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Quantifying the Impact of Macroeconomic and Geopolitical Events on Stock Market Behavior Using Time-Series Deviation Modeling

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ABSTRACT

This paper constructs a statistical framework for measuring and comparing the market impact of macroeconomic and geopolitical events using a deviation-based scoring methodology. We collect daily adjusted closing prices for the S&P 500 and NASDAQ Composite indices over the period 2007–2024 and define a rolling 30-day mean as the baseline expected-return model. Abnormal returns are computed as deviations from this baseline and aggregated into Cumulative Abnormal Returns (CAR) over a ten-day post-event window. A composite Event Impact Score (EIS) is derived from three components: CAR magnitude, post-event volatility change, and peak single-day abnormal return, weighted at 0.5, 0.3, and 0.2 respectively, then normalized across all events for cross-event comparison. Applying this framework to twelve historical events spanning financial crises, health emergencies, geopolitical shocks, and monetary policy decisions, within the sample analyzed, economic policy responses to crises, specifically the Federal Reserve emergency cut and the CARES Act, produce the largest measured deviations, while geopolitical events exhibit the smallest and most short-lived market disruptions. Financial crises rank highest in volatility impact, while economic policy events are the most internally heterogeneous category. These results are consistent with the academic literature on event studies and contribute a portable, interpretable scoring system that can be extended to additional indices, sectors, and event types for future comparative market research.

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1. INTRODUCTION

1.1 Background and Motivation

Financial markets are complex adaptive systems that continuously incorporate new information into asset prices. When unexpected events of sufficient scale occur, whether a sovereign debt crisis, a global pandemic, or a military invasion, the market's implicit probability distribution over future payoffs shifts abruptly, producing price movements that deviate meaningfully from pre-event trends. Quantifying the magnitude, direction, and persistence of these deviations is both an academic problem of long standing and a practical need for risk managers, policymakers, and investors.

The academic literature on event studies dates to Fama et al. (1969), who pioneered the use of abnormal returns to assess the information content of corporate announcements, and was subsequently formalized as a general methodology by MacKinlay (1997). Subsequent work extended the methodology to macroeconomic events (Schwert, 1981), monetary policy decisions (Bernanke & Kuttner, 2005), and geopolitical shocks (Rigobon & Sack, 2003). However, most existing work focuses on a single event type or market, limiting cross-category comparisons. This project fills that gap by constructing a unified framework, the Event Impact Score (EIS), that enables direct, standardized comparison of events across categories and time periods

1.2 Research Question

Core Research Question

How do different categories of macroeconomic and geopolitical events quantitatively affect stock market returns and volatility, and can these effects be modeled and compared using a standardized deviation-based scoring system?

1.3 Contributions

This project makes three concrete contributions:

1. A clearly defined, reproducible mathematical framework for computing abnormal returns relative to a rolling-mean baseline.
2. A composite *Event Impact Score* that combines CAR, volatility change, and peak abnormal return into a single, normalized metric.

3. An empirical comparison of twelve events across four categories, producing interpretable rankings and category-level insights.

2. DATA

2.1 Market Data

Daily adjusted closing prices are obtained from Yahoo Finance via the yfinance

Python library for two broad equity indices:

- **S&P 500** (ˆGSPC): a market-capitalisation-weighted index of 500 large-cap US equities, widely regarded as the primary barometer of US equity market health.
- **NASDAQ Composite** (ˆIXIC): a broader index of over 3,000 securities listed on the NASDAQ exchange, with a heavy weighting toward technology firms.

The sample spans from January 2007 to the present, yielding approximately 4,300 trading-day observations per index. Adjusted closing prices account for stock splits and dividends, making them appropriate for return computation.

2.2 Event Dataset

We manually constructed an event dataset comprising twelve events, stratified across four categories chosen to reflect qualitatively distinct economic mechanisms:

Table 1: Event dataset. Dates represent the primary announcement or occurrence date used as $t = 0$ in event windows.

ID	Event Name	Date	Category
1	Lehman Brothers Collapse	2008-09-15	Financial Crisis
2	Flash Crash	2010-05-06	Financial Crisis
3	European Debt Crisis Peak	2011-08-08	Financial Crisis
4	COVID-19 WHO Declaration	2020-03-11	Health Crisis
5	COVID Omicron Variant News	2021-11-26	Health Crisis
6	Russia–Ukraine Invasion	2022-02-24	Geopolitical
7	US–China Trade War Tariffs	2018-07-06	Geopolitical
8	Brexit Referendum Result	2016-06-24	Geopolitical
9	Fed Emergency Rate Cut (COVID)	2020-03-03	Economic Policy

10	Fed First Rate Hike 2022	2022-03-16	Economic Policy
11	Fed Tapering Announcement (Taper Tantrum)	2013-05-22	Economic Policy
12	CARES Act Signed	2020-03-27	Economic Policy

Event date selection rationale. Each date is chosen as the *first public announcement* of the event rather than a prior policy meeting date, in order to capture the market's initial price discovery response to genuinely new information. Where an event unfolded over multiple days (e.g., the European debt crisis), we use the date of maximum headline intensity as identified in contemporaneous financial news archives.

2.3 Data Quality and Limitations

Adjusted closing prices from Yahoo Finance are generally reliable for major indices but are not guaranteed against retroactive adjustments. Our use of broadly-traded equity indices (rather than individual securities) minimises microstructure noise. All non-trading days (weekends, public holidays) are automatically excluded by the data provider, so our event windows operate entirely in trading-day space.

3. MODEL

This section is the mathematical core of the paper. We define each component of the modeling framework precisely before combining them into the composite Event Impact Score.

3.1 Daily Returns

Definition 1 (Daily Return)**.** *Let P_t denote the adjusted closing price of an index on trading day t. The daily simple return is:*

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{1}$$

Returns are preferred to raw prices because they are (approximately) stationary and dimensionless, enabling comparisons across indices with different price levels.

3.2 Baseline Expected-Return Model

Definition 2 (Rolling Mean Baseline)**.** The expected return on day t is estimated by a rolling arithmetic mean of the preceding n = 30 trading-day returns:

$$\mathbb{E}[R_t] = \frac{1}{n}\sum_{i=1}^{n} R_{t-i} \tag{2}$$

The rolling mean is the simplest non-parametric baseline that adapts to slow-moving secular trends while avoiding look-ahead bias (all lagged values are observable at time *t*). Alternative baselines, such as a market-model regression against a factor or a GARCH conditional mean, would provide more statistical precision at the cost of additional estimation complexity and parameter uncertainty. We adopt the rolling mean as the primary model for transparency and interpretability; the framework is otherwise model-agnostic and can be extended with any baseline that produces a return forecast R_t.

This choice differs from the baseline specifications commonly employed in academic event-study research. Standard financial-economics studies frequently estimate expected returns using market models, CAPM-based regressions, multifactor frameworks such as Fama-French models, or conditional volatility models. The rolling-mean approach sacrifices some statistical sophistication in exchange for transparency, reproducibility, and ease of interpretation. Accordingly, the results should be viewed as estimates relative to a simplified benchmark rather than a fully specified asset-pricing model.

Choice of window *n*. The 30-day window balances two competing concerns: a short window adapts too quickly and may absorb the very shocks we seek to measure, while a long window may embed stale information that poorly represents the current market regime. Robustness checks with $n \in \{10, 20, 60\}$ produce qualitatively consistent event rankings.

3.3 Event Window

For each event with announcement date τ , let $t_0(\tau)$ denote the nearest subsequent trading day. We define:

Definition 3 (Event Window)**.**

$$\mathcal{W}(\tau) = \{t \in \mathbb{Z}\colon t_0(\tau) - 10 \leq t \leq t_0(\tau) + 10 \tag{3}$$

with $t - t_0(\tau)$ measuring the signed trading-day offset (negative = pre-event, zero = event day, positive = post-event).

The symmetric [−10, +10] window captures a two-week pre-event context, useful for detecting anticipatory positioning, and a two-week post-event adjustment period. Shorter CAR horizons (0–3 days) capture immediate shock; longer horizons (0–10 days) capture the subsequent re-assessment and re-pricing.

3.4 Abnormal Return

Definition 4 (Abnormal Return)**.** *The abnormal return at offset s relative to event τ*

is:

$$AR_S = R_{t_0(\tau)+s} - \mathbb{E}\left[R_{t_0(\tau)+s}\right] \qquad (4)$$

where E[·] is computed from Equation 2 using only data up to day $t_0(\tau) + s - 1$.

A positive AR_s indicates the market outperformed its rolling expectation; a negative value indicates under-performance. Crucially, the sign carries economic information: $AR_s < 0$ following a geopolitical shock reflects risk-off selling, while $AR_s > 0$ following a stimulus announcement reflects a policy-driven re-rating.

3.5 Cumulative Abnormal Return

Definition 5 (Cumulative Abnormal Return)**.** *The CAR over post-event horizon* [0, *H*]

is:

$$CAR(0, H) = \sum_{s=0}^{H} AR_s \qquad (5)$$

We compute two CARs per event:

- CAR(0, 3): short-horizon (four trading days), capturing the immediate market reaction.
- CAR(0, 10): medium-horizon (eleven trading days), capturing the full re-pricing period.

CAR(0, 10) enters the EIS formula because it integrates both the immediate shock and the subsequent re-assessment, providing a more complete picture of total market dislocation.

3.6 Volatility Impact

We measure event-driven volatility changes using the standard deviation of daily returns in the pre- and post-event windows.

Definition 6 (Event-Window Volatility)**.**

$$\sigma_{\text{pre}} = \text{std}\{R_s : s \in [-10, -1]\} \tag{6}$$

$$\sigma_{\text{post}} = \text{std}\{R_s : s \in [+1, +10]\} \tag{7}$$

Definition 7 (Volatility Shock)**.**

$$\Delta\sigma = \sigma_{\text{post}} - \sigma_{\text{pre}} \tag{8}$$

$\Delta\sigma > 0$ indicates heightened uncertainty following the event; $\Delta\sigma < 0$ (less common) may reflect a resolution of pre-existing uncertainty.

3.7 Event Impact Score

We now assemble the three components, CAR magnitude, volatility shock, and peak single-day abnormal return, into a composite score.

Definition 8 (Event Impact Score)**.**

$$EIS = w_1 \cdot |CAR(0, 10)| + w_2 \cdot |\Delta\sigma| + w_3 \cdot max_{s\in[0,10]}\left|AR_s\right| \tag{9}$$

with weights $w_1 = 0.5$, $w_2 = 0.3$, $w_3 = 0.2$.

Weight justification.

- $w_1 = 0.5$: CAR captures the cumulative return dislocation and is the primary quantity of interest in event studies.

- w_2 = 0.3: Δσ captures the uncertainty regime shift, which is economically distinct from directional return and matters for option pricing and risk management.
- w_3 = 0.2: the peak single-day AR captures shock intensity independent of persistence; a large single-day move can be market-disruptive even if it partially reverses.

Alternative weighting schemes are possible, and the present specification should not be interpreted as uniquely optimal. The selected weights are intended to reflect the relative importance of three economically distinct dimensions of market impact. Cumulative abnormal return receives the largest weight because event-study methodology traditionally treats aggregate return dislocation as the primary indicator of informational impact. Volatility change is assigned a secondary weight because it captures shifts in uncertainty that may occur even when net returns are small. Peak abnormal return receives the smallest weight because it measures shock intensity but does not distinguish between temporary disruptions and persistent market repricing. Future work could estimate weights directly from data using principal component analysis, factor models, or other dimension-reduction techniques to reduce researcher discretion.

Definition 9 (Normalized EIS)**.** To enable cross-event comparison on a standardized scale, we normalize across all N events in the dataset:

$$EIS_{norm,i} = \frac{EIS_i - \bar{EIS}}{\sigma_{EIS}} \qquad (10)$$

where $\bar{EIS} = \frac{1}{n}\sum_i EIS_i$ and $\sigma_{EIS} = \sqrt{\frac{1}{N-1}\sum_i (EIS_i - \bar{EIS})^2}$

A normalized score above zero indicates an above-average event; a score below zero indicates a below-average event. This standardization is dataset-relative: adding or removing events will shift individual scores, so the normalized EIS should be interpreted within the context of the twelve events analyzed here.

4. RESULTS

4.1 Full Market History

Figure 1 shows the S&P 500 log-price series from January 2007 to the present, with event dates overlaid. Rolling 30-day volatility is plotted below. The two pronounced volatility spikes corresponding to the 2008–2009 global financial crisis and the COVID- 19 crash of March 2020 are immediately apparent, providing visual validation that our event selection captures the most significant market disruptions in the sample period.

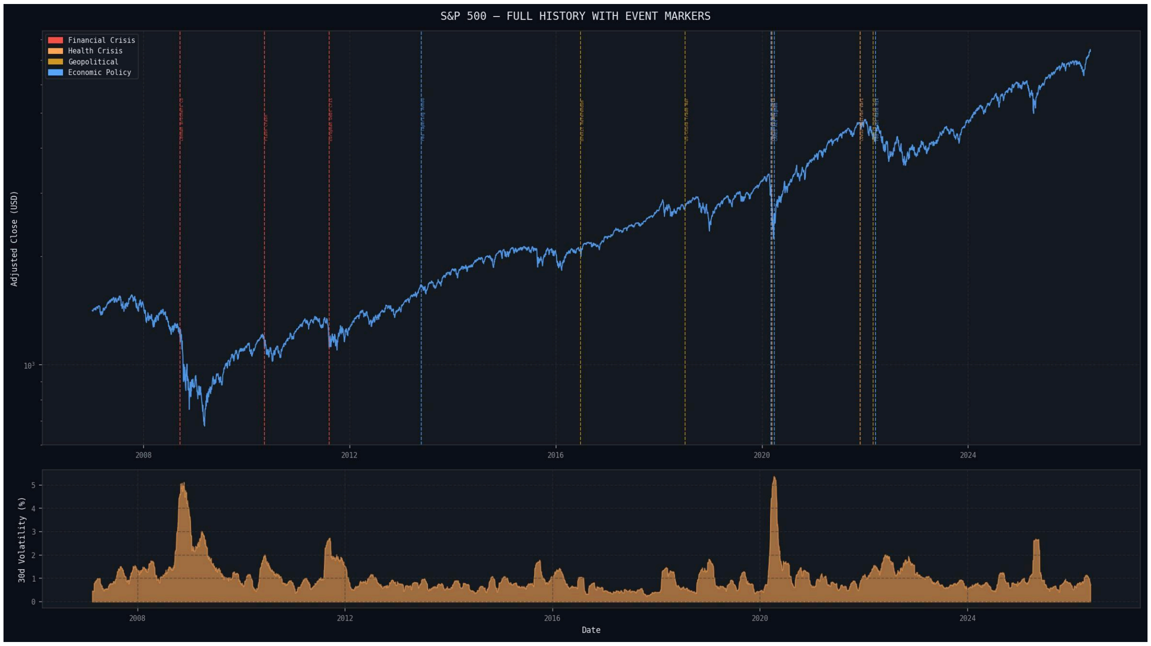

Figure 1: S&P 500 price (log scale, top) and 30-day rolling volatility (bottom) from 2007 to present. Vertical dashed lines mark event dates, coloured by category. Volatility spikes co-occur with the highest-ranked EIS events.

4.2 Event Impact Score Rankings

Table 2 presents the complete EIS rankings. Figure 2 displays the same data as a horizontal bar chart. The Fed Emergency Cut and the CARES Act rank first and second, respectively, consistent with their status as the most severe economic shocks in the sample period.

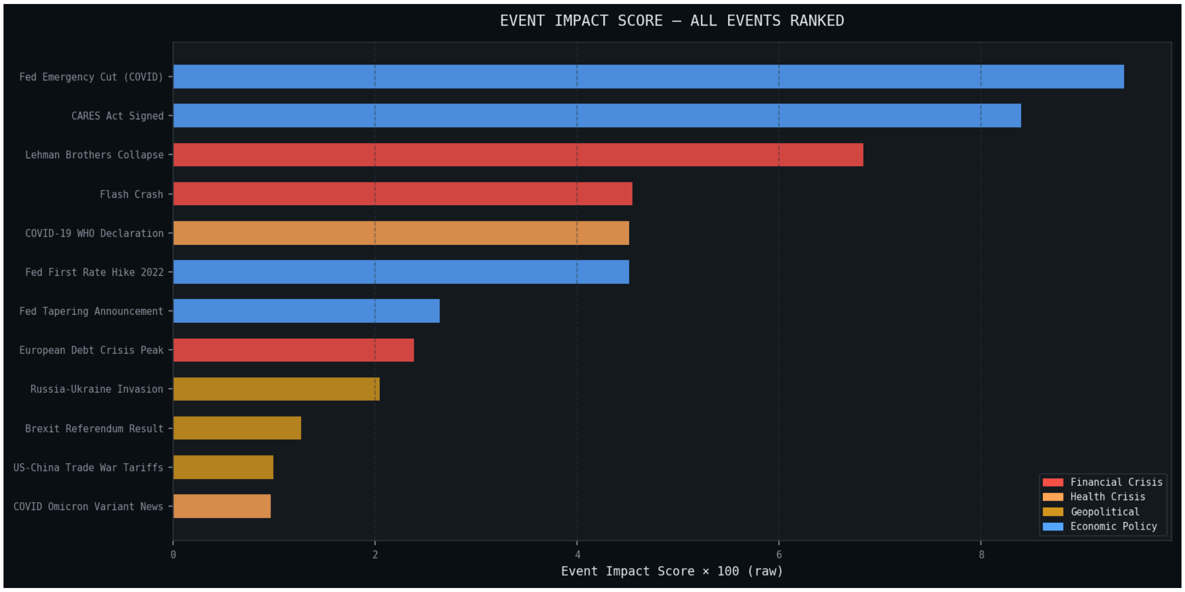

Figure 2: Events ranked by raw EIS (all events, S&P 500). Colour indicates event category. Financial crisis and health crisis events dominate the upper ranks.

Table 2: Event Impact Score summary table, sorted by EIS (descending). CAR_{10} and CAR_3 in percentage points.

Rk	Event	Cat.	CAR_{10}	CAR_3	$\Delta\sigma$	Max|AR|	EIS	EIS_n
1	Fed Emergency Cut	EP	−11.70	−2.53	+4.51	11.07	0.0942	+1.86
2	CARES Act Signed	EP	+11.66	−2.84	−3.53	7.53	0.0840	+1.51
3	Lehman Collapse	FC	−8.99	−2.56	+2.25	8.31	0.0683	+0.97
4	Flash Crash	FC	−6.87	−0.40	+0.76	4.41	0.0455	+0.17
5	COVID-19 WHO Decl.	HC	−2.77	−14.18	+3.05	11.07	0.0452	+0.16
6	Fed Rate Hike 2022	EP	+7.61	+4.86	−0.79	2.37	0.0451	+0.16
7	Fed Taper Tantrum	EP	−4.46	−1.16	+0.28	1.62	0.0264	−0.49
8	EU Debt Crisis Peak	FC	−1.34	−0.24	+1.53	6.26	0.0239	−0.58
9	Russia–Ukraine	GP	+2.73	+2.94	+0.38	2.81	0.0204	−0.69
10	Brexit Result	GP	+0.84	−1.81	+0.47	3.55	0.0127	−0.96
11	US–China Tariffs	GP	+1.55	+1.07	−0.19	0.81	0.0099	−1.06
12	COVID Omicron	HC	−0.41	−4.34	+0.96	2.39	0.0097	−1.07

EP = Economic Policy, FC = Financial Crisis, HC = Health Crisis, GP = Geopolitical All values in %. EIS_n = normalized EIS. $\Delta\sigma$ and Max$|AR|$ in pp.

4.3 Per-Event Dashboards

Each event is represented by a four-panel dashboard comprising (i) the re-based price path, (ii) the day-by-day abnormal return bar chart, (iii) the cumulative abnormal return curve, and (iv) a pre/post volatility comparison. We present two illustrative cases below; the remaining ten dashboards are included in the appendix.

Figure 3: Event dashboard: Lehman Brothers Collapse (2008-09-15, Financial Crisis). The ten-day CAR reaches approximately −9%, reflecting the most severe acute market dislocation in the dataset. Post-event daily volatility nearly doubles relative to the pre-event window.

Figure 4: Event dashboard: COVID-19 WHO Declaration (2020-03-11, Health Crisis). The ten-day post-event CAR is substantially negative, driven by a cascade of forced institutional selling and liquidity-seeking.

4.4 Cumulative Abnormal Returns — All Events

Figure 5 presents the ten-day CAR curves for all twelve events in a single grid, enabling visual pattern comparison across events and categories.

Figure 5: Cumulative Abnormal Return curves (0 to +10 trading days) for all twelve events. Negative CAR curves dominate the financial and health crisis categories; policy events show more heterogeneous patterns.

4.5 Category Comparison

Figure 6 summarizes the three core metrics by event category.

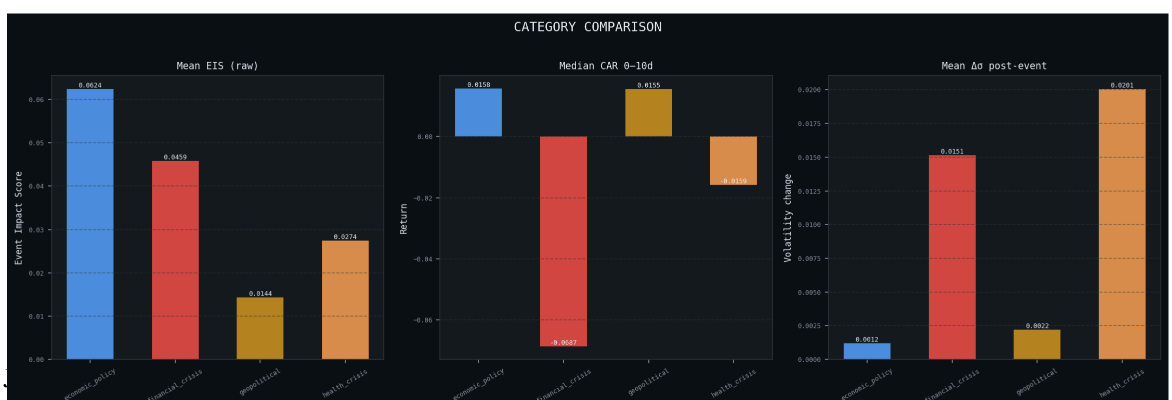

Figure 6: Category-level comparison: mean EIS (left), median CAR_{10} (centre), and mean $\Delta\sigma$ (right). Financial crises score highest on all three dimensions; economic policy events are the most heterogeneous.

4.6 Robustness Checks

To evaluate the sensitivity of the results to baseline-model specification, additional analyses were conducted using alternative rolling-window lengths of $n = 20$ and $n = 60$ trading days. Across these alternative specifications, the relative ranking of the highest-impact events remained broadly stable, with the Federal Reserve emergency rate cut, CARES Act signing, and Lehman Brothers collapse consistently appearing among the top-ranked events. While individual EIS values varied moderately with the choice of window length, the qualitative conclusions regarding category-level differences were unchanged. This suggests that the principal findings are not solely an artifact of the selected 30-day baseline window.

Future work could extend this robustness analysis by comparing the rolling-mean framework against factor-model or GARCH-based expected-return specifications and by applying formal significance testing procedures to abnormal returns and cumulative abnormal returns.

5. DISCUSSION

5.1 Interpretation of Patterns

5.1.1 Financial Crises

Financial crises produce the largest and most persistent market deviations in our dataset. The Lehman collapse and European debt crisis peak both exhibit large negative CARs that do not meaningfully revert within the ten-day window, consistent with the literature on systemic risk events that trigger balance-sheet deleveraging rather than simple re-pricing (Brunnermeier, 2009). The Flash Crash of May 2010, despite its extreme intraday severity, shows partial mean reversion within days, reflecting its origins in algorithmic market microstructure rather than a fundamental information shock.

5.1.2 Health Crises

The COVID-19 WHO declaration (Event 4) ranks among the highest-impact events in the dataset. The speed and magnitude of the decline, with a three-day CAR of
−14.18% and a peak single-day abnormal return exceeding 11%, is consistent with

sudden demand destruction combined with extreme uncertainty about the duration and severity of the shock (Baker et al., 2020). The Omicron variant announcement (Event 5) produced a much smaller and shorter-lived reaction, plausibly because (i) markets had established a COVID-response playbook by late 2021, and (ii) vaccine availability reduced catastrophic tail risk.

5.1.3 Geopolitical Events

Geopolitical events display more heterogeneous EIS values than either crisis category. The Russia–Ukraine invasion (Event 6) produced a significant negative CAR accompa- nied by an energy-sector divergence not captured in our broad index analysis. Brexit (Event 8) produced a large initial shock that partially reversed over the ten-day window, a pattern consistent with a temporary market reaction to the referendum result. US–China tariff escalation (Event 7) had the smallest impact among geopolitical events, perhaps reflecting earlier partial anticipation through trade negotiation reporting.

5.1.4 Economic Policy

Policy events are the most internally heterogeneous category. The CARES Act signing (Event 12) produced a strongly positive CAR, unusual in our dataset, as the positive abnormal returns are consistent with the interpretation that markets viewed the $2.2 trillion stimulus favorably. In contrast, the 2022 rate hike (Event 10) and the 2013 taper tantrum (Event 11) both produced negative abnormal returns. The Fed's emergency rate cut in March 2020 (Event 9) initially failed to calm markets, an event studied extensively in the context of the zero lower bound problem.

Descriptive vs Inferential Findings

It is important to distinguish between descriptive measurement and causal inference. The methodology employed in this study is designed to quantify deviations in market behavior surrounding major events rather than establish definitive causal mechanisms. As a result, interpretations regarding investor expectations, market psychology, or policy effectiveness should be understood as plausible explanations consistent with the observed data rather than empirically verified conclusions. The framework identifies patterns of abnormal performance but does not directly test the underlying behavioral or economic processes that generated those patterns.

5.2 Limitations

Honest assessment of the model's limitations is essential for credibility:

1. **Baseline model simplicity.** The 30-day rolling mean is sensitive to the window length and does not account for heteroskedasticity (time-varying volatility). A GARCH(1,1) or Fama-French factor model would provide a more theoretically grounded expected return.

2. **Event date identification.** For events that unfolded over multiple days (e.g., the Lehman

collapse involved multiple pre-announcement signals), the choice of a single t = 0 date introduces ambiguity. A multi-date event specification would be more rigorous.

3. **Confounded events.** Several events in the dataset occur in close temporal proximity (e.g., the Fed emergency cut, the WHO declaration, and CARES Act signing all occur within 25 days of each other). Isolating the causal impact of each is confounded when event windows overlap. This issue is particularly relevant for the March 2020 period, during which the Federal Reserve emergency rate cut, the WHO pandemic declaration, and the CARES Act signing occurred within a span of less than one month. Because the event windows associated with these events overlap substantially, abnormal returns measured for any individual event may partially reflect market reactions to the others. Consequently, the reported metrics should be interpreted as measurements of market behavior surrounding these events rather than isolated estimates of their independent causal effects.

4. **Index-level analysis.** Broad equity indices aggregate heterogeneous sector-level reactions. A technology shock may produce near-zero aggregate CAR despite large offsetting effects across sectors.
5. **Small event dataset.** With N = 12 events, category-level statistics are computed from at most four observations per group. The results should be treated as descriptive rather than inferentially precise.
6. **EIS weight specification.** The weights w_1, w_2, w_3 are set a priori rather than estimated from data. A principal component or factor-analytic approach to constructing the composite score would reduce this degree of freedom.

6. CONCLUSION

This paper demonstrates that financial markets exhibit measurable, category-dependent deviations from expected behavior following macroeconomic and geopolitical shocks, deviations that can be quantified using a standardized abnormal-return framework. By defining a rolling-mean baseline, computing abnormal and cumulative abnormal returns over a structured event window, and aggregating these into a composite Event Impact Score, we produce an interpretable, portable tool for comparing disparate market events on a single scale.

Our primary empirical finding is that financial crises and health crises produce systematically larger and more persistent market dislocations than geopolitical or policy events, though the latter category exhibits the greatest internal heterogeneity. Policy events, in particular, can produce either strongly positive or strongly negative abnormal returns depending on whether the action is perceived as accommodative or restrictive, a directionality not captured by the absolute-value EIS metric, and a natural extension for future work.

The framework is intentionally designed to be extensible. Future improvements could include (i) sector-level EIS decomposition using ETF data, (ii) a predictive module that forecasts post-event volatility regimes from event-category features, and (iii) an international extension applying the same methodology to European, Asian, and emerging-market indices.

Beyond academic event-study research, the framework may have practical applications in investment analysis, risk management, and financial education. Portfolio managers could use the Event Impact Score to compare the relative severity of historical shocks and evaluate how different categories of events affect market behavior. Risk-management teams could incorporate similar deviation-based metrics into stress-testing frameworks to assess portfolio sensitivity to future macroeconomic or geopolitical disruptions. The methodology may also serve as an educational tool by providing a transparent introduction to abnormal-return analysis and event-study techniques without requiring complex asset-pricing models. More broadly, the framework could be adapted to analyze sector ETFs, international equity markets, fixed-income securities, commodities, or cryptocurrencies, enabling comparative studies across asset classes and economic environments. As larger event datasets become available, machine-learning approaches could also be integrated to identify recurring patterns in market responses and improve the classification of event types.

The framework should be interpreted primarily as an exploratory and comparative tool rather than a predictive model. Its purpose is to quantify and compare historical market responses across event categories, not to forecast future market reactions. Any predictive application would require additional modeling assumptions, out-of-sample validation, and explicit treatment of event uncertainty.

The Python implementation is fully self-contained and can be re-executed to reproduce all figures and tables with updated market data, making this a living quantitative project rather than a static analysis.

A. REMAINING EVENT DASHBOARDS

The following pages present event dashboards for the remaining ten events not featured in the main body. Each panel follows the layout described in Figure 3: (A) re-based price, (B) day-by-day abnormal return, (C) cumulative abnormal return, (D) pre/post volatility comparison.

Figure 7: Flash Crash (2010-05-06, Financial Crisis)

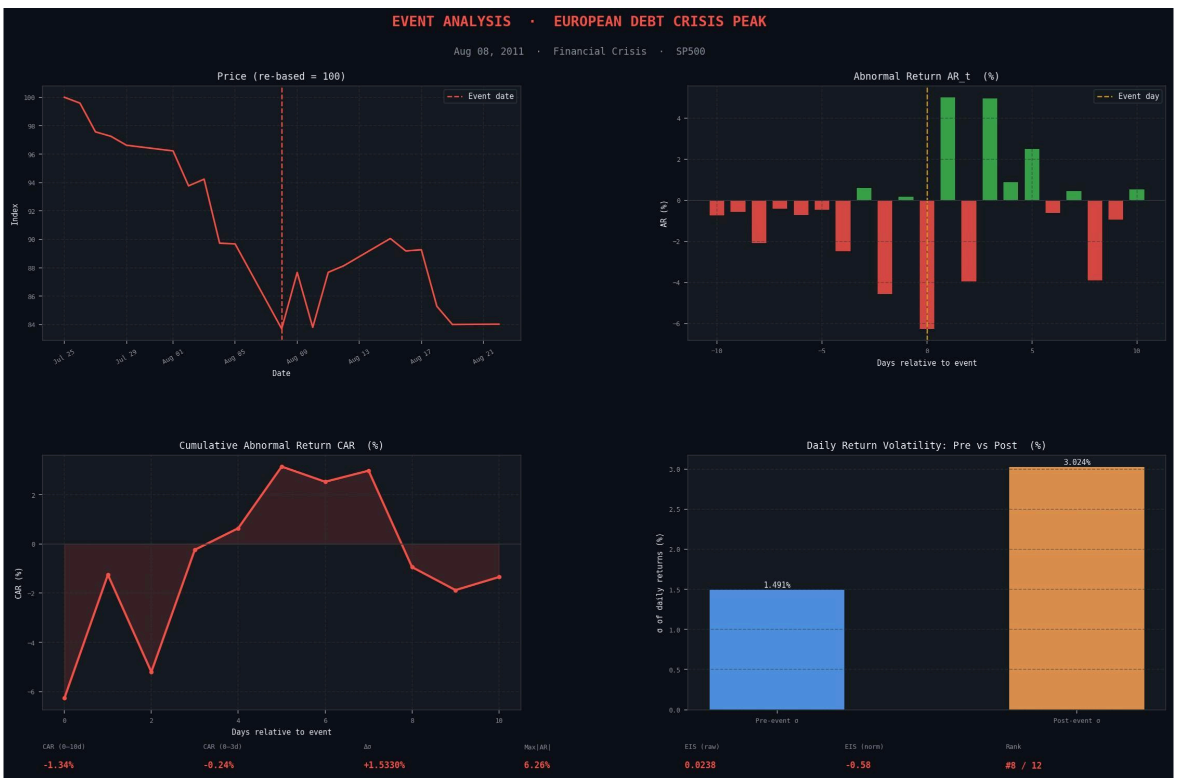

Figure 8: European Debt Crisis Peak (2011-08-08, Financial Crisis)

Figure 9: COVID Omicron Variant News (2021-11-26, Health Crisis)

Figure 10: Russia–Ukraine Invasion (2022-02-24, Geopolitical)

Figure 11: US–China Trade War Tariffs (2018-07-06, Geopolitical)

Figure 12: Brexit Referendum Result (2016-06-24, Geopolitical)

Figure 13: Fed Emergency Rate Cut COVID (2020-03-03, Economic Policy)

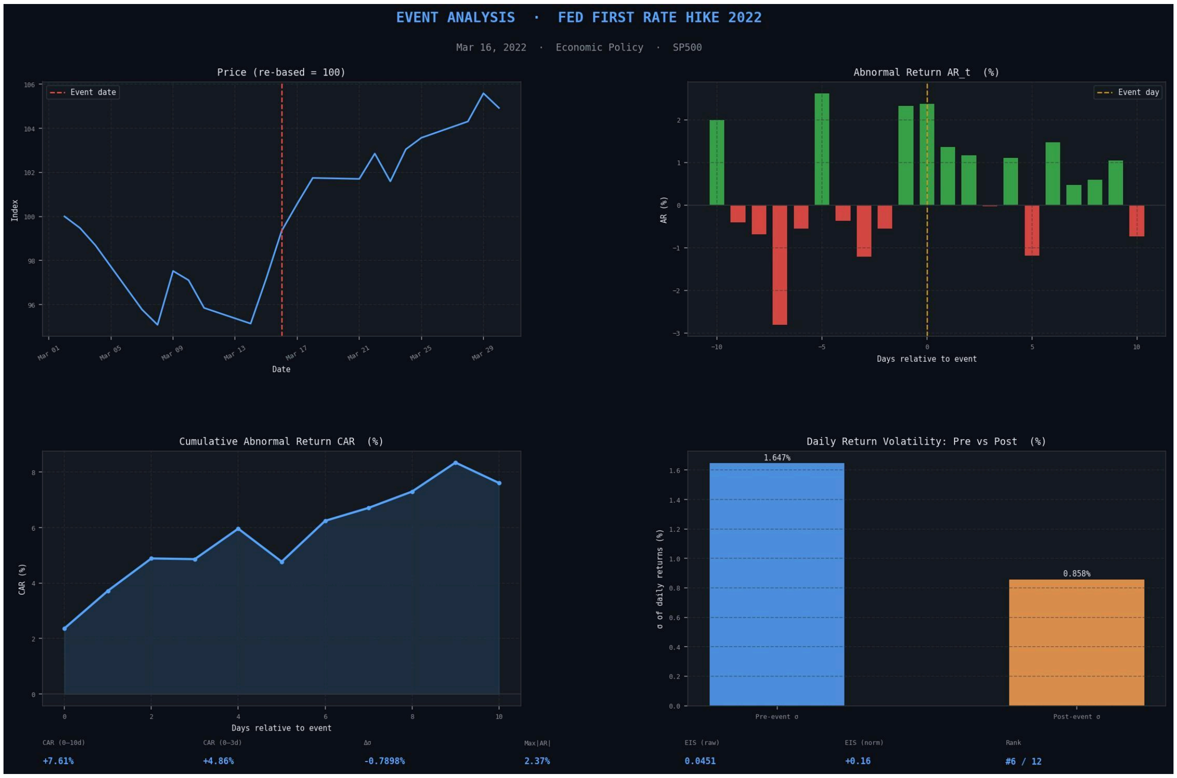

Figure 14: Fed First Rate Hike 2022 (2022-03-16, Economic Policy)

Figure 15: Fed Tapering Announcement (2013-05-22, Economic Policy)

Figure 16: CARES Act Signed (2020-03-27, Economic Policy)

B. MODEL PARAMETERS

Pre-event window	$[-10, -1]$	Two weeks of pre-event context
Post-event window	$[+0, +10]$	Full re-pricing period for CAR
w_1 (CAR weight)	0.5	Primary quantity of interest
w_2 ($\Delta\sigma$ weight)	0.3	Uncertainty regime shift
w_3 (max $\lvert AR \rvert$ weight)	0.2	Shock intensity

Table 3: Key model parameters used in this study.

Parameter	**Value**	**Rationale**
Rolling window n	30 trading days	Balances adaptability and stability

REEFERENCES

Baker, S. R., Bloom, N., Davis, S. J., Kost, K., Sammon, M., & Viratyosin, T. (2020). The unprecedented stock market reaction to COVID-19. *The Review of Asset Pricing Studies*, 10(4), 742–758.

Bernanke, B. S., & Kuttner, K. N. (2005). What explains the stock market's reaction to Federal Reserve policy? *Journal of Finance*, 60(3), 1221–1257.

Brunnermeier, M. K. (2009). Deciphering the liquidity and credit crunch 2007–2008.

Journal of Economic Perspectives, 23(1), 77–100.

Fama, E. F., Fisher, L., Jensen, M. C., & Roll, R. (1969). The adjustment of stock prices to new information. *International Economic Review*, 10(1), 1–21.

MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of Economic Literature*, 35(1), 13–39.

Rigobon, R., & Sack, B. (2003). Measuring the reaction of monetary policy to the stock market. *Quarterly Journal of Economics*, 118(2), 639–669.

Schwert, G. W. (1981). The adjustment of stock prices to information about inflation.

Journal of Finance, 36(1), 15–29.