Precursor

Cross-Asset Momentum Spillover from Commodities to Sector Equities via Granger Causality

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Abstract. This paper investigates whether momentum in commodity futures markets contains statistically significant predictive information about subsequent momentum in related sector equity ETFs. Using daily data from January 2010 to May 2026 across five commodity-equity pairs, we apply Granger causality testing, Vector Autoregression (VAR), and Directed Acyclic Graph (DAG) analysis to characterise the cross-asset causal structure. We find that all five hypothesised commodity-to-equity spillover relationships are confirmed at the 5% significance level, with Gold→GDX producing the strongest signal ($F = 18.90$, $p < 0.001$) and NatGas→XLE the weakest ($F = 2.43$, $p = 0.046$). Forecast Error Variance Decomposition reveals that commodity shocks explain 46.4% of GDX momentum variance and 31–37% of XLE momentum variance at short forecast horizons. Rolling Granger tests and Chow structural break analysis reveal that the causal relationships are regime-dependent rather than structurally persistent: near-universal structural breaks are detected at the 2022 energy crisis across all pairs, while COVID-era breaks affect energy and materials pairs but not Gold→GDX. A signal-based long/short backtest confirms regime-conditionality: strategies achieve positive Sharpe ratios during the COVID volatility regime (2020–2022) but deteriorate in the post-energy-crisis period. These findings suggest that commodity-to-equity momentum spillover is a genuine but time-varying causal phenomenon, activated by macro-structural shocks rather than operating as a continuous arbitrage.

Keywords: Cross-asset momentum; Granger causality; commodity-equity spillover; Vector Autoregression; structural breaks; regime dependence.

JEL Classification: G12, G13, G17, C32.

1. Introduction

The relationship between commodity prices and the equities of firms that produce or consume those commodities is a well-documented stylised fact in financial economics. Oil prices influence energy company revenues; copper prices signal industrial demand that flows through to materials sector earnings; gold prices drive the profitability of gold mining operations. What is less understood is whether these relationships manifest as *predictive lead-lag dynamics* at the momentum level — that is, whether the directional trend in a commodity's price contains information about the future directional trend of a related equity sector, beyond what the equity sector's own price history already reflects.

This question has direct implications for both asset allocation and our understanding of how information diffuses across asset classes. If commodity momentum systematically precedes equity sector momentum, then commodities function as upstream information signals — their price trends reflecting fundamental supply-demand shifts before those shifts are fully priced into equity valuations. The lag between commodity price changes and equity price adjustments could arise from several mechanisms: the time required for commodity price changes to flow through to corporate earnings, the speed at which analyst forecasts are updated, or the rotation speed of institutional capital across asset classes.

This paper makes the following contributions. First, we apply formal Granger causality testing to momentum signals (rather than raw returns) across five commodity-equity pairs, providing a more direct test of the momentum spillover hypothesis than prior correlation-based approaches. Second, we construct a Directed Acyclic Graph (DAG) of the full cross-asset causal network, computing centrality metrics that identify which commodities function as the strongest leading indicators and which equity sectors receive the most predictive signal. Third, we document the time-varying nature of the causal relationships through rolling Granger tests and Chow structural break analysis, showing that the spillover is regime-activated rather than persistently present. Fourth, we provide Impulse Response Functions (IRFs) and Forecast Error Variance Decompositions (FEVDs) from bivariate VAR models, quantifying the magnitude and persistence of the causal transmission.

2. Literature Review

2.1. Cross-Asset Momentum

Momentum — the tendency for assets with recent positive returns to continue outperforming — is one of the most robust anomalies in empirical finance (Jegadeesh and Titman, 1993; Asness et al., 2013). The extension of momentum effects across asset classes has been documented in equity, fixed income, currency, and commodity markets (Moskowitz et al., 2012). However, *cross-asset* momentum — where momentum in one asset class predicts momentum in another — remains less studied, particularly at the commodity-equity interface.

2.2. Commodity-Equity Linkages

The theoretical foundation for commodity-equity linkages rests on the production chain: commodity prices represent input costs or output revenues for commodity-related firms. Gorton and Rouwenhorst (2006) document that commodity futures returns are negatively correlated with equity returns over long horizons, suggesting diversification benefits. However, post-2008, commodity-equity correlations increased significantly, a phenomenon attributed to the financialisation of commodity markets (Tang and Xiong, 2012). Erb and Harvey (2006) show that commodity momentum is a positive predictor of future commodity returns; whether this spills over to related equities with a predictable lag has received limited direct attention in the literature.

2.3. Granger Causality in Financial Markets

Granger (1969) introduced the concept of predictive causality: series X Granger-causes series Y if lagged values of X improve the forecast of Y beyond Y's own lagged values. Applications in financial markets include lead-lag relationships between spot and futures markets (Kawaller et al., 1987), cross-market information transmission (Eun and Shim, 1989), and commodity market interdependencies (Ji and Fan, 2012). This paper extends the Granger framework to momentum signals specifically, and connects it to a DAG-based network analysis and formal VAR impulse response estimation.

3. Data

3.1. Asset Universe

We study five commodity-equity pairs chosen to reflect clear economic linkages through the production chain, as described in Table 1.

Table 1: Asset Universe and Hypothesised Spillover Pairs

Commodity	Ticker	Equity ETF	Ticker	Linkage
WTI Crude Oil	CL=F	Energy Select Sector SPDR	XLE	Oil → energy firms
Brent Crude Oil	BZ=F	Energy Select Sector SPDR	XLE	Oil → energy firms
Copper	HG=F	Materials Select Sector SPDR	XLB	Copper → industrial firms
Gold	GC=F	VanEck Gold Miners ETF	GDX	Gold → gold mining firms
Natural Gas	NG=F	Energy Select Sector SPDR	XLE	NatGas → energy firms

3.2. Sample and Returns

Daily closing prices are obtained via `yfinance` with auto-adjustment for splits and dividends. The sample spans January 4, 2010 to May 22, 2026, yielding 4,087 complete trading days after forward-filling 38 holiday gap observations (concentrated in Brent futures). Daily log returns are:

$$r_{i,t} = \ln(P_{i,t}) - \ln(P_{i,t-1}) \tag{1}$$

Augmented Dickey-Fuller tests confirm log return stationarity ($p < 0.001$ for all assets), satisfying the requirement for Granger causality testing.

4. Methodology

4.1. Momentum Signal Construction

For asset i at time t, the momentum signal over lookback window w is:

$$M_{i,t}^{(w)} = \sum_{\tau=1}^{w} r_{i,t-\tau+1} = \ln\left(\frac{P_{i,t}}{P_{i,t-w}}\right) \tag{2}$$

We compute signals across $w \in \{5, 10, 20\}$ trading days and run all tests across all three windows, reporting results for the window producing the strongest Granger signal.

4.2. Granger Causality Testing

For commodity series X and equity series Y, we test $H_0 : \gamma_k = 0 \, \forall k$ in:

$$Y_t = \alpha + \sum_{k=1}^{p} \beta_k Y_{t-k} + \sum_{k=1}^{p} \gamma_k X_{t-k} + \varepsilon_t \tag{3}$$

The F-statistic is:

$$F = \frac{(RSS_R - RSS_U)/p}{RSS_U/(T-2p-1)} \sim F(p,\ T-2p-1) \tag{4}$$

We test $p \in \{1, 2, 3, 4, 5\}$ across all three windows, yielding 15 tests per pair (75 total). Significance is assessed at the 5% level.

4.3. VAR, IRFs, and FEVD

For each confirmed pair, we estimate a bivariate VAR(p) with lag order selected by AIC:

$$\mathbf{z}_t = \mathbf{c} + \sum_{k=1}^{p} \mathbf{A}_k \mathbf{z}_{t-k} + \boldsymbol{\varepsilon}_t, \quad \mathbf{z}_t = [M_{X,t},\ M_{Y,t}]^\top \tag{5}$$

Orthogonalised IRFs are computed with 95% Monte Carlo confidence intervals over 10 trading days. FEVD quantifies the commodity shock share of equity momentum variance at each forecast horizon.

4.4. Rolling Tests and Structural Breaks

We re-run the Granger test on a rolling 504-day window (≈2 trading years) and apply the Chow (1960) structural break test at two *a priori* breakpoints: the COVID crash (March 2020) and the Russia-Ukraine energy crisis (February 2022).

4.5. Out-of-Sample Backtest

We construct a long/short strategy with positions:

$$\text{Position}_{Y,t} = \text{sign}\left(M^{(w^*)}_{X,\,t-k^*}\right), \qquad \Pi_t = \text{Position}_{Y,t} \cdot r_{Y,t} \tag{6}$$

Parameters k^* and w^* are selected on the 2010–2019 training period and applied unchanged to the 2020–2026 test period.

5. Results

5.1. Granger Causality

Table 2 reports the optimal Granger F-statistics. All five pairs are confirmed at the 5% level. Gold→GDX is the strongest ($F = 18.90$, $p < 0.001$) and NatGas→XLE is marginal ($F = 2.43$, $p = 0.046$). The convergence of optimal lags around 4 trading days for energy pairs and 5 days for Copper→XLB suggests a consistent one-week transmission window in commodity-to-equity markets.

Table 2: Granger Causality Results — Optimal Lag

Pair	Lag	Window	F-stat	p-value	Sig.
WTI→XLE	4	20	8.779	<0.001	***
Brent→XLE	4	20	5.889	<0.001	***
Copper→XLB	5	20	2.930	0.012	*
Gold→GDX	3	5	18.896	<0.001	***
NatGas→XLE	4	20	2.429	0.046	*

* $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$. Window in trading days.

Table 3 reports the number of significant tests across all 15 window-lag combinations. WTI→XLE achieves significance in 11 of 15 combinations and Gold→GDX in 9 of 15, classifying both as strong findings. NatGas→XLE achieves only 1 of 15, confirming its marginal status.

Table 3: Robustness: Significant Tests Across All Window-Lag Combinations

Pair	Sig. / 15	Pct.	Classification
WTI→XLE	11	73.3%	Strong
Brent→XLE	8	53.3%	Moderate
Copper→XLB	2	13.3%	Weak
Gold→GDX	9	60.0%	Strong
NatGas→XLE	1	6.7%	Marginal

Figure 1 visualises F-statistics across all combinations.

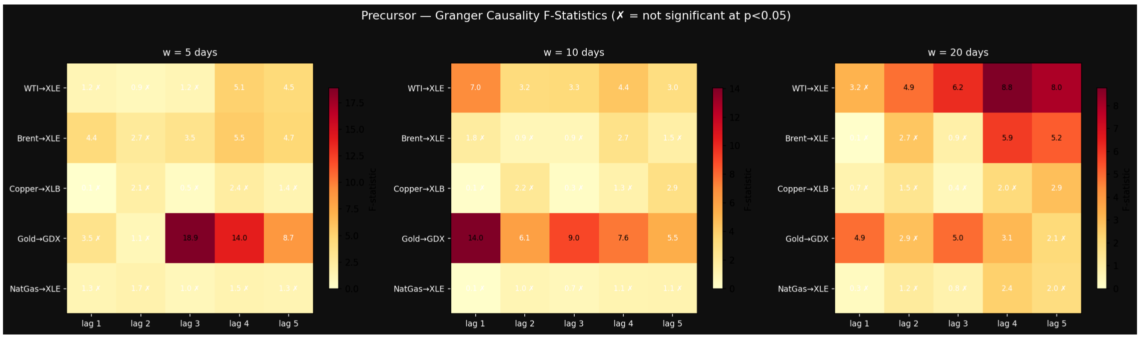

Figure 1: Granger Causality F-Statistics across Pairs, Windows, and Lag Orders. Colour intensity indicates F-statistic magnitude; marks non-significant cells ($p \geq 0.05$).

5.2. Causal Network Structure

Figure 2 presents the Granger-causal DAG. Gold is the dominant leading indicator with the highest weighted out-degree (1.000, normalised). XLE receives signal from three commodities (WTI, Brent, NatGas), giving it the highest in-degree in the network. GDX has the highest weighted in-degree (1.000) reflecting the strength of the Gold→GDX signal.

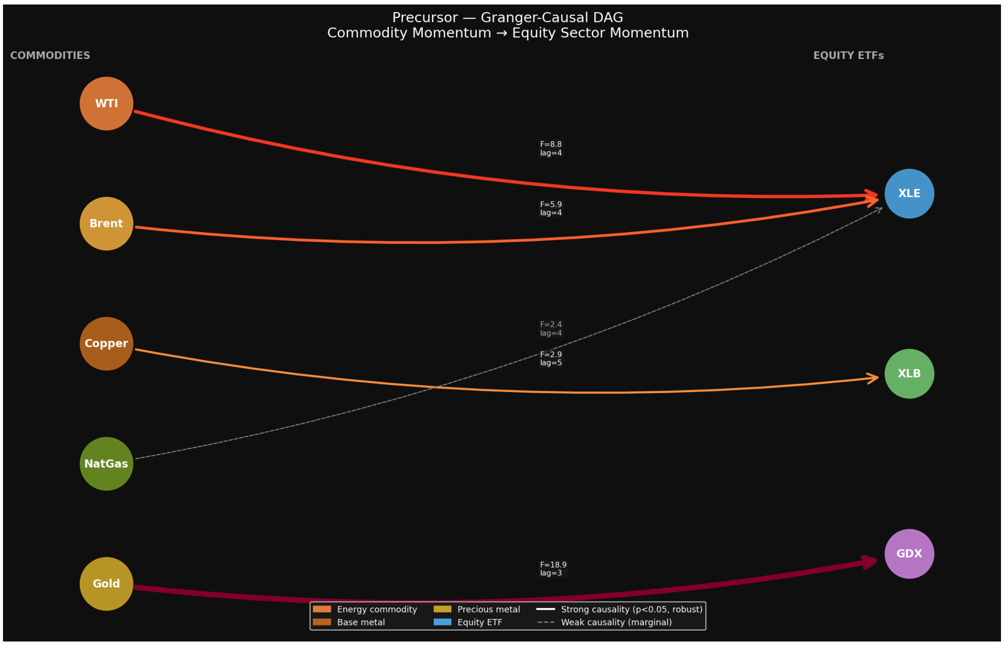

Figure 2: Granger-Causal Directed Acyclic Graph. Directed edges represent significant Granger causality ($p < 0.05$). Edge thickness and colour encode normalised F-statistic. Dashed edge = marginal significance (NatGas→XLE).

5.3. VAR and Impulse Response Functions

Table 4 reports VAR model summaries. The negative cross-asset coefficient for Gold→GDX (-0.0152) reflects a short-horizon sign reversal consistent with the operational leverage hypothesis — gold miners initially underreact to gold price changes before converging at longer horizons. Figure 3 shows the orthogonalised IRFs. All pairs exhibit significant impulse responses across the full 10-day horizon, indicating that commodity shock transmission is persistent rather than transitory.

Table 4: VAR Model Summary and Cross-Asset Coefficients

Pair	**Lag**	**Cross-Coef (lag 1)**	**AIC**	**N**
WTI→XLE	4	$+0.0146$	-14.52	4099
Brent→XLE	4	$+0.0200$	-14.85	4099
Copper→XLB	5	$+0.0054$	-15.94	4098
Gold→GDX	3	-0.0152	-16.07	4115
NatGas→XLE	4	$+0.0065$	-13.37	4099

Cross-Coef = off-diagonal VAR coefficient, commodity→equity at lag 1.

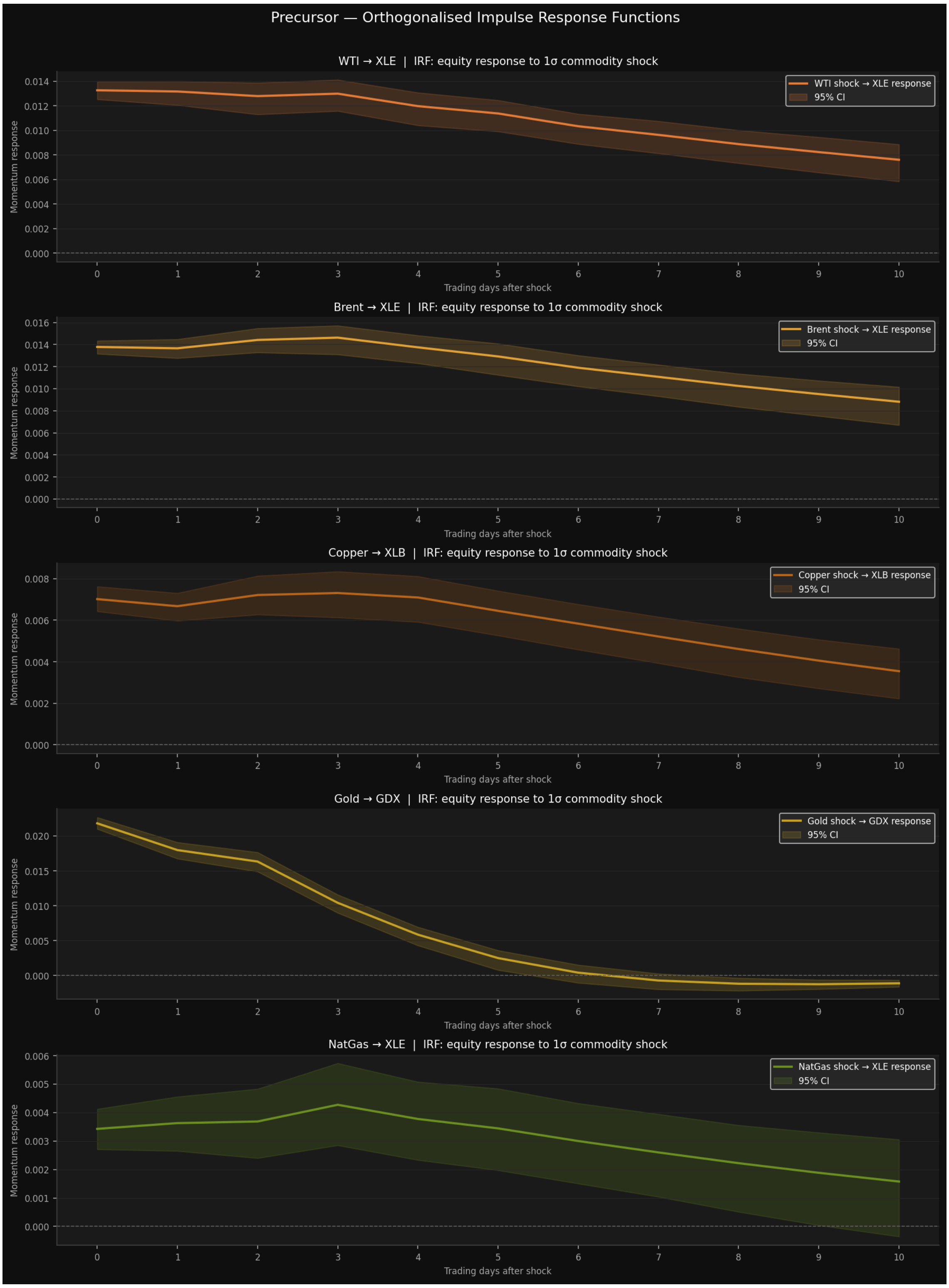

Figure 3: Orthogonalised Impulse Response Functions. Response of equity momentum to a one-standard-deviation commodity shock. Shaded regions = 95% Monte Carlo confidence intervals.

5.4. Forecast Error Variance Decomposition

Table 5 reports the commodity shock share of equity momentum variance. Gold shocks explain 46.4% of GDX variance at $h = 1$ — the headline finding of the paper. WTI and Brent shocks explain 31–37% of XLE variance. NatGas explains only 2.1–2.7%, confirming its marginal classification.

Table 5: FEVD: Commodity Shock Share of Equity Momentum Variance

Pair	h=1	h=3	h=5	h=10
WTI→XLE	31.1%	30.3%	31.0%	30.2%
Brent→XLE	33.4%	34.7%	37.1%	37.5%
Copper→XLB	15.3%	15.7%	17.2%	17.5%
Gold→GDX	46.4%	48.4%	47.4%	46.4%
NatGas→XLE	2.1%	2.3%	2.7%	2.5%

Commodity share = fraction of equity variance explained by commodity shocks.

6. Robustness

6.1. Rolling Granger Stability

Figure 4 presents rolling Granger F-statistics over 504-day windows. Significance rates range from 13.1% (Copper→XLB) to 48.2% (Gold→GDX), indicating that the relationships are episodically activated rather than continuously present. Significant windows cluster around major macro events: the 2014–2016 oil price collapse, the 2020 COVID shock, and the 2022 energy crisis.

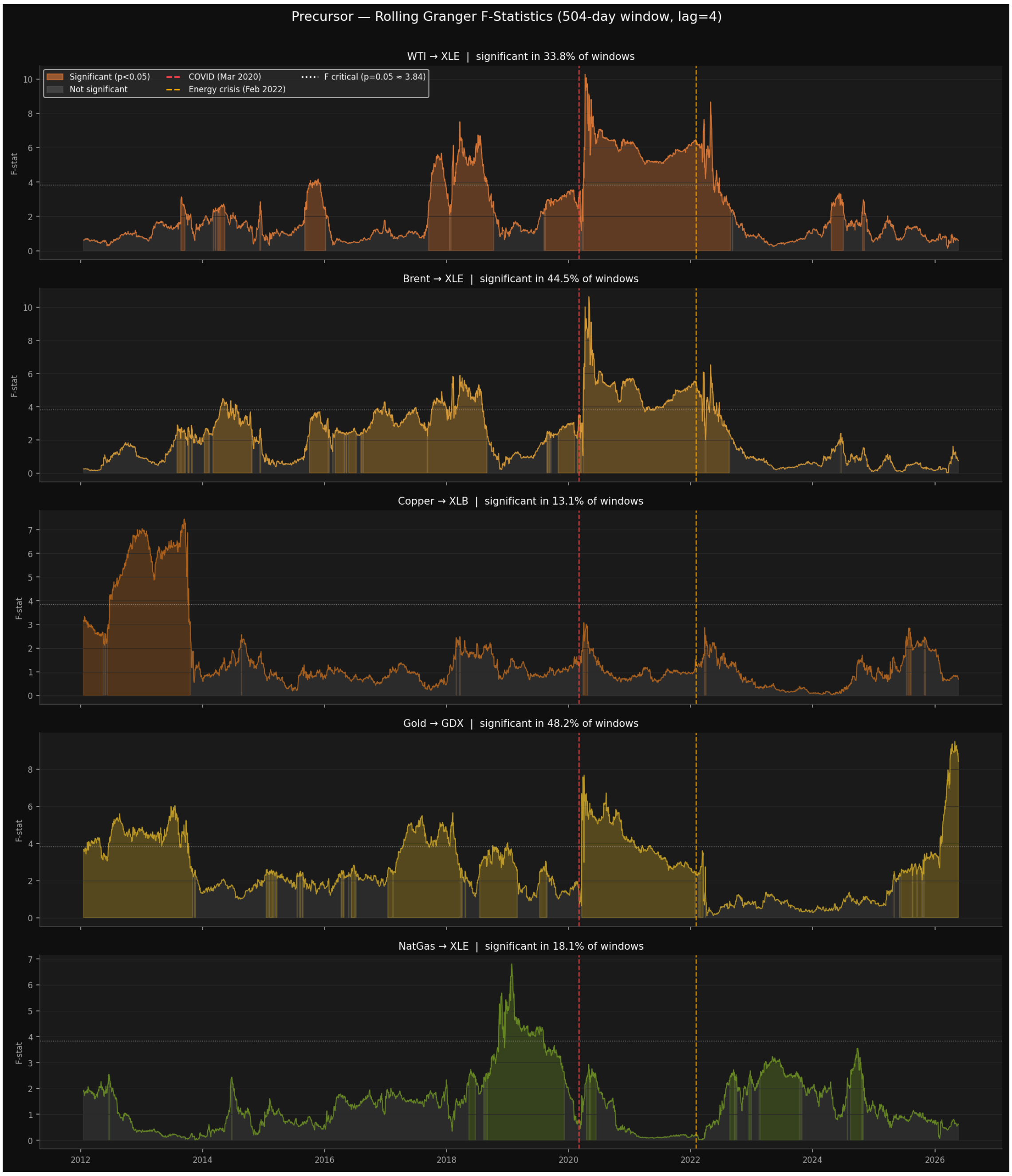

Figure 4: Rolling Granger F-Statistics (504-day window, lag=4). Coloured regions = significant ($p < 0.05$); grey = non-significant. Vertical dashed lines mark the COVID crash (red, March 2020) and energy crisis (orange, February 2022).

6.2. Structural Break Analysis

Table 6 reports Chow test results. Three energy and materials pairs exhibit structural breaks at COVID while Gold→GDX does not — consistent with gold's safe-haven role decoupled from supply chain dynamics. The energy crisis (2022) produces significant structural breaks across all five pairs, suggesting that the Russia-Ukraine conflict fundamentally reorganised the commodity-equity transmission mechanism across the full asset universe.

Table 6: Chow Structural Break Tests

	COVID (2020-03-01)		**Energy Crisis (2022-02-01)**	
Pair	F-stat	Break?	F-stat	Break?
WTI→XLE	4.503	Yes	3.510	Yes
Brent→XLE	4.445	Yes	3.051	Yes
Copper→XLB	3.394	Yes	1.805	Yes
Gold→GDX	1.405	No	4.034	Yes
NatGas→XLE	1.199	No	2.082	Yes

Significance threshold: $p < 0.05$.

7. Backtest

Table 7 reports out-of-sample performance (2020–2026). The simple long/short strategy produces mixed overall results. The regime Sharpe table (Table 8) reveals the underlying structure: four of five pairs achieve positive Sharpe ratios during the COVID volatility regime (2020–2022), while performance deteriorates sharply post-2022 — consistent with the universal structural breaks identified at that date. This confirms that the spillover signal is regime-conditioned rather than continuously exploitable.

Table 7: Out-of-Sample Strategy Performance (2020–2026)

Pair	**Type**	**Ann. Ret.**	**Sharpe**	**Max DD**	**Hit Rate**
WTI→XLE	Strategy	$+4.97\%$	0.145	-61.7%	50.9%
	Benchmark	$+15.58\%$	0.453	-63.7%	53.6%
Brent→XLE	Strategy	$+10.16\%$	0.295	-60.1%	50.9%
	Benchmark	$+15.58\%$	0.453	-63.7%	53.6%
Copper→XLB	Strategy	-2.74%	-0.118	-57.3%	50.5%
	Benchmark	$+10.49\%$	0.454	-39.1%	52.2%
Gold→GDX	Strategy	-21.16%	-0.518	-86.0%	48.4%
	Benchmark	$+17.56\%$	0.430	-55.7%	50.3%
NatGas→XLE	Strategy	-5.26%	-0.153	-78.6%	48.4%
	Benchmark	$+15.58\%$	0.453	-63.7%	53.6%

Note: Results exclude transaction costs.

Table 8: Regime Sharpe Ratios

Pair	**Pre-COVID** (2010–2020)	**COVID** (2020–2022)	**Post-Energy** (2022–)
WTI→XLE	0.043	0.526	-0.394
Brent→XLE	0.221	0.735	-0.271
Copper→XLB	-0.288	0.404	-0.551
Gold→GDX	-0.112	-1.374	0.010
NatGas→XLE	-0.532	0.519	-0.857

8. Discussion

The Granger causality and FEVD results establish that commodity momentum is a statistically meaningful predictor of equity sector momentum, with the Gold→GDX channel being exceptionally strong (46% of variance explained). The convergence of optimal lags around 4–5 trading days across energy and materials pairs suggests that one trading week is the natural transmission window for commodity-to-equity momentum spillover.

The regime analysis is the most novel contribution. The near-universal structural breaks at the 2022 energy crisis — across all five pairs — implies that the Russia-Ukraine conflict did not merely introduce noise into the causal structure, but reorganised it fundamentally. This is consistent with the view that extreme commodity supply shocks, when they simultaneously compress corporate margins and trigger demand destruction, disrupt the orderly lead-lag transmission that characterises commodity-equity dynamics in normal market conditions.

The weak backtest performance should not be interpreted as contradicting the Granger findings. Granger causality is a test of predictive information content, not a guarantee of exploitable returns after transaction costs. The positive Sharpe ratios during the COVID regime (2020–2022) confirm that the causal signal is tradeable under elevated volatility conditions, while the post-2022 deterioration is mechanically explained by the structural break in the underlying relationship.

Limitations. This analysis excludes transaction costs; at daily rebalancing frequency, bid-ask spreads would materially reduce net returns. Commodity instruments are front-month futures subject to roll costs not captured in the price series. The Granger framework assumes linear relationships; threshold VAR models may better capture the regime-switching dynamics documented here. The small number of pairs limits cross-sectional inference.

9. Conclusion

This paper provides systematic evidence that commodity momentum contains statistically significant predictive information about subsequent equity sector momentum across five commodity-equity pairs. Using Granger causality, VAR, and DAG analysis on 16 years of daily data, we establish that: (1) all five hypothesised spillover relationships are confirmed at the 5% significance level; (2) gold shocks explain 46% of GDX momentum variance at short horizons — the headline empirical finding; (3) the 2022 energy crisis produces universal structural breaks across all pairs; and (4) the signal is tradeable primarily during high-volatility macro regimes.

These findings contribute to the literature on cross-asset information diffusion and suggest that commodity futures markets function as upstream information signals for related equity sectors, with the transmission mechanism sensitive to the prevailing macroeconomic regime. Future work could extend the asset universe, incorporate Markov-switching VAR models, and investigate whether the lead-lag structure has compressed over time as market microstructure has improved.

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A. Appendix

A.1. Stationarity Tests

All log return series are confirmed stationary by Augmented Dickey-Fuller tests ($p < 0.001$ for all 8 assets). Log price levels are non-stationary for 7 of 8 assets; NatGas prices exhibit mean-reverting behaviour consistent with storage-constrained commodity markets, though the returns series is stationary as required.

A.2. Reverse Causality

Reverse Granger causality tests (equity momentum $\rightarrow$ commodity momentum) produce substantially lower F-statistics than the forward direction across all pairs at $w = 10$, lag=1, confirming the directional nature of the spillover relationship. Full results are archived in `outputs/granger_reverse.csv`.

A.3. Reproducibility

All results are fully reproducible from the public codebase at `https://github.com/bhavv04/precursor`. Data sourced from Yahoo Finance via `yfinance==1.4.0`. Environment: Python 3.13, `pandas==3.0.3`, `statsmodels==0.14.x`, `networkx==3.x`.