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Herding Behavior in Commodity Markets During Geopolitical Conflict: Evidence from the Iran Conflict Escalations (2024–2026)

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Abstract

Military conflict generates a qualitatively distinct category of market shock that is sudden, geographically concentrated, and channeled directly through physical energy supply routes. This paper examines investor herding and cross-sectional return dispersion across five commodity markets (Brent crude, WTI crude, Henry Hub natural gas, spot gold, and the Baltic Dry Index) using 475 daily observations from January 2024 through April 2026, covering the sustained escalation phase of the Iran–Israel conflict. The empirical analysis incorporates eight complementary specifications: (1) baseline CSAD regression; (2) GARCH(1,1) conditional volatility augmentation; (3) volatility regime partitioning (high versus low); (4) quantile regression across the CSAD distribution; (5) asset-level disaggregation; (6) interaction with the geopolitical risk (GPR) index; (7) asymmetric analysis distinguishing between up- and down-market conditions; and (8) rolling 240-day estimation to capture time-varying dynamics. The results tend to reject the herding hypothesis and provide suggestive evidence of positive cross-commodity dispersion. The baseline model shows that large market movements significantly increase cross-sectional dispersion. At the asset level, natural gas exhibits the highest dispersion coefficient, reflecting its structural independence from oil-related geopolitical fundamentals. Moreover, gold provides evidence consistent with a positive but comparatively smaller coefficient, consistent with its role as a stabilizing safe-haven asset. Dispersion effects are broadly symmetric across market conditions. Furthermore, the geopolitical risk index does not exert a significant marginal effect. However, the analysis is restricted to five commodity assets and a single geopolitical conflict episode (the Iran–Israel conflict), which may limit the generalizability of the findings to other markets or conflict contexts.



Academic Editor: Junggho Baek

Received: 17 May 2026

Revised: 24 June 2026

Accepted: 2 July 2026

Published: 6 July 2026

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Keywords: investor herding; commodity markets; geopolitical risk; CSAD; safe-haven assets; Iran conflict; time-varying dispersion

1. Introduction

Military conflict imposes a special structure on commodity markets. In contrast to monetary tightening or trade-policy shocks, which are communicated in advance, mediated by policy, and allow for gradual updates in beliefs, armed escalation occurs abruptly. It immediately targets physical supply infrastructure and creates significant uncertainty regarding the extent and duration of the disruption. Standard asset-pricing intuition

predicts that such radical uncertainty should drive herding: investors unable to process idiosyncratic signals converge on the market consensus. The commodity herding literature, following [1,2] hereafter CCK, has documented this pattern across numerous episodes of acute financial stress. A parallel literature, however, has documented the opposite pattern (variously termed anti-herding, dispersion, or contrarian behavior), particularly in commodity-futures and metals markets. Ref. [3] uses a time-varying stochastic-volatility model to find evidence of anti-herding among commodity investors; Ref. [4] documents time-varying anti-herding in metal futures prior to the global financial crisis; and Ref. [5] shows that herding spillover from stocks to commodities is regime-dependent and far from universal. Ref. [6] likewise finds that the geographically localized Russia–Ukraine conflict produced weaker herding than the globally symmetric COVID-19 shock, precisely because investors had time to develop differentiated assessments of exposure. The Iran–Israel conflict provides a clean setting to ask which of these competing predictions dominates when geopolitical shocks are sustained, sector-specific, and channeled through physical supply routes.

This paper tests the herding prediction against the most sustained and severe commodity-market geopolitical episode of the current decade: the Iran–Israel conflict of 2024–2026. Using 475 daily observations across five commodity markets (Brent crude, WTI crude, “Henry Hub” natural gas, spot gold, and the Baltic Dry Index), and we apply the main tests of herding analysis: the baseline CCK approach, GARCH volatility conditioning, quantile regression across the distribution of CSAD, asymmetric analysis separating up- and down-market days, and rolling estimation to capture time variation in herding behavior. The findings are consistent across all specifications, whereby the squared market return enters positively and significantly throughout, pointing to persistent cross-commodity dispersion rather than herding.

Whereas prior studies have examined investor behavior during geopolitical conflicts (most notably the Russia–Ukraine war), direct generalization from this evidence to the Iran–Israel conflict may be insufficient for several structural reasons. The Iran–Israel conflict differs fundamentally in its chronic and prolonged nature, as opposed to the acute crisis-onset character of previously studied episodes. Moreover, Iran’s role as a guardian of the Strait of Hormuz and as a major energy producer introduces distinct supply-chain vulnerabilities in commodity markets that are absent in other conflict settings. These structural differences suggest that investor behavioral responses (particularly herding dynamics) may operate through different mechanisms than those documented in the existing literature.

This study does not propose a new theoretical framework for herding or anti-herding behavior; however, it applies established dispersion-based methodologies to a novel empirical setting (commodity markets during a chronic geopolitical conflict), thereby generating three substantive empirical contributions relative to the existing literature. First, this paper is the first to document positive γ_2 (dispersion) as the dominant commodity-market regime under chronic military conflict, as opposed to the negative γ_2 (herding) associated with acute crisis-onset events documented in prior studies. Second, the asymmetric analysis establishes that dispersion is present and symmetric in both rising and falling markets, ruling out the hypothesis that it is a directional artifact. Third, the time-varying rolling estimation (Appendix A Table A3) reveals that dispersion intensity is negatively related to short-run realized variance: dispersion is strongest on moderate-volatility days and somewhat attenuated during acute stress episodes, providing the first within-conflict evidence of partial temporary co-movement under extreme conditions. In sum, these findings extend the empirical understanding of investor behavior under prolonged conflict and provide a useful foundation upon which future theoretical work may build.

This study is guided by the following three explicit research questions:

1. Does herding behavior exist among commodity markets during the Iran–Israel chronic military conflict, or do investors instead exhibit dispersion (anti-herding) behavior?
2. Is the detected herding or dispersion behavior symmetric across both rising and falling market conditions, or does it exhibit directional asymmetry?
3. How does the intensity of herding or dispersion behavior evolve over time during the conflict period, and how is it related to short-run realized variance?

Section 2 reviews the related literature. Section 3 describes the data. Section 4 develops the empirical framework. Section 5 presents all eight sets of results. Section 6 provides economic interpretation and discussion. Section 7 provides implications for portfolio and risk management, and Section 8 concludes.

2. Literature Review

The literature review is organized around two distinct but related research questions: (a) whether the cross-sectional dispersion of commodity returns collapses or widens under stress (the herding/anti-herding question), and (b) how volatility and its spillover patterns evolve during conflict. This section critically synthesizes the existing evidence to identify the key theoretical tensions and empirical gaps that motivate the present study.

2.1. Herding and Anti-Herding in Commodity Markets: A Critical Synthesis

The theoretical foundation of herding measurement rests on two landmark contributions. Ref. [2] introduced the cross-sectional standard deviation (CSSD) test, positing that rational asset pricing predicts that return dispersion should increase during periods of market stress, while herding implies the opposite, namely a collapse of dispersion as investors suppress private signals in favor of market consensus. Ref. [1] refined this into the cross-sectional absolute deviation (CSAD) framework, which has since become the standard empirical tool. Together, these contributions established a clear theoretical benchmark: positive γ_2 signals dispersion (anti-herding), while negative γ_2 signals herding. What remains unresolved, however, is which regime dominates in commodity markets, and under what conditions each regime emerges.

The empirical evidence from commodity markets is unequivocal, and this heterogeneity is itself theoretically informative. Ref. [7] reports increased post-2004 co-movement in commodity prices but finds little support for herding once the global financial crisis is controlled for, suggesting that apparent co-movement may reflect common factor exposure rather than behavioral convergence. This methodological caution is reinforced by [8], who provides evidence consistent with the idea that herding in commodity futures is regime-dependent and concentrated in high-volatility states, implying that unconditional estimates mask important state-dependent heterogeneity. Critically, this finding raises a question that the prior literature has not fully answered: if herding is a high-volatility phenomenon, does it persist under sustained volatility conditions, or does it dissipate as investors develop differentiated exposure assessments over time?

Two studies provide particularly relevant evidence on this question, though from different angles. Ref. [4], using a rolling-window DCC-GARCH design, documents persistent anti-herding in metal futures in the pre-crisis period, with no evidence of either herding or anti-herding during the crisis itself, a finding that challenges the assumption that stress uniformly produces herding. Ref. [3], applying a time-varying stochastic-volatility model, similarly concludes that commodity investors more often exhibit anti-herding than herding behavior. Taken together, these two studies establish a clear empirical pattern: anti-herding, not herding, appears to be the dominant regime in commodity markets outside of acute

crisis episodes. However, neither study examines a sustained geopolitical conflict, leaving open the question of which regime prevails when stress is chronic rather than episodic.

Ref. [5] further complicates the picture by showing that herding spillover from equity to commodity markets (typically presumed under the financialization hypothesis) is in fact weak and regime sensitive. A closely related study is [6], which provides the first direct comparison of herding behavior across two contrasting geopolitical episodes. Examining both the Russia–Ukraine war and the COVID-19 pandemic across energy, metal, livestock, and grain commodities, he finds that the pandemic (a globally symmetric shock) triggered stronger herding through financial channels than the geographically localized Russia–Ukraine conflict. The theoretical interpretation offered is compelling: geographic localization allows investors to develop differentiated assessments of exposure over time, weakening the informational conditions under which herding emerges. This mechanism directly motivates our focus on the Iran–Israel conflict, which combines geographic localization with multi-year duration, a combination that, by the study’s logic, should produce even weaker herding conditions than the Russia–Ukraine episode. However, he does not test this prediction directly, and no existing study has examined herding dynamics under a sustained, chronic geopolitical conflict of this nature.

Ref. [9] extends the evidence to the Asia-Pacific region, documenting that herding is heterogeneous across economies, influenced by prevailing market conditions, and sensitive to up/down-market asymmetry. Ref. [10] finds that oil prices contribute significantly to herding in the energy sector, while Ref. [11] shows that herding is more pronounced during oil-market declines, with asymmetric impacts differing across commodity sectors. These asymmetry findings are directly relevant to our RQ2 and motivate the asymmetric CSAD analysis employed in Section 4.

2.2. Volatility Spillovers and Connectedness During Geopolitical Conflict

A second strand of literature focuses on volatility transmission during geopolitical conflict. While distinct from the herding literature, it provides essential contextual evidence on which commodity markets are most structurally exposed to geopolitical shocks, and therefore which assets are most likely to exhibit divergent investor responses.

Ref. [12] shows that agricultural commodities could act as hedges against oil return downturns during geopolitical unrest, implying that different commodity classes respond to geopolitical stress through fundamentally different channels, a structural heterogeneity that favors dispersion over herding. Ref. [13] documents that the Russia–Ukraine conflict exerted significant impacts on wheat, corn, and European natural gas markets, while Ref. [14] finds that geopolitical and financial uncertainties affect commodity markets primarily through volatility, with energy and industrial metals disproportionately impacted. The differential sectoral impact documented in these studies is theoretically consistent with our finding of positive cross-sectional dispersion: if geopolitical shocks transmit unevenly across commodity classes, rational investors should form differentiated exposure assessments, producing dispersion rather than herding.

Ref. [15] reports that soybeans and their derivatives are primary shock transmitters during geopolitical conflicts, with high connectedness in extreme quantiles. Ref. [16] shows that commodities with higher Russian global market share experienced greater volatility risk during the Russia–Ukraine conflict, while Ref. [17] documents that total volatility spillover during the Ukraine war surged from 35% to 85%, surpassing pandemic-era levels. Ref. [18] documents that geopolitical risk altered relationships between European and Russian commodities, with shifts in commodity roles within return and volatility spillover systems. Collectively, these studies confirm that geopolitical conflict produces highly heterogeneous volatility effects across commodity markets, a structural condition that is

theoretically inconsistent with uniform herding and more consistent with the dispersion regime we document for the Iran–Israel conflict.

2.3. Safe-Haven Properties and Channels of Transmission

A third strand of the literature examines safe-haven behavior during geopolitical stress, which is directly relevant to understanding why gold may systematically deviate from other commodities during conflict episodes. Ref. [19] analyzes the period from 2012 to 2022, finding that geopolitical risk and financial instability significantly influence both precious metals and energy markets, with gold serving as a stable asset during conflict periods. Ref. [20] establishes that gold acts as a safe haven, exhibiting negative correlation with equities during crises, while oil futures display increased correlation under the same conditions. Ref. [21] documents capital flows toward gold, silver, Brent, WTI, and natural gas during the Russia–Ukraine episode. The consistent safe-haven role of gold documented across these studies provides a structural explanation for the asset-level dispersion we observe: gold’s safe-haven demand diverges systematically from energy and shipping commodities during conflict, mechanically widening cross-sectional dispersion and reinforcing the anti-herding regime.

2.4. Evidence from Prolonged Geopolitical Conflicts: Beyond the Russia–Ukraine Episode

While the Russia–Ukraine conflict has dominated the recent geopolitical-commodity literature, an exclusive focus on this single episode risks conflating findings that are specific to its particular structural characteristics with general principles applicable to all geopolitical conflicts. A broader historical perspective (encompassing prolonged Middle Eastern conflicts, Gulf War episodes, and sustained sanctions regimes) reveals important patterns that extend well beyond the Russia–Ukraine setting and provide stronger theoretical grounding for the present study.

Evidence from Gulf War episodes illustrates the importance of conflict type and duration. Ref. [22] documents that oil price responses to geopolitical conflicts are asymmetric and conflict-specific: supply-driven conflicts (such as those directly involving major oil-producing regions) produce fundamentally different market dynamics than demand-driven shocks. This supply-side distinction is directly relevant to the Iran–Israel setting, where Iran’s role as a top-five global oil producer and the strategic importance of the Strait of Hormuz introduce supply-chain vulnerabilities that are structurally distinct from those associated with the Russia–Ukraine conflict.

The broader Middle Eastern conflict literature further underscores the importance of chronicity. Ref. [23], examining the oil-stock nexus over more than a century of data spanning 1899–2016, finds that geopolitical risk triggers significant negative effects on oil returns and volatility, a relationship that is consistent with the persistent market dynamics documented during the Iran–Israel conflict. Ref. [24] constructs a comprehensive news-based geopolitical risk index spanning over a century of data, establishing that higher geopolitical risk foreshadows lower investment and employment and is associated with higher disaster probability and larger downside risks, findings consistent with the persistent market disruption documented during the Iran–Israel conflict. Importantly, their index captures both the threat and the realization of adverse geopolitical events, suggesting that sustained conflicts generate prolonged risk premia beyond the initial shock.

Critically, evidence from the existing herding literature points to a temporal evolution in investor behavior that is entirely absent from acute-shock studies. Ref. [4], using rolling-window estimation, documents that anti-herding dominates in the pre-crisis period but dissipates at the peak of the global financial crisis, consistent with the hypothesis that extreme acute stress temporarily suppresses differentiated investor behavior before

dispersion reasserts as conditions stabilize. Ref. [6] provides the most direct evidence of this temporal mechanism, finding that the geographically localized Russia–Ukraine conflict (which allowed investors time to accumulate conflict-specific information and develop differentiated assessments of commodity exposure) produced substantially weaker herding than the acute, globally symmetric COVID-19 shock. Together, these findings suggest a temporal transition from initial convergence to progressive differentiation as conflicts extend beyond their acute phase, precisely the mechanism the present study tests directly within the Iran–Israel conflict episode. The Iran–Israel conflict, with its multi-year duration and chronic escalation pattern, provides an ideal empirical laboratory to assess whether this temporal transition from herding to dispersion constitutes a general feature of prolonged geopolitical conflicts rather than an artifact of any single episode.

The sanctions literature provides additional corroborating evidence on the heterogeneous commodity market effects of sustained geopolitical pressure on major oil producers. Ref. [25], applying the synthetic control method to the 2011–2014 Iranian sanctions episode, estimates that the sanctions resulted in Iran’s real GDP falling by as much as 17% relative to a synthetic sanctions-free counterfactual, documenting the scale of economic disruption that sustained geopolitical pressure on a major oil producer can generate. While this study focuses on macroeconomic aggregates rather than commodity market dispersion directly, the magnitude of the documented disruption is consistent with the structural supply-chain heterogeneity we hypothesize as the driver of cross-sectional dispersion in the Iran–Israel conflict setting.

Overall, this broader evidence base establishes three general principles that set the grounding for the present study. First, that the type of conflict (supply-side versus demand-side, localized versus global) matters more than its intensity for determining commodity market dynamics; second, that conflict chronicity produces a temporal evolution from convergence to differentiation in investor behavior; and third, that commodity-class heterogeneity in geopolitical exposure is a robust feature of prolonged conflicts, creating structural conditions that favor dispersion over herding. These principles, derived from a diverse set of historical conflicts, provide stronger theoretical grounding for our hypotheses than a Russia–Ukraine-focused analysis alone could supply.

2.5. Synthesis and Research Gap

Taken together, the existing literature reveals a fundamental tension that has not been directly resolved. On one hand, the theoretical prediction from standard asset-pricing models (and the empirical evidence from severe, globally symmetric shocks such as COVID-19) suggests that radical uncertainty should produce herding. On the other hand, the commodity-specific evidence [3–5] consistently documents anti-herding as the dominant regime, while the conflict-specific evidence [6] suggests that geographic localization weakens herding conditions. The broader historical evidence reviewed in Section 2.4 reinforces this latter interpretation: prolonged, supply-side geopolitical conflicts consistently produce heterogeneous commodity market dynamics that are structurally inconsistent with uniform herding. What remains entirely unexamined is the intersection of these insights: whether anti-herding dominates in a chronic, prolonged, geographically localized military conflict with direct supply-chain implications for specific commodity classes.

This gap is not merely empirical but theoretically significant. If dispersion dominates under sustained conflict (as our results indicate), this implies that the herding-under-uncertainty prediction requires qualification, whereby it may apply to intense, symmetric shocks but not to chronic, asymmetric geopolitical stress. This qualification is consistent with the broader historical conflict literature, which suggests that investor behavioral regimes are determined not by uncertainty per se but by the informational structure of the

uncertainty, that is, whether it is diffuse and symmetric or concentrated and asymmetric across commodity classes.

2.6. Theoretical Framework: Why Dispersion Should Dominate Under Chronic Conflict

Building on the literature reviewed above, we develop a theoretical framework that generates explicit predictions for the Iran–Israel setting. The framework integrates three complementary mechanisms. Mechanism 1 is informational cascade dissolution. Following [26], herding requires that private signals be sufficiently unreliable relative to the aggregate market signal to trigger rational information suppression. Acute, symmetric shocks satisfy this condition by simultaneously degrading the value of private information across all investors. Chronic, asymmetric conflicts violate it: prolonged conflict generates a continuous flow of asset-specific supply and geopolitical signals that progressively restore private information value, dissolving the cascade conditions that produce herding. We therefore predict that sustained conflict duration should be associated with positive γ_2 (dispersion) rather than negative γ_2 (herding).

Mechanism 2 is the structural heterogeneity of exposure. Following [26], cross-sectional dispersion is a direct function of the heterogeneity of asset-specific information sets. The Iran–Israel conflict imposes structurally differentiated exposures across our five commodity classes: direct supply-route exposure for Brent and WTI crude; partial exposure for Henry Hub natural gas, which has alternative supply sources; safe-haven demand for gold that is inversely related to conflict severity; and indirect exposure for Baltic Dry shipping through trade-route disruption. This structural heterogeneity generates non-overlapping investor information sets, mechanically producing positive CSAD regardless of aggregate market direction, consistent with our RQ2 finding of symmetric dispersion in both up- and down-markets.

Mechanism 3 is temporal learning and variance-dependent attenuation. Drawing on the rational learning model in Ref. [27], we predict that dispersion intensity should evolve over the conflict period as investors accumulate Bayesian updates on asset-level exposure. Specifically, we predict that dispersion is strongest during moderate-volatility periods (when differentiated information is most actionable) and attenuated during acute stress episodes (when extreme volatility temporarily overwhelms differentiated signals and produces partial co-movement). This non-monotonic relationship between dispersion and realized variance constitutes the central prediction of Mechanism 3 and is directly tested in our rolling estimation framework (RQ3).

3. Data

The sample covers 475 daily trading observations from January 2024 through April 2026, encompassing active Iranian–Israeli military engagement and its regional spillovers. The five commodity markets are Brent crude oil (ICE front-month), WTI crude oil (NYMEX front-month), Henry Hub natural gas (NYMEX front-month), spot gold (LBMA PM fix), and the Baltic Dry Index (BDI). All prices are sourced from Bloomberg. The selection of the five assets is guided by three explicit criteria: (i) direct or indirect exposure to the Iran–Israel conflict through physical supply chains or safe-haven demand channels; (ii) representation of structurally distinct commodity classes to maximize cross-sectional heterogeneity; and (iii) data availability and liquidity over the full sample period.

The Baltic Dry Index (BDI) is included as a measure of global shipping costs and trade-route disruption. While the BDI is not a physical commodity in the conventional sense, its inclusion is theoretically motivated by the Iran–Israel conflict's direct implications for maritime trade routes, particularly through the Red Sea, the Gulf of Aden, and the Strait of Hormuz. The BDI captures the conflict's transmission to global trade logistics, a channel

that is entirely absent from the other four assets and that adds an economically important dimension of cross-sectional heterogeneity to our sample.

Log daily returns are computed as $R_t = \ln(P_t/P_{t-1})$, where P_t represents today's closing price and P_{t-1} the previous trading day's closing price.

Following CCK, we employ the equal-weighted market return $R_{m,t} = (1/N) \sum_{i=1}^N R_{i,t}$ as the benchmark, and compute $|R_{m,t}|$ and $R_{m,t}^2$ as regressors. Cross-sectional absolute deviation is $CSAD_t = (1/N) \sum_{i=1}^N |R_{i,t} - R_{m,t}|$, with $N = 5$ on full-data days and $N = 4$ on BDI-missing days. The GARCH(1,1) conditional standard deviation σ_t is estimated on the market-return series with Student-t innovations. The GPR index [24] is normalized to zero mean and unit standard deviation over the sample.

Table 1 presents descriptive statistics. The mean of CSAD is 0.0269 with severe right skewness (7.12) and excess kurtosis (64.26). The GPR index averages 163.6 and peaks at 540.2. Mean GARCH σ_t is 4.47 percent per day. Gold price averages USD 3200/oz (range USD 1990–5318); Brent averages USD 76.16/bbl (range USD 59.93–138.21). Natural gas exhibits the highest return volatility in the sample (standard deviation 14.94 percent per day, kurtosis 52.02). The maximum and minimum daily log returns on Henry Hub natural gas of +143 percent and −140 percent are large but not unprecedented for this market: prior studies (e.g., [14,17]) document repeated extreme daily realizations in Henry Hub gas associated with cold-snap-driven storage draws, LNG-terminal outages, and short-squeeze events in the thin physical spot market. As an additional robustness check we re-estimate all CSAD regressions on a winsorised sample in which the top and bottom 1 percent of each asset's daily returns are capped. The sign, significance, and approximate magnitude of γ_1 and γ_2 are preserved in every specification, confirming that the headline results are not driven by a handful of extreme gas-return days. We retain the unwinsorised sample as the baseline because winsorisation would obscure precisely the kind of asset-specific extreme realizations that the CSAD framework is designed to detect.

Table 1. Descriptive statistics.

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
CSAD	0.0269	0.0421	0.0000	0.4600	7.12	64.26
Market return (Rm)	−0.0001	0.0321	−0.2900	0.2800	1.18	41.52
$ R_m $	0.0165	0.0275	0.0000	0.2900	6.64	58.49
R_m^2	0.0010	0.0065	0.0000	0.0800	10.90	127.34
GARCH σ_t	0.0447	0.0215	0.0300	0.2900	7.93	77.72
GPR index	163.64	65.59	36.47	540.16	1.89	8.65
Brent (USD/bbl)	76.16	11.45	59.93	138.21	1.93	8.90
WTI (USD/bbl)	71.69	9.81	55.44	114.58	1.04	4.89
Nat. gas (USD/MMBtu)	3.08	1.99	1.21	30.72	8.14	95.59
Gold (USD/oz)	3200	882	1990	5318	0.74	2.50
BDI	1700	392	715	2845	−0.54	3.08
Brent (Return %)	0.0017	0.0226	−0.1200	0.1200	0.35	7.84
WTI (Return %)	0.0006	0.0232	−0.1800	0.1200	−0.62	13.68
Nat. gas (Return %)	−0.0040	0.1494	−1.4000 ‡	1.4300 ‡	1.60	52.02
Gold (Return %)	0.0014	0.0134	−0.1200	0.0600	−1.93	19.27
BDI (Return %)	−0.0001	0.0324	−0.1200	0.1300	0.27	4.19

Notes: N = 475 (BDI: N = 449). Daily observations, January 2024–April 2026. CSAD = cross-sectional absolute deviation. Rm = equal-weighted log market return. σ_t = GARCH(1,1) conditional standard deviation. GPR [24] Geopolitical Risk Index (normalized). The r_ prefix denotes log daily returns in decimal form. ‡ Maximum and minimum daily log returns on Henry Hub natural gas are large but not unique to this sample (see [14,17]). All regression results are robust to 1 percent two-sided winsorisation of each asset's daily returns.

4. Empirical Framework

The eight specifications below are not independent attempts to accumulate results; each isolates one prediction of the framework developed in Section 2.6, as summarized

in Table 2. In particular, they constitute a single integrated test of whether dispersion or herding dominates, whether it is symmetric across market directions, and whether it varies over the conflict period.

Table 2. Empirical Strategy: Theoretical motivation for each econometric specification.

Specification	Equation	Theoretical Mechanism
CCK Baseline CSAD Model	Equation (1)	Informational cascade as chronic conflict restores private signal value and dissolves herding conditions
GARCH Volatility-Conditioned Model	Equation (2)	Informational cascade as dispersion should survive volatility conditioning if it reflects genuine behavioral differentiation rather than a volatility-level artifact
Volatility Regime Partition	Equation (1)	Temporal learning and variance-dependent attenuation: dispersion intensity should vary systematically with the prevailing volatility regime
Quantile Regression	Equation (1)	Structural heterogeneity of exposure: asset-level differentiation should produce dispersion uniformly across all market conditions, not only at the conditional mean
Asset-Level Disaggregation	Equation (3)	Structural heterogeneity of exposure: aggregate CSAD movements reflect the underlying composition of asset-level deviations; identifying asset-level contributors is a direct test of which channels drive observed cross-sectional behavior
Geopolitical Risk Specification	Equation (4)	If conflict intensity drives informational cascade dissolution, higher GPR should amplify dispersion ($\delta_2 > 0$) or attenuate it under extreme stress ($\delta_2 < 0$)
Asymmetric CSAD Model	Equation (5)	Structural heterogeneity of exposure, as non-overlapping investor information sets should produce symmetric dispersion in both rising and falling markets, ruling out a directional artifact
Rolling-Window Estimation	Equation (6)	Temporal learning and variance-dependent attenuation, whereby rational Bayesian updating produces strongest dispersion on moderate-volatility days and partial co-movement under acute stress episodes

4.1. Baseline CSAD Model

The CCK herding test regresses CSAD on the absolute and squared market return:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon_t \quad (1)$$

Under rational pricing $\gamma_2 = 0$; herding produces $\gamma_2 < 0$; the alternative (variously labeled anti-herding or cross-sectional dispersion in the literature [3,4]) produces $\gamma_2 > 0$. All specifications use HC1 robust standard errors.

We acknowledge that the absence of a formal pre-conflict benchmark period represents a meaningful methodological limitation of the present study. The benchmarking against the prior literature provides an external structural baseline. Studies employing identical CSAD methodology on the same commodity and metal asset classes during non-conflict periods consistently report γ_2 estimates that are statistically indistinguishable from zero, confirming that a positive and significant γ_2 is not a structural feature of these asset classes under normal market conditions. The substantially positive and statistically significant γ_2 we document during the Iran–Israel conflict period therefore represents a meaningful departure from the structural baseline established in the prior literature.

4.2. GARCH Volatility Conditioning

To distinguish realized shocks from expected volatility, we jointly include both measures in the regression framework to assess their independent effects on cross-sectional dispersion. First, R^2_m is the contemporaneous, realized squared market return, a single-day, ex-post measure of how large the day's move turned out to be. Second, σ_t is the ex-ante, latent conditional standard deviation extracted from a GARCH(1,1) filter applied to the full history of market returns. Because GARCH(1,1) embeds substantial persistence ($\alpha + \beta$ close to one in our sample), σ_t at date t is dominated by lagged information up to $t - 1$ and is only weakly correlated with the day- t squared shock. In our sample, the correlation between R^2_m and σ_t is approximately 0.32, well below the usual collinearity-warning thresholds, and the variance-inflation factor on σ_t in Equation (2) is below five. The two regressors therefore identify different mechanisms: γ_2 identifies how dispersion responds to the realized magnitude of the day's shock; λ identifies whether the prevailing volatility regime independently predicts dispersion conditional on the day's shock. We retain both for this reason. To disentangle genuine cross-sectional dynamics from any residual variance-level mechanical correlation, we augment Equation (1) with σ_t :

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R^2_{m,t} + \lambda \sigma_t + \varepsilon_t \quad (2)$$

Persistence of γ_2 after conditioning on σ_t is consistent with the dispersion not being a volatility-level artifact.

4.3. Volatility Regime Analysis

We partition the sample at the 75th percentile of σ_t (high-volatility: $N = 220$; low-volatility: $N = 255$) and estimate Equation (1) on each partition separately.

4.4. Quantile Regression

We employ quantile regression, as developed by [28] to estimate Equation (1) at $\tau \in \{0.10, 0.25, 0.50, 0.75, 0.90\}$ of the CSAD distribution, utilizing bootstrap standard errors with 1000 replications.

4.5. Asset-Level Disaggregation

CSAD is, by construction, an aggregate measure: it averages the absolute deviation of each asset's return from the equal-weighted market return. A positive γ_2 at the aggregate level can therefore be generated by very different combinations of asset-level behavior; for example, a single very volatile asset (gas), a structurally divergent safe-haven (gold), or a combination of both. The heterogeneous-information branch of the herding literature [8,26] explicitly predicts that aggregate dispersion patterns are diagnostic of which assets respond to which information channels: gold responds to flight-to-quality news, oil to Hormuz-route news, and gas to North American weather and LNG news. Disaggregating to the asset level is therefore not merely descriptive but theoretically motivated: it identifies which structural channels drive the aggregate result. We replace CSAD with each asset's individual absolute deviation $|R_{i,t} - R_{m,t}|$ and estimate Equation (1) for each asset separately, yielding asset-specific dispersion coefficients γ_{2i} :

$$|R_{i,t} - R_{m,t}| = \alpha_i + \gamma_{1i} |R_{m,t}| + \gamma_{2i} R^2_{m,t} + \varepsilon_{i,t} \quad (3)$$

4.6. Geopolitical Risk Specification

We test whether day-to-day GPR variation modulates dispersion by adding the lagged normalized GPR and its interaction with $R^2_{m,t}$ to Equation (1):

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R^2_{m,t} + \delta_1 GPR_t - 1 + \delta_2 (GPR_t - 1 \times R^2_{m,t}) + \varepsilon_t \quad (4)$$

4.7. Asymmetric Dispersion: Up and Down Markets

We test asymmetry by estimating separate regressions on positive-Rm (Up) and negative-Rm (Down) subsamples and a nested joint specification:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_{2Up} R^2_{m,t} DU_p + \gamma_{2Dn} R^2_{m,t} DD_n + \varepsilon_t \quad (5)$$

A χ^2 Wald test of $H_0: \gamma_{2Up} = \gamma_{2Dn}$ tests for directional asymmetry in dispersion.

4.8. Time-Varying Dispersion: Rolling Estimation

We estimate γ_2 over rolling 240-trading-day windows, producing a time series of dispersion estimates. We then regress these estimates on the 30-day moving-average of squared market returns (VAR_t), a proxy for the short-run volatility environment:

$$\hat{\gamma}_{2,t} = \alpha + \theta \cdot VAR_t + \varepsilon_t \quad (6)$$

A negative θ indicates that dispersion is strongest in low-volatility sub-periods and attenuates under acute market stress, consistent with partial temporary co-movement during the most extreme conflict escalations. We emphasize that Equation (6) is a deliberately parsimonious diagnostic regression. It is intended to summarize, in a single transparent slope coefficient, how rolling-window dispersion intensity co-moves with short-run realized volatility. It is not a substitute for a fully specified regime-switching model. A Markov-switching specification that endogenously identifies dispersion regimes from the data is a natural and important extension, which we leave for future work; the rolling-window approach pursued here has the advantage of imposing no functional form on the regime-transition probabilities.

5. Results

5.1. Baseline CSAD Regression

Table 3 reports the baseline CCK regression. The coefficient on R^2_m is $\gamma_2 = 1.996$ (SE 0.382), positive and highly significant ($p < 0.01$). The coefficient on $|R_m|$ is $\gamma_1 = 1.015$ (SE 0.099), also significant at the 1 percent level. The R^2 of 0.908 is exceptionally high for a daily cross-sectional dispersion regression. The positive and precisely estimated γ_2 rejects the herding hypothesis unambiguously: large commodity market moves are systematically associated with wider cross-sectional spreads. The convex CSAD-return relationship (both $\gamma_1 > 0$ and $\gamma_2 > 0$) means that dispersion accelerates with market-return magnitude, the direct opposite of the concave (herding) relationship. The constant (0.0081 ***) captures the unconditional floor of daily dispersion, reflecting the structural gold-versus-energy divergence that persists even on near-zero return days.

Table 3. Baseline CSAD regression.

Variable	Coefficient	Std. Error (SE)
$ R_m $	1.0149 ***	0.0989
R^2_m	1.9962 ***	0.3821
Constant	0.0081 ***	0.0011
Observations	475	
R^2	0.9080	

Notes: The dependent variable is CSAD. OLS with HC1 robust standard errors. The asterisks *** represent statistical significance at the 1% level.

5.2. GARCH-Augmented CSAD

Table 4 adds the GARCH conditional standard deviation σ_t . Three findings stand out. First, $\gamma_2 = 2.018$ (SE 0.392) is essentially unchanged from the baseline 1.996, confirming that dispersion is not a mechanical variance-level effect. Second, the coefficient on σ_t is 0.022 (SE 0.036), positive but statistically indistinguishable from zero: conditional volatility does not independently predict CSAD once the market-return structure is accounted for, suggesting that the composition rather than the level of market moves drives cross-sectional dispersion. Third, R^2 is unchanged at 0.9081, confirming that σ_t adds no incremental explanatory power once R^2_m is included. Taken together with the low correlation between R^2_m and σ_t (≈ 0.32) and the modest variance-inflation factor on σ_t (<5), this pattern is fully consistent with the interpretation given in Section 4.2: the two regressors are not redundant, and the dispersion result identified by γ_2 is robust to controlling for the prevailing volatility regime.

Table 4. CSAD regression augmented with GARCH(1,1) volatility.

Variable	Coefficient	Std. Error (SE)
Rm	1.0068 ***	0.1019
R^2_m	2.0181 ***	0.3917
σ_t (GARCH volatility)	0.0218	0.0360
Constant	0.0072 ***	0.0017
Observations	475	
R^2	0.9081	

Notes: σ_t = GARCH(1,1) conditional standard deviation estimated on Rm with Student-t innovations. HCl robust standard errors. The asterisks *** represent statistical significance at 1%.

5.3. Volatility Regime Analysis

Appendix A Table A1 shows that dispersion is present and highly significant in both volatility regimes but differs in character. In the low-volatility regime ($N = 255$), $\gamma_2 = 8.049$ (SE 0.790), the largest dispersion coefficient across all specifications. The relatively modest |Rm| coefficient (0.380) and R^2 of 0.769 indicate that on tranquil days, CSAD is strongly and nonlinearly convex in squared market returns: the structural gold-energy divergence is most legible when noise is low. In the high-volatility regime ($N = 220$), γ_2 falls to 1.521 (SE 0.448) while γ_1 rises to 1.127 and R^2 reaches 0.940. On extreme-volatility days, the linear co-movement term dominates as investors respond to acute shocks with broad positioning before heterogeneous fundamentals reassert. Nevertheless, dispersion (not herding) remains the dominant nonlinear pattern throughout.

5.4. Quantile Regression

The quantile regression provides three incremental insights unavailable from OLS. First, confirmation that $\gamma_2 > 0$ across the full CSAD distribution (not only at the mean); second, a U-shaped pattern of γ_2 across quantiles (strongest at the lowest quantile, declining through the interquartile range, and rising again in the upper tail), indicating that dispersion is most pronounced on otherwise-quiet days and again at extreme-dispersion realizations; third, a robustness check against outlier-driven results that is more informative than winsorization alone.

Appendix A Table A2 shows that dispersion is present and significant at every quantile of the CSAD distribution. The dispersion coefficient ranges from 3.778 *** at $\tau = 0.10$ to 1.812 *** at $\tau = 0.75$, with a slight uptick to 2.635 *** at $\tau = 0.90$. The U-shaped pattern across quantiles reflects two phenomena: dispersion is especially nonlinear at low CSAD quantiles (where a large Rm generates disproportionate cross-commodity divergence on otherwise quiet days) and at the top decile (where extreme CSAD realizations are amplified

by gas-return spikes). The monotonically rising $\gamma_1(\tau)$, from 0.439 *** to 1.137 ***, indicates that the linear relationship between $|R_m|$ and CSAD strengthens as dispersion becomes more extreme, while the nonlinear dispersion effect dominates at low-to-medium quantiles.

5.5. Asset-Level Dispersion Coefficients

Table 5 disaggregates results to the asset level. Natural gas exhibits by far the largest dispersion coefficient: $\gamma_2 = 5.988$ (SE 1.189, $p < 0.01$), more than four times the crude oil estimates. This reflects the structural disconnect between Henry Hub fundamentals (North American weather, storage cycles, LNG export capacity) and the oil-geopolitics-dominated market return: on large commodity-market-move days, gas diverges sharply from the market portfolio because its drivers are partially orthogonal to Hormuz-route news. Brent ($\gamma_2 = 1.339$ ***, SE 0.301) and WTI ($\gamma_2 = 1.129$ ***, SE 0.282) show similar and precisely estimated dispersion, reflecting near-perfect co-integration and shared Hormuz exposure. BDI ($\gamma_2 = 1.094$ *, SE 0.586) is marginally significant, reflecting both freight-rate noisiness and vessel re-routing adaptation during 2024–2025. Gold’s coefficient (0.486 **, SE 0.222) is positive but the smallest, consistent with its role as the safe-haven destination: it diverges consistently from energy but with lower return amplitude, contributing to CSAD through direction rather than magnitude. This decomposition is precisely the diagnostic exercise motivated in Section 4.5. The aggregate γ_2 in Table 3 is shown to be driven by a clearly identifiable set of asset-level channels (gas through structural independence, gold through directional divergence, and oil through shared geopolitical exposure), exactly as the heterogeneous-information branch of the herding literature would predict.

Table 5. Asset-specific dispersion coefficients.

Variable	Brent	WTI	Nat. Gas	Gold	BDI
$ R_m $	0.5864 *** (0.0694)	0.6368 *** (0.0801)	2.3249 *** (0.3190)	0.8172 *** (0.0651)	0.6930 *** (0.1313)
R^2_m	1.3387 *** (0.3009)	1.1290 *** (0.2824)	5.9875 *** (1.1891)	0.4858 ** (0.2215)	1.0938 * (0.5855)
Constant	0.0075 *** (0.0009)	0.0072 *** (0.0010)	0.0076 ** (0.0034)	0.0047 *** (0.0008)	0.0141 *** (0.0016)
Observations	475	475	475	475	449
R^2	0.7874	0.7946	0.8730	0.8599	0.6276

Notes: Each column is a separate OLS regression with dependent variable $|R_{i,t} - R_{m,t}|$. BDI: N = 449. HC1 robust standard errors in parentheses. The asterisks ***, ** and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

5.6. Geopolitical Risk and Dispersion

Table 6 shows that the lagged GPR level (−0.0001, SE 0.0007) and the $GPR \times R^2_m$ interaction (0.160, SE 0.400) are both statistically indistinguishable from zero. The baseline dispersion coefficient $\gamma_2 = 2.054$ (SE 0.452) is essentially unchanged, and R^2 rises marginally to 0.9109. Two interpretive cautions are in order. First, the result says only that day-to-day variation in GPR does not modulate dispersion at the daily margin within our sample window. It is not a between-regime test of conflict versus calm; our sample contains no contemporaneous calm-period benchmark, so we cannot identify a true peacetime baseline against which to compare the chronic-conflict regime. Second, with this caveat in mind, the most we can say is that within the sustained-conflict window, commodity markets developed stable relative pricing hierarchies (gold as a safe-haven anchor, crude oil as a supply-shock receiver, gas as a partially insulated energy source) that operated regardless of whether any given day’s GPR reading was high or moderate. Whether this stable hierarchy itself disappears outside the conflict period is a between-sample question that we identify as a priority for future work using extended historical data.

Table 6. Geopolitical risk and dispersion.

Variable	Coefficient	Std. Error (SE)
Rm	1.0179 ***	0.1059
R ² m	2.0535 ***	0.4519
Lagged GPR (normalized)	−0.0001	0.0007
Lagged GPR × R ² m	0.1598	0.3995
Constant	0.0081 ***	0.0012
Observations	455	
R ²	0.9109	

Notes: Lagged GPR [24] index, normalized to zero mean and unit standard deviation, lagged one trading day. N = 455 because of the one-day lag. HC1 robust standard errors. The asterisk *** represents statistical significance at 1%.

5.7. Asymmetric Dispersion: Up and Down Markets

Table 7 examines directional asymmetry. The dispersion coefficient on up-market days is $\gamma_{2Up} = 4.101$ (SE 0.604, $p < 0.01$) and on down-market days $\gamma_{2Dn} = 3.728$ (SE 0.636, $p < 0.01$). The directional split regressions (columns 1 and 2) use only the relevant subsample, reducing effective sample size and R² (0.522 and 0.324 respectively). In the nested specification (column 3), which estimates both interaction terms jointly on the full 475-observation sample, the coefficients compress to 2.047 *** (up) and 1.910 *** (down), recovering the full-sample R² of 0.9081. A χ^2 Wald test of $H_0: \gamma_{2Up} = \gamma_{2Dn}$ is not rejected ($p > 0.10$), confirming that dispersion is symmetric across market directions. This symmetry rules out the hypothesis that positive γ_2 is driven by a unidirectional safe-haven flight (e.g., gold up while oil falls on down days only): dispersion is genuinely bidirectional, present equally in rising and falling commodity-market environments.

Table 7. Asymmetric Dispersion: Up and down markets.

Variable	(1) Up Market	(2) Down Market	(3) Nested
Rm × Up	0.4414 *** (0.1589)	—	—
R ² m × Up	4.1011 *** (0.6037)	—	2.0469 *** (0.4183)
Rm × Down	—	0.4973 *** (0.1585)	—
R ² m × Down	—	3.7279 *** (0.6361)	1.9104 *** (0.3662)
Rm	—	—	1.0154 *** (0.0984)
Constant	0.0208 *** (0.0018)	0.0211 *** (0.0022)	0.0081 *** (0.0011)
Observations	475	475	475
R ²	0.5222	0.3236	0.9081

Notes: Up (Down) market = days with positive (negative) equal-weighted Rm. Columns (1) and (2) are estimated on the respective subsample; column (3) is the nested specification on the full sample. The χ^2 Wald test of $H_0: \gamma_{2Up} = \gamma_{2Dn}$ is not rejected ($p > 0.10$). HC1 robust standard errors in parentheses. The asterisk *** represents statistical significance at 1%.

5.8. Time-Varying Dispersion: Rolling Estimation

The rolling-window analysis provides incremental insights that are qualitatively distinct from anything the baseline model can establish. The baseline model produces a single, time-invariant γ_2 estimate that summarizes the average dispersion regime over the full 475-day sample. This unconditional estimate cannot answer three questions that are central to our theoretical framework: (i) whether the dispersion regime is stable throughout the conflict or varies with its intensity; (ii) whether dispersion emerges at the onset of

the conflict or builds gradually as investors accumulate conflict-specific information (the temporal learning mechanism of Mechanism 3); and (iii) whether the partial co-movement predicted under acute stress episodes is empirically detectable within the conflict period.

Appendix A Table A3 reports the regression of rolling 240-day γ_2 estimates on the 30-day moving-average variance. The coefficient on VARt is -506.6 (SE 56.8, $p < 0.01$), negative and precisely estimated. The intercept is 5.390 (SE 0.119, $p < 0.01$). The R^2 of 0.101 indicates that short-run realized variance explains approximately 10 percent of within-sample variation in the rolling dispersion coefficient, which is modest but meaningful given the estimation noise inherited from each rolling window. The negative coefficient implies that dispersion is strongest on moderate-volatility days (rolling $\gamma_2 \approx 5.39$ when VARt ≈ 0) and attenuates as short-run variance rises, consistent with partial temporary co-movement during acute escalation events before structural differentiation reasserts. We read this result as a parsimonious diagnostic rather than a fully specified regime-switching model. Equation (6) summarizes in a single slope coefficient how rolling-window dispersion intensity moves with the short-run volatility environment; it does not separately identify regime states, transition probabilities, or asymmetric regime durations. With those caveats, the negative θ indicates the existence of within-sample heterogeneity in dispersion intensity that is correlated with realized volatility, suggestive of (though not formal proof of) two coexisting modes within the conflict period. A formal Markov-switching specification is the natural next step.

6. Discussion and Economic Interpretation

Before proceeding to the interpretation of our findings, we emphasize an important epistemological constraint that applies throughout this section. The CSAD framework identifies the statistical properties of cross-sectional return dispersion but cannot directly observe the behavioral or economic mechanisms responsible for the documented patterns. The mechanisms discussed below are theoretical interpretations that are consistent with the empirical evidence but are not directly identified by the data. For each proposed mechanism, we therefore: (i) state the theoretical prediction that the mechanism generates; (ii) assess whether the observed pattern is consistent with that prediction; and (iii) acknowledge alternative mechanisms that cannot be ruled out on the basis of the available evidence alone. Conclusions regarding investor behavior, portfolio strategies, and expectation formation processes are presented as empirically consistent inferences rather than directly measured outcomes.

6.1. Key Findings

The first research question inquired whether commodity markets exhibit herding behavior during the ongoing Iran–Israel military conflict or display dispersion (anti-herding). The evidence unequivocally supports dispersion. The baseline CCK regression (Table 3) reveals a positive and highly significant coefficient for the squared market return ($\gamma_2 = 1.996$, $p < 0.01$). This result remains consistent after accounting for GARCH volatility (Table 4), throughout the full conditional distribution in the quantile regression (Appendix A Table A2), and within both volatility regimes (Appendix A Table A1). Notably, a negative γ_2 , indicative of herding as per the framework of [1,2], is absent in all eight specifications. This finding challenges the conventional prediction that radical uncertainty induces herding, yet it aligns with the commodity-market evidence presented by [3,4], who identify anti-herding as the prevailing regime in commodity and metal futures outside of acute crises. It also concurs with [5], who demonstrate that equity-to-commodity herding spillover is weak and regime-dependent. Furthermore, it extends the analysis of [6], whose comparison of the COVID-19 and Russia–Ukraine episodes suggests that geographically

localized, prolonged conflicts diminish the informational conditions conducive to herding. The Iran–Israel conflict, being both localized and chronic, results in the dispersion regime anticipated by this logic.

The second research question asked whether the detected behavior is symmetric across rising and falling markets or exhibits directional asymmetry. The asymmetric specification (Table 7) shows that the dispersion coefficient is positive and significant in both up-markets ($\gamma_2\text{Up} = 4.101$) and down-markets ($\gamma_2\text{Dn} = 3.728$), and a χ^2 Wald test of $H_0: \gamma_2\text{Up} = \gamma_2\text{Dn}$ cannot be rejected ($p > 0.10$). Dispersion is therefore directionally symmetric. This rules out the interpretation that the positive γ_2 is an artifact of a one-sided safe-haven flight in which gold rises while energy falls only on down-market days. The result complements the asymmetry evidence of [9,11], who document up/down-market and sectoral asymmetries in energy-focused herding, by showing that at the cross-asset level spanning energy, precious metals, and shipping, the dispersion regime is instead bidirectional and invariant to market direction, consistent with the directionally invariant diversification role of gold relative to energy reported by [12,20].

The third research question investigates the temporal evolution of dispersion intensity during conflict and its relationship with short-run realized variance. The rolling-window estimation, detailed in Appendix A Table A3, regresses the 240-day rolling γ_2 against the 30-day moving-average variance, yielding a negative and precisely estimated slope ($\theta = -506.6$, $p < 0.01$) with an intercept of 5.390. This indicates that dispersion intensity is most pronounced on days of moderate volatility and diminishes as short-run variance increases, suggesting partial temporary co-movement during the most intense escalation episodes before structural differentiation reasserts itself. This temporal profile aligns with the pattern observed in [4], which identifies anti-herding behavior in the pre-crisis period that dissipates at the height of the global financial crisis, and is consistent with the surge-and-subside volatility-spillover dynamics documented by [17] during the Ukraine war. We interpret this as a concise diagnostic rather than a formal regime-switching test; a Markov-switching specification is proposed in Section 8 as the logical subsequent step. Collectively, the findings indicate that the Iran–Israel conflict is characterized by a dispersion regime that is robust across specifications, symmetric across market directions, and varies over time in accordance with the prevailing volatility environment.

6.2. Why Dispersion Rather than Herding?

The standard herding prediction applies to acute informational shocks: when news arrives without warning and investors cannot differentiate signal from noise, they rationally imitate the crowd. This is consistent with [6], which observes that the COVID-19 pandemic (an acute, globally symmetric shock) triggered stronger herding through financial channels than the more geographically localized Russia–Ukraine conflict, precisely because the latter allowed investors to develop differentiated assessments of exposure over time. Over the 475-day estimation window, the Iran–Israel conflict was likewise sustained and localized. The observed positive γ_2 is consistent with (though not direct proof of) investors having accumulated differentiated knowledge of which commodities were exposed and through which channels. Crude oil faces Hormuz-route and Aden corridor supply risk. Henry Hub natural gas is primarily North American and weather-driven. Gold responds to central-bank reserve diversification and geopolitical flight-to-quality flows. BDI tracks vessel re-routing capacity that has developed progressively. These distinct structural exposures are consistent with systematic divergence rather than convergence on large market-move days, providing a theoretically plausible (if not directly verified) explanation for the positive γ_2 we document consistently.

6.3. Interpreting the Positive γ_2 : Three Consistent Channels

We read the positive γ_2 as consistent with at least three non-mutually exclusive channels rather than committing to a single behavioral mechanism, none of which is directly observable from return data alone.

The first channel is cross-commodity rotation: heterogeneously informed investors may rebalance within the commodity complex toward gold and away from oil-linked exposures. This interpretation is consistent with the asset-level disaggregation results (Table 5), which reveal that gold's individual γ_2 is significantly smaller than those of the energy assets. However, confirming this channel would require fund-flow or position-level data to establish that the observed return divergence reflects deliberate reallocation rather than passive differential exposure. We therefore treat this as a theoretically motivated interpretation that is consistent with, but not proven by, the available evidence.

The second channel is speculative trading on heterogeneous information: traders with different prior beliefs about Hormuz-route disruption probabilities, LNG re-routing capacity, and Red Sea shipping risk may take opposite positions across commodities, producing wider cross-sectional deviations on news days. This interpretation is consistent with the symmetric dispersion documented across both up- and down-market states (Table 7), which rules out a unidirectional sentiment effect. However, the same pattern could arise from differential liquidity effects or varying margin requirements across commodity classes, alternatives that cannot be excluded from return data alone.

The third channel is amplified investor disagreement and, at the extreme, irrational speculation in the sense of [8]. The negative relationship between rolling γ_2 and short-run realized variance (Appendix A Table A3) is consistent with disagreement being highest during moderate-volatility periods, when differentiated signals are most actionable, and attenuating during acute stress episodes. However, at least two alternative explanations cannot be ruled out: (i) liquidity-driven co-movement, whereby acute volatility triggers margin calls and forced liquidations that mechanically co-move all commodity prices regardless of fundamentals; and (ii) risk-factor crowding, whereby common risk-factor exposures dominate idiosyncratic signals during stress episodes. Distinguishing between these competing explanations would require high-frequency position data or options-implied disagreement measures that are not available for our sample period.

We do not attempt to discriminate between these three channels in the present paper. The CSAD framework is informative about whether dispersion or herding dominates but is silent about whether the dispersion is driven by rational rotation, speculative differentiation, or irrational over-reaction. Distinguishing these channels is left for future work equipped with richer micro-level data.

6.4. Addressing the Mechanical Interpretation Concern

Rather than relying on narrative justification, we address the mechanical interpretation concern with two main empirical tests, the results of which are reported in the relevant tables.

First, CSAD is a benchmark-relative measure: each asset's deviation is computed against the equal-weighted market return, so a common scale change in all five series would leave CSAD unchanged. The CCK test conditions on $R^2_{m,t}$ (a second-moment object), meaning that a pure-trend mechanical effect would not generate a positive γ_2 . This is an analytical property of the estimator, not a post hoc defense.

Second, the Wald test result that $\gamma_{2Up} \approx \gamma_{2Dn}$ (Table 7, $p > 0.10$) provides direct empirical evidence against a mechanical interpretation: any sample-construction effect that mechanically produced dispersion would have to generate precisely symmetric coefficients across up- and down-market subsamples, which is an implausible coincidence.

6.5. Asset-Level Findings: Natural Gas and Gold

The outsized natural-gas dispersion coefficient is consistent with its structural independence from the oil-geopolitics complex. Henry Hub gas prices are determined by North American supply and demand factors, such as storage fluctuations, LNG-terminal capacity, and weather-related demand, which are generally independent of daily developments concerning the Hormuz route and the Red Sea. On occasions when crude oil prices experience significant fluctuations due to news of supply disruptions in the Middle East, gas prices are influenced by distinct factors, resulting in substantial absolute deviations from the oil-dominated market returns. The high standard deviation of gas returns (14.94% per day) and kurtosis (52.02) reflect the amplified effect of these idiosyncratic shocks on a thin physical spot market. This pattern is consistent with [14], who provides evidence consistent with the idea that geopolitical uncertainties affect commodity markets primarily through volatility, with responses varying markedly by sector. Gas's large γ_2 is therefore consistent with geopolitical independence rather than geopolitical sensitivity: it diverges from the market precisely because it responds to a structurally different set of fundamentals.

Gold's relatively smaller coefficient is consistent with its documented safe-haven role operating through a lower-amplitude, higher-persistence channel than gas. Ref. [19] finds that gold serves as a stable asset with safe-haven properties against geopolitical risk. Ref. [20] establishes that gold acts as a safe haven with a negative correlation to equities during crises. Ref. [18] identify gold as a net receiver of shocks during the Russia-Ukraine conflict. Consistent with this literature, gold's contribution to CSAD appears to operate through a persistent structural spread captured partly by the CSAD intercept rather than through episodic large-amplitude deviations, which is the channel through which gas contributes disproportionately to γ_2 .

6.6. Asymmetric and Time-Varying Dynamics

The failure to reject symmetry in the Wald test is consistent with commodity diversification benefits being directionally invariant across the conflict period. On down days, gold appreciates while oil falls, directly widening CSAD. On up days, oil rises on supply-disruption optimism while gas may respond to entirely different fundamentals, still producing elevated CSAD from heterogeneous cross-asset responses. This pattern is consistent with [12], who show that agricultural commodities can act as hedges against oil return downturns regardless of directional conditions. We note, however, that this finding pertains to the cross-asset level spanning gold, crude oil, natural gas, and shipping, and may not generalize to energy-specific contexts where [11] documents asymmetric herding patterns.

The rolling estimation result (dispersion intensity negatively related to short-run realized variance, Appendix A Table A3) is consistent with two coexisting regimes within the sustained-conflict period: a dominant structural dispersion regime on moderate-volatility days, and partial temporary co-movement on the most extreme-volatility days. The intercept of 5.390 gives the rolling γ_2 when variance is near zero; the slope of -506.6 indicates progressive attenuation as short-run variance rises. This pattern is consistent with [4], who find no herding or anti-herding during the peak of the global financial crisis.

7. Implications and Limitations

The following implications are derived directly from the empirical findings of this study. We emphasize at the outset that this study does not directly evaluate portfolio performance, optimize asset allocation strategies, or measure risk-adjusted returns under alternative diversification scenarios. The implications below are therefore presented as empirically consistent observations rather than investment recommendations, and should

be interpreted with the caution appropriate to inferences drawn from a reduced-form return-dispersion framework applied to five assets over a single conflict episode.

First, the consistently positive γ_2 documented across all specifications is consistent with the cross-asset correlation structure during the Iran–Israel conflict differing meaningfully from pre-conflict baselines. This is consistent with [17], who provides evidence consistent with that the volatility-spillover environment during the Ukraine conflict far exceeded pre-conflict baselines, implying that models relying on historical correlation structures may systematically mischaracterize the risk environment during sustained geopolitical stress. The actual cross-asset correlation between gold and energy in our sample is negative, a pattern consistent with [19], whose co-movement evidence during the Russia–Ukraine conflict is consistent with gold’s structural role as a portfolio stabilizer. We note, however, that we do not formally test whether pre-conflict VaR models are miscalibrated, nor do we estimate the magnitude of any such miscalibration; this would require explicit comparison of pre- and post-conflict correlation matrices and portfolio-level risk metrics that are beyond the scope of the present study.

Second, the outsized natural gas dispersion coefficient is consistent with Henry Hub gas returns being driven by structurally different fundamentals (weather, LNG-terminal capacity, North American storage dynamics) than crude oil during the conflict period. This is consistent with [16], who show that commodities with higher exposure to conflict-affected supply chains experienced greater volatility risk, a mechanism that applies to crude oil but not to Henry Hub gas. The empirical finding, therefore, suggests that gas and crude oil exposures are not duplicative within this conflict context. We caution, however, that this observation is specific to the Henry Hub spot price during the 2024–2026 period and may not generalize to other gas benchmarks, other time periods, or other geopolitical settings. We do not formally test portfolio variance reduction from combining gas and crude, and no claim is made about the optimality of any specific allocation.

Third, the failure to reject symmetry in the Wald test is consistent with the cross-sectional dispersion between gold and energy assets being present in both rising and falling market conditions during the conflict period. This is consistent with [20], who establish that gold’s negative correlation with risk assets persists across crisis and non-crisis phases. The empirical finding therefore suggests that gold–energy divergence is not confined to bear-market episodes within this sample. We note, however, that this finding pertains specifically to the cross-asset level within our five-commodity sample during the Iran–Israel conflict and may not generalize to broader commodity portfolios or different conflict settings. We do not formally compare the performance of gold-hedged versus unhedged commodity portfolios, and no directional recommendation is made.

Fourth, the negative relationship between rolling γ_2 and short-run realized variance (Appendix A Table A3) is consistent with dispersion intensity attenuating during acute stress episodes. This pattern suggests that the 30-day moving average of squared daily market returns (VARt) may serve as a monitoring indicator of dispersion intensity during sustained conflict periods: when VARt is elevated, the data are consistent with temporarily reduced cross-asset divergence; when VARt subsides, the structural dispersion regime appears to reassert. This is consistent with the conditional dynamics documented by [9] during high-volatility periods. We emphasize, however, that this implication is derived from a parsimonious diagnostic regression (Equation (6)) rather than a formally specified dynamic allocation model. We do not evaluate the risk-adjusted performance of any dynamic strategy based on VARt, and the practical value of this signal would need to be assessed through explicit back-testing that is beyond the scope of the present study.

Limitations and Directions for Future Research

The present study is subject to several important limitations that qualify the interpretation and generalizability of its findings. We identify five principal constraints.

The analysis is restricted to five commodity assets (Brent crude, WTI crude, Henry Hub natural gas, spot gold, and the Baltic Dry Index) over 475 daily observations spanning a single geopolitical conflict episode. This limited asset coverage raises two concerns. First, the five assets are structurally heterogeneous, spanning energy, precious metals, and shipping, which may mechanically inflate cross-sectional dispersion relative to a more homogeneous commodity sample. Although we address this concern through the Wald symmetry test and benchmarking against prior literature, a formal pre-conflict estimation window would provide cleaner identification. Second, the five-asset sample is insufficient to draw conclusions about broader commodity market dynamics: agricultural commodities, industrial metals, and other energy benchmarks (all of which may respond differently to geopolitical stress) are entirely absent from the analysis. Future research should extend the asset coverage to a broader commodity universe to assess the generalizability of the documented dispersion regime.

The dataset covers only the conflict period (January 2024–April 2026) and does not include a formal pre-conflict estimation window. This absence makes it impossible to formally attribute the observed positive γ_2 to the Iran–Israel conflict rather than to the structural characteristics of the selected asset portfolio. We address this limitation through two indirect strategies (external benchmarking against prior literature [3,4] and the internal time-variation in our rolling estimates), but acknowledge that neither fully substitutes for a direct pre-conflict baseline. Future research should incorporate an explicit pre-conflict benchmark period, ideally covering at least 12 months prior to the conflict escalation date, to enable formal difference-in-differences identification of conflict-driven behavioral regimes.

The CSAD framework is a reduced-form empirical tool that identifies correlations between cross-sectional return dispersion and market return moments. It does not establish causal relationships between the Iran–Israel conflict and investor behavior, nor does it identify the specific behavioral or economic mechanisms responsible for the documented dispersion. The three channels discussed in Section 6.3 (cross-commodity rotation, heterogeneous information processing, and investor disagreement) are theoretically motivated interpretations that are consistent with the data but are not directly identified by the CSAD estimator. Establishing causal identification would require either an instrumental variables approach, using exogenous conflict escalation events as instruments for geopolitical risk, or a natural experiment design comparing the conflict-period commodity sample against a contemporaneous control group of commodities with no exposure to the Iran–Israel shock. Both approaches are left for future work.

The study examines a single geopolitical conflict episode (the Iran–Israel conflict of 2024–2026), which limits the external validity of the findings. The documented dispersion regime may be specific to the structural characteristics of this particular conflict: its chronic duration, its geographic localization, Iran’s role as a major oil producer, and the strategic importance of the Strait of Hormuz. Whether the same dispersion regime would emerge in other prolonged geopolitical conflicts with different structural characteristics (involving non-energy-producing parties, different commodity supply chains, or different investor bases) cannot be determined from a single-episode study. Future research should examine herding and dispersion dynamics across multiple prolonged conflict episodes to assess whether the chronic-conflict dispersion regime constitutes a general empirical regularity or a context-specific finding.

The practical implications are derived from the empirical dispersion findings and are presented as empirically consistent observations rather than formally tested portfolio

strategies. The study does not evaluate portfolio performance (in terms of Sharpe ratios, maximum drawdown, or risk-adjusted returns) under alternative diversification scenarios, nor does it formally compare the performance of conflict-period versus pre-conflict allocation strategies. The claim that gold–energy diversification benefits are directionally invariant and that VArT may serve as a monitoring signal are inferences from the CSAD framework that would need to be validated through explicit portfolio back-testing before they could be operationalized as investment strategies. This constitutes an important avenue for future research.

8. Conclusions

This paper provides a comprehensive empirical and economic account of investor behavior across five commodity markets during the sustained Iran–Israel conflict of 2024–2026. Eight regression specifications (baseline CCK, GARCH-augmented, volatility-regime stratified, quantile, asset-specific, geopolitical risk, asymmetric market-state, and time-varying rolling) yield a consistent finding. Particularly, the squared market return consistently exhibits a positive and precise influence, indicating persistent cross-commodity dispersion rather than herding behavior. This dispersion is symmetric on both upward and downward market days, prevalent across the CSAD distribution, evident in both volatility regimes, and inversely related to short-term realized variance in time-varying estimation. Moreover, asset disaggregation identifies natural gas as the primary driver through its structural independence from oil-geopolitics fundamentals, and gold as the safe-haven anchor whose persistent appreciation generates the directional cross-commodity divergence.

We interpret these findings as consistent with three non-mutually exclusive channels. First, cross-commodity rotation toward differentiated safe-haven and supply-channel exposures (operating within the commodity complex rather than into it). Second, speculative trading on heterogeneous Strait of Hormuz-route and LNG-routing information, and amplified investor disagreement during sustained geopolitical uncertainty. Third, within our sample window, the daily fluctuations of the geopolitical-risk index do not alter the established pattern at the daily margin. This indicates that, once within the sustained-conflict regime, commodity markets have developed stable relative pricing hierarchies that remain unaffected by whether the geopolitical-risk index reading on any given day is high or moderate.

These findings carry direct implications for commodity portfolio construction, risk management, and academic literature on herding. For practitioners, sustained-conflict commodity environments feature structural diversification benefits (particularly through gold–energy negative correlation) that conventional panic-herding models miss and that are available symmetrically across both rising and falling markets. For researchers, the positive γ_2 documented here challenges the assumption that geopolitical stress uniformly generates commodity herding, and calls for a richer theoretical framework that distinguishes rapidly developing herding from sustained-conflict dispersion as distinct regimes with different drivers, durations, and asset-class implications. Future researchers have two extensions that are particularly promising. First, a Markov-switching specification that endogenously identifies dispersion regimes from the data. Second, a multi-conflict comparative design that places the present chronic-conflict sample alongside contemporaneous calm-period samples, sharpening the identification of which features of the dispersion regime are conflict-specific and which are general features of commodity markets.

Author Contributions: Conceptualization, I.N.K. and J.J.J.; methodology, I.N.K. and J.J.J.; software, I.N.K. and M.K.; validation, J.J.J., R.A. and M.K.; formal analysis, I.N.K. and J.J.J.; investigation, I.N.K., R.A. and M.K.; resources, J.J.J. and M.K.; data curation, M.K. and R.A.; writing—original draft preparation, I.N.K. and R.A.; writing—review and editing, I.N.K., J.J.J., R.A. and M.K.; visualization,

R.A. and M.K.; supervision, I.N.K. and J.J.J.; project administration, I.N.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The daily price data (Brent crude, WTI crude, Henry Hub natural gas, spot gold, and the Baltic Dry Index) analyzed in this study were obtained from publicly available sources. The data were processed and handled by the authors to construct the analytical sample used in this study, and are therefore available from the authors upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Herding Estimates by Volatility Regime.

Variable	Low Volatility		High Volatility	
	Coefficient	SE	Coefficient	SE
Rm	0.3801 ***	0.1212	1.1273 ***	0.1202
R ² m	8.0494 ***	0.7901	1.5211 ***	0.4478
Constant	0.0132 ***	0.0011	0.0068 ***	0.0016
Observations	255		220	
R ²	0.7692		0.9396	

Notes: High (low) volatility = days on which GARCH σ_t is above (at or below) its 75th percentile. HC1 robust standard errors. The asterisks *** represent statistical significance at 1%.

Table A2. Quantile Regression Estimates of Return–Dispersion Relationship.

Variable	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$
Rm	0.4387 *** (0.0478)	0.6303 *** (0.0420)	0.8166 *** (0.0549)	1.1046 *** (0.0727)	1.1367 *** (0.1334)
R ² m	3.7784 *** (0.2008)	3.1388 *** (0.1765)	2.9044 *** (0.2307)	1.8118 *** (0.3058)	2.6354 *** (0.5608)
Constant	0.0024 *** (0.0008)	0.0047 *** (0.0007)	0.0086 *** (0.0009)	0.0132 *** (0.0013)	0.0229 *** (0.0023)
Observations	475	475	475	475	475

Notes: Quantile regression at the stated quantiles of CSAD. Bootstrap standard errors (1000 replications) in parentheses. The asterisks *** represent statistical significance at 1%.

Table A3. Time-Varying Dispersion: Rolling γ_2 Estimation.

Variable	Coefficient	Std. Error (SE)
30-day MA variance	−506.5697 ***	56.7928
Constant	5.3895 ***	0.1191
Observations	236	
R ²	0.1013	

Notes: Dependent variable = 240-trading-day rolling γ_2 estimate from Equation (1). VART = 30-day moving average of R²m. OLS with HC1 robust standard errors. N = 236 rolling-window observations. The asterisks *** represent statistical significance at 1%.

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