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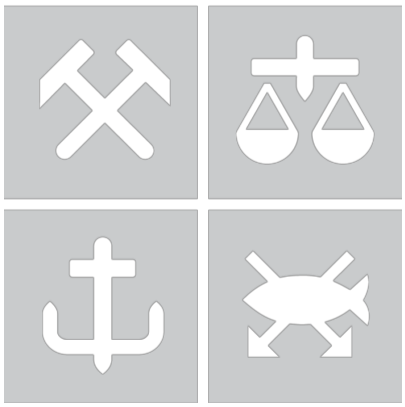
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Activist Short Selling and its Impact on Stock Prices

An event study analysis of market reactions to Hindenburg Research reports

Term paper on the course trading and market microstructure (FIN11)

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Abstract

This paper investigates how activist short seller reports influence stock prices, using Hindenburg Research as a representative case. Motivated by the growing prominence of short seller activism and its controversial role in financial markets, the study examines whether and how such reports generate systematic market reactions.

Employing an event study framework, we analyse all Hindenburg Research publications between 2021 and 2025 to measure abnormal stock returns around report release dates. The methodology combines market-model-based return estimation with statistical tests of significance, complemented by robustness checks using bootstrap resampling and leave-one-out analysis. By integrating these approaches, the paper provides empirical insights into the short-term price adjustments triggered by activist short selling and contributes to the broader understanding of how information shocks from financial activism shape market efficiency.

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Table of Abbreviations

AAR	Average Abnormal Return
AR	Abnormal Return
BN	Billion
CAAR	Cumulative Average Abnormal Return
CAR	Cumulative Abnormal Return
COVID-19	Coronavirus Pandemic 2019
ETF	Exchange Traded Fund
EU	European Union
LOO	Leave-One-Out
MAR	Market Abuse Regulation
OLS	Ordinary Least Squares
SEBI	Securities and Exchange Board of India
SEC	Securities and Exchange Commission
SSR	Short Selling Regulation
USD	US-Dollar

1. Introduction

Activist short selling has become an increasingly visible and controversial force in modern financial markets. In recent years, specialized research firms have attracted attention by publishing detailed reports that allege fraud and misrepresentation or argue that certain publicly listed firms are severely overvalued. These reports are often followed by sharp stock price declines as investors reassess the credibility and financial soundness of the targeted firms. Hindenburg Research has been one of the most influential players in this field, with its reports repeatedly triggering significant market reactions and widespread media coverage.

While such events frequently dominate financial headlines, systematic academic analysis of their market impact remains limited. Previous studies have shown that short sellers contribute to price efficiency and information discovery, yet few have isolated the direct and measurable effects of individual short seller reports on stock prices.

This paper addresses this gap by analysing how markets respond to Hindenburg Research reports published between 2021 and 2025. The guiding research question is: *How do financial markets absorb and reprice the information released by Hindenburg Research's activist short-seller reports, and what short- and medium-term effects does this have on equity prices?*

To answer this question, the study applies a classical event study framework to measure abnormal stock returns surrounding the publication of each report. Expected returns are estimated using the market model, and abnormal as well as cumulative abnormal returns (CAR) are calculated for different event windows to capture both immediate and delayed effects. Complementary regression analyses examine whether company characteristics, such as market capitalization, volatility, or industry affiliation, influence the magnitude of the reaction. Robustness is ensured through bootstrap resampling and leave-one-out analysis.

The remainder of this paper is structured as follows. Section 2 provides background information on Hindenburg Research, its operating model, and the concept of short selling activism. Section 3 outlines the theoretical foundations related to market

efficiency and information shocks, forming the basis for the study's hypotheses. Section 4 presents the empirical analysis, including methodology, results, and robustness checks. Section 5 interprets the findings in the context of financial theory and discusses policy implications, while Section 6 concludes with a summary and suggestions for future research. Through this structure, the paper provides a comprehensive empirical assessment of how financial markets absorb information released by activist short sellers and what this reveals about the efficiency and responsiveness of modern equity markets.

2. Hindenburg Research

2.1 Organizational profile of Hindenburg Research

Hindenburg Research LLC is a small, privately held investigative research firm headquartered in New York City. It describes itself as a forensic financial research firm and does not present itself as an asset manager or hedge fund, nor does it disclose assets under management in any public filings or on its website (Hindenburg Research, n.d.-b). It instead conducts forensic research and selectively takes short positions around the publication of its reports. Public information suggests that the firm operates with a small core team, reportedly consisting of eleven employees, complemented by external specialists on a project basis (Hindenburg Research, 2025). This organisational profile is central to understanding Hindenburg's role in the market, as its impact stems from information generation and reputation rather than financial scale. Hindenburg structures its short exposure on a case-by-case basis. In specific cases, such as the Adani report, Hindenburg has disclosed the use of synthetic short exposure through offshore counterparties and derivative instruments (Hindenburg Research, 2023). In other situations, where direct stock borrowing is feasible, conventional short sales appear possible. Beyond these isolated disclosures, the firm does not publicly reveal the timing or structure of its positions.

2.2 Activist short selling

In accordance with Bradshaw's (2025) definition, activist short selling can be described as the conversion of insights concerning potential instances of misconduct or overvaluation, which have been generated in private, into information which is subsequently made available to a general audience. The process is illustrated as follows.

Firstly, activist short sellers engage in intensive information production. Financial statements, regulatory filings, legal documents and industry data are analysed, and in some cases interviews or alternative data are used to supplement this analysis. Although a significant proportion of this material is accessible to the public, it is dispersed and analytically costly (Bradshaw, 2025). Activist short selling involves

combining these fragments into a coherent thesis, focusing on accounting inconsistencies, aggressive valuation assumptions or governance weaknesses.

Secondly, these findings are consolidated and published in the form of a public report. The report generally presents concrete allegations, supporting evidence and an explicit valuation conclusion, accompanied by the disclosure that the author holds a short position. The act of publication can be regarded as a discrete information event, representing the distribution of material that was previously accessible only to a limited group of informed analysts, to a more extensive audience comprising investors, media outlets, and regulators. Algorithms and professional traders frequently initiate immediate algorithmic and institutional trading responses, while other market participants, mainly retail investors, respond after the report is disseminated and discussed.

In this regard, activist short selling mitigates information asymmetries by converting costly, partially untransparent information into a more accessible format. Established activist short selling firms benefit from reputation effects and extensive media amplification, which magnify the speed and magnitude of the effect on the market.

Short selling is a prominent feature of most developed capital markets. However, it is subject to a defined regulatory framework, which is designed to balance market efficiency with protection against abuse. Consequently, activist short sellers such as Hindenburg Research are obligated to adhere to not only the general securities regulations, but also the specific regulations concerning disclosure and market manipulation.

2.3 Regulatory framework for activist short selling

In the United States, the primary legal foundation for securities is the Securities Exchange Act of 1934, along with the regulatory framework established by the U.S. Securities and Exchange Commission (SEC) (U.S. Securities and Exchange Commission, 2013). Regulation SHO specifies requirements for the practice of short selling (Regulation SHO - Regulation of Short Sales, 2025), while Rule 10b-5 prohibits fraudulent and misleading statements in connection with securities transactions (U.S. Securities and Exchange Commission, 2022). Activist short sellers

are at liberty to publish critical research and to profit from resulting price declines, provided that their statements are not knowingly false or materially misleading. In the case of reports being based on knowingly false information, this constitutes illegal market manipulation.

In the European Union, the Short Selling Regulation requires notification of net short positions exceeding 0.2% of a company's issued share capital and public disclosure once a threshold of 0.5% is crossed (Short Selling Regulation, n.d.). The Market Abuse Regulation (MAR; Regulation (EU) No 596/2014, 2014) prohibits the dissemination of information that gives false or misleading signals about financial instruments, a point also emphasised in Bergt (2023). Comparable regulatory regimes exist in other major jurisdictions.

2.4 The Adani case as an illustrative example

The report by Hindenburg Research concerning the Indian conglomerate Adani Group provides a clear illustration of these mechanisms. On 24 January 2023, Hindenburg Research published a report accusing Adani of manipulating its stock price, utilising concealed offshore entities to obscure its network, and engaging in deficient transparency and governance practices (Hindenburg Research, 2023). The report was published after Hindenburg had established short exposure to “Adani Group Companies through US-traded bonds and non-Indian-traded derivative instruments” (Hindenburg Research, 2023), rather than through conventional borrowed-share shorting.

The market reaction was both immediate and unusually severe. Within nine days of the report's release, the combined market capitalisation of Adani's listed entities had fallen by more than one hundred billion US dollars (Ahmed, 2023). Adani Enterprises witnessed a 27% decline in value within a single trading day, while several other group companies recorded daily losses exceeding 10%. Concurrently, rating agencies and international financial institutions conducted a reassessment of their risk exposure to the conglomerate, and index providers initiated a review of the inclusion of Adani securities.

The Adani Group strongly rejected the allegations, framing them as an attack on both the company and the Indian economy. Indian regulators did not validate Hindenburg's accusations of stock-price manipulation, but they began examining Adani's disclosure practices, ownership structures, and related-party arrangements shortly after the report's release. A Reuters report from 13 February 2023 documented that the Securities and Exchange Board of India (SEBI) confirmed it was enquiring into both the allegations raised in the Hindenburg report and the trading activity immediately preceding and following its publication, including potential irregularities around the sharp price movements (Chaturvedi et al., 2023). This case exemplifies the informational and regulatory complexities inherent in high-profile activist short-selling episodes.

3. Theoretical background: market efficiency

3.1 Market efficiency and information processing

The Efficient Market Hypothesis (EMH), as proposed by Fama (1970), states that market prices fully and correctly reflect all available information, implying that publicly known information cannot be used to systematically outperform the market. Among its three forms, the semi-strong form is of central relevance here, as it predicts immediate price adjustments following public disclosures such as activist short seller reports. This view is consistent with prior research emphasising that the speed of information incorporation is a key indicator of market quality (Easley & O'Hara, 1992; Fama, 1970; Harris, 2003).

Information affects prices through two mechanisms: its relevance for valuation and the rapidity with which market participants act upon it (Harris, 2003, p. 235). Empirical evidence shows that institutional investors, professional traders, and algorithmic systems typically respond almost instantly to new information, driving prices toward their new equilibrium (Easley & O'Hara, 1992). Arbitrageurs further accelerate this adjustment by exploiting short-lived mispricing (Harris, 2003, p. 347). The speed of information incorporation is thus not only theoretically crucial but also an explicit object of measurement in this study, which tracks abnormal returns in narrow event windows to assess how rapidly markets react to short seller disclosures.

3.2 Implications for this study

The previously mentioned theory has a clear implication for what is to be expected in this study. When activist short sellers publish new findings that include detailed evidence or concerns about possible overvaluation, markets are expected to react quickly and adjust prices to the new information. Assuming the validity of this assumption, short seller reports can be regarded as informative events that should prompt an immediate negative price reaction, as the market adjusts its perception of the firm's value.

The previously discussed theoretical considerations directly translate into empirically testable expectations for this study. Since activist short seller reports publicly disclose value-relevant information, theory predicts that markets should react swiftly and adjust prices almost immediately after publication. If the semi-strong form of market efficiency holds, such reports function as discrete information shocks that trigger an abrupt reassessment of firm value.

Against this background, the following hypotheses are proposed:

H1: *The publication of Hindenburg Research reports causes an immediate and significant negative market reaction, especially reflected in a strongly negative* CAR *in the event window* $[0; +1]$.

H2: *Most of the price adjustment occurs on the publication day itself, meaning that the AAR on day 0 should exhibit the strongest decline, with only minimal drift in the days immediately following the report.*

4. Data analysis

To address the research question, this study employs a standard event study framework to empirically quantify the market reaction to short seller reports published by Hindenburg Research. In addition to testing the central hypotheses concerning the immediate price impact, the analysis also incorporates supplementary tests examining whether firm characteristics or medium-term return dynamics influence the magnitude or persistence of the event-day reaction.

4.1 Methodology

The analysis includes all firms that were the subject of at least one report published on Hindenburg Research's official website between 2021 and 2025, resulting in a final sample of 31 companies. Earlier cases were deliberately excluded to avoid distortions caused by the exceptional volatility during the COVID-19 pandemic, which could compromise comparability. Likewise, firms targeted by multiple Hindenburg reports in close temporal proximity were omitted to prevent event overlap and ensure clean identification.

The event window defines the time span around each publication and serves as the central observation period of the study. A broad window of $[-4; +4]$ trading days around the event captures potential anticipatory and delayed reactions, while a narrower specification of $[0; +1]$ focuses on the immediate market response and forms the core of the analysis. Expected returns are estimated within an estimation window of 120 trading days prior to the event, excluding the last two days before publication to mitigate potential information leakage.

Expected returns are computed using the market model, which expresses the daily stock return as a linear function of the overall market return:

$$R_{i,t} = \alpha_i + \beta_i \cdot R_{M,t} + \varepsilon_{i,t}$$

Here, $R_{i,t}$ denotes the return of stock i at day t, $R_{M,t}$ the return of the corresponding market index, either the Nasdaq Composite or Russell 2000, depending on firm size, while α_i and β_i represent the intercept and market sensitivity, respectively.

Parameters are estimated via ordinary least squares (OLS) regression over the estimation period.

Abnormal returns ($AR_{i,t}$) represent deviations between observed and model-predicted returns:

$$AR_{i,t} = R_{i,t} - \widehat{R_{i,t}}$$

Cumulative abnormal returns ($CAR_{i,[\tau_1,\tau_2]}$) are obtained by summing abnormal returns over the defined time interval:

$$CAR_{i,[\tau_1,\tau_2]} = \sum_{t=\tau_1}^{\tau_2} AR_{i,t}$$

Firm-level CARs are subsequently aggregated into average CARs ($CAAR$) to capture the overall market effect. To assess statistical significance, one-sample t-tests are applied to mean CARs. Furthermore, cross-sectional regressions are conducted to examine whether firm-specific factors such as market capitalization or pre-event volatility influence the magnitude of the reaction.

All computations were carried out using R for statistical testing and visualization, and Microsoft Excel for data preprocessing. Historical daily price data were sourced from Investing.com, while the exact event dates were manually verified using the official publications at Hindenburgresearch.com.

4.2 Results

The explanatory power of the market model varies substantially across the firms in the sample. The R^2 values from the 120-day estimation window range from 0.03 to 0.69, with a median of 0.14. This dispersion is expected given that many companies in the dataset are small-cap, highly volatile, or operate in speculative growth sectors, such that their returns are only loosely tied to broad market movements. The estimated betas reflect this heterogeneity as well, ranging from 0.17 to 2.70. Importantly, such variation does not invalidate the use of the market model in short-horizon event studies. If α and β are estimated over a sufficiently long and stable pre-

event window, the market model produces unbiased and reliable abnormal returns, even when explanatory power is low (MacKinlay, 1997). This is consistent with the broader empirical literature, which emphasises that for short event windows, model misspecification tends to have minimal impact on inference (Kothari & Warner, 2006). Moreover, more than 90% of firms in the sample exceed an R^2 of 0.05, and roughly two-thirds exceed 0.10, indicating a systematic, though heterogeneous, relationship to market movements. Given the limited trading history of several firms and the short event window, more complex multifactor models would introduce unnecessary estimation noise. The market model therefore remains the most appropriate and robust benchmark for this analysis.

Firm	MarketCap	Event Date	Beta	R^2
Carvana	25.15	01/02/2025	1.05	0.14
Sezzle	1.76	12/18/2024	2.08	0.11
PACS Group	6.66	11/04/2024	1.05	0.26
Roblox	27.18	10/08/2024	1.02	0.15
iLearning Engines	0.82	08/29/2024	2.41	0.06
Super Micro Computer	12.35	08/27/2024	2.58	0.31
Axos Financial	2.83	06/04/2024	1.14	0.42
Equinix	59.62	03/20/2024	0.66	0.21
LPP	7.63	03/15/2024	1.04	0.33
Temenos	6.78	02/15/2024	1.25	0.18
LifeStance Health	2.24	02/01/2024	1.22	0.17
EHang	0.87	11/07/2023	2.70	0.28
Freedom Holding	4.41	08/15/2023	0.44	0.09
Icahn Enterprises	6.84	05/02/2023	0.17	0.09
Block	41.42	03/23/2023	2.06	0.69
Welltower	45.06	12/07/2022	0.73	0.31
Establishment Labs	0.84	10/19/2022	1.58	0.53
Ebix	0.76	06/16/2022	1.50	0.31
LunaiBioworks	0.2	06/01/2022	0.89	0.04
Singularity Future	0.09	05/05/2022	1.74	0.08
Bollinger Innovations	0.36	05/04/2022	1.53	0.03
Natera	5.18	03/08/2022	1.56	0.42
Standard Lithium	1.06	02/03/2022	1.67	0.09
Tecnoglass	1.34	12/09/2021	1.32	0.12
DraftKings	17.7	06/15/2021	1.23	0.17
Humbl	5.60	05/20/2021	3.99	0.07
Purecycle Technologie	2.52	05/06/2021	1.48	0.13
Ebang International	0.92	04/06/2021	1.94	0.07
Lordstown Motors	0.17	03/12/2021	1.69	0.10
Ormat Technologies	3.93	03/01/2021	0.47	0.09
Clover Health	4.66	02/02/2021	0.51	0.04

Table 1: Overview of companies evaluated with Market Cap (in bn USD), Event Date, Beta Values and R^2

4.2.1 General effect

To capture the market's immediate reaction to Hindenburg Research publications, the analysis first examines the cumulative abnormal returns (CAR) within the $[0; +1]$ event window. This measure reflects how strongly stock prices respond to newly released information within one trading day after the report's publication. Individual $CAR_{[0;+1]}$ values were computed for each company and compiled for statistical evaluation. The results reveal a pronounced heterogeneity in price responses: CARs range from -95.82% to $+0.82\%$, with the overwhelming majority displaying sharp negative reactions (see Figure 1). Only three firms show slightly positive returns below one percent during the event window. The broad range of outcomes suggests substantial cross-sectional variation in how investors process and react to the reports, yet the overall pattern points toward a clearly downward bias. A one-sample t-test was conducted to assess the statistical relevance of these reactions. The test indicates that 16 of the 31 $CAR_{[0;+1]}$ values are significantly different from zero at the 5% level, implying that the observed market movements are unlikely to be random. This finding provides robust evidence that Hindenburg's short seller reports systematically trigger negative price responses across a large portion of the sample.

Firm	$CAR_{[0;+0]}$	$CAR_{[0;+1]}$	$t\ value$	$Significance$
Carvana	-2.05%	-16.13%	-3.40	0.05
Sezzle	3.04%	2.28%	1.19	–
PACS Group	-33.31%	-40.47%	-12.45	0.01
Roblox	-3.62%	-1.25%	-0.29	–
iLearning	-74.36%	-82.79%	-4.98	0.01
Super Micro	-2.37%	-19.80%	-3.05	0.05
Axos Financial	-2.86%	-1.72%	-0.73	–
Equinix	-3.23%	-5.02%	-2.75	0.05
LPP	-41.61%	-22.95%	-8.68	0.01
Temenos	-0.32%	-0.54%	-2.48	0.05
LifeStance	0.04%	-0.01%	-0.03	–
EHang	-16.08%	-9.50%	-1.49	–
Freedom	-2.73%	-0.54%	-3.39	0.05
Icahn	-21.99%	-43.28%	-37.38	0.01
Block	-18.21%	-20.90%	-6.13	0.01
Welltower	-4.53%	-3.86%	-1.67	0.1
Establishment	-6.92%	-4.94%	-1.26	–
Ebix	-41.20%	-30.48%	-4.46	0.05
LunaiBioworks	-32.36%	-34.94%	-3.43	0.05
Singularity	-25.97%	-36.72%	-2.40	0.05
Bollinger	0.34%	-9.11%	-0.46	–

Natera	5.01%	−39.79%	−10.35	0.01
Standard	−25.42%	−11.04%	−1.13	–
Tecnoglass	−42.71%	−58.37%	−13.03	0.01
DraftKings	−3.28%	−2.28%	−0.46	–
Humbl	−20.94%	−11.43%	−0.44	–
Purecycle	−51.73%	−51.30%	−7.67	0.01
Ebang	−13.42%	−15.17%	−1.14	–
Lordstown	−16.37%	−8.12%	−0.81	–
Ormat	−2.96%	−4.57%	−1.05	–
Clover Health	0.20%	−0.09%	−0.02	–

Table 2: Overview of the $CAR_{[0;+0]}$ and $CAR_{[0;+1]}$-values and their significance

Beyond the firm-level perspective, an aggregate analysis of the cumulative abnormal returns (CAR) was conducted to assess whether the market reaction exhibits a consistent pattern across the entire sample. By averaging the individual $CAR_{[0;+1]}$ values, a measure of the collective short-term effect, the cumulative average abnormal return ($CAAR$), is obtained.

The results reveal a pronounced and statistically significant decline in stock prices following the release of Hindenburg Research reports. The average $CAAR$ amounts to -18.87%, with a t-value of -5.07 and a p-value below 0.01, indicating a highly significant deviation from zero. This provides robust empirical evidence of a systematic short-term downward adjustment in stock valuations triggered by Hindenburg's publications.

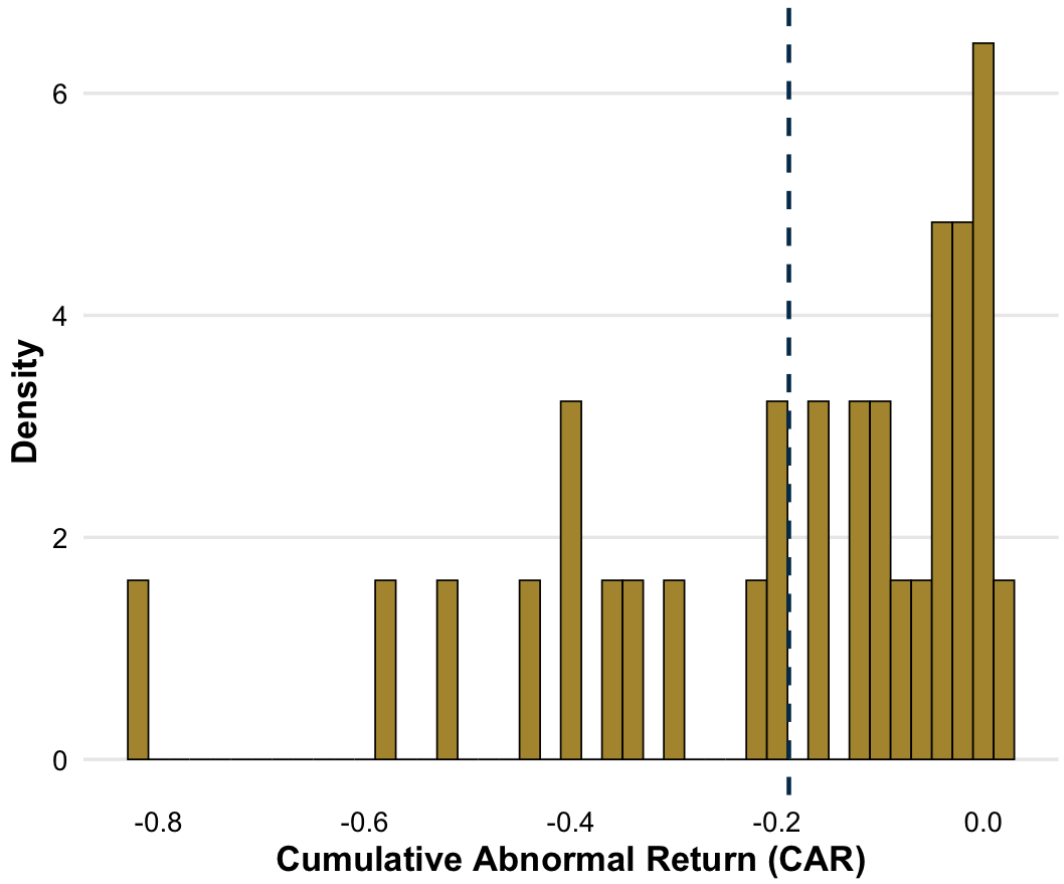


Figure 1: Distribution of $CAR_{[0;+1]}$-values

4.2.2 Time frame and advance information

A key finding of the analysis concerns the timing and intensity of the market's response to Hindenburg Research reports. Figure 3 illustrates the average abnormal returns (AAR) over a window from four trading days before to four days after the publication date. The most pronounced effect occurs on the event day (day 0), when share prices drop by an average of -16.19%. This sharp decline represents the central information shock of the event and is clearly visible in the time series as an abrupt and substantial downward spike.

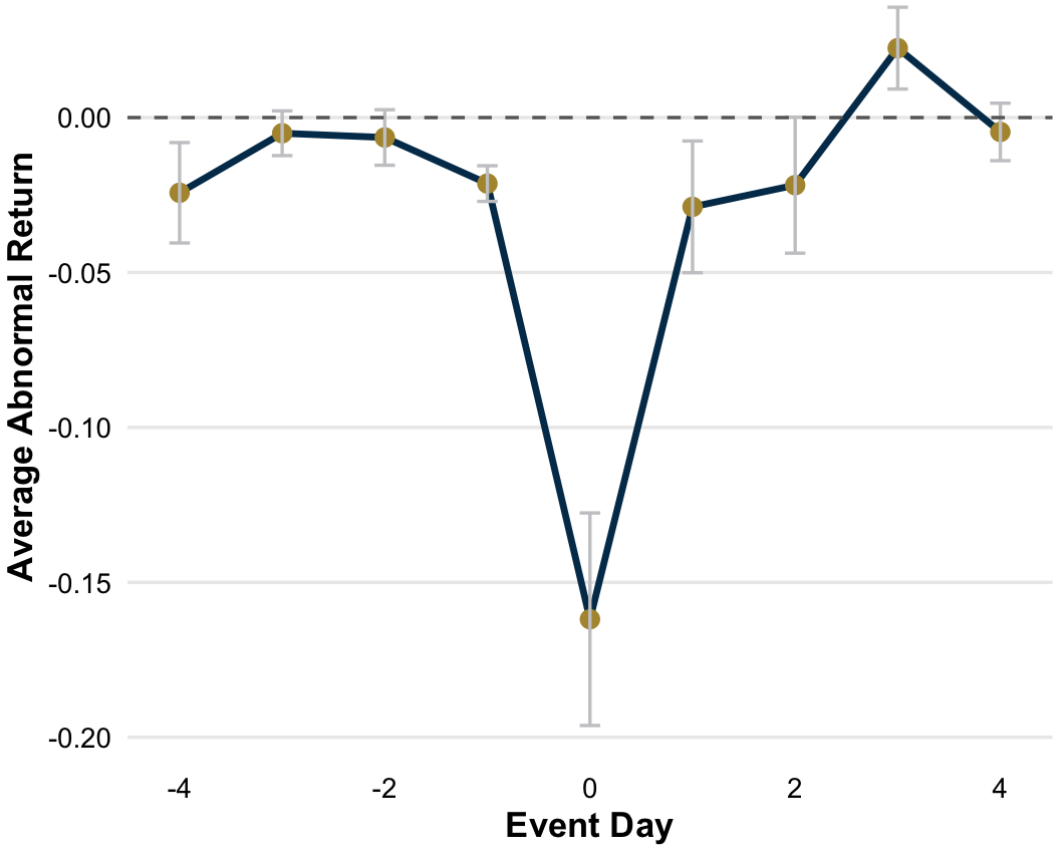


Figure 2: Daily AAR-values in period [-4; +4]

In the two following days returns remain negative (-2.88% and -2.18%, respectively), indicating a continuation of selling pressure immediately after publication. A modest rebound follows on day $+3$ ($+2.24\%$), but the brief recovery quickly fades as prices fall again on day $+4$ (-0.46%). Overall, the pattern suggests that markets incorporate the new information rapidly and almost completely on the day of release, with only mild post-event adjustments.

Interestingly, the data also hint at pre-event movements, implying that some investors may have acted on advance information, market rumours, or speculation prior to publication. Day -1 stands out with an average return of -2.13%, a figure nearly identical to day $+1$ and statistically significant at the 5% level. A further negative deviation of -2.43% appears on day -4; however, this observation is driven by a single extreme outlier (-47.22%). Excluding this case, the mean deviation drops to only -0.09%, eliminating statistical significance. These findings suggest that

leakage or anticipatory trading cannot be ruled out entirely, although such effects appear limited to isolated cases rather than a systematic pattern.

4.2.3 Regression analysis of determinants of market reaction

To explore potential determinants of the market reaction to short seller reports, a multiple linear regression analysis was conducted. The dependent variable is the cumulative abnormal return (CAR) within the event window [0; +1], while the explanatory variables include the logarithm of market capitalisation ($MarketCap$), the pre-event standard deviation of returns (sd), and a binary industry dummy (ind) distinguishing industrial (0) from service firms (1). The regression model is specified as follows:

$$CAR_n = \alpha + \beta_1 \cdot MarketCap_n + \beta_2 \cdot sd_n + \beta_3 \cdot ind_n + \varepsilon_n$$

The estimation results reveal that none of the coefficients are statistically significant. Market capitalisation exhibits a positive but insignificant association with abnormal returns ($\beta = 0.0280$; $p = 0.305$), while both the standard deviation ($\beta = -0.413$; $p = 0.714$) and the industry dummy ($\beta = -0.0202$; $p = 0.825$) show weak negative signs. The explanatory power of the model is low, with an R^2 of 0.07, indicating that only a small portion of the cross-sectional variation in CARs can be explained by these variables.

The graphical analysis supports these findings. Scatter plots reveal no systematic pattern between CARs and the tested firm characteristics. Although the regression lines show slight upward or downward slopes, they remain within broad confidence intervals, suggesting a high degree of noise. Overall, the evidence implies that firm size, pre-event volatility, and industry classification exert no meaningful influence on the magnitude of price reactions to Hindenburg Research reports.

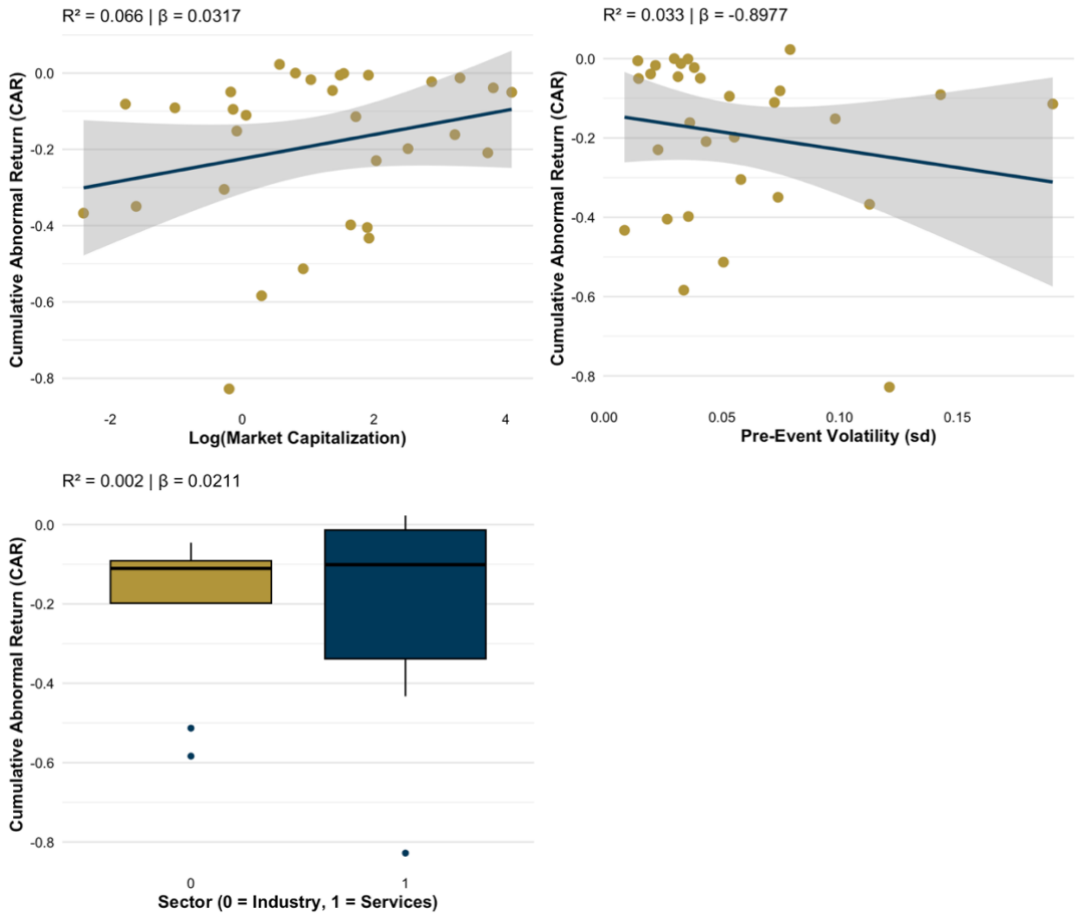


Figure 3: Regression analysis on factors Market Cap, Pre-Event Volatility and Sector

4.2.4 Medium run effect and long-term consequences

To assess whether the effects of Hindenburg Research's reports persist beyond the immediate event window, medium-term $CARs$ were analysed over the interval $[+2, +20]$ trading days. A two-sided t-test on the firm-level $CARs$ yields a mean of -0.13% with $t = -0.4458$ and $p = 0.6589$, indicating no statistically detectable deviation from zero. Using the cumulative window $CAR_{[1;+20]}$ produces the same conclusion, suggesting that cumulative performance the day after the publication and later exhibits no systematic drift.

The descriptive plots reinforce these findings. The boxplot of $CAR_{[1;+20]}$ and $CAR_{[2;+20]}$ shows a tight distribution around zero with a few negative outliers, illustrating that most firms' medium-term returns remain close to their expected benchmarks. Complementing these cross-sectional views, the CAAR curve from event day -5 to $+20$ shows the characteristic sharp decline on the event day

followed by a rapid stabilisation, with no relevant upward or downward trend in the post-event days.

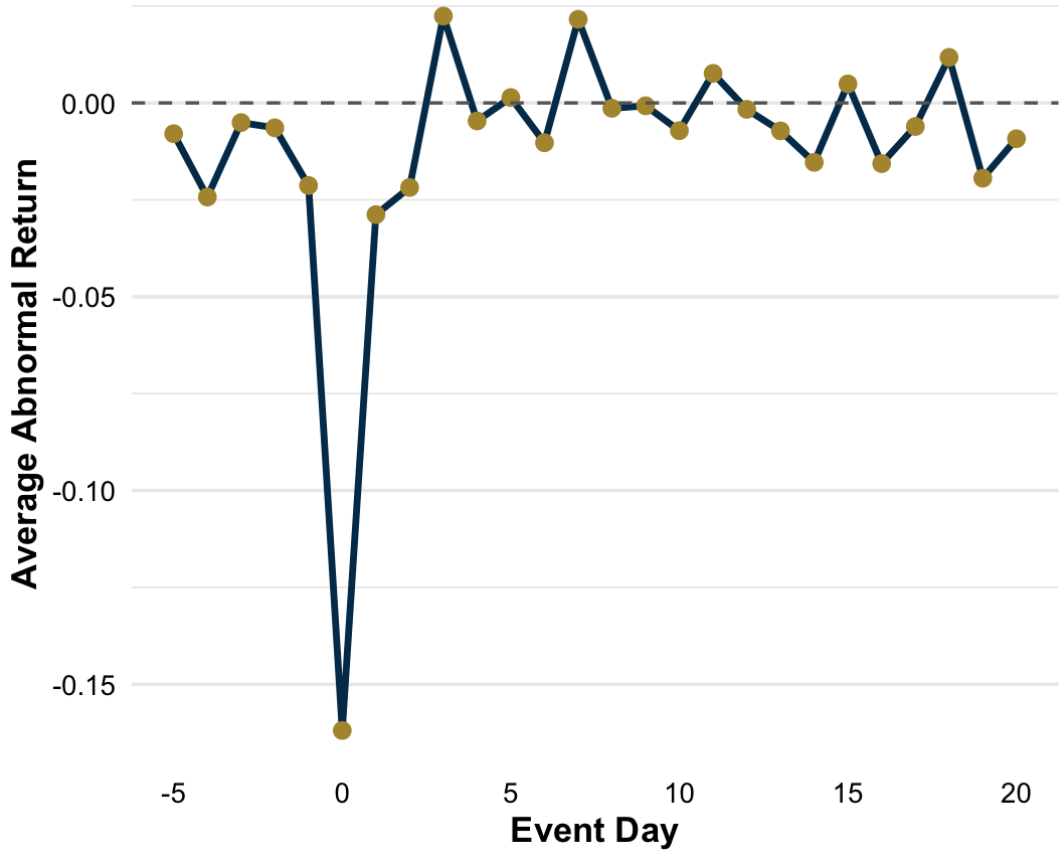


Figure 4: *Daily AAR-values in period [-5; +20]*

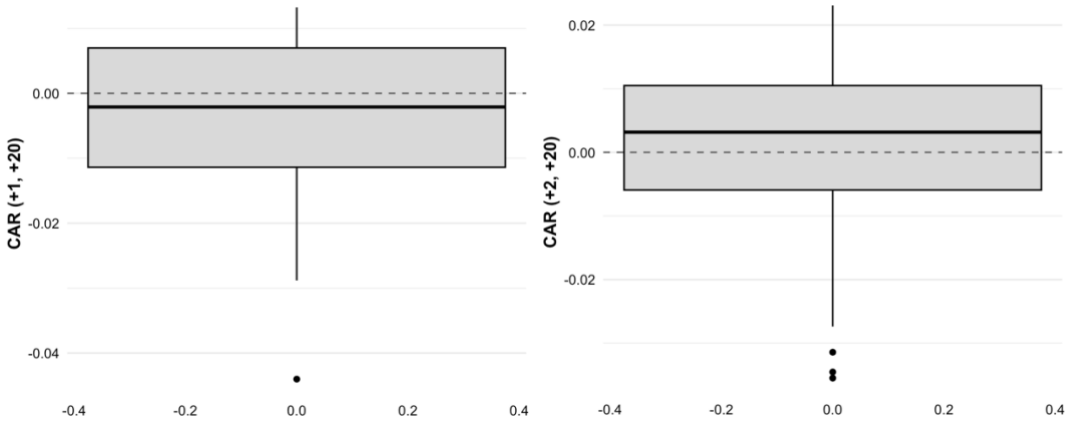


Figure 5: Boxplot Diagrams on $CAR_{[1;+20]}$ and $CAR_{[2;+20]}$

Taken together, the statistical evidence and graphical patterns consistently indicate that the market reaction to Hindenburg's reports is sharp but short-lived: following the initial shock, abnormal returns neither continue to decline nor exhibit a systematic rebound over the subsequent 20 trading days.

A key distinction emerges when comparing average abnormal returns (AAR) with cumulative average abnormal returns (CAAR). While AAR reflects the day-to-day price reaction and can normalise quickly after the event, CAAR aggregates these movements over time and therefore retains the impact of the initial information shock. As a result, even small positive AARs in the days following publication cannot offset the substantial immediate losses.

While roughly one quarter of the firms eventually recover to positive cumulative average abnormal returns, indicating full or even excessive rebound, the majority continue to exhibit persistent price declines over the subsequent two weeks. On average, the cumulative average abnormal return over the extended window $CAAR_{[0;+14]}$ remains distinctly negative at -21.71%, which is statistically significant at the 5% level. The contrast between quickly stabilising AARs and persistently negative CAARs thus illustrates that, despite short-lived rebounds, the overall valuation effect of Hindenburg reports remains strongly negative in the medium term.

To assess potential long-term effects, the analysis compares the average abnormal returns and return volatility of the affected firms over a post-event window $[+20$ to $+120]$ with the corresponding pre-event period. The objective is to determine whether Hindenburg Research's reports induced lasting structural changes in stock price behaviour beyond the immediate reaction observed around the publication date. In other words, the procedure tests for shifts in mean abnormal returns and volatility.

The paired t-tests show no statistically significant differences between pre- and post-event means. Average abnormal returns decrease only marginally from 0.00% to -0.31% ($t = -0.09$; $p = 0.9293$), indicating that the drift of returns after the event is not systematically higher or lower than before. Likewise, the change in volatility is negligible: the average standard deviation drops slightly from 0.0542 to 0.0538 ($t = -0.053$; $p = 0.9578$). These results imply that the return-generating

process stabilises quickly after the event. Importantly, the absence of a mean shift does not imply that prices fully reverse to their pre-event levels. It simply means that, after adjusting to the news, prices do not continue to trend abnormally upward or downward relative to the market.

4.3 Robustness checks

To assess the robustness of the main findings, two complementary tests were conducted in addition to the standard event study framework. First, a bootstrap procedure with $10{,}000$ resampled means of the cumulative average abnormal return ($CAAR$) for the period $[0; +1]$ was applied. This non-parametric approach relaxes the distributional assumptions underlying classical t-tests and provides an empirically grounded confidence interval. The resulting 95% interval, entirely within the negative range $[-0.26; -0.12]$, confirms the statistical robustness and consistency of the observed market reaction.

Second, a leave-one-out (LOO) analysis was employed, sequentially excluding each firm from the sample and recalculating the average $CAAR$. This test evaluates the sensitivity of the results to potential outliers or single influential observations. The findings demonstrate that the average effect remains consistently negative across all iterations, with no substantial variation in the $CAAR$. This consistency strengthens the conclusion that the market reaction to Hindenburg reports represents a generalised and broad-based phenomenon, rather than the result of isolated cases. .

5. Interpretation

5.1 Market reactions in the context of market efficiency and microstructure theory

The hypotheses formulated in Section 3 state, first, that the publication of short seller reports triggers an immediate and significant negative adjustment of share prices (H1) and, second, that the bulk of this adjustment materialises on the event day itself, with only limited subsequent drift (H2). Both hypotheses are grounded in the semi-strong form of the market efficiency hypothesis (Fama, 1970), which states that publicly available information is incorporated into prices efficiently and without delay.

The empirical results presented in Section 4 offer substantial support for these propositions. The cumulative abnormal returns (CAR) exhibited a substantial decline of -18.87% on average within the narrow event window $[0; +1]$, with a p-value of less than 0.01. This finding validates H1 by demonstrating a systematic and sizeable negative market reaction following the release of Hindenburg reports. In addition, the strongest price decline occurs on the day of publication, while the subsequent days show only marginal further adjustment. This pattern aligns with H2 and indicates that markets absorb the information contained in the reports almost instantaneously, leaving little room for delayed reactions or information drift.

The observations provide substantial support for the semi-strong form of market efficiency (Fama, 1970). According to Easley and O'Hara (1992) and Harris (2003), the speed with which information is incorporated into prices is a key quality feature of efficient markets. The immediate reaction of market participants to Hindenburg's publications indicates that they perceive them as reliable information signals, leading to adjustments in their positions. Hindenburg, therefore, functions as an external information intermediary, facilitating the transfer of private knowledge concerning corporate misconduct into the public discourse and thereby stimulating price discovery.

In addition, weak pre-publication movements in the days leading up to publication suggests the existence of information asymmetries. Individual market participants appear to be acting as informed traders (‘insiders’) in the sense of the Kyle model

(1985). They possess anticipatory knowledge or the ability to interpret market signals that indicate an imminent publication. Even though Hindenburg maintains strict confidentiality regarding the target companies and publication dates, there is evidence of increased short interest positions in individual cases (Ahn et al., 2024). This points to anticipatory trading, which is characteristic of markets with incomplete information distribution. The sharp drop in prices immediately after the event corresponds to typical patterns of market microstructure and can be interpreted as a reaction to an information shock, while at the same time microstructural frictions occur, as would be theoretically expected after such events (cf. Harris, 2003). Even though our analysis does not explicitly measure volatility within the narrow event window, this pattern is consistent with the short-term market distortions described in the literature following sudden information disclosure. However, the observed recovery of abnormal returns after a few days indicates high price resilience, a key feature of high-quality markets where liquidity and return dynamics normalise quickly after shocks (cf. Harris, 2003). The study's findings indicate that conventional structural company characteristics, including market capitalisation, historical volatility and sector affiliation, are not explanatory of the strength of the price reaction. The variability of the effects is therefore evidently determined more by qualitative and behavioural factors. The credibility of the allegations, Hindenburg's reputation, media coverage (Tetlock, 2007) and investor confidence in the management concerned are key factors to be considered. This qualitative dimension indicates an interface between rational information processing and behavioural economic mechanisms. Markets exhibit a response to not only the existence of new information, but also to its perceived credibility and severity.

In the long term, the effects are transitory only in terms of abnormal returns, not in terms of price levels. Average abnormal returns normalise shortly after the event, but the cumulative abnormal returns remain persistently negative because the initial price drop is not reversed. This pattern indicates that the abnormal returns exhibit a brief but intense reaction, whereas the resulting price drop remains permanent. The analysis thus confirms a temporary disruption in return dynamics which is different than a classical overreaction, as the underlying price level does not reverse but stabilises at a new equilibrium (cf. Barberis et al., 1998).

The results of the study demonstrate that activist short sellers, such as Hindenburg Research, fulfil a market-disciplining role. By highlighting irregularities and overvaluations, they contribute to the reduction of information asymmetries and the enhancement of price discovery. Simultaneously, these events generate short-term frictions in return dynamics. This tension between market discipline and market disruption is characteristic of modern financial markets, whose information architecture encompasses both efficiency and fragility.

5.2 Implications for retail investors

Retail traders could only benefit from the price reactions identified in this study if they were able to act at a speed that is structurally beyond their reach. The results for H1 and H2 show that the largest price adjustment occurs on the publication day itself, with abnormal returns reverting to zero shortly after. While this study does not use intraday data, the abrupt decline on day 0 strongly suggests that the significant price adjustment occurs within minutes, if not seconds. Only market participants with high-frequency trading systems and automated decision-making processes can exploit such narrow time windows.

By contrast, retail traders typically receive information with a delay through news outlets, financial portals or social media, and tend to make decisions hours later or the next day. By that time, the adjustment process is already complete: prices do not rebound towards their pre-event level, but stabilise at the new, lower equilibrium. As no positive correction follows, there are no arbitrage opportunities available to retail investors, neither intraday nor on the next trading day.

In theory, the only profitable reaction would be to take an immediate short position at the moment the information shock occurs. In practice, such a strategy requires execution latencies and technological capabilities which retail investors do not possess. This underlines a central characteristic of modern financial markets: Information shocks are absorbed extremely rapidly, and any potential arbitrage gains are almost entirely captured by professional traders with superior execution speed and infrastructure.

5.3 Regulatory considerations and policy implications

The findings raise key questions about the regulation and legitimacy of short seller reports. Such publications operate in a regulatory grey area between legitimate disclosure of information and potential market manipulation. Credible and verifiable information disclosures generally promote the efficiency of capital markets by revealing hidden risks and correcting mispricing. Activist short sellers can play an important disciplinary role by uncovering misrepresentations, challenging inflated valuations, and reducing information asymmetries that would otherwise persist. Their research can facilitate more accurate price discovery and improve the allocation of capital by prompting reassessments of firms with questionable fundamentals. However, it is important to note that aggressive communication strategies or allegations that lack sufficient factual basis can result in unnecessary market distortions.

Appropriate regulation should therefore focus on transparency rather than restriction. Sensible measures would include mandatory disclosure of existing short positions, description of the research methods used, and clear identification of potential conflicts of interest. These disclosure requirements increase transparency for supervisory authorities and investors without hindering the legitimate flow of information. Investor protection represents a further relevant consideration. The rapid pace of market reactions puts private investors at a disadvantage, as they receive information with a delay. To prevent sudden panic selling and market instability, temporary trading halts, known as circuit breakers, could be useful in the event of exceptionally sharp price movements. Stock exchange platforms could further be required to communicate the publication of such reports transparently and to monitor their distribution technically. Despite short-term turbulence, however, the positive contribution of activist short sellers to market transparency and information distribution outweighs the negative effects.

Short selling or publication restrictions, as discussed in times of crisis, would be counterproductive. From a microstructural perspective, such restrictions can impair price discovery, reduce liquidity and make it more difficult to process new information efficiently (Harris, 2003). Efficiency arises when discipline through information is allowed to continue, while targeted disinformation is sanctioned. The

empirical results therefore argue in favour of a regulated but open information architecture that maximises transparency without restricting market participants' freedom of communication.

5.4 Limitations and directions for future research

Despite the robustness checks in section 4.3, several methodological limitations must be acknowledged. The most evident constraint concerns the relatively small sample size of 31 firms. However, the selected sample is well-suited for an exploratory event study design focused on a single, high-profile short seller. Small samples naturally entail higher sensitivity to outliers and lower statistical power, but the combination of bootstrap and LOO procedures effectively mitigates these concerns and ensures the internal reliability of the results. The sample was deliberately restricted to post-2021 cases to preserve data consistency and exclude potential distortions from the extraordinary market conditions during the COVID-19 pandemic.

Another limitation relates to the use of the market model for estimating expected returns. Despite its suitability for short-horizon event analysis, the use of the market model is not without limitations. Several firms exhibit relatively low R^2 values, reflecting a high degree of idiosyncratic volatility, which may reduce the precision of the estimated normal returns. Moreover, the model assumes a stable linear relationship between firm returns and the market, an assumption that may be imperfect for highly speculative or episodically volatile stocks, characteristics common among targets of Hindenburg reports. Alternative models such as the Fama-French three-factor framework or industry-adjusted returns could capture additional sources of systematic risk, but they would require longer estimation windows and may be unreliable at daily frequency. These considerations highlight that while the market model is the most appropriate choice for this dataset, the results should be interpreted with awareness of the inherent noise in firm-level return processes.

Furthermore, the cross-sectional regression exploring determinants such as firm size, pre-event volatility, and industry classification yielded no statistically significant results. This absence of explanatory power may reflect either a genuine lack of correlation or the omission of important control variables. Factors such as leverage, public sentiment, severity of allegations, or corporate governance quality could

potentially shape the magnitude of price reactions but were not available in the dataset.

Finally, the exclusive focus on Hindenburg Research represents both a strength and a limitation. Restricting the analysis to a single short seller ensures methodological consistency and internal validity, given Hindenburg's established reputation, structured reporting style, and extensive media reach. Thus, while the findings robustly capture the market's response to Hindenburg's publications, they should be interpreted with caution when generalising to the broader universe of short seller activity.

Future research could fill these gaps by comparing Hindenburg's cases with other prominent short sellers such as Muddy Waters, Citron Research or Wolfpack Research. Sentiment analysis or media monitoring could measure how the market perceives the credibility of such reports and how this perception influences pricing. Intraday event studies would also be valuable for analysing the speed and sequence of information diffusion within minutes or hours. Finally, follow-up effects on related markets such as options, credit default swaps or ETFs could be examined to analyse how widely the impact of information shocks spreads throughout the financial system.

6. Conclusion

The study demonstrates that Hindenburg Reports trigger significant short-term price reactions, and that these patterns are consistent with the semi-strong form of the market efficiency hypothesis. The immediate price adjustments illustrate that new value-relevant information is processed without delay, while the rapid normalisation of returns indicates functioning arbitrage. Activist short sellers occupy an independent role within this mechanism, as they serve to reduce information asymmetries, expose valuation errors and thereby enhance the quality of price formation. However, this process simultaneously generates temporary market instability in the form of short-lived return distortions.

The results show clear differences in the ability of different market participants to exploit these information shocks. Investors with professional investment strategies that are algorithmic or event-driven can take advantage of the rapid response of the market, acting immediately after the publication of relevant information. Retail investors typically receive information with a delay and are therefore structurally unable to benefit from the initial price slide. This asymmetry indicates an efficient, though highly speed-dependent, flow of information.

The findings provide a consistent picture: activist short selling enhances market quality via the information channel, but leads to short-term volatility and instability, which primarily affects less informed market participants. The key implication is that markets benefit from credible information disclosure, but at the same time require mechanisms that limit unnecessary market distortions without impairing the efficiency of the information process.

Declaration on the use of AI tools in the work on this paper

Name (and version) of the AI tool: ChatGPT 5.0

Purpose of using the tool: Help with R code and literature research

We are aware that we are responsible for all content of this paper, including the parts where AI tools are used. We are responsible for ensuring that the paper complies with ethical rules for privacy and publication.

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Appendix

R-Script

Section 4.2.1

```
library(ggplot2)

car_values <- Sum_2$CAR
ttest <- t.test(car_values, mu = 0, alternative = "less", conf.leve
l = 0.95)
cat("=== One-Sided t-Test for Sum_2$CAR ===\n")
cat("Number of firms:", length(car_values), "\n")
cat("Mean (CAR):", round(mean(car_values, na.rm = TRUE), 4), "\n")
cat("Standard deviation:", round(sd(car_values, na.rm = TRUE), 4),
"\n")
cat("t-value:", round(ttest$statistic, 4), "\n")
cat("p-value:", signif(ttest$p.value, 4), "\n")
cat("95% confidence interval:", round(ttest$conf.int[1], 4), "to",
    round(ttest$conf.int[2], 4), "\n")
cat("Significant at 5% level?", ifelse(ttest$p.value < 0.05, "Yes",
"No"),
    "\n")

color1 <- rgb(177, 149, 58, maxColorValue = 255)
color2 <- rgb(201, 202, 204, maxColorValue = 255)
color3 <- rgb(0, 57, 90, maxColorValue = 255)

clean_theme <- theme_minimal(base_size = 13) +
  theme(
    panel.background = element_rect(fill = "white", color = NA),
    plot.background = element_rect(fill = "white", color = NA),
    panel.grid.major = element_line(color = "gray90"),
    panel.grid.minor = element_blank(),
    axis.text = element_text(color = "black"),
    axis.title = element_text(face = "bold"),
    plot.title = element_blank()
  )

ggplot(Sum_2, aes(x = CAR)) +
  geom_histogram(binwidth = 0.02, fill = color1, color = "black") +
  geom_vline(xintercept = mean(Sum_2$CAR), color = color3, linetype
= "dashed", linewidth = 1) +
  labs(x = "CAR", y = "Frequency") +
  theme_minimal(base_size = 13) +
  theme(
    panel.grid.major.x = element_blank(),
    panel.grid.minor = element_blank(),
    panel.background = element_rect(fill = "white", color = NA),
    plot.background = element_rect(fill = "white", color = NA),
    axis.text = element_text(color = "black"),
    axis.title = element_text(face = "bold")
  )
```

```
ggplot(Sum_2, aes(y = CAR)) +
  geom_boxplot(fill = color2, color = "black") +
  geom_hline(yintercept = mean(Sum_2$CAR), color = color3, linetype
= "dashed",
             linewidth = 1) +
  labs(y = "CAR") + clean_theme

if ("Company" %in% names(Sum_2)) {
  ggplot(Sum_2, aes(x = reorder(Company, CAR), y = CAR)) +
    geom_col(fill = color3) + coord_flip() + geom_hline(yintercept
= 0,
                                linetype = "dashed", color = color2)
+
    labs(x = "Company", y = "CAR") + clean_theme
}

library(dplyr)
library(tidyr)
library(ggplot2)

Before_long <- Before %>%
  pivot_longer(cols = -Firm, names_to = "Day", values_to = "AR") %>
%
  mutate(Day = as.numeric(Day))

ttest_results <- Before_long %>%
  group_by(Day) %>%
  summarise(
    Mean_AR = mean(AR, na.rm = TRUE),
    SD_AR = sd(AR, na.rm = TRUE),
    N = sum(!is.na(AR)),
    t_stat = Mean_AR / (SD_AR / sqrt(N)),
    p_value = 2 * pt(-abs(t_stat), df = N - 1),
    Significance = case_when(
      p_value < 0.001 ~ "***",
      p_value < 0.01  ~ "**",
      p_value < 0.05  ~ "*",
      p_value < 0.1   ~ ".",
      TRUE ~ ""
    )
  )

ggplot(ttest_results, aes(x = Day, y = Mean_AR)) +
  geom_line(color = color3, linewidth = 1.2) +
  geom_point(color = color1, size = 2.8) +
  geom_errorbar(aes(ymin = Mean_AR - SD_AR / sqrt(N),
                    ymax = Mean_AR + SD_AR / sqrt(N)),
                width = 0.2, color = color2) +
  geom_hline(yintercept = 0, linetype = "dashed", color = "gray40")
+
  scale_x_continuous(breaks = c(-4, -2, 0, 2, 4)) +
  labs(x = "Event Day", y = "Average Abnormal Return") +
  theme_minimal(base_size = 13) +
```

```
  theme(
    panel.grid.major.x = element_blank(),
    panel.grid.minor = element_blank(),
    panel.background = element_rect(fill = "white", color = NA),
    plot.background = element_rect(fill = "white", color = NA),
    axis.text = element_text(color = "black"),
    axis.title = element_text(face = "bold")
  )
```

Section 4.2.3

```
library(tidyverse)
library(sandwich)
library(lmtest)
library(car)
library(broom)

model <- lm(CAR ~ MarketCap + sd + ind, data = Regression)
robust_se <- coeftest(model, vcov = vcovHC(model, type = "HC1"))
cat("Robuste Regressionsergebnisse:\n")
print(robust_se)
regression_table <- tidy(model, conf.int = TRUE)
print(regression_table)
cat("R-squared:", round(summary(model)$r.squared, 4), "\n")
cat("Adjusted R-squared:", round(summary(model)$adj.r.squared, 4),
"\n")

color1 <- rgb(177, 149, 58, maxColorValue = 255)
color2 <- rgb(201, 202, 204, maxColorValue = 255)
color3 <- rgb(0, 57, 90, maxColorValue = 255)

model_cap <- lm(CAR ~ MarketCap, data = Regression)

ggplot(Regression, aes(x = MarketCap, y = CAR)) +
  geom_point(color = color1, size = 3) +
  geom_smooth(method = "lm", se = TRUE, color = color3, linewidth =
1.2) +
  labs(x = "Log(Market Capitalization)",
       y = "Cumulative Abnormal Return (CAR)",
       subtitle = paste("R² =", round(summary(model_cap)$r.squared,
3),
                        "| β =", round(coef(model_cap)[2], 4))) +
  theme_minimal(base_size = 13) +
  theme(
    panel.grid.major.x = element_blank(),
    panel.grid.minor.x = element_blank(),
    panel.grid.major.y = element_line(color = "gray90"),
    panel.background = element_rect(fill = "white", color = NA),
    plot.background = element_rect(fill = "white", color = NA),
    axis.text = element_text(color = "black"),
    axis.title = element_text(face = "bold")
  )

model_sd <- lm(CAR ~ sd, data = Regression)
```

```
ggplot(Regression, aes(x = sd, y = CAR)) +
  geom_point(color = color1, size = 3) +
  geom_smooth(method = "lm", se = TRUE, color = color3, linewidth =
1.2) +
  labs(x = "Pre-Event Volatility (sd)",
       y = "Cumulative Abnormal Return (CAR)",
       subtitle = paste("R² =", round(summary(model_sd)$r.squared,
3),
                        "| β =", round(coef(model_sd)[2], 4))) +
  theme_minimal(base_size = 13) +   theme(
    panel.grid.major.x = element_blank(),
    panel.grid.minor.x = element_blank(),
    panel.grid.major.y = element_line(color = "gray90"),
    panel.background = element_rect(fill = "white", color = NA),
    plot.background = element_rect(fill = "white", color = NA),
    axis.text = element_text(color = "black"),
    axis.title = element_text(face = "bold")
  )

model_ind <- lm(CAR ~ ind, data = Regression)
ggplot(Regression, aes(x = as.factor(ind), y = CAR, fill = as.facto
r(ind))) +
  geom_boxplot(color = "black", outlier.color = color3) +
  scale_fill_manual(values = c(color1, color3)) +
  labs(x = "Sector (0 = Industry, 1 = Services)",
       y = "Cumulative Abnormal Return (CAR)",
       subtitle = paste("R² =", round(summary(model_ind)$r.squared,
3),
                        "| β =", round(coef(model_ind)[2], 4))) +
  theme_minimal(base_size = 13) +
  theme(
    panel.grid.major.x = element_blank(),
    panel.grid.minor.x = element_blank(),
    panel.grid.major.y = element_line(color = "gray90"),
    panel.background = element_rect(fill = "white", color = NA),
    plot.background = element_rect(fill = "white", color = NA),
    axis.text = element_text(color = "black"),
    axis.title = element_text(face = "bold"),
    legend.position = "none"
  )

model_ind <- lm(CAR ~ ind, data = Regression)
ggplot(Regression, aes(x = ind, y = CAR)) +
  geom_jitter(width = 0.1, color = color1, size = 3, alpha = 0.7) +
  geom_smooth(method = "lm", se = TRUE, color = color3, linewidth =
1.2) +
  labs(x = "Industry Dummy (0 = Industry, 1 = Services)",
       y = "Cumulative Abnormal Return (CAR)",
       subtitle = paste("R² =", round(summary(model_ind)$r.squared,
3),
                        "| β =", round(coef(model_ind)[2], 4))) +
  theme_minimal(base_size = 13) +
  theme(
    panel.grid.major.x = element_blank(),
```

```
    panel.grid.minor.x = element_blank(),
    panel.grid.major.y = element_line(color = "gray90"),
    panel.background = element_rect(fill = "white", color = NA),
    plot.background = element_rect(fill = "white", color = NA),
    axis.text = element_text(color = "black"),
    axis.title = element_text(face = "bold")
  )
```

Section 4.3

```
library(ggplot2)

bootstrap_mean <- function(data, n_iter = 10000) {
  means <- numeric(n_iter)
  for (i in 1:n_iter) {
    sample_data <- sample(data, size = length(data), replace = TRUE
)
    means[i] <- mean(sample_data)
  }
  return(means)
}

boot_means <- bootstrap_mean(Sum_2$CAR, n_iter = 10000)
ci <- quantile(boot_means, probs = c(0.025, 0.975))
caar_observed <- mean(Sum_2$CAR)
cat("Bootstrap 95% Confidence Interval for CAAR (0,1):\n")
print(ci)
cat("\nObserved CAAR: ", round(caar_observed, 4), "\n")

ggplot(data.frame(boot_means), aes(x = boot_means)) +
  geom_histogram(binwidth = 0.002, fill = "#B1953A", color = "white
",
                 alpha = 0.9) +
  geom_vline(xintercept = caar_observed, color = "#00395A", linetyp
e = "dashed", linewidth = 1.2) +
  geom_vline(xintercept = ci[1], color = "gray40", linetype = "dott
ed",
             linewidth = 1) +
  geom_vline(xintercept = ci[2], color = "gray40", linetype = "dott
ed",
             linewidth = 1) +
  labs(x = "Bootstrap Means of CAR", y = "Frequency") +
  theme_minimal(base_size = 13) +
  theme(
    panel.grid.major.x = element_blank(),
    panel.grid.minor.x = element_blank(),
    panel.grid.major.y = element_line(color = "gray90"),
    panel.background = element_rect(fill = "white", color = NA),
    plot.background = element_rect(fill = "white", color = NA),
    axis.text = element_text(color = "black"),
    axis.title = element_text(face = "bold")
  )

library(tidyverse)
```

```
loo_results <- data.frame(
  left_out = character(),
  CAAR_loo = numeric(),
  stringsAsFactors = FALSE
)
for (i in 1:nrow(Sum_2)) {
  temp_data <- Sum_2[-i, ]
  caar_loo <- mean(temp_data$CAR)
  loo_results <- rbind(loo_results, data.frame(
    left_out = Sum_2$Company[i],
    CAAR_loo = caar_loo
  ))
}

print(loo_results)
ggplot(loo_results, aes(x = reorder(left_out, CAAR_loo), y = CAAR_l
oo)) +
  geom_col(fill = "#00395A") +
  geom_hline(yintercept = mean(Sum_2$CAR), color = "#B1953A", linet
ype = "dashed", linewidth = 1) +
  coord_flip() +
  labs(
    title = NULL,
    x = "Left-Out Company",
    y = "CAAR without this Company"
  ) +
  theme_minimal(base_size = 13) +
  theme(
    panel.grid.major.x = element_blank(),
    panel.grid.minor.x = element_blank(),
    panel.grid.major.y = element_line(color = "gray90"),
    panel.background = element_rect(fill = "white", color = NA),
    plot.background = element_rect(fill = "white", color = NA),
    axis.text = element_text(color = "black"),
    axis.title = element_text(face = "bold")
  )
```