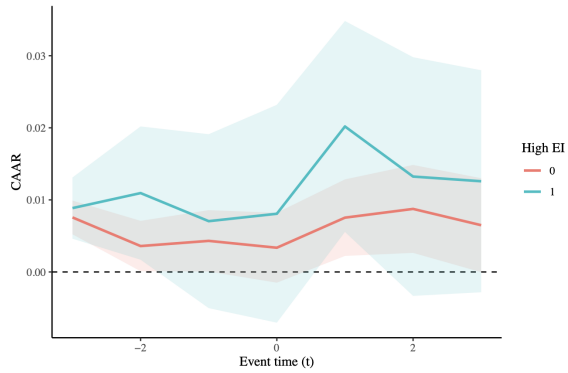
(a) Cabinet Approves Gas Price Brake



(b) Bundestag Passes Gas Price Brake Law



(a) Bundesrat Approval and Formal Adoption of Gas Price Brake



(b) Gas Price Brake Operational

Figure 16: Per-event CAAR: HighEI vs LowEI [-3, +3]

Note: These figures plot the CAAR over the event window [-3, +3] for each event.

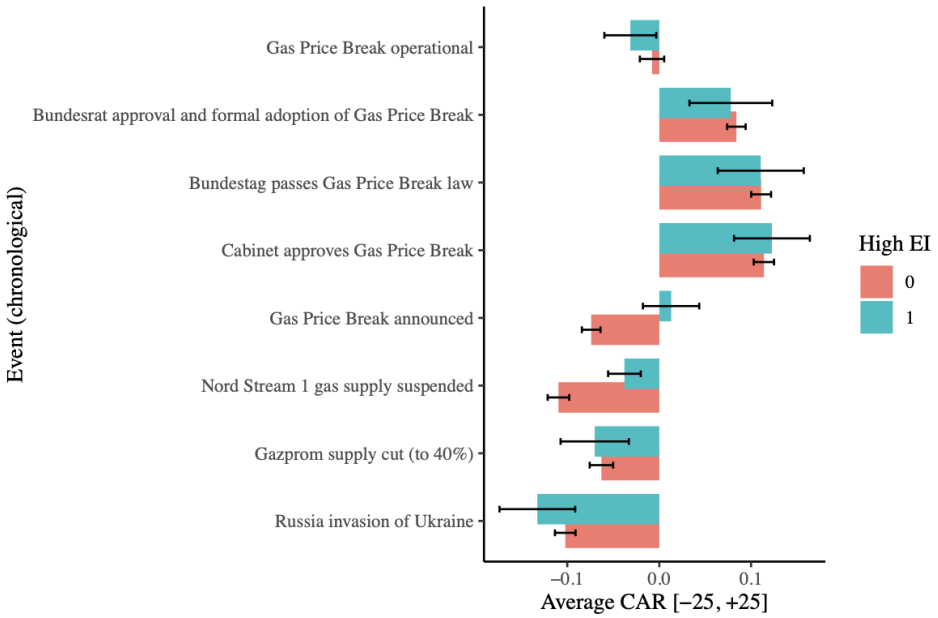


Figure 17: Average CAR by Group and Event (long horizon [-25, +25])

Note: The figure summarises the long-window [-25, +25] average CARs for each event, split by HighEI and LowEI firms, providing a concise, event-by-event visualisation of the reversal in the HighEI-LowEI performance gap. Acts as a robustness check to Figure 9. Bars > 0 indicate positive abnormal returns and bars < 0 indicate negative returns.

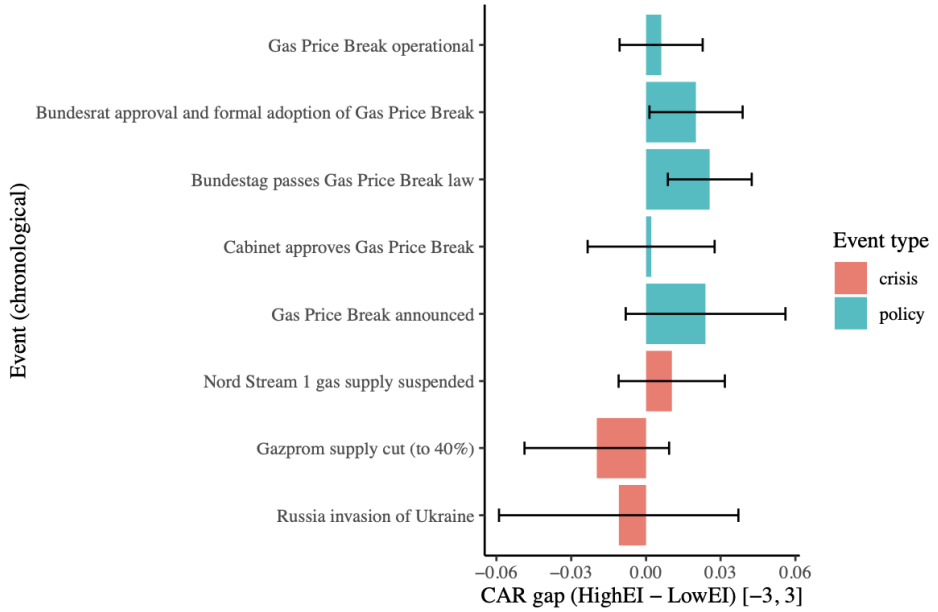


Figure 18: HighEI - LowEI Gap (Welch), [-3, +3]

Note: The figure summarises HighEI–LowEI CAR gaps with 95% Welch confidence intervals for each event. Bars to the right (gap > 0), HighEI outperforms; to the left, HighEI underperforms.

A.1.2 H3a and H3b Robustness

Table 10: Event Study: Cross-Event CAR Regression (Leverage) Robustness

	HighEI sample	**Manufacturing**	**All industries**
Variables			
Size (log mkt cap)	−0.002 (0.002)	0.000 (0.002)	0.000 (0.002)
Market-to-book	0.004 (0.003)	0.000 (0.000)	0.000 (0.000)
HighLeverage × Policy	0.007 (0.009)	0.000 (0.004)	0.004 (0.003)
Fixed effects			
Event	Yes	Yes	Yes
Industry	Yes	Yes	Yes
S.E.: Clustered by	firm & event	firm & event	firm & event
Observations	168	1,499	3,009
R^2	0.219	0.111	0.111
Within R^2	0.016	0.000	0.001

$^{\cdot}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: The table shows cross-sectional regressions of [-3, +3] CAR on the HighLeverage x Policy interaction within the HighEI sample (main regression), manufacturing sample and full sample, to act as a robustness check to Table 5. All regressions are controlling for size, market-to-book and event and industry fixed effects. Standard errors are clustered at firm and event level.

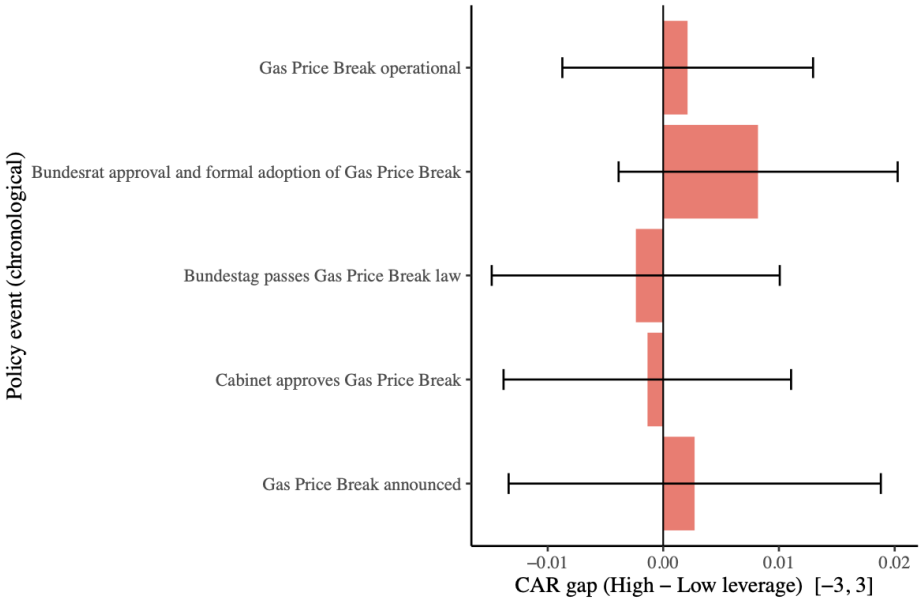


Figure 19: Per-event Welch Gaps (High – Low Leverage) within Full Sample for Policy Events

Note: The figure plots High - Low Leverage CAR gaps with 95% Welch confidence intervals for the full sample of firms on GPB dates. Acts as robustness check to Figure 10. Bars to the right (gap > 0) indicate that HighLeverage firms outperform LowLeverage peers, while bars to the left indicate underperformance.

Table 11: Event Study: Cross-Event CAR regression (ESG) robustness

	HighEI sample	**Manufacturing**	**All industries**
Variables			
Size (log mkt cap)	−0.007 (0.006)	−0.002 (0.003)	−0.003 (0.002)
Market-to-book	0.005˙(0.003)	0.001 (0.000)	0.001 (0.001)
HighESG × Policy	0.030 (0.019)	0.012 (0.008)	0.010 (0.009)
Fixed effects			
Event	Yes	Yes	Yes
Industry	Yes	Yes	Yes
S.E.: Clustered by	firm & event	firm & event	firm & event
Observations	160	999	1,718
R^2	0.225	0.174	0.186
Within R^2	0.042	0.006	0.005

˙ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: The table shows cross-sectional regressions of [-3, +3] CAR on the HighESG x Policy interaction within the HighEI sample (main regression), manufacturing sample and full sample, to act as a robustness check to Table 6. All regressions are controlling for size, market-to-book and event and industry fixed effects. Standard errors are clustered at firm and event level.

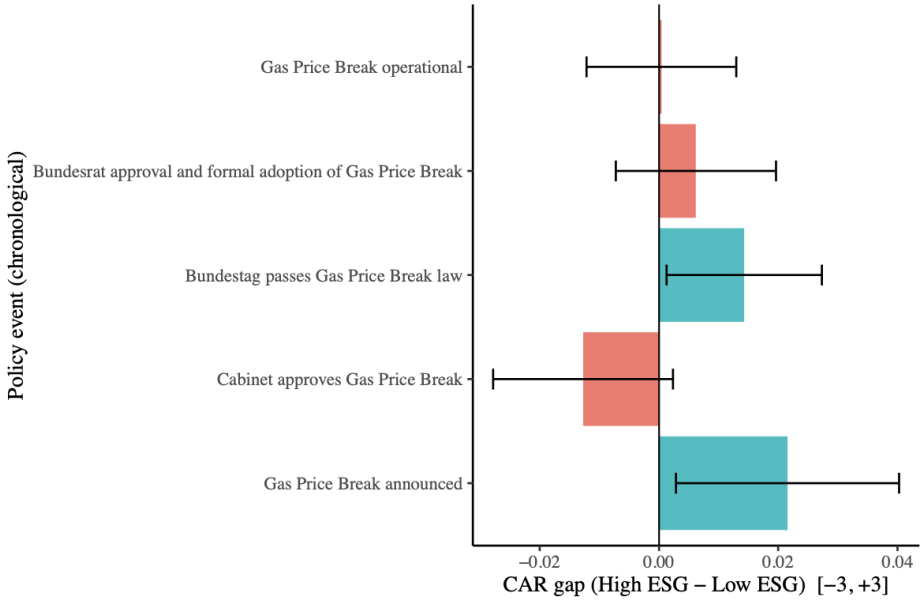


Figure 20: Per-event Welch Gaps (High–Low ESG) within Full Sample for Policy Events

Note: The figure plots High - Low ESG CAR gaps with 95% Welch confidence intervals for the full sample of firms on GPB dates. Acts as a robustness check to Figure 11. Bars to the right (gap > 0) indicate that HighESG firms outperform LowESG peers, while bars to the left indicate underperformance. The blue color indicates significant gap, while red means insignificant.

A.2 Difference-in-Differences Details

A.2.1 Pre-trends Statistical Analysis

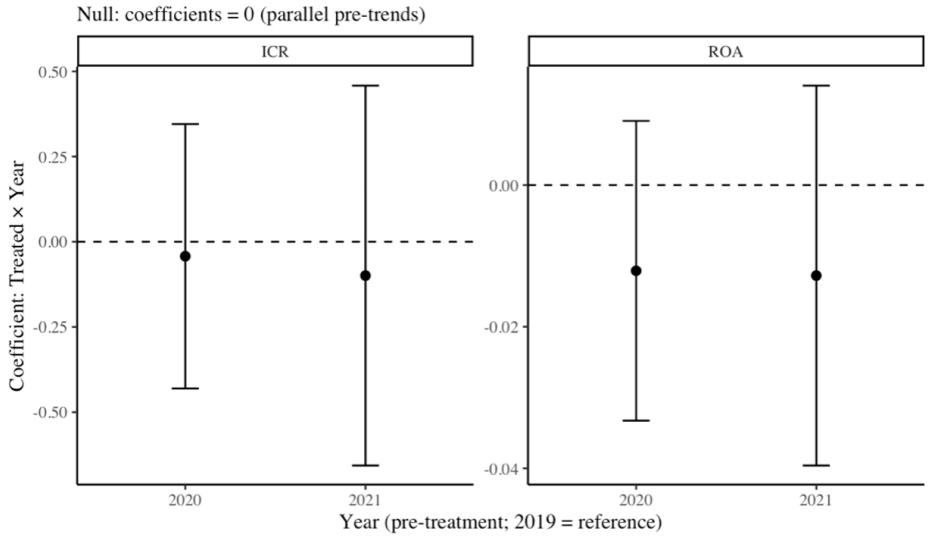
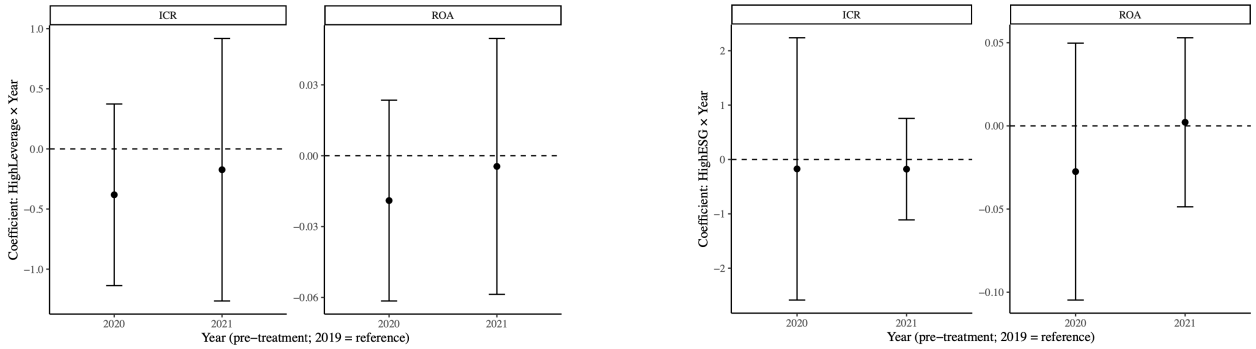


Figure 21: Pre-Trend Check, Interactions for 2020 and 2021 with 95% CI

Note: This figure plots the coefficients on the HighEI x 2020 and HighEI x 2021 interactions from the baseline DiD model for ICR (left figure) and ROA (right figure), with 95% confidence intervals.



(a) Leverage (b) ESG

Figure 22: Pre-Trend Check for Moderators, Interactions for 2020 and 2021 with 95% CI

Note: These figures provide additional pre-trend interaction estimates for the leverage and ESG moderators with 95% confidence intervals.

A.2.2 H1 and H2 Robustness

Table 12: Linear Hypothesis (Wald) Tests for Treatment Effects

	ROA		ICR (asinh)	
Hypothesis (H_0)	χ^2 (1 df)	p-value	χ^2 (1 df)	p-value
Single-parameter tests				
HighEI: 2022 = 0	5.693	0.017*	1.288	0.257
HighEI: Post2023 = 0	6.010	0.014*	2.592	0.107
Joint test				
HighEI: Post2023 - HighEI: 2022 = 0	1.587	0.208	1.008	0.316

Note: This table summarises single-parameter and joint Wald tests for the HighEI x 2022 and HighEI x Post2023 coefficients in the baseline DiD model (Model 1) and formally testing whether the treatment effects differ from zero and from each other. Wald χ^2 tests with 1 degree of freedom, computed from the DiD models with firm and year fixed effects. SEs are clustered by firm and year.

$^{\cdot}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 13: ROA: Baseline vs Alternative Clustering

	Baseline	**Firm–clustered**	**Industry–clustered**
Variables			
Log(Assets)	0.016$^{\cdot}$ (0.007)	0.016* (0.007)	0.016* (0.006)
HighEI × 2022	−0.012$^{\cdot}$ (0.005)	−0.012 (0.009)	−0.012 (0.013)
HighEI × Post2023	−0.020$^{\cdot}$ (0.008)	−0.020* (0.010)	−0.020*** (0.005)
Fixed effects			
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
S.E.: Clustered by	firm & year	firm	industry
Observations	9,750	9,750	9,750
R^2	0.625	0.625	0.625
Within R^2	0.005	0.005	0.005

$^{\cdot}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: This table serves as robustness check for Model 1 and the results in Table 7. The table compares the main regressions ROA DiD estimates under alternative clustering schemes (firm and industry).

Table 14: ICR (asinh): Baseline vs Alternative Clustering

	Baseline	**Firm–clustered**	**Industry–clustered**
Variables			
Log(Assets)	0.558** (0.108)	0.558*** (0.110)	0.558*** (0.116)
HighEI × 2022	−0.133 (0.117)	−0.133 (0.236)	−0.133 (0.309)
HighEI × Post2023	−0.303 (0.188)	−0.303 (0.225)	−0.303* (0.142)
Fixed effects			
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
S.E.: Clustered by	firm & year	firm	industry
Observations	9,750	9,750	9,750
R^2	0.619	0.619	0.619
Within R^2	0.009	0.009	0.009

$^{\cdot}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: This table serves as robustness check for Model 1 and the results in Table 7. The table compares the main regressions ICR DiD estimates under alternative clustering schemes (firm and industry).

Table 15: Model 1: Manufacturing Sample

	ROA	**ICR (asinh)**
Variables		
log(Assets)	0.031* (0.011)	0.716* (0.265)
HighEI × 2022	−0.008 (0.005)	−0.031 (0.138)
HighEI × Post2023	−0.019· (0.008)	−0.282 (0.202)
Fixed effects		
Firm	Yes	Yes
Year	Yes	Yes
S.E.: Clustered by	firm & year	firm & year
Observations	3,294	3,294
R^2	0.601	0.572
Within R^2	0.011	0.008

$\cdot$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: This table serves as robustness check for Model 1 and the results in Table 7. The table presents regression results when estimating the main regression within the manufacturing subsample.

Table 16: ICR Specifications: asinh vs. log1p

	asinh(ICR)	**log1p(ICR)**
Variables		
log(Assets)	0.558** (0.108)	0.098 (0.101)
HighEI × 2022	−0.133 (0.117)	0.094 (0.088)
HighEI × Post2023	−0.303 (0.188)	0.098 (0.142)
Fixed effects		
Firm	Yes	Yes
Year	Yes	Yes
S.E.: Clustered by	firm & year	firm & year
Observations	9,750	8,036
R^2	0.619	0.740
Within R^2	0.009	0.001

Note: Observations lost because log1p requires positive values.

$^{\cdot}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: This table serves as robustness check for Model 1 and the results in Table 7. This table compares ICR DiD estimates using asinh(ICR) and log1p(ICR) transformations, to understand whether the main solvency results are sensitive to the functional form.

A.2.3 H3a and H3b Robustness

Table 17: Model 2a: Leverage as a Continuous Variable (Within HighEI Sample)

	ROA	**ICR (asinh)**
Variables		
log(Assets)	0.091 (0.038)	0.756 (0.524)
Leverage × 2022	0.019* (0.006)	0.356* (0.130)
Leverage × Post2023	0.029* (0.009)	0.427$^{\cdot}$ (0.182)
Fixed effects		
Firm	Yes	Yes
Year	Yes	Yes
S.E.: Clustered by	firm & year	firm & year
Observations	576	576
R^2	0.541	0.530
Within R^2	0.054	0.015

$^{\cdot}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: This table serves as robustness check for Model 2a and the results in Table 8. The table presents estimates where leverage is a continuous variable within the HighEI sample, instead of the HighLeverage dummy.

Table 18: Model 2a (ROA): Leverage Moderation Main Regression (HighEI Sample) in Comparison to All Manufacturing Sample and Full Sample

	HighEI	**Manufacturing**	**DDD (all firms)**
Variables			
log(Assets)	0.086 (0.040)	0.032* (0.011)	0.017· (0.007)
HighLeverage × 2022	0.023* (0.008)	0.005 (0.006)	0.014* (0.004)
HighLeverage × Post2023	0.037· (0.015)	0.009 (0.007)	0.014* (0.004)
HighEI × 2022	—	−0.016* (0.006)	−0.015* (0.006)
Post2023 × HighEI	—	−0.032* (0.010)	−0.030* (0.010)
HighLev × HighEI × 2022	—	0.017· (0.007)	0.009 (0.007)
HighLev × Post2023 × HighEI	—	0.028 (0.015)	0.023 (0.015)
Fixed effects			
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
S.E.: Clustered by	firm & year	firm & year	firm & year
Observations	576	3,294	9,750
R^2	0.536	0.602	0.626
Within R^2	0.044	0.015	0.009

$^{\cdot}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: This table serves as robustness check for Model 2a and the results in Table 8. The table compares ROA leverage moderation DiD estimates across the HighEI sample (main specification), the manufacturing sample and the full sample using a triple-difference (DDD) specification.

Table 19: Model 2a (ICR): Leverage Moderation Main Regression (HighEI Sample) in Comparison to All Manufacturing Sample and Full Sample

	HighEI	**Manufacturing**	**DDD (all firms)**
Variables			
log(Assets)	0.688 (0.554)	0.698* (0.268)	0.561**(0.109)
HighLeverage × 2022	0.624* (0.233)	−0.018 (0.188)	0.122 (0.080)
HighLeverage × Post2023	0.656 (0.370)	−0.237 (0.213)	0.022 (0.101)
HighEI × 2022	—	−0.333 (0.193)	−0.364$^{\cdot}$ (0.176)
Post2023 × HighEI	—	0.700$^{\cdot}$ (0.305)	−0.599$^{\cdot}$ (0.268)
HighLev × HighEI × 2022	—	0.641$^{\cdot}$ (0.251)	0.501$^{\cdot}$ (0.223)
HighLev × Post2023 × HighEI	—	0.893$^{\cdot}$ (0.390)	0.633 (0.357)
Fixed effects			
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
S.E.: Clustered by	firm & year	firm & year	firm & year
Observations	576	3,294	9,750
R^2	0.529	0.573	0.620
Within R^2	0.013	0.011	0.010

$^{\cdot}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: This table serves as robustness check for Model 2a and the results in Table 8. The table compares ICR leverage moderation DiD estimates across the HighEI sample (main specification), the manufacturing sample and the full sample using a triple-difference (DDD) specification.

Table 20: Model 2b: ESG as a Continuous Variable (Within HighEI Sample)

	ROA	**ICR (asinh)**
Variables		
log(Assets)	0.068 (0.050)	4.134 (2.677)
ESG × 2022	0.001 (0.012)	0.293 (0.530)
ESG × Post2023	0.003 (0.011)	0.208 (0.497)
Fixed effects		
Firm	Yes	Yes
Year	Yes	Yes
S.E.: Clustered by	firm & year	firm & year
Observations	102	102
R^2	0.461	0.603
Within R^2	0.016	0.085

$^{\cdot}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: This table serves as robustness check for Model 2b and the results in Table 9. The table presents estimates where ESG is a continuous variable within the HighEI sample, instead of the HighESG dummy.

Table 21: Model 2b (ROA): ESG Moderation Main Regression (HighEI) in Comparison to Manufacturing Sample and Full Sample

	HighEI	**Manufacturing**	**All firms**
Variables			
log(Assets)	0.067 (0.048)	0.037 (0.021)	0.031 (0.019)
HighESG × 2022	0.040 (0.021)	−0.006 (0.002)	−0.001 (0.005)
HighESG × Post2023	0.011 (0.012)	−0.004 (0.018)	−0.001 (0.008)
HighEI × 2022	—	−0.024 (0.022)	−0.015 (0.022)
Post2023 × HighEI	—	−0.025 (0.021)	−0.021 (0.017)
HighESG × HighEI × 2022	—	0.045$^{\cdot}$ (0.021)	0.040 (0.021)
HighESG × Post2023 × HighEI	—	0.013 (0.013)	0.009 (0.012)
Fixed effects			
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
S.E.: Clustered by	firm & year	firm & year	firm & year
Observations	102	666	1,170
R^2	0.471	0.522	0.552
Within R^2	0.034	0.022	0.016

$^{\cdot}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: This table serves as robustness check for Model 2b and the results in Table 9. The table compares ROA ESG moderation DiD estimates across the HighEI sample (main specification), the manufacturing sample and the full sample using a triple-difference (DDD) specification.

Table 22: Model 2b (ICR): ESG Moderation Main Regression (HighEI) in Comparison to Manufacturing Sample and Full Sample

	HighEI	**Manufacturing**	**All firms**
Variables			
log(Assets)	4.124 (2.549)	1.208 (0.535)	0.787 (0.445)
HighESG × 2022	1.285 (0.925)	0.084 (0.228)	0.029 (0.157)
HighESG × Post2023	0.734 (0.785)	0.049 (0.341)	0.273 (0.226)
HighEI × 2022	—	−0.616 (1.033)	−0.388 (1.044)
Post2023 × HighEI	—	−0.918 (0.893)	−0.771 (0.881)
HighESG × HighEI × 2022	—	1.143 (0.166)	1.189 (0.051)
HighESG × Post2023 × HighEI	—	0.503 (0.889)	0.253 (0.877)
Fixed effects			
Firm	Yes	Yes	Yes
Year	Yes	Yes	Yes
S.E.: Clustered by	firm & year	firm & year	firm & year
Observations	102	666	1,170
R^2	0.613	0.575	0.577
Within R^2	0.108	0.028	0.019

$^{\cdot}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: This table serves as robustness check for Model 2b and the results in Table 9. The table compares ICR ESG moderation DiD estimates across the HighEI sample (main specification), the manufacturing sample and the full sample using a triple-difference (DDD) specification.

Table 23: Model 2b: Environmental Pillar Only (Within HighEI Sample)

	ROA	**ICR (asinh)**
Variables		
log(Assets)	0.067 (0.048)	4.124 (2.549)
HighEnv × 2022	0.040 (0.021)	1.285 (0.925)
HighEnv × Post2023	0.011 (0.012)	0.734 (0.785)
Fixed effects		
Firm	Yes	Yes
Year	Yes	Yes
S.E.: Clustered by	firm & year	firm & year
Observations	102	102
R^2	0.471	0.613
Within R^2	0.034	0.108

$^{\cdot}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Note: This table serves as robustness check for Model 2b and the results in Table 9. The table presents the results when estimating using the environmental pillar score only instead of full ESG score.

A.3 AI

In line with SSE's guidelines on the use of generative AI, we used ChatGPT as a support tool during the thesis production. First, we used ChatGPT to check the logic of our R code. When we did this, we realised that ChatGPT sometimes produced inconsistent or infeasible suggestions, thus we did not copy proposed code directly. Rather, we treated the outputs as ideas and adapted our scripts where appropriate and needed, while always verifying the code and results ourselves. Second, we used ChatGPT for language support, such as asking for suggestions to check grammar or improve clarity, flow and structure in some selected sentences. Here too, a key risk with AI is that outcomes sometimes mask or lose intended meaning or analytical depth; therefore, we made sure to always critically analyse the output and use it more as inspiration rather than transfer outputs directly.