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Article

Geopolitical Shocks and Short-Term Mean Reversion in Indian Equity Markets: Evidence from Four Event Studies

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Abstract: This study examines how geopolitical and systemic shocks affect short-term abnormal returns in Indian equity markets and investigates the role of foreign portfolio flows in these market reactions. Using event study methodology, the study analyses four episodes covering distinct shock types: the Russia-Ukraine war (February 2022), the COVID-19 pandemic declaration (March 2020), the Pulwama attack (February 2019), and the Galwan Valley clash (June 2020). Abnormal returns are calculated on the Nifty 50 and six sectoral indices using a 120-day pre-event estimation window. Daily net FII equity investment data, sourced from NSDL's FPI archive, is used to test the capital-flow hypothesis directly, alongside MCX gold prices and India VIX as supporting indicators of flight-to-safety behaviour. The paper tests four hypotheses: that shocks produce statistically significant abnormal returns; that the magnitude of abnormal returns is associated with FII outflow intensity; that abnormal returns exhibit mean reversion within 15 to 30 trading days; and that globally integrated sectors experience stronger market reactions than relatively defensive sectors. Existing work has generally studied price reactions and capital flow dynamics separately, with much of the empirical base focused on Western or globally diversified markets (Berkman, Jacobsen, & Lee, 2011; Fratzscher, 2012). This analysis combines both in a single India-specific framework across multiple shock types. Results show that FII outflows closely track the initial shock phase of each event but do not fully explain the subsequent price recovery, and that cumulative abnormal returns consistently begin reverting before the underlying geopolitical situation resolves, pointing toward short-term behavioural overreaction rather than immediate efficient repricing.
Keywords: Event study, geopolitical risk, abnormal returns, mean reversion, foreign institutional investment, Indian equity markets

1. Introduction

On February 24, 2022, Russia invaded Ukraine. The Nifty 50 dropped sharply over the following sessions, FII outflows spiked, and gold prices rose as investors moved toward safer assets. While India had no direct military involvement, the crisis affected markets through global commodity prices, inflation expectations, and investor risk sentiment rather than immediate changes in most corporate earnings. Yet the scale and speed of the reaction raised questions about whether markets were pricing long-term economic consequences or temporarily responding to heightened uncertainty (Caldara & Iacoviello, 2022). Within about four weeks, without the conflict being resolved, most of those losses had been recovered.

This pattern is not specific to Russia-Ukraine. The same thing happened when COVID-19 was declared a pandemic in March 2020: the Nifty fell nearly 38% in weeks and then staged a recovery while the health crisis was still at its peak. It happened after the Pulwama suicide bombing in February 2019, when India-Pakistan tensions rose overnight and markets fell sharply, then recovered once the immediate military risk passed. It happened again after the Galwan Valley clash in June 2020, when an India-China border confrontation triggered a wave of selling followed by a gradual drift back up. Across four events with different origins and economic implications, markets displayed a recurring pattern of sharp initial reactions followed by varying degrees of recovery, raising the question of whether these movements reflected temporary overreaction (De Bondt & Thaler, 1985) or rational adjustment (Fama, 1991).

The question this research asks is whether that pattern represents markets pricing new information correctly, or markets overreacting and then correcting. The distinction matters because it determines whether price movements during geopolitical crises reflect genuine changes in fundamental value or temporary dislocations driven by fear and capital flight (Shleifer & Vishny, 1997). If markets simply priced the shock correctly, there should be no recovery without a corresponding improvement in the situation. However, if prices experience statistically significant abnormal returns followed by mean reversion without a comparable improvement in fundamentals, this provides evidence of short-term mispricing.

India is a particularly useful setting for this question. It has large, liquid equity markets with daily FII flow data published via NSDL, which makes the capital flow mechanism at the centre of this paper's argument directly measurable. It is also an emerging market, meaning it is more exposed to global risk-off sentiment than developed markets: FIIs tend to reduce emerging market exposure broadly during crises, regardless of country-specific conditions (Fratzscher, 2012; Bekaert & Harvey, 2000). In recent years India has experienced both domestically originating shocks and externally driven ones, which makes it possible to test whether the mispricing mechanism holds across different types of events.

The paper is organised as follows. The literature review covers the theoretical debate between market efficiency and behavioural finance, the empirical evidence on how markets respond to geopolitical events, and research on capital flows in emerging markets during risk-off periods. The methodology section explains the event study design, the four case studies, and the data sources. The findings section presents the abnormal return calculations, the evidence on capital flows and flight-to-safety behaviour, and the sectoral analysis across Nifty IT, Energy, Metal, Bank, FMCG, and Pharma. The conclusion addresses the implications of the results, the distinction between mispricing and genuine correction, and what the findings suggest for investors and policymakers.

2. Literature Review

Any study asking whether equity markets misprice assets has to start from the theory that says such mispricing should not persist: the Efficient Market Hypothesis. Fama's (1970) "Efficient Capital Markets: A Review of Theory and Empirical Work," published in the *Journal of Finance*, remains the field's benchmark statement of this idea. Fama defined three forms of efficiency, weak, semi-strong, and strong, of which the semi-strong form is most relevant here: prices adjust rapidly to all publicly available information, so abnormal returns following a geopolitical shock should not persist once that information is incorporated.

In a later update, Fama (1991) acknowledged evidence of return predictability but argued it reflected rational variation in risk premiums rather than genuine inefficiency. The important concession is that even within the EMH tradition, the question is not whether any predictability exists but whether it is rational or behavioural. This study examines whether geopolitical shock responses are better explained by behavioural overreaction or rational adjustments in risk expectations. Grossman and Stiglitz (1980), in the *American Economic Review*, identified a deeper problem: if markets were perfectly efficient, there would be no incentive to gather information, and the mechanism that produces efficiency would break down. Markets must carry some mispricing in equilibrium. During geopolitical shocks, when information is unclear and fast-changing, that friction is at its most acute.

Kahneman and Tversky's (1979) Prospect Theory, published in *Econometrica*, is the psychological foundation for market overreaction. Their experiments showed that people evaluate outcomes relative to a reference point, and that losses feel more painful than equivalent gains feel good. This loss aversion means investors may react more sharply to a given decline in value than to an equivalent gain, which helps explain disproportionate selling pressure as prices fall during a crisis. Prospect Theory's other key finding, that people become risk-seeking once already facing a loss, instead predicts reluctance to sell rather than panic selling, a separate and partly offsetting behavioural force. It is loss aversion, rather than this risk-seeking tendency, that is treated as the primary mechanism behind the abnormal returns this paper measures.

Shiller (1981), in the *American Economic Review*, showed that stock price volatility is far too high to be explained by subsequent changes in dividends: prices move dramatically even when underlying cash flows do not. Sentiment and psychology drive a significant portion of price movement in normal times, which suggests that during a shock they may dominate even further. De Bondt and Thaler (1985), in the *Journal of Finance*, provided direct empirical evidence: portfolios of prior losers significantly outperformed prior winners over the following three to five years, which fits a pattern of stocks overreacting to bad news and then correcting. They also found the overreaction asymmetric, larger for losers than winners, in line with what loss aversion would predict.

Shleifer and Vishny (1997), in the *Journal of Finance*, explained why mispricing does not get corrected instantly even when rational investors can see it. Arbitrageurs managing outside capital face redemption pressure when a position moves against them temporarily. If prices keep falling after an arbitrageur buys, investors may withdraw their money at the worst moment, forcing the position to close. Mispricing can therefore become self-reinforcing in extreme periods. This offers a possible explanation for why selling pressure may continue during periods of uncertainty even after substantial price declines, and why correction can take weeks rather than hours.

Nofsinger and Sias (1999), in the *Journal of Finance*, documented a strong positive correlation between changes in institutional ownership and returns, and found that institutional investors herd, buying and selling the same stocks simultaneously. During geopolitical shocks, FIIs may respond to common global risk signals, often reducing exposure to emerging markets during periods of heightened uncertainty. This collective exit can amplify the abnormal return beyond what any single institution's fundamental reassessment would produce. This herding dynamic is particularly pronounced in emerging markets, where FII participation is large relative to domestic institutional ownership (Bekaert & Harvey, 2000).

Caldara and Iacoviello (2022), in the *American Economic Review*, built the Geopolitical Risk Index (GPR) from text analysis of major newspaper coverage of wars, terrorist attacks, and military tensions across a hundred-year sample. The index spikes at the Korean War, the Cuban Missile Crisis, and September 11, among others. Their main finding is that higher GPR foreshadows lower investment and employment and is associated with larger downside economic risks. They also decompose it into a Threats sub-index, capturing anticipation, and an Acts sub-index, capturing realisation, finding both channels carry consequences. The GPR Index provides useful external validation for the severity ranking used informally in this paper, with Russia-Ukraine and COVID-19 treated as the highest-severity events and Pulwama and Galwan as more contained ones. A formal comparison against GPR scores is a natural next step for this line of research.

Berkman, Jacobsen, and Lee (2011), in the *Journal of Financial Economics*, constructed a crisis severity index from 447 international political crises between 1918 and 2006 and found that changes in crisis risk have a large impact on both the mean and volatility of global stock returns. Their cross-sectional results also showed that crisis risk is priced differently across industries, with sectors more exposed to geopolitical risk earning higher returns as compensation. This supports the sectoral asymmetry argument in this analysis: energy, metals, and IT would be expected to behave differently from FMCG and pharma during geopolitical events precisely because their crisis sensitivity differs.

The event study framework used here originates with Fama, Fisher, Jensen, and Roll (1969) in the *International Economic Review*, which established the approach of modelling expected returns from a pre-event window and isolating the abnormal component around the event date. MacKinlay (1997), in the *Journal of Economic Literature*, provided the definitive methodological guide, covering the market model, CAR construction, and statistical testing, the approach this study follows. Recent event studies applying this methodology to the Russia-Ukraine war found significant negative abnormal returns globally, with pronounced effects in European markets (Grinius & Baležentis, 2025). India showed negative abnormal returns on the event date but did not sustain them across the full post-event window (Joshi, Baker, & Aggarwal, 2023), which lines up with the mean reversion hypothesis this research formalises.

Fratzscher (2012), in the *Journal of International Economics*, used high-frequency portfolio capital flow data from 50 countries to show that global push factors, particularly a common risk factor, dominate country-specific conditions in driving capital flows during crises. Capital left emerging markets during the 2008 crisis not because their fundamentals deteriorated but because global risk appetite collapsed. A similar logic applies here: a geopolitical shock triggers a global risk-off move, and India is sold as part of the emerging market category, regardless of its own economic position.

Bekaert and Harvey (2000), in the *Journal of Finance*, found that while foreign investor participation improves emerging market liquidity in normal times, it amplifies volatility during stress periods. Rapid FII outflows can amplify short-term volatility and increase downward pressure on equity prices during stress periods. In India, daily FII flow data, obtained for this study via NSDL's FPI archive (Section 3.6), makes this mechanism directly measurable. Baele, Bekaert, and Inghelbrecht (2010), in the *Review of Financial Studies*, documented how stock-bond correlations turn sharply negative during uncertainty, as investors move out of equities into bonds simultaneously. This pattern has been documented across a range of crisis types, from financial crashes to geopolitical events (Berkman, Jacobsen, & Lee, 2011), and is proxied in this study through gold prices and India VIX movements, tracked in Section 3.7.

Research Gap

The literature reviewed above treats these dimensions largely in isolation. Berkman, Jacobsen, and Lee (2011) and Caldara and Iacoviello (2022) study crisis severity and price reactions across international samples, but without a capital-flow mechanism or sector-level analysis. Fratzscher (2012) and Bekaert and Harvey (2000) study capital flow dynamics during crises, but not abnormal returns directly. Recent single-event studies of the Russia-Ukraine war capture one shock in isolation rather than testing whether a pattern holds across shock types (Joshi, Baker, & Aggarwal, 2023; Grinius & Baležentis, 2025). To the best of the author's knowledge, no existing study combines abnormal return measurement, capital flow data, mean reversion testing, and sectoral asymmetry within a single India-specific framework across multiple geopolitical shock types. This paper aims to address that gap, while acknowledging the scope limitations discussed in Section 3.9.

3. Methodology

3.1 Research Design

This paper uses an event study to measure how Indian equity markets respond to geopolitical shocks. The event study approach works by first establishing what returns normally look like for an index during a period before the shock, referred to in this paper as the estimation window and defined precisely in Section 3.4, and then measuring how much actual returns deviated from that baseline around the time of a shock. That deviation, called the abnormal return, is examined as a potential indicator of short-term mispricing when combined with evidence of mean reversion. If markets are efficient, abnormal returns should be negligible or correct quickly, as new information is absorbed (Fama, 1970). If they are large, persistent, and then gradually reverse, that points to overreaction followed by mean reversion, the central argument of this study (De Bondt & Thaler, 1985; Shiller, 1981).

This method is well suited to this analysis for a simple reason: geopolitical shocks have a specific date of onset, which helps separate the event's effect from normal market movement. The framework follows MacKinlay (1997), which remains the standard methodological reference for event studies in financial economics.

3.2 Event Selection

Four events are studied, chosen to cover different types of geopolitical shock rather than multiple instances of the same type. The reasoning is straightforward: if the same pattern appears across events with very different origins and economic implications, it is harder to explain away as coincidence or event-specific noise.

The Russia-Ukraine war (February 24, 2022) is the primary case. Russia's invasion was sudden, the date is unambiguous, and the shock was large enough to move markets globally (Grinius & Baležentis, 2025). India had limited direct trade exposure to either country, which makes it a useful test: if Indian equity markets fell sharply despite limited fundamental connection, the reaction requires a different explanation than earnings deterioration.

The COVID-19 pandemic declaration (March 11, 2020) is included as a systemic global shock case. Although not a traditional geopolitical event, it represents an external uncertainty shock with significant effects on investor behaviour and capital flows, a sudden, exogenous event where the scale of the market reaction far exceeded any reasonable near-term revision to corporate fundamentals. The Nifty 50 fell nearly 38% in a matter of weeks and then staged a recovery while the health crisis was still intensifying, a pattern that is difficult to explain without invoking mispricing and correction.

The Pulwama attack (February 14, 2019) is included as the domestic shock case. A suicide bombing in Kashmir escalated India-Pakistan tensions sharply and within days brought the two countries close to military confrontation. This is the only event in the dataset that originated inside India, which allows a comparison between how markets respond to domestically versus externally originating shocks.

The Galwan Valley clash (June 15, 2020) is the bilateral strategic shock case. Indian and Chinese troops clashed along the Line of Actual Control, resulting in casualties and the most serious India-China military confrontation in decades. This event occurred during the COVID-19 recovery period, which creates a complication discussed in the limitations section, but it is included because it tests whether a geopolitical shock can produce measurable abnormal returns even when markets are already in a volatile recovery phase.

3.3 Index and Sector Selection

The Nifty 50 is the primary index. It is the most widely tracked large-cap benchmark for Indian equities, covers 50 companies across all major sectors, and has deep liquidity, making daily price movements meaningful rather than noise-driven.

Six sectoral indices are analysed alongside it. Nifty IT, Nifty Energy, and Nifty Metal are chosen as globally integrated sectors, since their revenues and cost structures are tied to global prices, foreign demand, and currency movements, meaning a global geopolitical shock should affect them through multiple channels simultaneously. Nifty Bank is included because it is the sector most directly exposed to FII flow dynamics and domestic interest rate movements (Bekaert & Harvey, 2000). Nifty FMCG and Nifty Pharma are included as the domestic defensive comparison, since both are largely insulated from global commodity prices and foreign demand, and their revenues are driven by domestic consumption that does not disappear during a geopolitical event abroad. The hypothesis tested in Section 4 is that the first group shows deeper negative abnormal returns than the second (Berkman, Jacobsen, & Lee, 2011).

3.4 Estimation and Event Windows

The estimation window, the period used to calculate normal, pre-shock return behaviour, is set at 120 trading days, running from 129 to 10 trading days before each event date, consistent with standard event study practice (Brown & Warner, 1985; MacKinlay, 1997). A 120-day window is long enough to generate stable estimates of each index's typical return pattern without going so far back that the historical data stops reflecting current market conditions. The five-trading-day buffer between the end of the estimation window and the start of the event window follows MacKinlay's (1997) recommendation that the gap be at least as large as the pre-event portion of the event window, guarding against pre-event contamination: if rumours or early signals begin moving prices in the days before a shock is officially confirmed, including those days in the baseline would make the baseline look artificially worse and understate the abnormal return.

The event window runs from five trading days before the event date to thirty trading days after. The pre-event portion allows detection of any anticipatory price movement. The thirty-day post-event window is the primary period for testing mean reversion, long enough to observe whether prices drift back toward their pre-event trajectory (De Bondt & Thaler, 1985).

3.5 Calculating Abnormal Returns

The core measurement in this analysis is the abnormal return, the difference between what an index actually returned on a given day and what it would have been expected to return, where "expected" is defined using the market model: the statistical relationship between the index's daily returns and its benchmark's daily returns, estimated over the 120-day pre-event window (MacKinlay, 1997). This distinction matters because markets move every day for reasons unrelated to any specific event. To isolate the shock's effect, it is necessary to first establish this baseline of expected return behaviour and then measure the deviation from it.

For each index, this expected-return relationship is estimated using the 120-day pre-event window. Specifically, the index's daily returns are regressed against its benchmark's daily returns, either the Nifty 50 for sectoral indices, or the MSCI Emerging Markets Index for the Nifty 50 itself. The MSCI EM Index is used for the Nifty 50 rather than a domestic alternative because it better captures the global risk-off channel through which FII flows are theorised to operate (Fratzscher, 2012; Bekaert & Harvey, 2000). This regression produces alpha and beta estimates that capture how much the index typically moves, and by how much per unit of benchmark movement, under ordinary conditions (Fama, Fisher, Jensen, & Roll, 1969).

During the event window, this estimated relationship is used to generate a predicted return for each day, based on the benchmark's actual movement that day. The abnormal return is the actual return minus that predicted return. A negative abnormal return means the index fell more than the model would have predicted given how the benchmark moved, the excess decline is what this paper attributes to the shock. A positive abnormal return in the recovery phase means the index is gaining back more than the model predicts, which is the mean reversion signal (De Bondt & Thaler, 1985).

Daily abnormal returns are then accumulated across the event window to produce a Cumulative Abnormal Return, or CAR. This single number captures the total excess loss, or gain, attributable to the event over the full window (MacKinlay, 1997). Statistical testing, reported in Section 5, is used to assess whether the CAR values observed are large enough to be meaningful rather than the result of normal day-to-day randomness.

3.6 Capital Flow Data

Daily net FII equity investment data was obtained from NSDL's FPI Archive for each of the four event windows, covering net buy and sell figures in ₹ crore. This allows a direct test of H2: for each event, net FII flow is summed over the pre-event window [-5, event day] and the post-event window [+1, +30], and compared against the corresponding CAR values using Pearson's correlation coefficient across the four events. The use of high-frequency capital flow data to test the relationship between foreign investor positioning and equity returns follows the approach of Fratzscher (2012), who demonstrated that global push factors, captured through portfolio flow data, dominate domestic fundamentals in explaining emerging market price movements during risk-off episodes. Daily DII flow data for these windows falls outside the scope of this study and is discussed as a limitation in Section 3.9.

3.7 Supporting Variables

Two additional variables are tracked to build a more complete picture of what is happening during each event window. MCX gold prices are tracked as a flight-to-safety indicator. If equity abnormal returns are negative while gold prices are rising in the same window, it suggests capital is rotating into safe-haven assets rather than responding to a genuine deterioration in Indian corporate fundamentals (Baele, Bekaert, & Inghelbrecht, 2010). India VIX, the implied volatility index derived from Nifty 50 options pricing, is tracked as a fear gauge. A sharp VIX spike at the event date is consistent with the market pricing elevated uncertainty rather than reacting to specific new information about corporate earnings. VIX normalisation in the weeks following the shock provides a natural marker for when the market has absorbed the event, and that normalisation would be expected to correspond with mean reversion in abnormal returns if the mispricing argument holds.

3.8 Hypotheses

Four hypotheses structure the empirical analysis:

H1: Geopolitical shocks produce statistically significant abnormal returns on the Nifty 50 relative to normal market model expectations.

H2: The magnitude of negative cumulative abnormal returns during the event window is positively correlated with the magnitude of net FII outflows over the same period.

H3: Cumulative abnormal returns mean-revert to near zero within 15 to 30 trading days following each shock, consistent with temporary mispricing rather than a permanent repricing of fundamentals.

H4: Globally integrated sectors, Nifty IT, Nifty Energy, and Nifty Metal, exhibit deeper negative abnormal returns during event windows than relatively defensive sectors, Nifty FMCG and Nifty Pharma.

3.9 Limitations

Four limitations are worth stating clearly. First, the Galwan Valley event window overlaps with the COVID-19 recovery period, meaning the abnormal returns measured in that window may reflect both shocks simultaneously. The estimation window approach controls for this as far as possible, but the two effects cannot be fully separated. Second, including COVID-19 as a geopolitical shock is a definitional choice that not all researchers would make. This paper justifies it on structural grounds, since the event fits the pattern of an exogenous shock producing market reactions disproportionate to near-term fundamental change (Shiller, 1981), but it is acknowledged as a boundary case. Third, four events is a small sample. The findings are best understood as evidence that this pattern exists and is identifiable, not as a basis for precise statistical claims about how large or how long it is on average. Fourth, the FII correlation reported in Section 5.2 rests on only four events, which limits its statistical power; it is best read as suggestive rather than conclusive. Daily DII flow data for these windows was outside this study's scope, and would be needed to test directly whether domestic buying offsets FII selling during the recovery phase.

4. Data and Case Studies

4.1 Pulwama Attack, February 14, 2019

On February 14, 2019, a suicide bomber struck a CRPF convoy in Pulwama, Jammu and Kashmir, killing 40 soldiers. The attack was claimed by Jaish-e-Mohammed and set off a rapid escalation in India-Pakistan tensions. India conducted airstrikes at Balakot on February 26, Pakistan retaliated, an Indian pilot was captured and then returned, and for roughly two weeks the two countries were closer to open conflict than they had been in years. By early March the immediate crisis had passed, but the geopolitical temperature remained elevated through the end of the event window. The GPR Index (Caldara & Iacoviello, 2022) records a moderate spike around this period, consistent with its classification here as a lower-severity shock relative to COVID-19 and Russia-Ukraine.

The market's reaction on the day of the attack was contained. The Nifty 50 closed at 10,746 on February 14, down from 10,793 the previous day, a fall of 0.44%, with an abnormal return of -0.41%. Part of this is explained by timing: the attack happened during trading hours, leaving the market only a few hours to react. The larger reaction came in the days after. By February 19, the Nifty had reached its window low of 10,604, a total decline of 1.75% from the pre-event level. The CAR over the [-5, event] window was -2.72%, capturing the accumulation of selling across the days surrounding the attack. This gradual price adjustment, rather than a single-day shock, fits the idea that markets incorporate information as it emerges (Fama, 1970).

What happened next is the more notable part. By February 21, five trading days after the attack, the Nifty had already recovered to 10,791, essentially flat with pre-event levels. The Balakot airstrikes on February 26 triggered another brief dip and pushed VIX to its window peak of 18.90 on February 28, but the broader trend was upward. By March 29, the Nifty had climbed to 11,623, a gain of 7.69% from the pre-event level. The CAR in the [+1, +30] window was +8.75%: the index did not just recover its losses, it outperformed the model's expectations. The market recovered more quickly than the geopolitical situation itself de-escalated. This mirrors De Bondt and Thaler's (1985) overreaction hypothesis, in which stocks that decline sharply in response to negative news tend to outperform over the subsequent period as the initial reaction is corrected.

VIX averaged 15.65 in the five days before the event, moved to 15.73 on the event day, peaked at 18.90 around the time of Balakot, and settled back to 16.65 by the window's end. This trajectory broadly tracks the geopolitical narrative, with fear rising gradually with escalation and falling as de-escalation took hold. The relatively modest VIX peak during Pulwama fits the broader pattern that lower-severity crises tend to produce more contained market reactions (Berkman, Jacobsen, & Lee, 2011).

Gold's behaviour provides additional insight into investor risk perception during the Pulwama event window. It rose modestly from 1,319 pre-event to a peak of 1,348 on February 25, and then fell back to 1,298 by the end of the window, below where it started. During a sustained flight-to-safety episode, gold prices would typically remain elevated throughout the period of heightened uncertainty. The fact that it reversed completely suggests investors judged the conflict risk as temporary from an early stage, even while equity prices were falling. This distinguishes the Pulwama episode from the higher-severity events examined in this study.

At the sectoral level, none of the six indices produced a statistically significant result during the Pulwama window. When aggregate market movements are modest, sectoral effects tend to get lost in the noise (Berkman, Jacobsen, & Lee, 2011). Nifty IT was the weakest performer at a CAR of -7.05% over the [+1, +30] window, which likely reflects broader global risk-off sentiment rather than anything specific to India-Pakistan tensions (Fratzscher, 2012). Nifty Metal was the strongest at +9.53%, and Nifty Pharma posted a positive abnormal return on the event day itself (+1.43%), in keeping with defensive sector behaviour during domestically originating shocks. Overall, the Pulwama episode reads as a mild and short-lived market overreaction that reversed rapidly despite continued geopolitical uncertainty.

4.2 COVID-19 Pandemic Declaration, March 11, 2020

The WHO declared COVID-19 a global pandemic on March 11, 2020. By that point, markets had already been selling off for weeks, with the Nifty falling from around 12,200 in January to 10,451 by March 9. By the time of the WHO declaration, much of the market reaction had already taken place: the Nifty barely moved on March 11, closing at 10,458, up 0.07% from the previous session. The abnormal return on the event day was effectively zero. This does not suggest that markets were calm; rather, it is consistent with investors having already incorporated much of the expected information into prices before the WHO's official declaration (Fama, 1970). The CAR in the [-5, event] window was -6.24%, reflecting the accumulation of fear-driven selling in the days immediately before. This anticipatory pricing echoes the GPR Threats sub-index documented by Caldara and Iacoviello (2022), which captures the market impact of escalating risk before a shock formally materialises.

What followed the declaration was severe. The next day, March 12, the Nifty fell 8.3% in a single session, to 9,590. By March 16 it was at 9,197. By March 23, it had reached 7,610, a decline of 27.18% from the pre-event level. Over this same stretch, VIX climbed from 30.80 on the event day to a peak of 83.61, a reading that had never been seen in Indian market history and has not been reached since. The t-statistic for the Nifty 50 during this window was -2.446, comfortably clearing the 5% significance threshold and indicating that price movements of this scale are unlikely to reflect normal variation around the baseline. Shiller (1981) demonstrated that price volatility routinely exceeds what changes in underlying fundamentals can justify; the COVID crash represents an extreme instance of this excess volatility, alongside the mechanisms of loss aversion and herding documented by Kahneman and Tversky (1979) and Nofsinger and Sias (1999) respectively.

The recovery began before any fundamental improvement in the pandemic situation. From the March 23 low of 7,610, the Nifty had climbed back to 8,317 by March 25, two days later, and continued higher through April. The CAR in the [+1, +15] window was -21.45%, but by the end of the [+1, +30] window it had recovered to -8.40%, a positive swing of over 13 percentage points within the window itself. The full recovery to pre-pandemic levels took longer, but the mean reversion was clearly underway by late March while COVID deaths were still rising globally.

The early recovery occurred despite continued deterioration in the public health situation, suggesting that investors were reassessing the magnitude of future economic damage rather than responding to immediate improvements in pandemic conditions. This aligns with Shleifer and Vishny's (1997) limits of arbitrage framework: once redemption pressure and mandate constraints ease slightly, rational investors begin correcting the overshoot even before the fundamental situation improves.

Gold moved decisively throughout this window. Pre-event gold stood at 1,517. It rose to a peak of 1,769 on April 13, a gain of 16.63%, and ended the window at 1,722, still 13.55% above pre-event levels. This sustained increase in gold prices fits the safe-haven demand pattern expected during periods of heightened uncertainty (Baele, Bekaert, & Inghelbrecht, 2010) and supports the capital rotation hypothesis examined in this study. Unlike Pulwama, where gold's brief rise fully reversed, the COVID gold move persisted through the entire 30-day window.

Sectorally, COVID produced the most pronounced asymmetry in the dataset. Nifty Bank was the worst performer, posting a CAR of -10.66% over the [+1, +30] window. With a beta of 1.31, the highest in the dataset, it amplified every downward move, and it sits at the intersection of FII flow sensitivity, credit risk, and interest rate expectations, all of which deteriorated simultaneously (Bekaert & Harvey, 2000). Nifty Pharma was the other extreme, with a CAR of +27.91% and a t-statistic of 2.18, statistically significant. A global pandemic created an immediate revenue tailwind for pharmaceutical companies, and markets priced this quickly. Nifty FMCG posted +7.89%, also in line with defensive positioning. Nifty IT came in at -5.05%, negative, but considerably less severe than banking, partly because dollar-denominated IT revenues received a partial boost from rupee depreciation. The divergence between defensive and cyclical sectors during COVID provides the strongest empirical support for H4 among the four case studies (Berkman, Jacobsen, & Lee, 2011).

4.3 Galwan Valley Clash, June 15, 2020

On the night of June 15-16, 2020, Indian and Chinese soldiers clashed in the Galwan Valley along the Line of Actual Control in eastern Ladakh, resulting in 20 Indian fatalities, the first combat deaths on the India-China border since 1975. The incident marked a significant shift in bilateral relations, triggering a wave of restrictions on Chinese apps, goods, and investment that continued for years.

This event is the most methodologically difficult of the four, and that should be said plainly before discussing the numbers. Galwan happened during the COVID-19 recovery period, when the Nifty had already fallen from its January highs and was climbing back. India VIX was averaging 32.49 in the five days before the clash, a level that in a normal year would signal acute market stress on its own. The estimation window for this event captures a period of COVID-era elevated volatility, which affects the baseline and introduces additional noise into the abnormal return calculations. Accordingly, the findings for this event should be interpreted with greater caution than those of the other case studies.

The market reaction on the event day was visible but contained. The Nifty closed at 9,814 on June 15, down from 9,973 the previous Friday, a fall of 1.60%. It dipped slightly further to 9,881 on June 17 before stabilising. The CAR over the [-5, event] window was -2.65%. These numbers are modest in absolute terms, though a 1.60% single-day fall in a market already characterised by high volatility is not trivial.

Among the four events examined, Galwan exhibited the fastest post-event recovery. By June 22, five trading days after the clash, the Nifty was already above the pre-event level. By the end of the 30-day window on July 27, it had reached 11,132, a gain of 11.62% from pre-event, with a CAR of +15.76%. The caveat applies directly here: this strong positive reading reflects both mean reversion from the Galwan-specific short-term deviation and the continuation of the COVID-era recovery trend already underway before the clash. These two effects cannot be cleanly separated with the event study methodology used in this paper.

Gold rose 11.15% from pre-event to the end of the window, though again the global gold bull run of mid-2020 was driven by multiple factors beyond Galwan, including US dollar weakness, Federal Reserve policy, and lingering COVID uncertainty.

The most notable sectoral result from Galwan is Nifty IT's CAR of +7.39% over the [+1, +30] window. The Indian government's ban on 59 Chinese apps in June 2020, including TikTok and UC Browser, created a direct market opportunity for Indian technology companies positioned to benefit. Markets appear to have incorporated these expectations relatively quickly into prices, in line with the semi-strong form of the EMH (Fama, 1970). Nifty Pharma was the weakest at -14.78%, with a statistically significant t-statistic of -2.18, though this likely reflects a rotation out of the overcrowded COVID-era pharma trade and broader COVID-recovery dynamics rather than the border clash itself.

4.4 Russia-Ukraine War, February 24, 2022

Russia launched its full-scale invasion of Ukraine on February 24, 2022. This is the most unambiguously geopolitical event in the dataset. India had limited direct trade exposure to either country at the time, with Russian oil imports accounting for only 2 to 3% of India's total crude sourcing, but the shock hit Indian markets hard anyway, through a global risk-off mechanism documented in other emerging-market crises (Fratzscher, 2012; Bekaert & Harvey, 2000): investor uncertainty increases, global risk appetite declines, foreign investors often reduce exposure to emerging markets, and capital shifts toward relatively safer assets irrespective of country-specific fundamentals. Caldara and Iacoviello (2022) record a sharp spike in the GPR Index around the invasion date, among the largest in their post-2000 sample, which provides independent confirmation of the shock's severity.

The event-day reaction was the sharpest in this investigation. The Nifty closed at 16,248 on February 24, down from 17,063 the previous day, a single-session fall of 4.78%. The abnormal return on the event day was -4.82%. Unlike COVID-19, where the event-day reading was near zero because the shock was already priced, the Russia-Ukraine invasion produced a sharp and immediate abnormal market reaction that reads more as temporary overreaction than rational repricing (De Bondt & Thaler, 1985). The pre-event CAR of -6.51% reflects anticipatory selling in the weeks prior as diplomatic warnings accumulated, but the invasion itself generated an additional and substantial downward movement beyond the pre-event decline.

The slide continued through early March as the commodity consequences of the war became clearer. Crude oil moved toward $130 per barrel, wheat prices spiked, and sanctions on Russia were announced in rapid succession. By March 7, the Nifty had reached 15,863, a total decline of 7.03% from the pre-event level. Within two trading days, the recovery had already begun: by March 11, the Nifty was back at 16,630. By April 11, the end of the 30-day window, it had climbed to 17,675, above the pre-invasion level. The CAR in the [+1, +30] window was +7.49%, a swing of roughly 14 percentage points from the pre-event trough. Russia was still fighting in Ukraine when this recovery completed. Joshi, Baker, and Aggarwal (2023) similarly document that India's abnormal returns during the Russia-Ukraine event did not persist across the full post-event window, which this study's 30-day CAR data confirms and extends.

Gold followed the expected safe-haven pattern. Pre-event gold stood at 1,910, rising to a peak of 2,043 on March 9, a gain of 6.96%, before settling back to 1,945 at the window's end, a residual gain of 1.82%. The partial reversal in gold prices as equity markets recovered fits temporary risk reallocation rather than a permanent shift in investor demand (Baele, Bekaert, & Inghelbrecht, 2010). The sectoral results here are the most striking in the paper because they partially invert H4.

Nifty Metal posted the strongest CAR at +12.56% over the [+1, +30] window, and Nifty Energy followed at +8.61%, both positive, both among the globally integrated sectors H4 predicts should suffer most. The reason is that Russia and Ukraine are major global suppliers of metals and energy. Sanctions and supply disruption pushed commodity prices higher globally, and Indian metal and energy companies, primarily producers rather than consumers, benefited from rising output prices. H4's assumption that global integration creates vulnerability holds when the shock creates a demand collapse or risk-off selling (Berkman, Jacobsen, & Lee, 2011). When the shock instead creates a commodity price spike, the direction flips for commodity-producing sectors. Rather than contradicting H4, this finding suggests that the nature of global exposure is as important as the degree of global exposure.

Nifty Bank was the weakest performer at a CAR of -2.62%, which fits markets pricing in the RBI's likely rate response to the inflationary pressure the commodity spike was creating. Nifty FMCG and Nifty Pharma both posted modestly positive CARs of +5.29% and +6.76% respectively, in line with defensive rotation, though neither result was statistically significant.

5. Findings and Analysis

5.1 H1: Do Geopolitical Shocks Produce Significant Abnormal Returns?

H1 is supported, with an important nuance about shock severity.

Russia-Ukraine produced the sharpest event-day abnormal return in the sample (-4.82%, pre-event CAR of -6.51%), though statistical significance at the index level was only formally established for COVID-19 ($t = -2.446$, [+1, +15] CAR of -21.45%). Both events nonetheless show abnormal returns large enough, relative to typical daily fluctuations, to be economically meaningful. Pulwama and Galwan are more modest. Pulwama produced a -0.41% abnormal return on the event day and a pre-event CAR of -2.72%, with no sectoral result reaching statistical significance. Galwan produced a -1.60% event-day reading against an already volatile backdrop. Both events show abnormal returns that point in the same direction as H1, but the magnitudes are small relative to the surrounding noise.

The pattern across all four events suggests that H1 should be understood as conditional rather than absolute. The findings suggest that larger geopolitical shocks are associated with larger abnormal returns, with the magnitude of the response influenced by both the severity of the shock and its transmission into the Indian economy (Caldara & Iacoviello, 2022; Berkman, Jacobsen, & Lee, 2011). A domestic terrorist incident with limited escalation produces a modest and short-lived abnormal market reaction. A global systemic shock with multiple transmission channels produces a larger, statistically significant, and more sustained reaction. The type and scale of the shock appears to shape the scale of the market reaction, which, while intuitive in retrospect, has practical implications for how investors might think about pricing geopolitical risk in real time.

5.2 H2: Does Mispricing Correlate with FII Outflows?

H2 receives strong support in the pre-event window and weak support in the post-event window, and the contrast between the two is itself informative.

Net FII flows were summed over the pre-event window [-5, event day] for each of the four events and compared against the corresponding CAR values. The correlation is strong: $r = 0.964$ ($t = 5.09$, $df = 2$), which clears conventional significance thresholds despite the very small sample. This relationship is not driven solely by the COVID-19 observation; excluding it, the remaining three events still produce $r = 0.99$. Deeper pre-event price declines are closely associated with larger FII net outflows across all four events: Russia-Ukraine and COVID-19, the two highest-severity shocks, saw the largest pre-event outflows (approximately ₹11,555 crore and ₹15,475 crore respectively) alongside the deepest pre-event CARs; Pulwama and Galwan, the milder shocks, saw near-neutral or even positive net FII flows alongside the mildest CARs. This echoes Fratzscher's (2012) finding that global push factors, captured here through FII net flows, are a primary driver of capital movement from emerging markets during risk-off episodes, and Nofsinger and Sias's (1999) documentation of institutional herding behaviour that can amplify price movements beyond what individual fundamental assessments would produce.

The post-event [+1, +30] window tells a different story. The correlation between post-event CAR and post-event net FII flow is weaker and not statistically significant ($r = 0.545$, $t = 0.92$, $df = 2$). More notably, in three of the four events, COVID-19, Galwan, and Russia-Ukraine, FIIs remained net sellers over the full 30-day recovery window even as the Nifty 50's CAR turned strongly positive. Only in Pulwama did the recovery coincide with net FII buying. This divergence fits Shleifer and Vishny's (1997) limits of arbitrage argument: institutional investors facing redemption pressure and mandate constraints may continue reducing positions even as prices recover, leaving the correction to be driven by other market participants. This suggests that the initial price decline in each event tracks FII selling closely, but the subsequent recovery is not simply a function of foreign capital returning; some other mechanism, such as domestic institutional or retail buying, short covering, or a reassessment of fundamentals independent of foreign positioning, appears to be driving the recovery phase.

These results should be read with real caution given the sample size. A four-event correlation, even one that formally clears a significance threshold, rests on very few degrees of freedom, and the coefficient could shift meaningfully with additional events. The finding is best understood as suggestive evidence that FII flows track the shock phase of these events closely but do not fully explain the recovery phase, a distinction that this study's original design was not able to test directly.

5.3 H3: Do Abnormal Returns Mean-Revert Within 15 to 30 Trading Days?

H3 receives the most consistent support of the four hypotheses, and the evidence for it forms one of this paper's central empirical contributions.

For Russia-Ukraine, the CAR swung from -6.51% pre-event to +7.49% by day +30. For Pulwama, from -2.72% to +8.75%. For Galwan, from -2.65% to +15.76%. In every case, the index ended the 30-day post-event window in notably better shape than the pre-event window would have predicted, meaning not just that it recovered, but that it recovered more than the baseline would have generated on its own (De Bondt & Thaler, 1985).

COVID-19 is the qualified case. The [+1, +15] CAR of -21.45% shows that mean reversion had not begun within the first two weeks. By day +30 the CAR had improved to -8.40%, a positive swing of over 13 percentage points within the window, confirming that reversion was underway even if not yet complete. The full COVID recovery took longer, which is expected given the shock's severity, since a 27% crash takes more than 30 trading days to fully retrace.

The clearest feature of the H3 results holds across all four events: the market trough in every case preceded any resolution of the geopolitical situation. The Nifty recovered from the Russia-Ukraine crash while Russia was still advancing into Ukraine. It recovered from the COVID crash while the pandemic was still intensifying. It recovered from Pulwama before India-Pakistan tensions had fully de-escalated. One interpretation that fits this timing is that the recovery reflected a reassessment of the shock's likely economic damage, rather than an improvement in the external situation itself (Kahneman & Tversky, 1979), though this study's design does not permit isolating investor motivation directly. Shleifer and Vishny (1997) offer a complementary explanation: as redemption pressure and institutional constraints ease in the weeks following a shock, arbitrage capital re-enters the market and pushes prices back toward fundamental value, producing the mean reversion pattern observed here. The initial market reaction appears to have priced in a more severe economic impact than was ultimately realised, and the recovery happened as that overshoot became apparent to the market.

Taken together, these findings provide the strongest empirical support for the paper's short-term overreaction hypothesis across the four events examined.

5.4 H4: Do Globally Integrated Sectors Show Deeper Mispricing Than Defensive Domestic Ones?

H4 is partially supported and partially refined by the data.

During COVID-19, the hypothesis holds cleanly. Nifty Bank (-10.66%) and Nifty IT (-5.05%) significantly underperformed Nifty Pharma (+27.91%) and Nifty FMCG (+7.89%). The globally integrated sectors were hit hardest; the domestic defensives held up or gained. Nifty Pharma's statistically significant +27.91% reading is the strongest single sectoral result in the entire dataset. Berkman, Jacobsen, and Lee (2011) find that sectors with greater geopolitical exposure experience larger crisis-period volatility, which broadly matches this finding, though the pharma result illustrates that geopolitical shocks can also create genuine fundamental opportunities in specific sectors, not only fear-driven distortions.

During Russia-Ukraine, the commodity sectors inverted the hypothesis in a theoretically explicable way. Nifty Metal (+12.56%) and Nifty Energy (+8.61%) were the strongest performers, globally integrated sectors that benefited because the specific nature of the shock was a commodity supply disruption that raised output prices for Indian producers. As discussed in Section 4.4, this does not contradict H4 so much as expose an assumption embedded within it, that global integration only ever hurts a sector. Here it helped, because the shock itself raised the price of what these sectors sell. This echoes Berkman, Jacobsen, and Lee's (2011) broader finding that crisis sensitivity is industry-specific rather than uniformly negative across globally exposed sectors.

Nifty Bank stands out across events. It was the weakest performer in both COVID-19 (-10.66%) and Russia-Ukraine (-2.62%), making it the weakest-performing sector in both of the two highest-severity shocks in this sample. This matches Bekaert and Harvey's (2000) documentation that FII-sensitive financial sectors experience the sharpest volatility amplification during stress periods, given banking's position at the intersection of capital flow dynamics, domestic credit conditions, and interest rate expectations.

For Pulwama and Galwan, sectoral effects were too modest and statistically insignificant to draw strong conclusions. When aggregate market movements are small, the systematic geopolitical transmission channel is drowned out by idiosyncratic sector-level noise (Berkman, Jacobsen, & Lee, 2011).

5.5 Summary

Three patterns emerge consistently across the four events. First, geopolitical shocks are associated with statistically meaningful abnormal returns relative to expected market behaviour, with the size of the temporary overreaction broadly proportional to the shock's severity (Caldara & Iacoviello, 2022; Berkman, Jacobsen, & Lee, 2011). Second, abnormal returns exhibit evidence of mean reversion within the 30-day post-event window across all four case studies, beginning before the underlying geopolitical situation resolves, suggesting that declining uncertainty plays an important role in the recovery process (De Bondt & Thaler, 1985; Shleifer & Vishny, 1997), although the influence of broader macroeconomic developments cannot be entirely ruled out. Third, the sectoral pattern during severe shocks generally shows defensive domestic sectors outperforming globally integrated ones, with the specific exception of commodity-producing sectors during commodity supply shocks.

Within this sample, gold appeared to be a more consistent indicator of sustained fear-driven capital rotation than VIX, which spiked across all four events regardless of severity (Baele, Bekaert, & Inghelbrecht, 2010). Gold moved significantly and sustained its gains only during the two more severe events, COVID-19 and Russia-Ukraine, tracking shock severity more faithfully than VIX did. For settings without access to daily FII data, gold price movement during the event window may serve as a useful indirect proxy, though the direct FII correlation reported in Section 5.2 provides a stronger signal where such data is available.

6. Conclusion

This paper asked whether geopolitical shocks lead to short-term mispricing in Indian equity markets and whether capital flight is the mechanism behind it. Across four events spanning three years and four different types of shock, the findings provide consistent evidence of short-term abnormal market reactions that are better explained by behavioural overreaction (Kahneman & Tversky, 1979; De Bondt & Thaler, 1985) than by efficient repricing of new fundamental information (Fama, 1970). The evidence on the capital-flow mechanism is directly supported for the shock phase of each event, though the recovery phase appears to involve forces beyond FII positioning alone.

Among this study's empirical contributions, the most consistent is the finding, established in Section 5.3, that mean reversion in every event began before the underlying geopolitical situation had actually resolved. A second contribution, established in Section 5.2, is the divergence between FII positioning and price recovery: FII outflows track the initial shock closely (Fratzscher, 2012; Nofsinger & Sias, 1999) but do not fully explain the subsequent recovery, pointing to other forces at work during that phase (Shleifer & Vishny, 1997). The mean-reversion timing pattern remains the strongest single piece of evidence for short-term overreaction in this study: it is more consistent with a market correcting an initial misread of a shock's severity (De Bondt & Thaler, 1985) than with a market simply catching up to good news, though the two cannot be definitively distinguished with this design.

The magnitude of the market response also appears to vary systematically with shock severity (Caldara & Iacoviello, 2022; Berkman, Jacobsen, & Lee, 2011). Pulwama produced a mild, short-lived, behaviourally driven price adjustment with a pre-event CAR of -2.72% and a full recovery within two weeks. Russia-Ukraine produced a sharp -4.82% single-day abnormal return followed by a 14 percentage point swing in the 30-day window. COVID-19 was the extreme case at the index level, with a t-statistic of -2.446 and a [+1, +15] CAR of -21.45% that partially reversed even within the event window. The magnitude of abnormal returns appears to increase with both the severity of the shock and the strength of its economic transmission into India, not simply the fact that a shock occurred.

The behavioural explanation for why this happens sits in the space between Kahneman and Tversky's loss aversion and Shleifer and Vishny's limits of arbitrage. Retail investors may sell more aggressively than changes in fundamentals alone would justify because falling prices trigger disproportionate fear (Kahneman & Tversky, 1979). Institutional investors, even when they can see the overshoot, face mandate limits and redemption pressure that can delay correction (Shleifer & Vishny, 1997). A temporary window of pricing inefficiency may emerge from the first force and gradually narrow as the second constraint eases, which aligns with the mean reversion observed in the CAR data across all four events (Grossman & Stiglitz, 1980).

The sectoral analysis provides additional insight into how different industries respond to geopolitical shocks. Nifty Pharma's statistically significant +27.91% CAR during COVID-19 is the strongest single sectoral result in the dataset, and suggests that geopolitical shocks can generate genuine fundamental repricing in specific sectors alongside temporary behavioural distortions elsewhere in the market (Berkman, Jacobsen, & Lee, 2011). Nifty Bank's relatively weak performance across the two most severe events (Bekaert & Harvey, 2000) suggests it is among the sectors most exposed to geopolitical transmission through financial conditions and investor sentiment. The Russia-Ukraine commodity inversion, where Nifty Metal and Nifty Energy outperformed despite being globally integrated, extends the interpretation of H4: global integration appears to create vulnerability during demand shocks, but opportunity during supply shocks where Indian companies are net producers of the disrupted commodity.

The most valuable extension of this work would be direct daily DII flow data for these windows, allowing a formal test of whether domestic institutional buying offsets FII selling during the recovery phase, the mechanism implied by the divergence documented in Section 5.2, alongside a larger sample of events to strengthen the statistical power of the correlation reported here (Fratzscher, 2012). Beyond that, incorporating real-time sentiment data would allow more precise identification of the behavioural mechanism (Shiller, 1981).

Overall, this paper finds that markets often overreact to major geopolitical and systemic shocks in the short run (De Bondt & Thaler, 1985; Kahneman & Tversky, 1979). In the events examined, prices began reverting before the underlying crises had fully resolved. The evidence points to the existence of temporary deviations between observed market prices and values implied by prevailing expectations, although the precise magnitude of those deviations cannot be observed directly. By examining the dynamics of abnormal returns, capital flows, mean reversion, and sectoral responses across multiple shocks, this study contributes to a better understanding of how Indian equity markets respond to periods of heightened geopolitical uncertainty.

While the results do not conclusively establish the presence of mispricing in every case, they consistently indicate that major geopolitical shocks are followed by temporary abnormal market reactions that exhibit evidence of mean reversion. This pattern fits short-term behavioural overreaction better than it fits immediate, fully efficient price adjustment (Fama, 1970; Grossman & Stiglitz, 1980), and understanding it may matter for how investors respond to crises and how policymakers think about confidence restoration during periods of geopolitical stress.

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