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Geopolitical Shocks and Stock Market Dynamics: A Behavioral–Econophysics Framework

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ABSTRACT

This study develops an interdisciplinary framework linking geopolitical shocks to financial markets through macroeconomic fundamentals, perceived risk, and collective sentiment. Perceived risk shifts investors between optimistic and pessimistic states, while imitation can generate bistable sentiment. Energy prices affect fundamental valuations differently in net energy-importing and exporting economies. When markets share the same sensitivities to common risk and sentiment, cross-market comparisons remove common global components and reveal differences in energy exposure. The empirical analysis examines escalating tensions involving Iran in early March 2026. The daily Geopolitical Risk index exceeded four times its February average and Brent crude rose about 34% within a week, yet an event study finds no statistically significant abnormal return of the S&P 500, although the confidence interval does not rule out a sizeable decline; the index fell about 2% in the first week and about 8% by the end of March. A synthetic control constructed from five non-US equity markets shows that US equities outperformed by about 3.5 percentage points over the first two trading days, mainly against oil-importing markets; this gap is stable across fitting windows of 20 to 120 days but becomes small when a 250-day window places almost all weight on Canada, another net oil exporter, and the advantage narrowed sharply at the end of March. A vector autoregression (VAR) indicates that the volatility–return relationship is predominantly contemporaneous. The findings are consistent with, but do not establish, a weak-herding regime and an energy channel moderated by the US net energy position, because collective sentiment and herding are not measured directly. Drawing on feedback dynamics, state transitions, and equilibrium adjustments in physics and chemistry, the framework connects investor behavior with macroeconomic exposure to explain heterogeneous financial responses to geopolitical uncertainty.

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1. Introduction

Financial markets often react sharply to geopolitical events such as military conflicts, terrorist attacks, economic sanctions, or sudden escalations in international tensions [1,2]. Episodes of geopolitical instability—particularly those involving the Middle East and global energy markets—have historically been associated with rapid declines in equity prices and increases in market volatility [3,4]. These recurring dynamics suggest that geopolitical shocks represent an important source of financial market instability and investor uncertainty [5].

Recent developments in behavioral finance emphasize the role of investor psychology, expectations, and information diffusion in explaining such dynamics [6-8]. During periods of heightened uncertainty, investors respond not only to economic fundamentals but also to perceived risk and the behavior of other market participants. As investors observe the actions of others, expectations adjust endogenously [9], creating feedback mechanisms that may temporarily push asset prices away from their fundamental values.

At the same time, an expanding interdisciplinary literature has applied insights from physics, chemistry, and biology to the study of economic and financial systems [10-14]. From this perspective, financial markets can be viewed as complex adaptive systems composed of many interacting agents whose collective behavior generates aggregate market outcomes.

Insights from chemical reaction dynamics provide an additional perspective for understanding investor behavior. In chemical systems, molecules transition between states through reaction processes whose rates depend on environmental conditions such as temperature, the activation energy of the reaction, and the concentrations of the reacting species [15,16]. In this sense, investor sentiment dynamics resemble reaction processes in which the proportions of optimistic and pessimistic investors evolve over time, consistent with nonlinear dynamic models of financial markets that emphasize noise-driven fluctuations and expectation shifts [17].

Motivated by these interdisciplinary insights, this paper develops a theoretical framework that integrates macroeconomic fundamentals, investor risk perception, and collective sentiment dynamics to analyze the transmission of geopolitical shocks to financial markets. The literatures on geopolitical risk, investor sentiment and econophysics each explain part of this transmission, but they have largely developed separately. The contribution of the framework lies in combining them in a single system whose implications can be confronted with data; Section 2 sets out how it differs from existing approaches.

The empirical application is the escalation of geopolitical tensions involving Iran in early March 2026. The daily Geopolitical Risk (GPR) index of Caldara and Iacoviello [4] rose from an average of about 118 in February 2026 to 274 on Sunday 1 March and 501 on Monday 2 March. Brent crude rose by about 34% between 27 February and 6 March. Yet the S&P 500 was essentially unchanged on 2 March and only about 2% lower at the end of the first week, although it fell further, by about 8%, by the end of March. The question this paper asks is therefore why the initial response of US equities to a geopolitical and energy shock of this size was smaller than that of foreign markets, and how long that relative advantage lasted. In terms of the model, the question has three parts, which correspond to the three hypotheses of Section 3.4: how large the total response of the US market was (H1), whether its response differed from that of foreign markets in the way that differences in net energy exposure predict (H2), and whether the response showed the discontinuous, self-reinforcing adjustment that strong herding among investors would produce (H3). The last part is where collective investor expectations enter: the model predicts a muted and quickly stabilizing response only when imitation is weak enough for sentiment to have a single equilibrium.

Three findings emerge. First, an event study finds no abnormal return of the S&P 500 that is statistically distinguishable from zero, either on the first trading day after the escalation or over windows of up to six trading days. Second, a synthetic control constructed from five non-US equity markets indicates that US equities

outperformed the counterfactual by about 3.5 percentage points over the first two trading days, a gap larger than on more than 99% of 455 placebo dates. The outperformance is concentrated against oil-importing markets; the Canadian market, which belongs to a net oil exporter, moved much like the US market. The outperformance persisted for most of March but narrowed sharply in the final week, and at a horizon of one month it cannot be distinguished from placebo variation. Third, a vector autoregression shows that the relationship between perceived risk and equity returns is almost entirely contemporaneous: lagged changes in perceived risk do not predict subsequent returns, but the cumulative effect on the price level does not reverse while volatility remains elevated, and that higher oil prices are not associated with lower US equity returns either contemporaneously or with a lag.

These findings are consistent with the model when the energy channel depends on net energy exposure and when herding is weak enough that collective sentiment remains in a single, monostable regime. Because collective sentiment and the strength of herding are not measured directly, the findings are consistent with this interpretation but do not establish it. The paper makes three contributions. It extends the behavioral–econophysics framework with an imitation term that makes the conditions for phase-transition-like regime shifts explicit, and with an energy channel that differs across economies. It shows that, when sensitivities to common risk and sentiment are similar across markets, a comparison against foreign markets measures differential exposure rather than the total effect of a global shock, which clarifies what event studies and synthetic controls can and cannot measure in this setting. And it documents a large geopolitical shock to which US equities responded far less than oil-importing markets.

2. Literature Review

The first strand of literature investigates how geopolitical developments influence financial markets. Bloom [18] shows that uncertainty shocks generate a rapid drop and rebound in economic activity. Baker, Bloom, and Davis [19] show that policy-related uncertainty can have significant effects on investment, financial market volatility, and macroeconomic performance. Pastor and Veronesi [20] similarly demonstrate that political uncertainty can generate large fluctuations in asset prices as investors revise expectations about future policy outcomes. More recently, Caldara and Iacoviello [4] developed the Geopolitical Risk Index (GPR1), which quantifies geopolitical tensions using news-based indicators. Subsequent studies document links between geopolitical risk and asset markets, with effects varying across countries and their exposure to conflict [21-23].

A second strand of literature emphasizes the role of investor sentiment and behavioral dynamics in financial markets. Shiller [24,25] argues that investor sentiment and narrative dynamics often drive financial market fluctuations. Similarly, Barberis et al. [26] and De Long et al. [27] show that behavioral biases and noise traders can cause persistent deviations of prices from fundamental values. Empirical evidence further suggests that investor sentiment plays an important role in explaining stock market volatility and returns [28-30].

A third body of research examines the macroeconomic channels through which geopolitical events affect financial markets. Monetary policy and interest rate changes are known to influence equity valuations through their effects on discount rates and expected corporate earnings [31]. Energy prices represent another important transmission channel. Energy price shocks can affect inflation, economic activity, and financial markets, with effects varying across regions [32-34]. Bernanke et al. [35] argue that a substantial part of the macroeconomic effect of oil shocks operates through the monetary policy response. Kilian and Park [3] show that the response of US stock returns to oil price changes depends on whether those changes reflect supply disruptions or shifts in demand. The equity effect of higher oil prices also depends on a country's net energy position: in a net exporting economy, higher prices raise the earnings

[1] https://www.matteoiacoviello.com/gpr.htm

of domestic energy producers and partly offset cost increases elsewhere. The United States has been a net exporter of petroleum on an annual basis since 2020 [36].

Finally, an interdisciplinary literature has emerged that applies concepts from physics and complex systems theory to financial markets. Known as econophysics, this field models financial markets as complex systems composed of interacting agents whose collective behavior generates emergent market dynamics [37,38]. Models developed in this literature often incorporate stochastic processes and agent-based interactions to explain phenomena such as volatility clustering, herd behavior, and market instability [39-41]. Kirman [42] and Lux [43] show how imitation among agents can generate abrupt switches between optimistic and pessimistic regimes, a mechanism that this paper incorporates in its sentiment dynamics.

Each of these strands captures part of the transmission of geopolitical shocks, but they are rarely combined. Studies of geopolitical risk measure the response of asset prices but treat investor behavior as a reduced-form reaction to uncertainty [4,18-23]. Behavioral studies document the role of sentiment and imitation but rarely link them to an exogenous risk process or to country-specific fundamentals [24-30]. Econophysics models such as those of Kirman [42] and Lux [43] generate regime switches from imitation among agents, but without a channel through which the same shock affects economies with different energy exposure differently, and without a mechanism through which news reduces perceived risk. The framework developed in this paper combines these elements in one system: perceived risk is driven by geopolitical shocks and dissipated by information; it shifts investors between optimistic and pessimistic states whose aggregate is subject to imitation; and it acts on prices together with fundamental valuations that depend on each economy's net energy position. The contribution is therefore not the use of imitation or nonlinear adjustment in isolation, but their integration, which yields explicit conditions under which collective sentiment becomes bistable (Proposition 2) and a testable implication for comparisons across markets (Proposition 3).

3. Theoretical Framework

3.1. Conceptual Framework

Geopolitical shocks influence financial markets through the interaction of macroeconomic fundamentals, investor risk perceptions, and collective expectations. Events such as military conflicts or sanctions create uncertainty about future economic conditions by disrupting supply chains, altering inflation expectations, and prompting potential policy responses.

Short-run market reactions, however, cannot be explained solely by observable fundamentals. During periods of heightened uncertainty, investors often shift away from risky assets toward safer instruments, amplifying price fluctuations beyond what macroeconomic changes alone would imply.

Building on these insights, this study conceptualizes stock price dynamics following geopolitical shocks as the outcome of three interacting mechanisms.

(1) Fundamental Valuation Channel. The net effect of higher energy prices differs across economies: it is negative where energy is mainly a cost, and smaller or even positive where domestic energy producers account for a large share of earnings.

(2) Psychological Fear Channel. Geopolitical shocks also affect markets through changes in perceived risk.

(3) Behavioral Interaction Channel. Investor sentiment evolves through social interaction and information diffusion. Rising uncertainty can shift expectations toward pessimism, while credible information may gradually restore confidence. When investors imitate one another strongly enough, collective sentiment can have two stable states, so that a shock can tip the market from one to the other.

Together, these mechanisms generate a typical market response to geopolitical shocks: an initial decline in asset prices driven by uncertainty and risk aversion, followed by gradual stabilization as information reduces uncertainty and expectations recover. The relative strength of the three channels determines whether that response is a sharp but temporary decline, a muted adjustment, or a persistent shift to a pessimistic regime.

3.2. Theoretical Model

3.2.1. Stock Price Dynamics

Let $P(t)$ denote the market price of a representative stock index at time t. Let $X(t)$ denote the benchmark valuation implied by macroeconomic fundamentals (discounted expected earnings). In the absence of large disturbances, prices tend to adjust toward $X(t)$ as mispricing is arbitraged away. However, geopolitical shocks and sentiment shifts can temporarily push prices away from benchmark valuation.

The stock price evolves according to:

$$dP(t)=\Big[\underbrace{\kappa\left(X(t)-P(t)\right)}_{\text{equilibrium adjustment}}-\underbrace{\beta_F F(t)}_{\text{risk perception effect}}+\underbrace{\beta_O\left(2O(t)-1\right)}_{\text{collective market sentiment}}-\underbrace{\beta_S S(t)}_{\text{geopolitical shock impact}}\Big]dt+\underbrace{\sqrt{T_0+T_F F(t)+T_S S(t)}}_{\text{state-dependent volatility}}\,dW_t \quad (1)$$

where W_t is a standard Brownian motion. The use of Brownian motion follows the classical stochastic diffusion framework widely applied in physics to describe random particle motion and later adapted to financial markets to model asset price dynamics [44-46].

The drift component combines four mechanisms: (i) mean reversion toward fundamentals, reflecting the gradual correction of mispricing through arbitrage activity, (ii) downward pressure generated by increased investor risk perception, (iii) sentiment-driven demand effects arising from collective investor expectations, and (iv) the direct negative impact of geopolitical shocks. The interaction among investors that generates term (iii) is specified in Section 3.2.3.

The coefficient κ governs the speed of the correction in term (i). It is not derived from a structural model of arbitrage; it is a reduced-form parameter that summarizes how quickly arbitrage, portfolio rebalancing and the incorporation of information close the gap between $P(t)$ and $X(t)$. It is therefore expected to be higher in liquid markets with few constraints on arbitrage, and lower when liquidity is thin, arbitrage capital is limited or the benchmark valuation itself is uncertain. The baseline specification treats κ as positive and constant, which is adequate for the short horizons of the empirical analysis. Under prolonged geopolitical instability, however, the conditions that sustain arbitrage may deteriorate, and a constant κ may overstate the speed of correction. A simple extension makes the speed of adjustment depend on perceived risk:

$$\kappa(t)=\frac{\kappa_0}{1+\lambda F(t)},\ \kappa_0>0,\ \lambda\geq 0 \quad (2)$$

so that the correction slows down while perceived risk remains elevated. In this case, deviations from fundamental valuation created by a geopolitical shock last longer the longer the shock keeps perceived risk high; the extension slows the convergence described in Proposition 3 without changing its direction. It is not estimated in this paper, and the value κ = 0.3 used in the illustrative simulation of Section 3.3 is a calibrated rather than an estimated value.

The volatility component is state-dependent, increasing when perceived risk F(t) or geopolitical shock intensity S(t) rises. Fluctuations whose intensity depends on the state of the system, known as multiplicative noise, are common in physical and chemical systems, particularly near instabilities [47].

The parameters T_0, T_F and T_S play the role of temperature in a Langevin equation: they set the intensity of random fluctuations around the deterministic path, with T_0 the baseline level and T_F and T_S the increase in that intensity per unit of perceived risk and shock intensity. Unlike in a physical Langevin equation, however, the noise intensity is not tied to the rate of mean reversion κ by a fluctuation–dissipation relation, so the analogy concerns only the role of these parameters as noise intensities. In the empirical analysis $P(t)$ is measured as the logarithm of the index, so that the drift terms are read as percentage changes.

3.2.2. Risk Perception Dynamics

Let $F(t)$ denote the level of perceived risk in financial markets at time t, capturing the degree of investor anxiety or uncertainty regarding future economic and geopolitical developments. The dynamics of perceived risk are described by the following differential equation:

$$\frac{dF(t)}{dt} = \underbrace{\gamma_S S(t)}_{\text{direct geopolitical shock effect}} + \underbrace{\gamma_G G(t)}_{\text{broader geopolitical risk environment}} - \underbrace{\big(\delta_R + \delta_I I(t)\big)F(t)}_{\text{dissipation, accelerated by information}} \quad (3)$$

The first term, $\gamma_S S(t)$, captures the direct effect of discrete geopolitical shocks. The second term, $\gamma_G G(t)$, represents the influence of the broader geopolitical risk environment. Even in the absence of a specific event, persistent geopolitical tensions—such as regional instability, strategic rivalries, or ongoing conflicts—can elevate baseline levels of investor anxiety and increase market sensitivity to new information.

The third term combines two forces. The rate δ_R captures the gradual dissipation of uncertainty over time: as investors process information and adapt their expectations, the initial shock to perceived risk tends to fade even in the absence of fully resolving geopolitical tensions. The rate $\delta_I I(t)$ reflects the stabilizing role of credible information, such as policy announcements, diplomatic progress, or clarification of economic exposure, which speeds up that dissipation.

In the empirical analysis, $S(t)$ corresponds to the onset of the escalation, $G(t)$ is measured by the daily GPR index, and $F(t)$ is proxied by the VIX. The information flow $I(t)$ is not observed directly; the model requires only that it never falls below a positive floor, $I(t) \geq I_0 > 0$, reflecting the continuous arrival of news even during a crisis. Because $I(t)$ is not measured, the empirical analysis cannot separate a decline in perceived risk that is driven by information from one that reflects the gradual dissipation captured by δ_R or other influences. The parameters δ_I and k_2 are therefore not identified, and equation (3) is used to interpret the data rather than estimated. The floor I_0 is a technical condition that ensures a positive baseline flow of news; it does not imply that news is always reassuring or that perceived risk must decline. Information flow could be measured in future work from the frequency and content of official statements, from news-based uncertainty indices, or from text-based measures of geopolitical communication, which would allow the dissipation term in equation (3) to be estimated (Section 6.1).

3.2.3. Collective Expectations and Sentiment Switching

Let $O(t)$ denote the proportion of optimistic investors and $\Pi(t)$ denote the proportion of pessimistic investors. The population shares satisfy:

$$\underbrace{O(t) + \Pi(t)}_{\text{distribution of investor expectations}} = 1 \quad (4)$$

Expectations shift endogenously as investors respond to perceived risk $F(t)$, stabilizing information $I(t)$, and the expectations of other investors. The switching dynamics are:

$$\frac{dO(t)}{dt} = -\underbrace{k_1 F(t) O(t)}_{\text{transition toward pessimism}} + \underbrace{k_2 I(t) \Pi(t)}_{\text{restoration of optimism}} + \underbrace{k_3\, O(t)\Pi(t)(2O(t)-1)}_{\text{imitation (herding)}}, \qquad \frac{d\Pi(t)}{dt} = -\frac{dO(t)}{dt} \tag{5}$$

These equations describe transitions between two behavioral states in a manner analogous to a reversible chemical reaction, such as an isomerization, in which molecules switch between two configurations at rates set by rate constants and external conditions [48,49]. In particular, the transition toward pessimism has the form of a pseudo-first-order reaction in which perceived risk acts like a co-reactant whose concentration is held fixed by the environment, so that it changes both the effective transition rate and the steady-state composition. Without herding and with F and I held fixed, the ratio of the steady-state shares of pessimistic and optimistic investors, $\Pi^*/O^* = k_1 F/k_2 I$, plays the role of an apparent equilibrium constant.

When perceived risk $F(t)$ increases, the transition rate from optimism to pessimism accelerates through the term $k_1 F(t) O(t)$, reflecting the tendency of investors to adopt more cautious expectations during periods of heightened uncertainty. Conversely, the arrival of credible information $I(t)$ increases the transition from pessimistic to optimistic expectations through the term $k_2 I(t)\Pi(t)$.

The third term captures imitation. Encounters between optimistic and pessimistic investors occur at a rate proportional to $O(t)\Pi(t)$, and in each encounter the view held by the majority is more likely to spread; the factor $2O(t) - 1$ therefore pushes sentiment further in the direction it already leans, a mechanism related to the recruitment model of Kirman [42] and close to the herding model of Lux [43]. In chemical terms, the imitation term corresponds to a pair of autocatalytic reactions, $2\mathrm{O} + \Pi \rightarrow 3\mathrm{O}$ and $\mathrm{O} + 2\Pi \rightarrow 3\Pi$, and has the same cubic form as the Schlögl [50] model, the standard chemical example of bistability and of a nonequilibrium phase transition. Interaction terms of this kind are also the basis of statistical physics models of markets, in which local imitation among agents generates large-scale fluctuations [40,51].

The assumption that the majority view is more likely to spread describes the aggregate effect of social interaction, not the behavior of every investor. Individual investors form expectations from private information, risk preferences and their own reading of public news; some trade against the prevailing view; and information is distributed unevenly among them. The two-state framework does not model this heterogeneity explicitly. Instead, independent expectation formation is captured by the switching rates $k_1 F(t)$ and $k_2 I(t)$, which do not depend on the views of others, and imitation by k_3. The relative size of the imitation strength $c = \frac{k_3}{2}$ and the overall switching rate $b = k_2 I + k_1 F$, introduced below, measures how strongly social interaction dominates independent judgment. When k_3 is small, the model reduces to independent switching (Proposition 1), and the majority view does not prevail in any self-reinforcing sense; the bistability of Proposition 2 requires that imitation be strong enough, $c > b$. The specification is motivated by evidence of herding among institutional investors and of the social transmission of investor views [9,29,30].

It is convenient to work with the aggregate sentiment index $m(t) = 2O(t) - 1$, which ranges from -1 (fully pessimistic) to $+1$ (fully optimistic). Substituting $O = (1 + m)/2$ and $\Pi = (1 - m)/2$ into equation (5) gives

$$\frac{dm(t)}{dt} = a(t) - b(t)\, m(t) + c\left(m(t) - m(t)^3\right), \qquad a = k_2 I - k_1 F, \quad b = k_2 I + k_1 F, \quad c = \frac{k_3}{2} \tag{6}$$

Here a is the net push of information over fear, b is the overall switching rate, and c is the strength of herding. Because $dm/dt = -2k_1 F \leq 0$ at $m = 1$ and $dm/dt = 2k_2 I \geq 0$ at $m = -1$, the index always stays within $[-1, 1]$.

These equations generate a feedback mechanism in which increases in perceived risk shift the distribution of expectations toward pessimism, while stabilizing information gradually restores optimism.

3.2.4. Fundamental Valuation Dynamics

The benchmark valuation $X(t)$ evolves according to underlying macroeconomic fundamentals that influence the expected profitability and discounting of future corporate earnings. The evolution of the benchmark valuation is therefore described as

$$\frac{dX(t)}{dt} = \underbrace{\chi_0}_{\text{baseline economic growth}} - \underbrace{\chi_r(r(t)-\bar{r})}_{\text{interest rate effect on discounting}} - \underbrace{(\chi_c-\chi_e\theta)\big(Oil(t)-\overline{Oil}\big)}_{\text{net energy effect on fundamentals}} \quad (7)$$

The first component, χ_0, represents the baseline growth of economic fundamentals under normal macroeconomic conditions.

The second component captures the interest rate channel. When the prevailing interest rate $r(t)$ rises above its long-run benchmark $\bar{r}$, the present value of future earnings declines because higher discount rates reduce the valuation of future cash flows.

The third component represents the energy cost channel. Changes in energy prices, represented by $Oil(t)$, influence corporate production costs and inflationary pressures throughout the economy. When energy prices rise above their long-run benchmark $\overline{Oil}$, production costs increase and profit margins may decline, thereby reducing the fundamental valuation of equities. The coefficient χ_c measures this cost effect. Higher energy prices also raise the earnings of domestic energy producers, an effect measured by $\chi_e\theta$, where $\theta \in [0, 1]$ indexes the economy's net energy exposure ($\theta = 0$ for an economy that imports all of its energy). The net coefficient $\chi_c - \chi_e\theta$ is therefore largest for energy importers and can be close to zero, or negative, for net exporters.

Because the oil price deviation enters the rate of change of *X(t)* rather than its level, a temporary rise in oil prices leaves a permanent difference in the level of the benchmark valuation, equal to the net coefficient times the cumulative oil price deviation. The economic interpretation is that earnings lost while energy costs are high are not deferred but lost: they reduce retained earnings, investment and the productive capital of energy-using firms. If the oil price deviation instead entered the level of *X(t)*, its effect on valuations would disappear as oil prices normalize. Section 3.3 compares the two specifications.

3.3. Properties of the Model and an Illustrative Simulation

Three properties of the model organize the empirical analysis.

Proposition 1 (sentiment without herding). Let $c = 0$ and hold $F > 0$ and $I \geq I_0 > 0$ fixed. Then $m(t)$ converges monotonically, at rate $b = k_2 I + k_1 F$, to the unique equilibrium $m^* = (k_2 I - k_1 F)/(k_2 I + k_1 F) \in (-1, 1)$, which is decreasing in F and increasing in I. If instead $I = 0$, then $m^* = -1$: pessimism becomes an absorbing state.

Proof. With $c = 0$, equation (6) is linear with solution $m(t) = m^* + (m(0) - m^*)e^{-bt}$. The comparative statics follow from differentiating m^*.

The second part of Proposition 1 holds perceived risk fixed. When F(t) instead follows equation (3) with $I(t) = 0$, the optimistic share evolves as $O(t) = O(0)\exp(-k_1 \int F ds)$. If the background risk $G(t)$ is bounded away from zero, perceived risk has a positive floor, the integral diverges and pessimism is absorbing. If $G(t) = 0$, the integral is finite and a single shock leaves a positive optimistic share, but a small one: in the calibration of Figure 1 it falls from 0.77 to about 0.002. The floor on the information flow therefore rules out a market that remains almost entirely pessimistic after a single shock, which is not what is observed after geopolitical crises.

Proposition 2 (herding and bistability). Let $c > 0$ and define $\kappa_m = c - b$. If $\kappa_m \leq 0$, equation (6) has a unique stable equilibrium. If $\kappa_m > 0$, it has two stable equilibria, one optimistic and one pessimistic, separated by an unstable equilibrium, if and only if

$$|a| < a_c \equiv \frac{2\,\kappa_m^{3/2}}{3\sqrt{3c}} \qquad (8)$$

When rising fear lowers a below $-a_c$, the optimistic equilibrium disappears and sentiment jumps to the pessimistic equilibrium. Restoring optimism then requires a to rise above $+a_c$, not merely back to its pre-shock value.

Proof. Write the right-hand side of (6) as $g(m) = a + \kappa_m m - cm^3$. For $\kappa_m \leq 0$, g is strictly decreasing, so it has one root, which is stable. For $\kappa_m > 0$, g has a local minimum and maximum at $m = \mp\sqrt{\kappa_m/(3c)}$, where it takes the values $a \mp \frac{2}{3}\kappa_m\sqrt{\kappa_m/(3c)}$. Three real roots exist if and only if these values have opposite signs, which is condition (8). The outer roots satisfy $g' < 0$ and are stable; the middle root is unstable.

Proposition 2 gives a precise meaning to the analogy with phase transitions: the jump at $a = -a_c$ is a saddle-node bifurcation, and the gap between the thresholds for falling into and climbing out of pessimism is a form of hysteresis. In the language of statistical physics, equation (6) is a gradient system, $\frac{dm}{dt} = -V'(m)$, with $V(m) = -am - \frac{\kappa_m m^2}{2} + \frac{cm^4}{4}$, which has the same form as the Landau free energy of a mean-field Ising magnet in an external field a. The point $\kappa_m = 0$, together with $a = 0$, corresponds to a critical point, the cusp of the bifurcation diagram, while the thresholds $\pm a_c$ correspond to spinodals, the limits of metastability in a first-order (discontinuous) transition, rather than to the thermodynamic transition point $a = 0$. It also shows that the analogy applies only when herding is strong relative to the overall switching rate. Because a rise in *F* raises b and therefore lowers κ_m, very high fear speeds up individual switching and can itself weaken bistability. Proposition 2 treats *F* and *I* as fixed. Because perceived risk enters both a and b, the thresholds $\pm a_c$ themselves move as F changes, so the proposition is a quasi-static approximation. Its accuracy depends on the rate at which sentiment returns to equilibrium, $-g'(m*)$, rather than on b alone. Because this rate approaches zero near the bifurcation, a phenomenon known in physics as critical slowing down, sentiment can lag behind even slow changes in F close to the threshold. The simulation in Figure 1 shows the transition when F varies over time.

Proposition 3 (differential energy exposure). Consider two markets i and j that are exposed to the same shock $S(t)$ and share the same global risk perception $F(t)$ and sentiment $m(t)$, but differ in net energy exposure, $\theta_i > \theta_j$. Then the common terms in equation (1) cancel in the difference between the two price paths, and

$$\frac{d(X_i - X_j)}{dt} = \chi_e\,(\theta_i - \theta_j)\big(Oil(t) - \overline{Oil}\big) \qquad (9)$$

so that, when oil prices rise above their benchmark, the fundamental valuation of the market with greater net energy exposure rises relative to the other, and the expected price gap $P_i - P_j$ moves toward $X_i - X_j$ at rate κ.

Proof. Subtract equation (7) for market j from that for market i; the terms in χ_0 and χ_r cancel when the two markets share the same baseline growth and interest rate deviation. Taking expectations of the difference of equation (1) for the two markets eliminates the terms in F, m and S.

Proposition 3 implies that, when markets share the same sensitivities to the common shock, to perceived risk and to sentiment, comparing a market with foreign markets removes the common components of a global shock and leaves differences in exposure. Actual indices also differ in sector composition, currency, regional risk and trading hours, so the comparison isolates energy exposure only to the extent that these other differences are small or controlled for. This is what the synthetic control in Section 5 measures; Section 5.3 also reports a comparison that excludes the energy sector.

The common-sensitivity assumption is a benchmark that makes the role of energy exposure transparent, not a description of actual markets. Differences in institutional environments, sector composition, the composition of investors and the degree of integration with global markets can make the coefficients of equation (1) differ across markets. If market i has its own coefficients κ_i, $\beta_{F,i}$, $\beta_{O,i}$ and $\beta_{S,i}$, the expected change in the price gap becomes

$$\frac{E\left(d(P_i - P_j)\right)}{dt} = \kappa_i(X_i - P_i) - \kappa_j(X_j - P_j) - (\beta_{F,i} - \beta_{F,j})F + (\beta_{O,i} - \beta_{O,j})m - (\beta_{S,i} - \beta_{S,j})S \quad (10)$$

and the common terms no longer cancel. A cross-market gap then combines the differential energy exposure of Proposition 3 with differences in the response to the common rise in risk and sentiment, and the two cannot be separated without further structure. This qualification affects the interpretation of Section 5 in two ways. First, the synthetic control gap should be read as the relative response of the US market, consistent with but not uniquely attributable to its net energy position. Second, if US equities were simply less sensitive to perceived risk than foreign equities, $\beta_{F,US} < \beta_{F,j}$, the gap would be expected against all donor markets. The facts that it is concentrated against oil importers and small against Canada, and that it survives the exclusion of the energy sector and of any single donor (Section 5.3), are more easily explained by differences in energy exposure than by a uniformly lower sensitivity of US equities to risk. These checks reduce, but do not remove, the dependence of the comparative results on the common-sensitivity benchmark.

Figure 1 illustrates these properties with a deterministic simulation of equations (1), (3), (6) and (7), expressed as deviations from the pre-shock steady state. The calibration is illustrative and is not estimated: $\kappa = 0.3$, $\beta_F = 0.25$, $\beta_O = 0.3, \beta_S = 0.2, \gamma_S = 1, \delta_R = 0.5, \delta_I = 1, k_1 = 0.6, k_2 = 1, I(t) = I_0 = 0.2$, and pre-shock perceived risk $F = 0.1$, with time measured in trading days. The shock sets $S(t) = 1$ for five days, and the oil price deviation rises toward 30% with a time constant of two days and decays after the shock ends with a time constant of ten days. Weak herding sets $c = 0.1$, which satisfies $\kappa_m < 0$ before the shock; strong herding sets $c = 2.5$. The net energy coefficient $\chi_c - \chi_e\theta$ is 0 for the net exporter and 0.01 for the net importer.

With weak herding, sentiment falls to about -0.64 during the shock and recovers fully, and the price of the net exporter falls by about 2.1% before returning to within 0.2% of its pre-shock level. The net importer follows the same path during the shock but ends about 3.3% lower because its fundamental valuation has been reduced. With strong herding, sentiment jumps to the pessimistic equilibrium near the end of the shock and remains there after the shock ends, and the price keeps falling, to about 5.1% below its pre-shock level after 23 days. The persistent loss of the net importer follows from the specification of equation (7). In an alternative in which the oil price deviation lowers the level of X(t), with a 30% oil price increase reducing the benchmark valuation by 3%, the price of the net importer falls by 4.0% at the trough on day 6 and recovers to within 0.8% of its pre-shock level by day 23 and 0.1% by day 40, whereas under equation (7) it remains about 3.6% lower after 40 days.

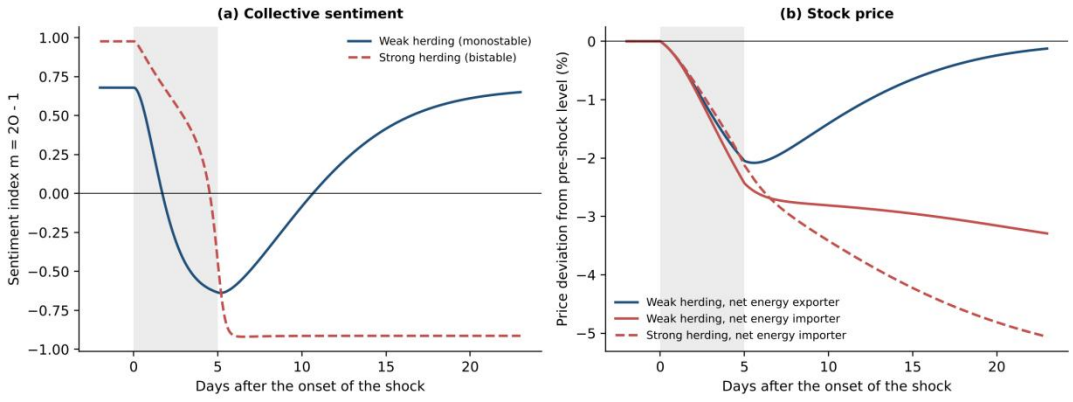


Figure 1. Illustrative simulation of the model. Panel (a): aggregate sentiment m = 2O - 1 under weak and strong herding. Panel (b): price deviation from the pre-shock level. The shaded area marks the five days during which the geopolitical shock is active. Parameter values are given in the text.

3.4. Empirical Implications and Identification

First, the event study measures the abnormal return of the S&P 500 around the escalation. In the model, a shock affects prices directly through $-\beta_S S(t)$ and indirectly through the induced changes in $F(t)$ and $m(t)$; the event study measures the sum of these effects and cannot separate β_S, β_F and β_O. Its role is to measure the size of the total movement of the US market around the event, which also includes the effect of any other news in the window (Section 4.3).

Second, the synthetic control compares the S&P 500 with a weighted combination of non-US equity markets that reproduces its pre-event daily returns. Because the escalation was a global shock, the donor markets were also affected, so the comparison does not measure what US equities would have done in the absence of the shock. By Proposition 3, it measures instead how the US market responded relative to foreign markets exposed to the same global risk and sentiment. Under the common-coefficient assumption of Proposition 3, the gap reflects differences in exposure such as the net energy position, together with any other differences between the markets that the synthetic control does not remove.

Third, the vector autoregression (VAR) describes the dynamic relationships between equity returns, changes in the VIX as a proxy for perceived risk $F(t)$, and changes in the oil price. Collective sentiment $m(t)$ is not observed separately, so the VAR cannot distinguish the fear channel from the sentiment channel; it can, however, show whether the effect of perceived risk on returns is immediate or builds over time, which is only indirectly informative about the monostable and bistable regimes of Proposition 2.

The VIX is used as the proxy for $F(t)$ because it is observed daily, is forward-looking and is the most widely used market-based measure of perceived equity risk. It is, however, not a direct measure of investor psychology. As the price of expected volatility under the risk-neutral measure, it combines investors' expectations of future volatility with the volatility risk premium they demand, and it is also affected by conditions in the options market, such as hedging demand. Movements in the VIX therefore mix changes in perceived risk, risk aversion and sentiment, and do not capture the psychological and behavioral aspects of investment decisions that the model represents separately by $F(t)$ and $m(t)$. This has two implications for the empirical findings. First, the VAR and the contemporaneous regression estimate reduced-form relationships between market-implied volatility and returns, not the structural coefficient β_F of equation (1). Second, the finding that the VIX does not predict later returns rules out delayed effects of market-implied volatility, but not delayed effects of components of investor psychology that the VIX does not reflect.

More generally, the behavioral mechanisms of the model are not validated directly by the empirical analysis, because collective sentiment $m(t)$ and the strength of imitation k_3 are not measured separately. The empirical results can show whether the data are consistent with the weak-herding case of the model, but they cannot rule out other explanations of the same patterns, such as fast but heterogeneous processing of information by investors. The findings should therefore be read as consistent with, rather than as evidence for, the behavioral mechanisms of the model. Section 6.1 describes how these mechanisms could be tested directly.

The model therefore yields three hypotheses for an economy with high net energy exposure and weak herding. H1: the total response of its equity market is small relative to the size of the geopolitical and energy shock. H2: its equity market outperforms a combination of foreign markets with lower net energy exposure, and the outperformance is concentrated against energy importers. H3: the effect of perceived risk on returns is contemporaneous, in the sense

that lagged changes in perceived risk do not predict further returns, and the price level moves with perceived risk, with no sign of a discontinuous shift to a pessimistic regime. The hypotheses correspond to the propositions of Section 3.3 and thus to distinct mechanisms of the model. H1 follows from Proposition 1 and from the energy channel of equation (7): without strong herding, sentiment moves continuously with perceived risk, and in a net energy exporter higher oil prices do not lower fundamental valuations. H2 is the empirical counterpart of Proposition 3. H3 corresponds to the monostable case of Proposition 2, $\kappa_m \leq 0$, in which collective expectations adjust to perceived risk without the jumps and hysteresis that arise when $\kappa_m > 0$. Because collective sentiment is not observed separately, H3 is an indirect implication of the role of collective expectations rather than a direct test of it.

4. Data and Empirical Design

4.1. Data

Daily closing values of the S&P 500 index, the CBOE Volatility Index (VIX), the Brent crude oil spot price, the 10-year US Treasury yield, and the exchange rates used to convert foreign returns into US dollars (H.10 noon buying rates) are obtained from the Federal Reserve Economic Data (FRED) database of the Federal Reserve Bank of St. Louis. Daily closing values of the S&P/TSX Composite (Canada), All Ordinaries (Australia), Hang Seng (Hong Kong), Nikkei 225 (Japan) and Euro Stoxx 50 (euro area) indices are obtained from Yahoo Finance. The daily GPR index is obtained from the website of Caldara and Iacoviello [4]. The sample runs from June 2023 to March 2026. In the source data, the All-Ordinaries index has no observations for 27 February and 6 March 2026, so its return on 2 March spans two trading days; the results are therefore also reported without the Australian market.

The five donor markets were selected to provide variation in net energy position while limiting the comparison to large, liquid and internationally integrated equity markets with daily index and exchange-rate data over the full sample. Canada is a net exporter of both oil and total energy; Australia is a net importer of oil but a net exporter of total energy; and Hong Kong, Japan and the euro area are net importers of both (Table 4). The markets also differ in economic structure, from the resource-intensive Canadian and Australian indices to the manufacturing-oriented Japanese and euro-area indices and the finance-oriented Hong Kong index, and they cover North America, the Asia-Pacific region and Europe. All five are developed markets with open capital accounts and a high degree of integration into global financial markets, which makes it plausible that they were exposed to the same global risk and sentiment, as Proposition 3 requires. Markets in the Middle East were not included because their direct exposure to the conflict would confound the comparison with regional risk. The donor pool is nevertheless small. With five donors the smallest attainable in-space placebo p-value is 1/6; the results describe the response relative to a selected group of developed markets rather than to global equity markets as a whole; and they cannot be generalized to emerging markets or to other net energy exporters, such as Norway, without further evidence.

All returns are daily log returns in percent. Foreign index returns are converted into US dollar returns using the change in the corresponding exchange rate; because the H.10 rates are recorded at noon in New York, this conversion is an approximation for markets that close earlier in the day.

4.2. Event Timing

The timing of the event is taken from the GPR index, which is built from newspaper coverage. The index was 110.6 on Saturday 28 February, rose to 273.9 on Sunday 1 March, and peaked at 500.8 on Monday 2 March. The escalation therefore became public over the weekend, and the first trading session in which all markets could respond

was Monday 2 March. The event day is accordingly defined as $t = 0$ = 2 March 2026. Table 1 reports market conditions around the event.

Table 1. Market conditions around the escalation.

Date	S&P 500	Return (%)	VIX	Brent (USD)	10-year yield (%)	GPR
Thu 26 Feb	6,908.86	−0.54	18.63	71.66	4.02	167.3
Fri 27 Feb	6,878.88	−0.43	19.86	71.32	3.97	197.1
Sat 28 Feb	–	–	–	–	–	110.6
Sun 1 Mar	–	–	–	–	–	273.9
Mon 2 Mar (t=0)	6,881.62	0.04	21.44	77.24	4.05	500.8
Tue 3 Mar	6,816.63	−0.95	23.57	83.28	4.06	391.1
Wed 4 Mar	6,869.50	0.77	21.15	81.56	4.09	465.9
Thu 5 Mar	6,830.71	−0.57	23.75	88.59	4.13	413.4
Fri 6 Mar	6,740.02	−1.34	29.49	95.74	4.15	314.7

Notes: S&P 500, VIX, Brent spot price and 10-year Treasury yield from FRED; daily GPR index from Caldara and Iacoviello [4]. Returns are daily log returns.

4.3. Event Study

Abnormal returns are computed with the constant-mean model [52]. The expected return μ and the standard deviation σ of daily returns are estimated over the window $[t - 260, t - 11]$, which contains 250 trading days and ends two weeks before the event; a shorter window of 120 days, $[t - 130, t - 11]$, is used as a check. The abnormal return on day $t+k$ and the cumulative abnormal return over a window of L days are

$$AR_{t+k} = R_{t+k} - \hat{\mu}, \qquad CAR = \sum_{k} A\,R_{t+k}, \qquad t_{CAR} = \frac{CAR}{\hat{\sigma}\sqrt{L}} \qquad (11)$$

and the test statistic is compared with a t distribution with $n - 1$ degrees of freedom, where n is the length of the estimation window [53]. For single days, a nonparametric p-value is also reported: the share of days in the estimation window whose absolute abnormal return is at least as large as that of the event day. Confidence intervals for the cumulative abnormal returns are reported both from the t distribution and from the empirical distribution of L-day sums of abnormal returns in the estimation window. Because the constant-mean model attributes every deviation from the mean return to the event window, the abnormal returns also contain the effect of any other news that arrived during the window. This limitation matters most for news about monetary policy, inflation and the economic outlook, which affect equity prices through discount rates and expected earnings. Several features of the episode limit, but do not eliminate, this concern. No meeting of the Federal Open Market Committee took place in the event window; the next scheduled meeting was held on 17–18 March 2026. The 10-year Treasury yield changed little over the first trading days (3.97% on 27 February, 4.05% on 2 March and 4.06% on 3 March; Table 1), and adding the change in the yield to the VAR and to the contemporaneous regression leaves the results unchanged (Sections 5.4 and 5.5). At the same time, part of the movement in yields and inflation expectations was itself a response to the oil shock, so controlling for it would remove part of the effect of interest. The abnormal returns should therefore be interpreted as the total movement of the US market in the event window, which includes the effect of the escalation together with that of any contemporaneous news, rather than as a cleanly identified effect of the geopolitical shock. News that affected all markets alike is differenced out in the synthetic control, but US-specific news is not, so the same caveat applies to the cross-market gap.

4.4. Synthetic Control

The synthetic control method [54,55] constructs a weighted combination of the five donor markets whose daily returns track those of the S&P 500 before the event:

$$r_t^{Synth} = \sum_{j=1}^{J} w_j \, r_t^{(j)}, \qquad w_j \geq 0, \quad \sum_{j=1}^{J} w_j = 1, \qquad \tau_t = r_t^{SPX} - r_t^{Synth} \qquad (12)$$

The weights minimize the mean squared prediction error over the 60 trading days before the event. The post-event window covers the first two trading days, 2 and 3 March, and the cumulative gap $\sum \tau_t$ over that window is the statistic of interest. The baseline uses US dollar returns with all markets compared on the same calendar day, which is appropriate because the news arrived over a weekend. The two-day window is chosen as the baseline for three reasons.

First, the news continued to develop on Monday 2 March, when the GPR index peaked, and the Asia-Pacific markets closed before most of that day's developments and before the US market opened, so part of their response to the same information appears only on 3 March; a two-day window ensures that every market has traded a full session after the bulk of the news and reduces the effect of the approximate timing of the exchange-rate conversion. Second, Proposition 3 concerns the initial divergence in valuations caused by a common shock, before other news accumulates, and a short window keeps the comparison close to that mechanism. Third, placebo inference loses power as the window lengthens (Section 5.5). The baseline therefore measures the initial relative response, not the full effect of the geopolitical shock, whose consequences may emerge gradually and persist as a conflict continues. Section 5.3 reports windows of one, three and five days, and Section 5.5 extends the comparison to 21 trading days; because unrelated news accumulates over longer windows, these longer-horizon estimates are descriptive, and the paper does not measure the medium- or long-term effects of geopolitical risk.

Two forms of inference are used. In the in-space placebo, each donor market is treated in turn as if it were the treated unit [55]; with six markets, the smallest attainable p-value is $1/6$. In the in-time placebo, the procedure is repeated with every earlier trading day in the sample as a pseudo-event date [56], and the p-value is the share of pseudo-event dates with an absolute two-day gap at least as large as the one observed. This p-value is the rank of the observed gap among gaps produced by the same procedure on earlier dates, not a p-value derived from a sampling distribution. Because a synthetic control fitted to daily returns need not match the mean return of the treated market, two adjustments for the pre-event mean gap are also reported: subtracting twice the average daily pre-event gap from the two-day gap, and estimating the weights on returns demeaned over the fitting window [57,58]. Finally, to examine whether differences in sector composition drive the gap, the comparison is repeated with the S&P 500 and the S&P/TSX stripped of their energy sectors, using the returns of sector exchange-traded funds over a range of sector weights.

4.5. Vector Autoregression

A VAR [59] is estimated on daily data from 2 January 2024 to 4 March 2026 (536 observations[2]). The baseline system is

$$y_t = \nu + A_1 y_{t-1} + \varepsilon_t, \qquad y_t = \left(R_t, \, \Delta VIX_t, \, \Delta ln \, Oil_t\right)' \qquad (13)$$

where ν is a vector of constants, R_t is the S&P 500 return in percent, ΔVIX_t is the change in the VIX in index points, and $\Delta \ln Oil_t$ is the log change in the Brent price in percent, the same measure used in the impulse responses and in

[2] The sample of 536 daily observations provides sufficient degrees of freedom for a three-variable system and allows stable estimates of the impulse responses.

equation (14). The lag length is one[3]. Impulse responses are identified with a recursive (Cholesky) ordering in which the oil price, measured as a log change, is ordered first, the VIX second and the equity return last, with 95% bootstrap confidence intervals based on 500 replications. As a check on state dependence, local projections [60] of cumulative returns over horizons of up to 20 trading days are also estimated, with controls for one lag of each variable and Newey–West standard errors with h + 1 lags, allowing the effect of a change in the VIX to differ when the VIX on the previous day was above its 75th percentile. All returns, including the future returns in the dependent variable, fall on or before 27 February 2026. A high-volatility state is not the same as a state of strong herding, so these estimates check for state dependence rather than test for bistability. Because the VAR's lag coefficients cannot capture effects that occur within the same day, the contemporaneous relationship is also estimated directly,

$$R_t = \alpha + \beta_V \, \Delta VIX_t + \beta_{Oil} \, \Delta \ln Oil_t + u_t \qquad (14)$$

using data up to 27 February 2026 and Newey and West [61] standard errors with five lags. Equation (14) is a descriptive decomposition: the VIX and equity prices are determined jointly, so β_V is not a causal effect. Two robustness checks add a dummy for the tariff-related market turmoil of 3–10 April 2025 and add the change in the 10-year Treasury yield, the discount-rate variable of equation (7).

5. Results

5.1. The Size of the Shock

Figure 2 and Table 1 show the scale of the shock. The daily GPR index, which averaged about 118 in February 2026, reached 500.8 on 2 March and remained above 300 on every trading day of the first week. Brent crude rose by 8.0% (log change) on 2 March and by 7.5% on 3 March, and by 6 March it was 34% above its level of 27 February.

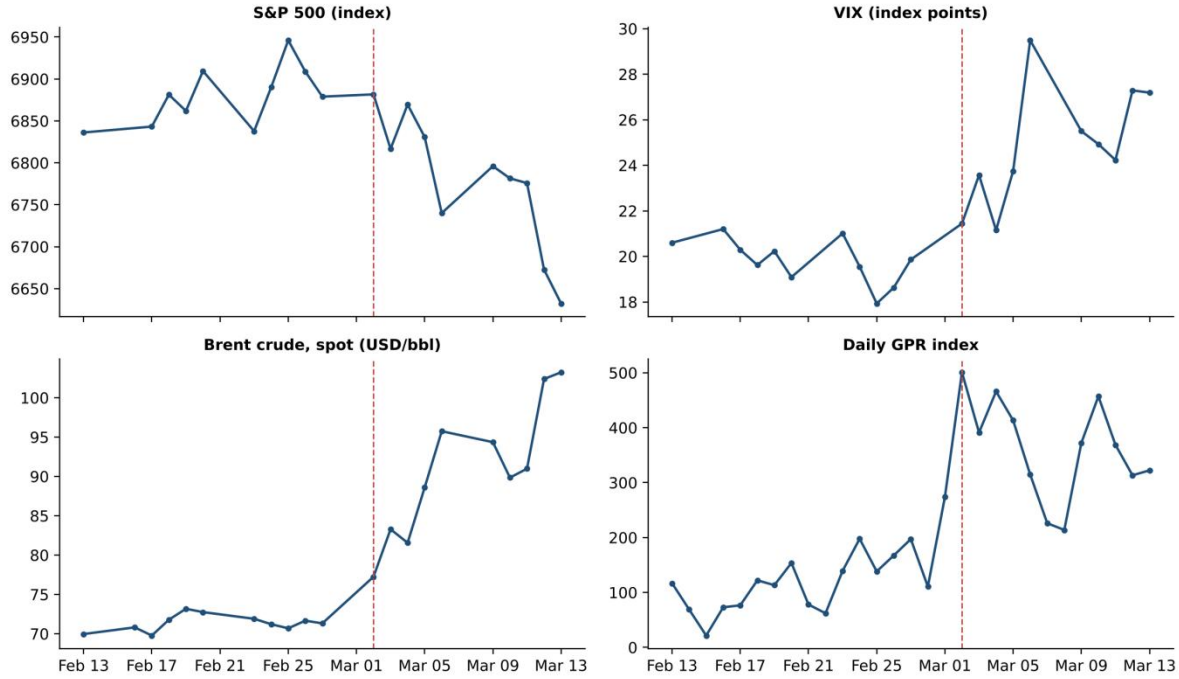


Figure 2. S&P 500, VIX, Brent crude oil price and daily GPR index, 13 February–13 March 2026. The dashed line marks the event day, 2 March 2026.

[3] The Akaike, Hannan–Quinn and Schwarz criteria and the final prediction error, computed for up to ten lags, all select one lag.

5.2. Event Study

Table 2 and Figure 3 report the event study. The abnormal return on the event day is -0.005 %, and the nonparametric *p*-value is 1.00: every day in the estimation window had an absolute abnormal return at least as large. The cumulative abnormal return over the first five trading days is -2.26% with the 250-day estimation window ($p = 0.39$) and -2.33%with the 120-day window ($p = 0.16$). No abnormal return distinguishable from normal daily variation was detected. This is not evidence that the effect was small: the 95% confidence interval for the five-day cumulative abnormal return runs from −7.43% to +2.91% with the 250-day window and from −5.61% to +0.95% with the 120-day window, and the interval based on the empirical distribution of five-day sums runs from −6.88% to 2.04%. The data are therefore consistent with H1 but cannot rule out an economically large decline.

Table 2. Abnormal returns of the S&P 500 around the escalation.

	AR / CAR (%)	*t*	*p*	AR / CAR (%)	*t*	*p*
Estimation window	[t − 260, t − 11]			[t −130, t − 11]		
Panel A: daily abnormal returns						
t - 1 (27 Feb)	−0.48	−0.41	0.68	−0.49	−0.67	0.51
t (2 Mar)	−0.01	−0.00	1.00	−0.02	−0.03	0.98
t + 1 (3 Mar)	−0.99	−0.85	0.40	−1.01	−1.36	0.18
t + 2 (4 Mar)	0.73	0.62	0.54	0.71	0.96	0.34
t + 3 (5 Mar)	−0.61	−0.52	0.60	−0.62	−0.84	0.40
t + 4 (6 Mar)	−1.38	−1.18	0.24	−1.39	−1.88	0.06
Panel B: cumulative abnormal returns						
[0,1]	−1.00	−0.60	0.55	−1.03	−0.98	0.33
[-1, 1]	−1.48	−0.73	0.47	−1.52	−1.18	0.24
[0, 4]	−2.26	−0.86	0.39	−2.33	−1.41	0.16
[-1, 4]	−2.74	−0.95	0.34	−2.82	−1.56	0.12

Notes: Constant-mean model. The 250-day window gives $\hat{\mu} = 0.044\%$and $\hat{\sigma} = 1.173\%$ the 120-day window gives $\hat{\mu} = 0.058\%$ and $\hat{\sigma} = 0.741\%$. Two-sided *p*-values from a *t* distribution with *n*-1 degrees of freedom.

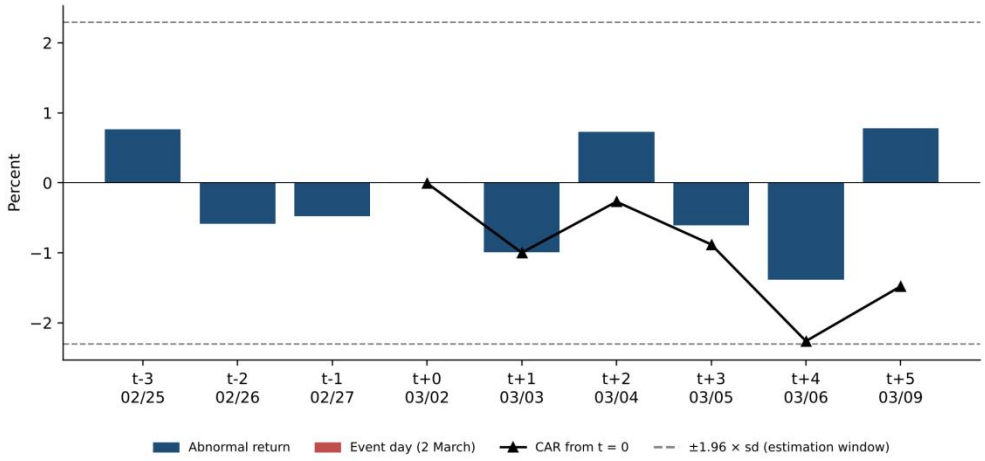


Figure 3. Daily abnormal returns and cumulative abnormal returns of the S&P 500, estimation window [t - 260, t - 11]. Dashed lines mark ±1.96 standard deviations of daily returns in the estimation window.

5.3. Synthetic Control

Table 3 reports the synthetic control estimates. In the baseline specification, the synthetic control places weights of 0.33 on Canada, 0.28 on Australia, 0.25 on the euro area and 0.14 on Hong Kong, and reproduces the daily returns of the S&P 500 with a root mean squared prediction error of 0.58 percentage points over the 60 days before the event. The cumulative two-day gap is 3.45 percentage points. Only 0.4% of the 455 pseudo-event dates produce a gap of that absolute size ($p = 0.004$), and the US market has the second-largest ratio of post-event to pre-event prediction error among the six markets in the in-space placebo. The other three specifications give gaps between 3.0 and 3.9 percentage points with in-time p-values between 0.003 and 0.007.

Table 3. Synthetic control estimates, event day 2 March 2026.

	Baseline: USD, same day	Local currency, same day	Local currency, Asia next day	USD, Asia next day
Donor weights				
Canada (S&P/TSX)	0.334	0.289	0.346	0.325
Australia (All Ordinaries)	0.283	0.260	0.067	0.112
Hong Kong (Hang Seng)	0.135	0.069	0.058	0.077
Japan (Nikkei 225)	0.000	0.000	0.019	0.069
Euro area (Euro Stoxx 50)	0.248	0.382	0.509	0.418
Fit and gaps (percentage points)				
Pre-event RMSPE	0.58	0.50	0.49	0.59
Gap, 2 March	1.83	1.34	1.37	2.11
Gap, 3 March	1.62	1.68	1.84	1.76
Cumulative two-day gap	3.45	3.02	3.20	3.88
Inference				
Post/pre MSPE ratio	8.76	9.24	10.97	10.98
In-space rank (of 6)	2	1	1	2
In-time placebo p-value	0.004	0.007	0.007	0.003
Number of pseudo-event dates	455	455	582	582

Notes: Weights minimize the mean squared prediction error of daily returns over the 60 trading days before the event. Gaps are the S&P 500 return minus the synthetic control return. The in-time p-value is the share of pseudo-event dates with an absolute two-day gap at least as large as the observed gap. With six markets, the smallest attainable in-space p-value is 1/6.

Table 4 shows where the gap comes from. Measured in dollars, the S&P 500 lost 0.91% over the two days and the Canadian market 1.85%, whereas the four markets of net oil importers lost between 3.1 and 8.0%. The ordering matches H2 when net exposure is measured by oil: the two North American markets of net oil exporters held up best, and the euro area and Japanese markets, which belong to the economies most dependent on imported energy, fell the most.

Measured by total energy, however, Australia is a net exporter because of its coal and gas exports, and its market fell by 4.73%, more than the Hong Kong market. The average two-day dollar return is −5.33% for net oil importers and −1.38% for net oil exporters, but −5.54% for net energy importers and −2.49% for net energy exporters, because Australia moves from the first group to the second. Over the first two days, the evidence therefore supports an oil channel more clearly than a channel based on total energy exposure; Section 5.5 shows that this ranking reverses over a longer horizon.

Table 4. Dollar returns by market on the first two trading days (%).

Market	2 March	3 March	Two-day total	Net oil position	Net energy position
United States (S&P 500)	0.04	−0.95	−0.91	Net exporter	Net exporter
Canada (S&P/TSX)	0.05	−1.90	−1.85	Net exporter	Net exporter
Australia (All Ordinaries)	−2.19	−2.54	−4.73	Net importer	Net exporter
Hong Kong (Hang Seng)	−2.16	−0.91	−3.07	Net importer	Net importer
Japan (Nikkei 225)	−2.27	−3.24	−5.51	Net importer	Net importer
Euro area (Euro Stoxx 50)	−3.62	−4.40	−8.02	Net importer	Net importer
Synthetic control (baseline)	−1.79	−2.57	−4.36	–	–

Notes: Daily log returns converted to US dollars. The Australian return for 2 March spans 27 February and 2 March because the source data have no observation for 27 February. Net oil position refers to crude oil and petroleum products; Australia is a net exporter of energy overall because of its coal and gas exports.

Table 5 reports robustness checks for the baseline specification. The one-day gap on 2 March alone is 1.83 percentage points ($p = 0.022$). Beyond that, the gap remains between 2.3 and 4.6 percentage points, with in-time p-values of 0.04 or less, when the post-event window is extended to three days or, excluding Australia to avoid the data gap, to five days; when the fitting window is shortened to 20 or 40 days or lengthened to 120 days; when Australia or any other single donor is dropped; and when the synthetic control is replaced by an equally weighted average of the five markets.

The one exception is informative. When the weights are fitted over 250 days, the synthetic control places a weight of 0.97 on Canada, and the gap falls to 0.98 percentage points ($p = 0.26$). This is what H2 predicts, since Canada is also a net oil exporter: the US outperformance is a gap relative to energy importers, not relative to all foreign markets. The same result also shows that the estimate depends on the fitting window, which determines which donors receive weight. Consistency with the hypothesis does not by itself resolve this sensitivity, and the 60-day estimate is best read as a comparison with a basket weighted towards oil-importing markets.

The 60-day window is used as the baseline because the synthetic control is intended to reproduce the co-movement of the S&P 500 with foreign markets in the period immediately preceding the event. Correlations between national equity markets change over time, and a short window reflects the relationships that prevailed when the shock arrived while still providing 60 observations to fit four free weights. A longer window gives weight to earlier periods in which these relationships may have been different. The 250-day window, which begins in early March 2025, includes the tariff turmoil of April 2025, a shock centered on US trade policy in which the US and Canadian markets were exposed to closely related news; a fit over this period may therefore place weight on Canada for reasons unrelated to conditions in early 2026.

The sensitivity nevertheless qualifies the main finding, and it is stated explicitly here. The gap is stable, between 3.45 and 3.90 percentage points, for fitting windows of 20, 40, 60 and 120 days, and it falls only when the window is extended to 250 days and the weight on Canada rises to 0.97. Excluding Canada raises the gap to 4.61 percentage points. The result is therefore robust in a specific sense: US equities outperformed a basket of foreign markets that includes oil importers, and this does not depend on the choice among fitting windows of 20 to 120 days. It is not robust as a statement about US outperformance relative to all foreign markets, since against Canada alone the gap is small and statistically insignificant. The conclusions of the paper are stated in this narrower form.

Table 5. Robustness of the synthetic control gap (baseline: USD, same day).

Specification	Cumulative gap (pp)	In-time *p*-value
Baseline (60-day fit, 2-day window)	3.45	0.004
One-day window (2 March)	1.83	0.022
Three-day window (2–4 March)	3.53	0.015
Five-day window (2–6 March), excluding Australia	3.83	0.011
20-day fitting window	3.90	< 0.003
40-day fitting window	3.51	0.004
120-day fitting window	3.53	< 0.003
250-day fitting window (Canada weight 0.97)	0.98	0.26
Excluding Canada	4.61	0.009
Excluding Australia	3.24	0.009
Excluding Hong Kong	3.82	< 0.003
Excluding Japan	3.45	0.004
Excluding euro area	2.29	0.037
Equal-weighted average of the five markets	3.73	0.013

Notes: "< 0.003" indicates that none of the 455 pseudo-event dates produced a gap as large as the observed one. In the row "Excluding Australia" the panel retains the dates on which the Australian series has gaps; in the five-day row Australia is removed from the panel so that the window covers 2–6 March.

Figure 4 shows the daily gaps over the fitting window and around the event. The figure also shows a limitation of a synthetic control fitted to daily returns: it matches day-to-day co-movement but not the cumulative trend: over the 60-day fitting window, the cumulative return of the S&P 500 was about 10.6 percentage points below that of the synthetic control. The estimates should therefore be read as a short-window differential response, not as a statement about relative levels. Figure 5 shows the in-time placebo distribution.

The average daily gap over the fitting window is −0.176 percentage points. Subtracting twice this amount from the two-day gap gives 3.80 percentage points (in-time $p < 0.003$), and a synthetic control estimated on demeaned returns gives 3.88 percentage points ($p < 0.003$). The volatility-adjusted placebo, which scales each gap by the pre-event RMSPE of its own fit, gives $p < 0.003$, and the post/pre MSPE ratio gives $p = 0.013$. Weights fitted on the 60 days ending ten days before the event predict the last ten pre-event days with an RMSPE of 0.89 percentage points, compared with 0.54 within the fitting window.

Sector composition is a further difference between the markets: energy producers account for a much larger share of the S&P/TSX than of the S&P 500. When the S&P 500 is replaced by an index that excludes its energy sector, constructed from the returns of the Energy Select Sector SPDR fund with energy weights between 2 and 5%, the two-day gap is between 3.47 and 3.49 percentage points (3.47 percentage points, $p = 0.004$, at a weight of 3%). Excluding the energy sector from the Canadian donor as well, with weights between 13 and 21%, gives gaps between 3.54 and 3.66 percentage points. Differences in the weight of energy producers in the indices therefore cannot explain the US outperformance. The remaining gap may also reflect other differences in sector composition, such as the weight of technology and financial firms, as well as currencies and regional risk, so this comparison does not identify a channel that operates through energy-using firms.

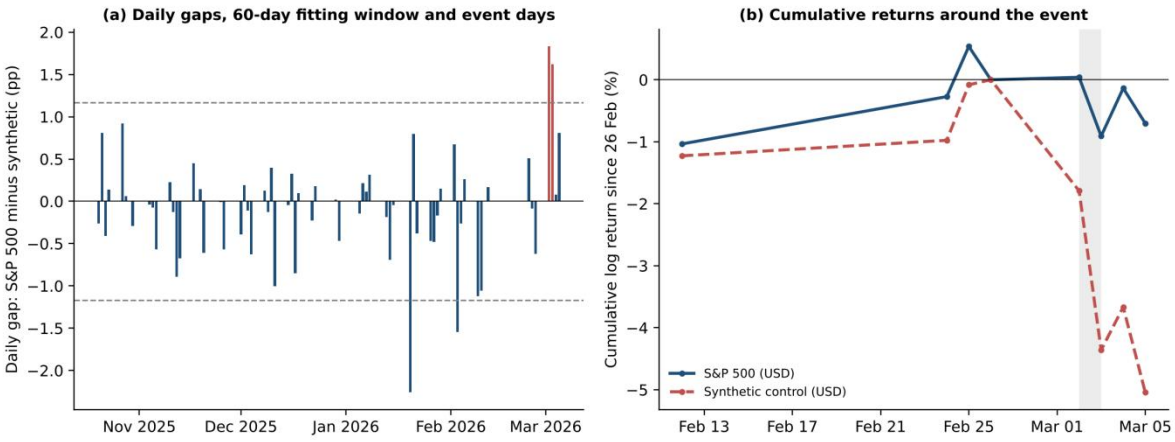


Figure 4. Synthetic control, baseline specification. Panel (a): daily gap between the S&P 500 and the synthetic control over the 60-day fitting window and the event days (red); dashed lines mark ±2 times the pre-event RMSPE. Panel (b): cumulative dollar returns since 26 February 2026; the shaded area marks 2–3 March.

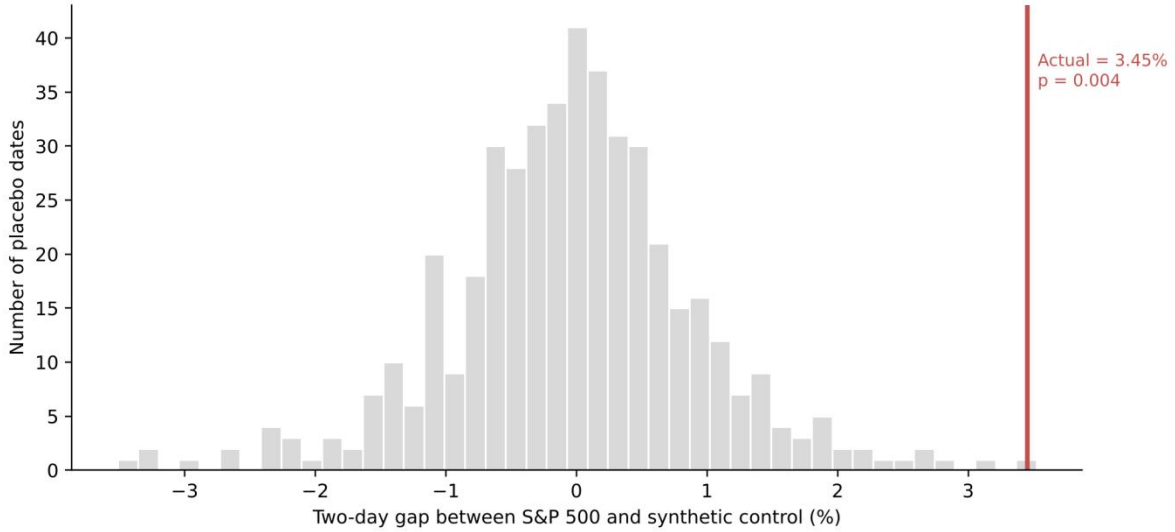


Figure 5. In-time placebo distribution of the two-day gap (baseline specification, 455 pseudo-event dates). The red line marks the gap observed on 2–3 March 2026.

5.4. Dynamic Relationships: VAR Evidence

Table 6 reports the VAR, with the oil price measured in log changes. None of the lagged variables helps to predict the next day's equity return: the coefficients on the lagged change in the VIX (0.046) and the lagged log change in the oil price (0.024) are small and statistically insignificant, and the system has very little persistence (the largest root of the companion matrix has modulus 0.153). Adding a dummy for the April 2025 tariff turmoil or of the change in the 10-year yield leaves these conclusions unchanged; the yield change does not predict equity returns either (coefficient 0.006, $p = 0.48$).

The relationship between volatility and returns is instead contemporaneous: the correlation between the residuals of the return and VIX equations is −0.84. In the impulse responses (Figure 6), a one-standard-deviation shock to the

VIX (about 2.0 index points) lowers the S&P 500 return by 0.82% on impact (95% interval −1.00 to −0.63), followed by a small rebound of 0.09% the next day, after which the response is indistinguishable from zero.

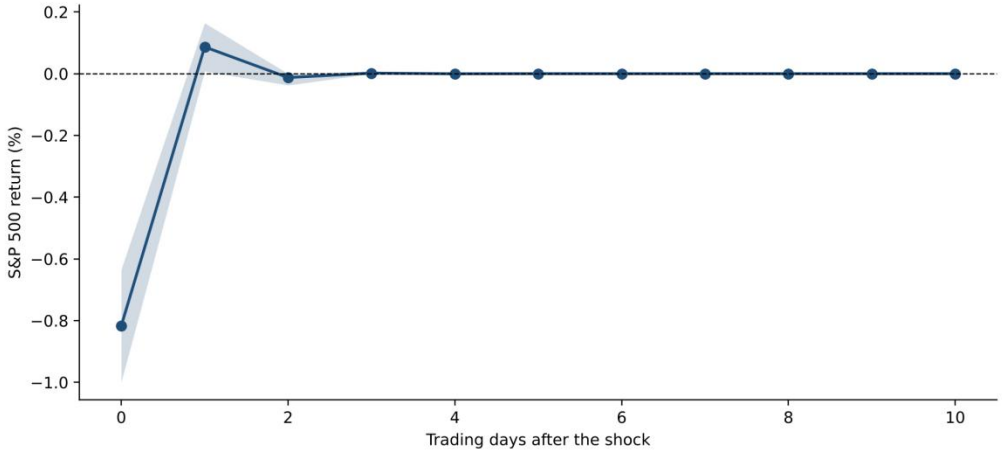


Figure 6. Response of the S&P 500 return to a one-standard-deviation shock to the VIX, VAR(1) with Cholesky ordering oil, VIX, return. The shaded area is the 95% bootstrap confidence interval (500 replications).

The return response goes back to zero after one day, but this does not mean that the price level recovers. The cumulative response, which is the effect on the log price level, is −0.73% after one day (95% interval −0.91 to −0.53) and −0.74% after ten days (−0.92 to −0.55) (Figure 7). The level effect persists because the shock to the VIX itself persists: the cumulative response of the VIX is 2.01 points on impact and 1.79 points after ten days, so in this linear system the price level recovers only to the extent that the VIX falls back. A one-point rise in the VIX is associated with a cumulative return of −0.41% on the same day and −0.33% over ten days (95% interval −0.45 to −0.20); on days when the VIX was already above 18.63, the ten-day effect is −0.29% (−0.44 to −0.14), so the point estimates give no sign that the effect of volatility on prices is amplified in volatile states.

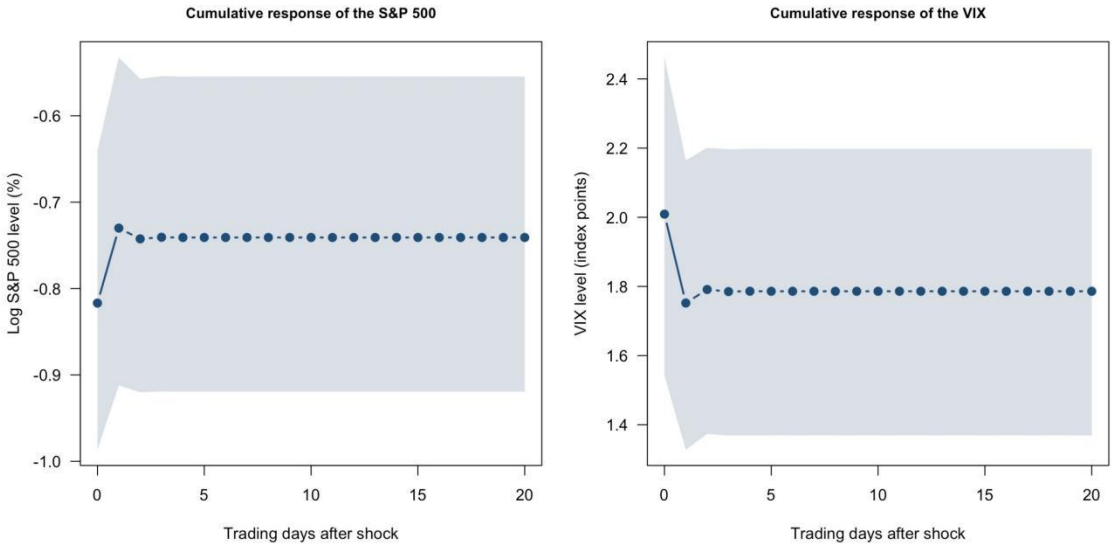


Figure 7. Cumulative responses of the log S&P 500 level (left) and of the VIX level (right) to a one-standard-deviation shock to the VIX, VAR(1) with Cholesky ordering oil, VIX, return. The shaded areas are 95% bootstrap confidence intervals (500 replications).

The path of the index after the first week qualifies the short-run evidence. Over the following three weeks, however, as the conflict persisted and Brent rose above $120, the S&P 500 fell further, to 8.10% below its 27 February close on 30 March (Figure 8), almost twice the decline of 4.35% implied by the rise in the VIX. Section 5.5 examines this period.

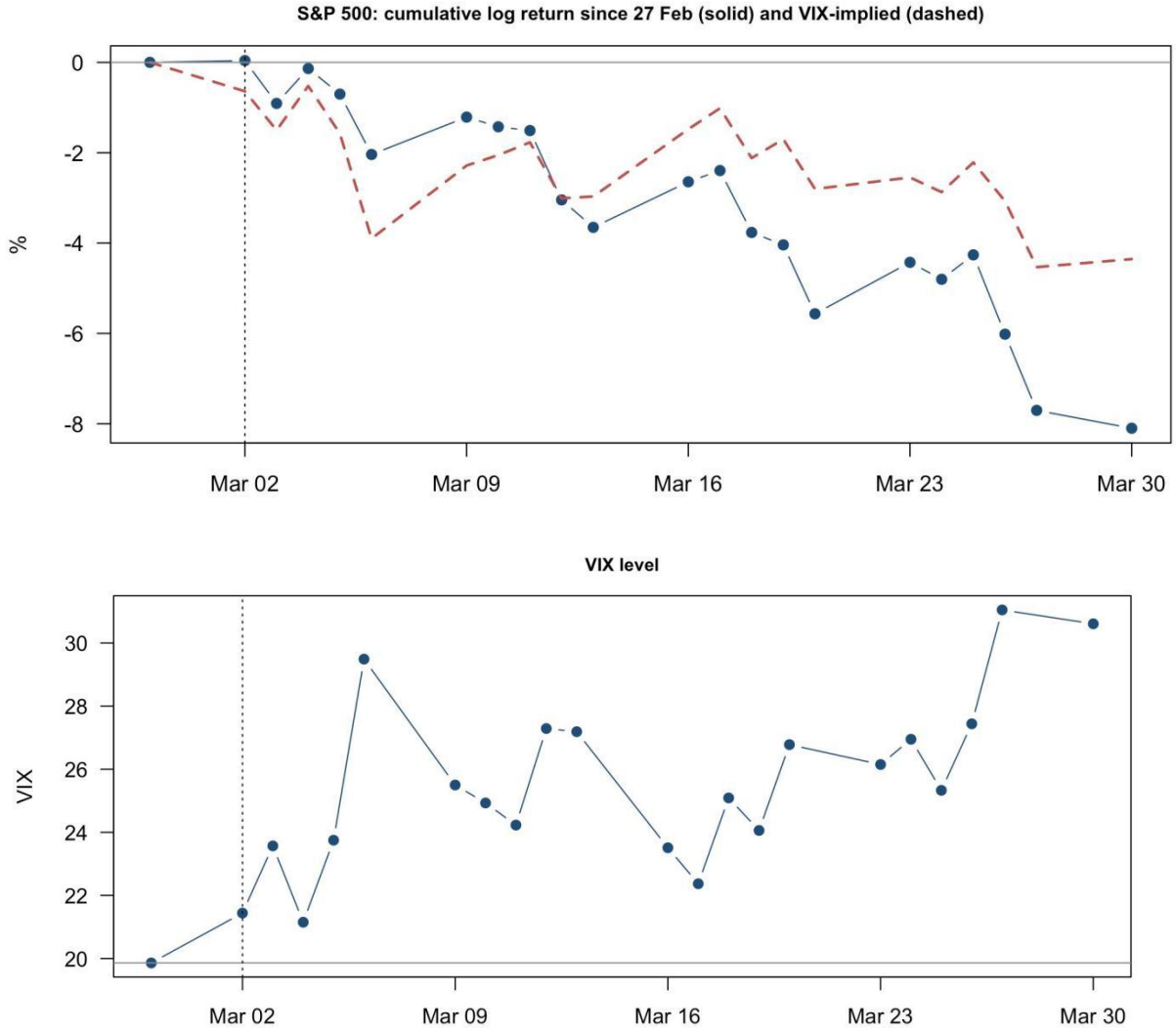


Figure 8. Upper panel: cumulative log return of the S&P 500 since 27 February 2026 (solid) and the return implied by the cumulative change in the VIX and the coefficient in Table 7 (dashed). Lower panel: VIX level. The dotted line marks the event day, 2 March 2026.

Table 6. VAR(1) estimates, 2 January 2024 – 4 March 2026 (oil price in log changes).

	R_t	ΔVIX_t	$\Delta \ln Oil_t$
R_{t-1}	0.008 (0.081)	−0.109 (0.166)	−0.114 (0.158)
ΔVIX_{t-1}	0.046 (0.039)	−0.172** (0.080)	−0.072 (0.076)
$\Delta \ln Oil_{t-1}$	0.024 (0.022)	−0.083* (0.046)	0.044 (0.044)
Constant	0.067 (0.043)	0.027 (0.088)	0.021 (0.084)
Residual correlation with R_t	1.000	−0.843	0.132
Observations	536	536	536
With April 2025 tariff dummy: equation for R_t			
ΔVIX_{t-1}	0.058 (0.039)		

	R_t	ΔVIX_t	$\Delta ln\ Oil_t$
$\Delta ln\ Oil_{t-1}$	0.014 (0.022)		
Tariff dummy (3–10 April 2025)	−1.380*** (0.404)		

Notes: Standard errors in parentheses. *, **, *** denote significance at the 10, 5 and 1% levels. Lag length selected by AIC, HQ, SC and FPE (all choose one lag). Largest modulus of the companion-matrix roots: 0.153. Portmanteau test with 10 lags: $\chi^2 = 87.77$, $p = 0.28$.

Table 7 reports the contemporaneous regression (14). A one-point increase in the VIX is associated with a same-day S&P 500 return that is 0.41% lower, and the regression explains 71%of the variance of daily returns. The coefficient on the oil price change is positive (0.017) and not statistically significant: over this sample, higher oil prices were not associated with lower US equity returns.

The lower panel applies the estimated coefficients to the event week. Over the five trading days from 2 to 6 March, the fitted returns sum to −3.03% and the actual returns to −2.05%. The US market thus fell somewhat less than the rise in volatility alone would have predicted, and almost all of the decline that did occur is accounted for by the contemporaneous rise in the VIX, not by the oil price.

Table 7. Contemporaneous relationship between returns, volatility and oil prices.

Panel A: regression (14), 2 January 2024 – 27 February 2026	Coefficient	Std. error	p
Constant	0.075	0.021	0.000
ΔVIX_t (index points)	−0.405	0.042	0.000
$\Delta \ln Oil_t$ (%)	0.017	0.013	0.194
R^2 / observations	0.713	533	

Panel B: event week (%)	ΔVIX_t	$\Delta lnOil_t$	VIX contribution	Oil contribution	Fitted R_t	Actual R_t
2 March	1.58	7.97	−0.64	0.14	−0.43	0.04
3 March	2.13	7.53	−0.86	0.13	−0.66	−0.95
4 March	−2.42	−2.09	0.98	−0.04	1.02	0.77
5 March	2.60	8.27	−1.05	0.14	−0.84	−0.57
6 March	5.74	7.76	−2.33	0.13	−2.12	−1.34
Sum, 2–6 March					−3.03	−2.05

Notes: Newey–West standard errors with five lags. Fitted values include the constant (0.075). The regression is a descriptive decomposition; the VIX and equity returns are jointly determined.

5.5. Beyond the First Week

The event study and the synthetic control measure the response over the first two to five trading days. This section extends the comparisons to 30 March, 21 trading days after the event, keeping the weights estimated over the 60 days before the event. Because news unrelated to the escalation accumulates over longer windows, these estimates are descriptive, and placebo inference loses power as the window lengthens: the standard deviation of the placebo gaps rises from 0.96 percentage points over two days to 2.82 over 21 days.

Table 8 and Figure 9 show the cumulative gap between the S&P 500 and the synthetic control. The US outperformance persisted for most of March. The raw gap reached 4.34 percentage points on 5 March, was 3.30 points after five trading days ($p = 0.028$) and was still 4.06 points on 23 March. It then disappeared in the last three sessions of the month, when the S&P 500 fell by 3.8%, and stood at 0.98 points on 30 March ($p = 0.63$). Whether

some outperformance remains at one month depends on the treatment of the pre-event mean gap. Over the 60 days before the event, the S&P 500 underperformed the synthetic control by 0.18 percentage points a day; if that drift is assumed to continue, the adjusted gap on 30 March is 4.68 points, and the synthetic control estimated on demeaned returns gives 4.96 points, but neither can be distinguished from placebo variation at that horizon (p = 0.165 and 0.145). Without adjustment the gap is not significant beyond the first week (p = 0.14 at 10 and 15 trading days), whereas with either adjustment it is significant at the 5% level for windows of up to 15 trading days. The evidence for H2 is therefore strong for the first week; over the first three weeks its significance depends on the adjustment for the pre-event mean gap; and at one month there is none.

Table 8. Synthetic control gap by window length, 2–30 March 2026 (percentage points)

Window	Days	Raw	p	Adjusted	p	Demeaned	p	Placebo SD
2–3 Mar	2	3.45	0.004	3.80	< 0.003	3.88	< 0.003	0.96
2–6 Mar	5	3.30	0.028	4.18	0.019	4.29	0.017	1.46
2–13 Mar	10	2.78	0.141	4.55	0.039	4.76	0.030	1.94
2–20 Mar	15	3.40	0.143	6.04	0.031	6.35	0.029	2.36
2–30 Mar	21	0.98	0.628	4.68	0.165	4.96	0.145	2.82

Notes: Baseline synthetic control (USD returns, same day), with weights estimated over the 60 trading days before the event. Raw is the cumulative gap; Adjusted subtracts the window length times the average daily pre-event gap (−0.176 percentage points); Demeaned is the gap from a synthetic control estimated on returns demeaned over the fitting window. p-values are from in-time placebos with windows of the same length that end before the event (449 to 468 pseudo-event dates); "< 0.003" indicates that no pseudo-event date produced a gap as large as the observed one. Placebo SD is the standard deviation of the raw placebo gaps. Donor returns on local holidays are set to zero, so that the next day's return, which spans both days, enters the cumulative gap.

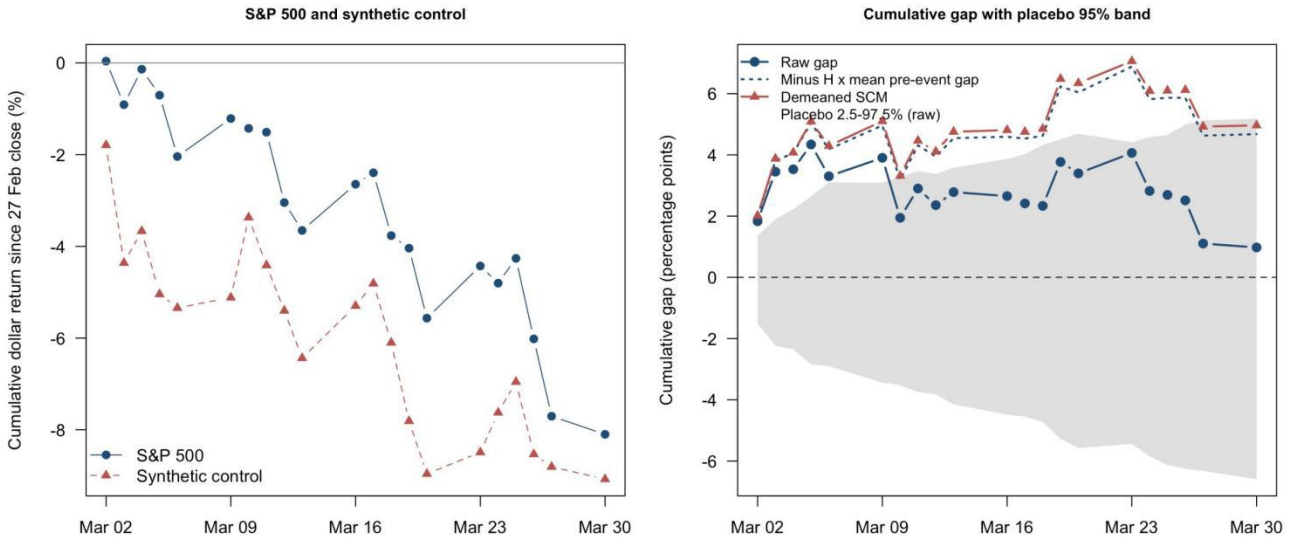


Figure 9. Left: cumulative dollar returns of the S&P 500 and the baseline synthetic control since 27 February 2026. Right: cumulative gap (raw, minus the window length times the average daily pre-event gap, and from the demeaned synthetic control), with the 2.5th–97.5th percentile range of raw in-time placebo gaps of the same length (shaded).

By market, the pattern of the first days partly survives. Over 2–30 March, the euro area and Japanese markets, which belong to the economies most dependent on imported energy, fell by 13.39% and 14.78% in dollar terms, against 8.10% for the United States and 9.36% for Canada. Australia and Hong Kong, however, fell by less than the United States (5.72% and 7.51%). As a result, the difference between the average returns of net oil exporters and net oil importers narrows from 3.95 percentage points over two days to 1.62 points over the month, whereas the difference by total energy position, which places Australia among the exporters, widens from 3.05 to 4.17 points (−7.72% against −11.89%). Over the month, total energy exposure therefore separates the markets better than oil exposure, the reverse of the two-day result.

The decline of the S&P 500 in late March is also not explained by the variables in the contemporaneous regression. Extending equation (14) with the change in the 10-year Treasury yield and estimating it on pre-event data, the cumulative return of −8.10% by 30 March decomposes into −4.40 points attributable to the rise in the VIX, +1.13 points to the rise in the oil price, −0.23 points to the 38 basis point rise in the 10-year yield, +1.55 points from the constant, which captures the normal daily drift, and a residual of −6.16 points (Figure 10). The yield coefficient is small and insignificant, so the discount-rate channel, as measured by the 10-year yield, accounts for little of the decline. The oil price contributes positively because, over the estimation sample, higher oil prices were associated with slightly higher US returns. The main result is therefore that a decline remained that the pre-event relationships cannot explain. One possible reason is that the equity response to oil depends on the source of the price change [3], so that a sustained, supply-driven rise to above $120 may have depressed US equities even though the United States is a net oil exporter. The residual also contains other news that arrived during March, however, and these data cannot identify it as a loss caused by the oil supply shock.

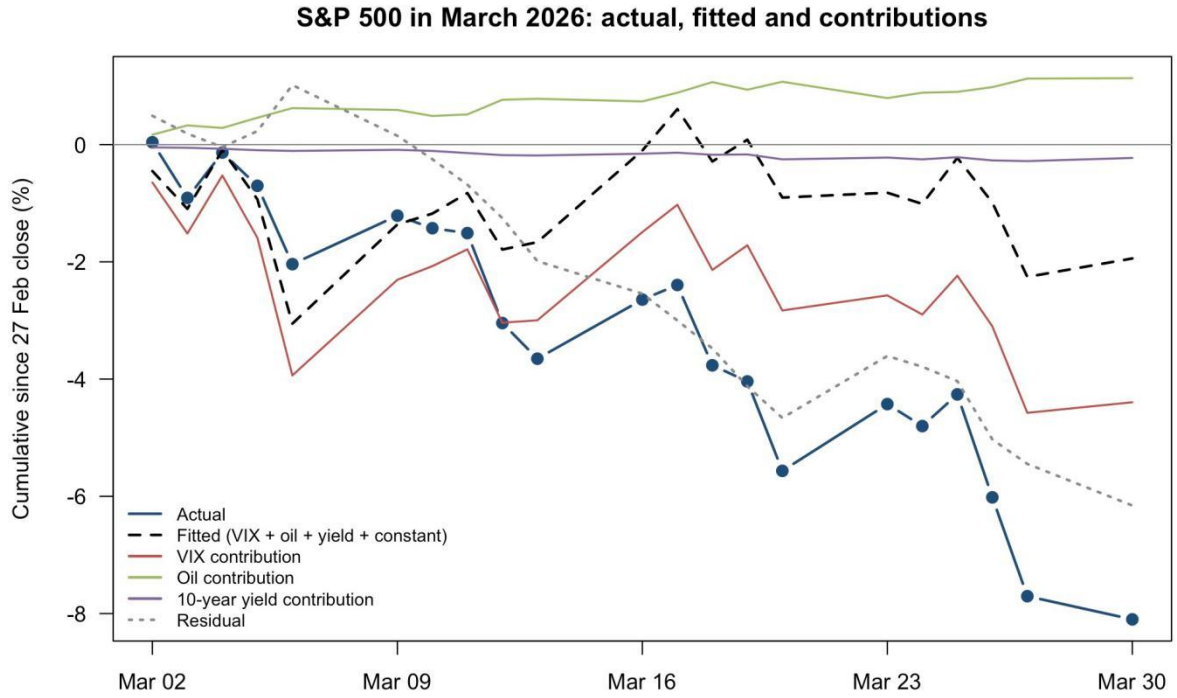


Figure 10. Cumulative return of the S&P 500 since 27 February 2026, fitted values from the contemporaneous regression with the VIX, the oil price and the 10-year yield estimated on pre-event data, the contribution of each variable, and the residual.

5.6. Interpretation

Taken together, the results are consistent with the three hypotheses of Section 3.4, with qualifications. No statistically significant US abnormal return was detected, but the confidence interval does not rule out a large decline, so the evidence for H1 is weak. US equities outperformed a combination of foreign markets by about 3.5 percentage points over two days, and the outperformance was concentrated against oil-importing markets while disappearing against Canada (H2); this advantage persisted for most of March but had largely disappeared in raw terms by 30 March. The effect of volatility on returns was contemporaneous, with no predictive effect on later returns, and over the first week the price level moved with the VIX (H3). In terms of the model, the episode is consistent with the weak-herding, net-exporter case of Figure 1, although the data do not measure the strength of herding: a common rise in perceived risk produced a modest decline whose persistence depended on how long perceived risk remained elevated, while the energy channel that depressed fundamental valuations in importing economies was largely offset in the United States. Within the first week, the data show no discontinuous shift to pessimism of the kind that Proposition 2 associates with strong herding; whether the later decline reflects such a shift cannot be determined from these data.

These interpretations rest on a single episode and on proxies. The VIX measures perceived risk but does not separate fear from collective sentiment, and the synthetic control compares markets that differ in many respects besides energy exposure, including sector composition and currency regime, and oil exposure is not the same as total energy exposure, as the Australian case shows. The evidence is therefore consistent with the energy-exposure mechanism but does not establish it.

6. Discussion

The framework also explains why the response can be small: in the March 2026 episode, a very large rise in geopolitical risk and oil prices was accompanied by a muted and statistically insignificant response of US equities, and a much larger decline in energy-importing markets.

The results point to a structural determinant of the market response: the same oil price shock lowers fundamental valuations in energy-importing economies but has little net effect, or a positive one, where domestic energy production is large. A country's net energy position may therefore help determine how much of a geopolitical shock its equity market absorbs, although the evidence in this paper is consistent with this mechanism rather than establishing it.

Net energy position is correlated with other structural characteristics that may also shape the response to geopolitical shocks, including sector composition, exchange-rate regimes, financial structure and proximity to the conflict. The present design addresses these factors only in part. Excluding the energy sector from the US and Canadian indices leaves the gap essentially unchanged, so the result is not driven by the weight of energy producers in the indices (Section 5.3). Returns are measured in US dollars, so currency movements are part of the comparison rather than controlled for. The Australian case, a net oil importer but a net energy exporter, shows that the relevant concept of energy exposure itself matters, and the range of losses among the oil importers, from 3.1 to 8.0%, indicates that other characteristics also play a role. With five donor markets and one episode, the effect of net energy position cannot be separated statistically from these characteristics. A direct test would relate the returns of a broad cross-section of national equity markets to quantitative measures of net energy exposure while controlling for sector composition, exchange-rate regime, financial openness and distance from the conflict, and would pool several geopolitical episodes so that the energy effect is identified from variation in oil price movements across events.

The empirical analysis indicates that a common global rise in risk was accompanied by declines of 3 to 8% in the dollar value of oil-importing markets over two days, compared with about 1 to 2% in the US and Canadian markets. This pattern highlights the interconnected nature of global financial markets and suggests that geopolitical shocks may propagate internationally through common risk-perception channels rather than affecting individual markets in isolation [62], while differences in exposure determine how strongly each market is affected.

In periods of heightened geopolitical uncertainty, effective communication strategies and coordination among policy institutions may play an important role in preventing destabilizing feedback loops between investor expectations and financial conditions [63,64]. Proposition 2 suggests a specific reason for this: when herding is strong, a shock that pushes sentiment past a threshold can leave the market in a pessimistic state that persists after the shock has faded, so preventing the threshold from being crossed is easier than reversing the shift afterwards. The model indicates how such measures would operate. Timely and credible public information, such as assessments of energy supply and of exposure to the conflict issued by governments and central banks, raises the information flow $\mathrm{I(t)}$, which accelerates the dissipation of perceived risk in equation (3) and the restoration of optimism in equation (5). Measures that limit the rise in energy prices, such as coordinated releases of strategic petroleum reserves, act on fundamental valuations through the energy channel of equation (7), particularly in energy-importing economies. Liquidity provision, including central bank swap lines, supports market functioning and arbitrage, and thereby the speed κ at which prices return to fundamental valuation. Coordination across institutions matters in the model because what moves sentiment is the balance between information and fear, $a = k_2 I - k_1 F$: statements that contradict one another may raise perceived risk as much as they add to information. These implications follow from the structure of the model. The empirical analysis of this paper does not evaluate the effect of any communication or coordination measure, and the recommendations should therefore be read as hypotheses for policy design rather than as prescriptions supported by the evidence presented here.

6.1. Limitations and Directions for Future Research

Despite these insights, the framework developed in this study remains subject to several limitations. The empirical analysis rests on a single episode, the donor markets of the synthetic control were themselves affected by the shock, and collective sentiment is not observed separately from perceived risk. A natural next step is to test Proposition 3 directly by relating the event-day returns of a broad cross-section of national equity markets to their net energy positions, and by pooling several geopolitical episodes identified from spikes in the daily GPR index. The event window may also contain news unrelated to the escalation (Section 4.3), the VIX is an imperfect proxy for perceived risk (Section 3.4), and the synthetic control estimate depends on the composition of the comparison group (Section 5.3).

The behavioral mechanisms of the model could be tested directly with additional data. Survey-based and market-based sentiment indicators, such as the sentiment index of Baker and Wurgler [28], investor surveys, put–call ratios and fund flows, could provide measures of $m(t)$ that are separate from the VIX, and data on investor positioning would show whether investors moved together. Herding could be measured with dispersion-based tests, which examine whether the cross-sectional dispersion of individual stock returns falls when the market moves strongly [65,66]. The nonlinear implications of Proposition 2 could be examined with regime-switching models of sentiment or returns [67], by testing whether the distribution of sentiment becomes bimodal in periods of high geopolitical risk, and by looking for the rise in variance and autocorrelation that precedes a saddle-node bifurcation in nonlinear systems [68]. Information flow $I(t)$ could be measured from the frequency and content of official statements or from news-based indices. Combining these measures across several geopolitical episodes would make it possible to

estimate the strength of imitation and to test whether it determines the persistence of market responses, as the model predicts.

7. Conclusion

This study develops an interdisciplinary framework for understanding how geopolitical shocks influence financial markets by integrating macroeconomic fundamentals, investor risk perception, and collective expectation dynamics.

The empirical analysis of the escalation of geopolitical tensions involving Iran in early March 2026 is consistent with several implications of the theoretical framework, though in a form that differs from the usual picture of a sharp decline and recovery. Despite a rise in the GPR index to more than four times its February average and a 34% rise in the oil price within a week, the S&P 500 showed no statistically significant abnormal return in the first week, although the confidence interval is wide, and it fell by about 8% by the end of March as the conflict continued. Relative to a synthetic control built from five non-US markets, US equities outperformed by about 3.5 percentage points over the first two trading days, and the outperformance was concentrated against oil-importing markets; the advantage persisted for most of March but narrowed sharply at the end of the month. The VAR shows that the link between volatility and returns is contemporaneous, with no predictive effect on later returns, although the price level remains lower while volatility stays elevated, and that oil price increases were not associated with lower US equity returns.

It is important to distinguish what the model establishes from what the data show. The bistability of collective sentiment, the hysteresis of the transition to pessimism and the cancellation of common terms in cross-market comparisons are properties of the theoretical model, derived in Propositions 1–3. The empirical analysis documents a muted and statistically insignificant US response, an outperformance of US equities relative to oil-importing markets whose size depends on the composition of the comparison group, and a contemporaneous relationship between market-implied volatility and returns. These findings are consistent with the weak-herding, net-exporter case of the model, but collective sentiment, the strength of imitation and the independent effect of net energy exposure were not measured, and the evidence does not establish the behavioral mechanisms of the model. The contribution of the paper is therefore a tractable framework that integrates behavioral and macroeconomic channels and yields testable implications, together with evidence from one episode that motivates, rather than completes, the empirical testing of those implications.

More broadly, the framework suggests that financial markets can be interpreted as complex adaptive systems in which collective behavior emerges from interactions among heterogeneous agents. From this perspective, feedback between perceived risk and collective sentiment can amplify the effect of geopolitical shocks in the way that feedback amplifies disturbances in nonlinear dynamical systems, and shifts in investor sentiment between optimistic and pessimistic states are analogous to phase transitions in statistical physics. In the episode studied here, such amplification was not observed in the first week, which is what the model predicts when imitation is weak; whether stronger herding in other episodes produces the regime shifts of Proposition 2 is a question for future empirical work.

Publishing Ethics

All sources have been appropriately acknowledged. The study did not involve human participants, animal subjects, or identifiable personal data; therefore, ethical approval and informed consent were not required.

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Data Availability

Data sharing is not applicable to this article.

Conflicts of Interest

The author declares no conflicts of interest.

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