Estimating and Analyzing the Transmission of Oil Price Shocks Across the Energy Value Chain Using Volatility Modeling

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Introduction & Motivation

Context:

- Oil price fluctuations are among the most important macroeconomic shocks affecting global energy markets and firm profitability.
- Changes in crude oil prices have ripple effects across different stages of the energy value chain – upstream (exploration & production), midstream (transportation & storage), and downstream (refining, chemicals, manufacturing).
- However, the same oil price change can affect these sectors differently due to variations in cost structures, exposure levels, and contract types.

Introduction & Motivation

Motivation for Study:

- To understand which segments gain or lose from oil price changes.
- To quantify and compare volatility transmission across the value chain.
- To identify structural breaks or asymmetric responses during major events (e.g., COVID-19, OPEC shocks, Ukraine war).

Objective:

Analyze Volatility Over Time: To investigate how the volatility of returns for each individual sector (upstream and midstream) behaves over the sample period (October 2016 to Oct 2025).

Detect Structural Breaks: To use an iterative algorithm (modified ICSS) to detect significant structural breaks in the unconditional variance of each sector's returns and determine if these shifts coincide with major market or economic events.

ModelVolatility Transmission: To use an augmented bivariate Generalized ARCH (GARCH) model to estimate the degree and direction of volatility transmission (spillover) between the upstream and midstream energy sectors, while controlling for any detected structural breaks.

Energy Value Chain Overview

1. **Upstream:**
   - Involves exploration and production of crude oil.
   - Directly benefits from oil price increases as revenues rise.
2. **Midstream:**
   - Focuses on transportation, storage, and pipelines.
   - Moderately affected – revenues are often based on volume rather than price.
3. **Downstream:**
   - Includes refining, petrochemicals, and manufacturing that use oil as an input.
   - Adversely affected by oil price hikes due to increased input costs.

Literature Review

Hillebrand (2005):

- Showed that structural breaks in the unconditional variance of oil prices can distort volatility estimation in GARCH models.
- Introduced methods to account for such breaks.

Sadorsky (1999):

- Found that oil price volatility significantly affects stock returns of oil and energy companies.
- Highlighted that the impact is asymmetric – negative oil shocks have stronger effects.

Inclan & Tiao (1994):

- Developed the IT cumulative sum of squares (CUSUMSQ) test to detect variance shifts in time series.
- Useful for identifying structural breaks in volatility regimes.

Literature Review

Kilian (2009):

- Distinguished between supply-driven and demand-driven oil price shocks.
- Showed that the economic effects depend on the underlying cause of the price movement.

Basher & Sadorsky (2006):

- Applied multivariate GARCH models to analyze oil price volatility spillovers into emerging markets.

Main Paper of Study (Reference Paper):

"Volatility Transmission Between Upstream and Midstream Energy Sectors" (2023) by Ewing, Malik

https://doi.org/10.1016/j.iref.2024.02.074

Research Paper Framework

1. **Model Used:**

1.1 Univariate GARCH model

$$R_t = \mu + \rho R_{t-1} + \varepsilon_t$$

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}$$

- μ: mean (expected return)
- εt: error term or innovation at time t
- εt   N(0,ht): normally distributed with mean 0 and variance ht
- ht: conditional variance (volatility at time t)
- ω: mean variance level or long-term average volatility (must be > 0)
- α: news term, measures the impact of recent shocks (the previous period's squared residual, ε^2t-1
- β: persistence term, measures the influence of past volatility (the previous period's conditional variance, ht-1

Research Paper Framework

Volatility Breaks:

The study challenges the stable volatility assumption of standard GARCH by detecting structural breaks, which is necessary for accurate transmission modeling.

Methodology

- Tool: Modified Iterative Cumulative Sum of Squares (ICSS) Algorithm.
- Purpose: Endogenously detect the timing and number of volatility shifts.

Major Event Coincidence

The upward Upstream volatility shifts align precisely with:

- October 2014: The onset of the massive crude oil price crash (supply glut).
- October 2018: Significant market decline amid global growth and trade war fears.

Research Paper Framework

1.2 Univariate GARCH(1,1) with Structured Volatility Breaks

$$R_t = \mu + \rho R_{t-1} + \varepsilon_t$$

$$h_t = \omega + d_1 D_1 + \ldots + d_n D_n + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}$$

-Detects Structural breaks(sudden jumps in volatiltiy) by ICSS algorithm

-Di(1,2,...n): Indicator functions for the volatility regime change events.

-di(1,2,...n): respective weights of those events -indicates the magnitude of the shock

-

Research Paper Framework

1.2. Bivariate GARCH model

$$H_{t+1} = C'C + B'H_tB + A'\varepsilon_t\varepsilon_t'A$$

where:

- Ht = conditional variance-covariance matrix
- εt= vector of residuals
- A,B,C = parameter matrices

2. Data Used:

- The XOP ETF tracks the S&P Oil & Gas Exploration & Production Select Industry Index (SPSIOP), which is an equal-weighted index of petroleum exploration and production companies.
- Midstream companies: The ENFR ETF tracks the Alerian Midstream Energy Index (AMNA), which is a weighted index of North American energy infrastructure and pipeline companies.

Methodology – Our Implementation

1. **Data Collection:**
   - Sectoral indices for Upstream, Midstream, and Downstream firms (e.g., S&P Energy Subsector indices or firm-level returns).
   - Time Period: [Specify range, e.g., Oct 2016 - Oct 2025]

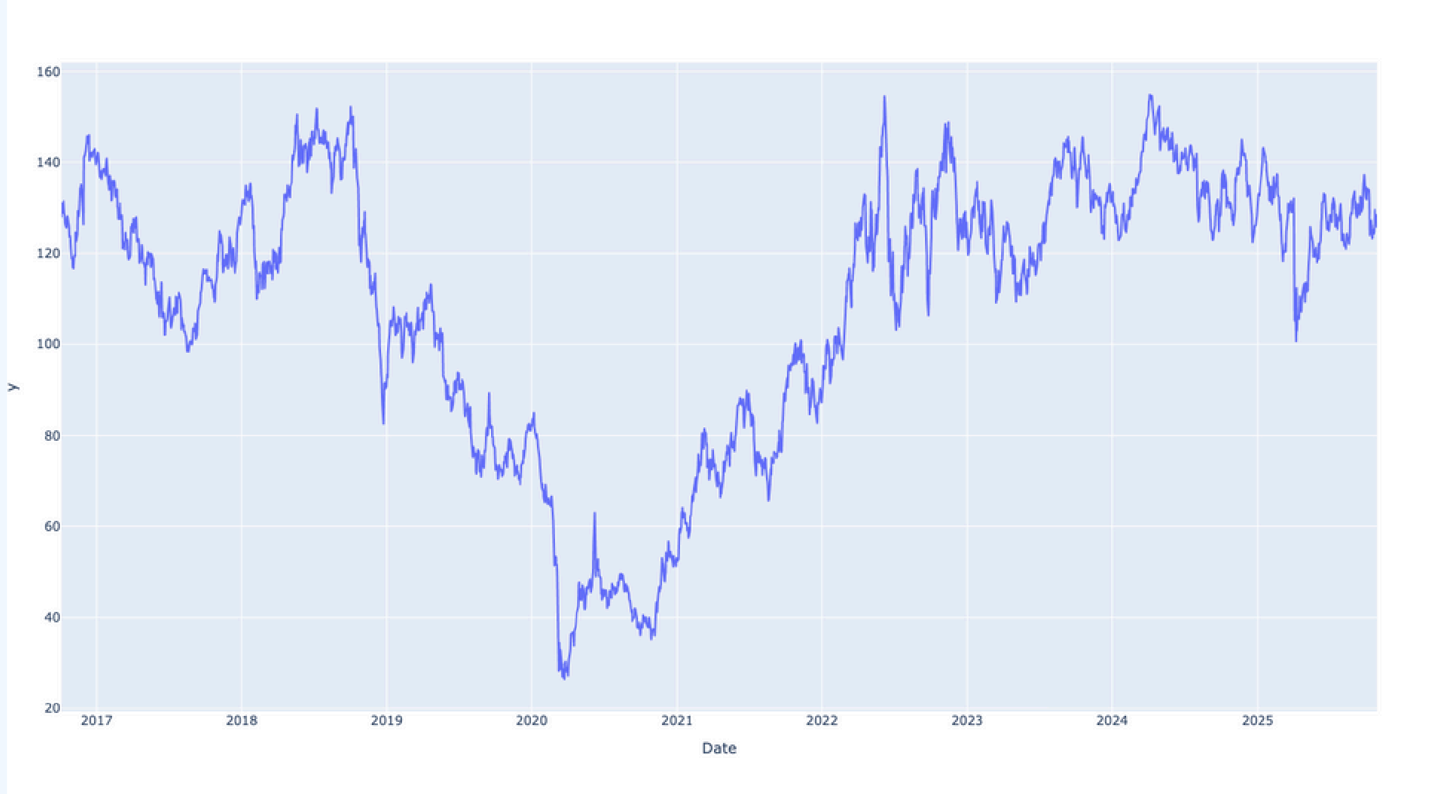
2. **Steps Followed:**
   - Data cleaning and transformation (log returns).
   - Stationarity tests – Augmented Dickey-Fuller (ADF).
   - Structural break detection – Inclan & Tiao (1994) IT test.
   - Volatility equation estimation using GARCH(1,1) and BEKK-GARCH.

Comparison with Reference Paper

Aspect	Reference Paper	Our Findings	Comparison
Model Used	BEKK-GARCH	BEKK-GARCH	✅ Same framework
Sectors	Upstream & Midstream	Upstream & Midstream	Extended scope
Data Period	2013–2021	2016-2025	Updated dataset
Volatility Link	Strong Up→Mid, Weak Mid->up	Strong Up→Mid, Weak Mid->Up	Consistent
Additional Insights	Structural breaks less encountered	Many Structural breaks encountered	Broader analysis

Preliminary Analysis

Upstream index close price



Midstream index close price

Log Returns are Confirmed to be stationary from ADF Test and KPSS test
ARCH LM p-value: 1.0421576484120803e-27

Results and Conclusions

Garch(1,1) model(upstream):

```
                     Constant Mean - GARCH Model Results
==============================================================================
Dep. Variable:                   up_log_ret   R-squared:                       0.000
Mean Model:                   Constant Mean   Adj. R-squared:                  0.000
Vol Model:                            GARCH   Log-Likelihood:               -4968.89
Distribution:      Standardized Student's t   AIC:                           9947.78
Method:                  Maximum Likelihood   BIC:                           9976.43
                                              No. Observations:                 2272
Date:                      Thu, Oct 30 2025   Df Residuals:                     2271
Time:                              16:41:03   Df Model:                            1
                               Mean Model
============================================================================
                 coef    std err          t      P>|t|      95.0% Conf. Int.
----------------------------------------------------------------------------
mu             0.0368  4.045e-02      0.909      0.363 [-4.252e-02,  0.116]
                             Volatility Model
============================================================================
                 coef    std err          t      P>|t|       95.0% Conf. Int.
----------------------------------------------------------------------------
omega          0.0630  3.209e-02      1.963  4.969e-02   [8.524e-05,  0.126]
alpha[1]       0.0534  1.716e-02      3.109  1.880e-03 [1.971e-02,8.699e-02]
beta[1]        0.9354  2.040e-02     45.862      0.000     [  0.895,  0.975]
                              Distribution
========================================================================
                 coef    std err          t      P>|t|  95.0% Conf. Int.
------------------------------------------------------------------------
nu             6.9273      1.172      5.912  3.377e-09 [  4.631,  9.224]
========================================================================
```

The estimated **GARCH(1,1)** model is:

$$r_t = \mu + \varepsilon_t, \quad \varepsilon_t = z_t\sqrt{h_t}, \quad z_t \sim t_\nu(0,1)$$

where the **conditional variance** evolves as:

$$\boxed{h_t = 0.0630 + 0.0534\,\varepsilon_{t-1}^2 + 0.9354\,h_{t-1}}$$

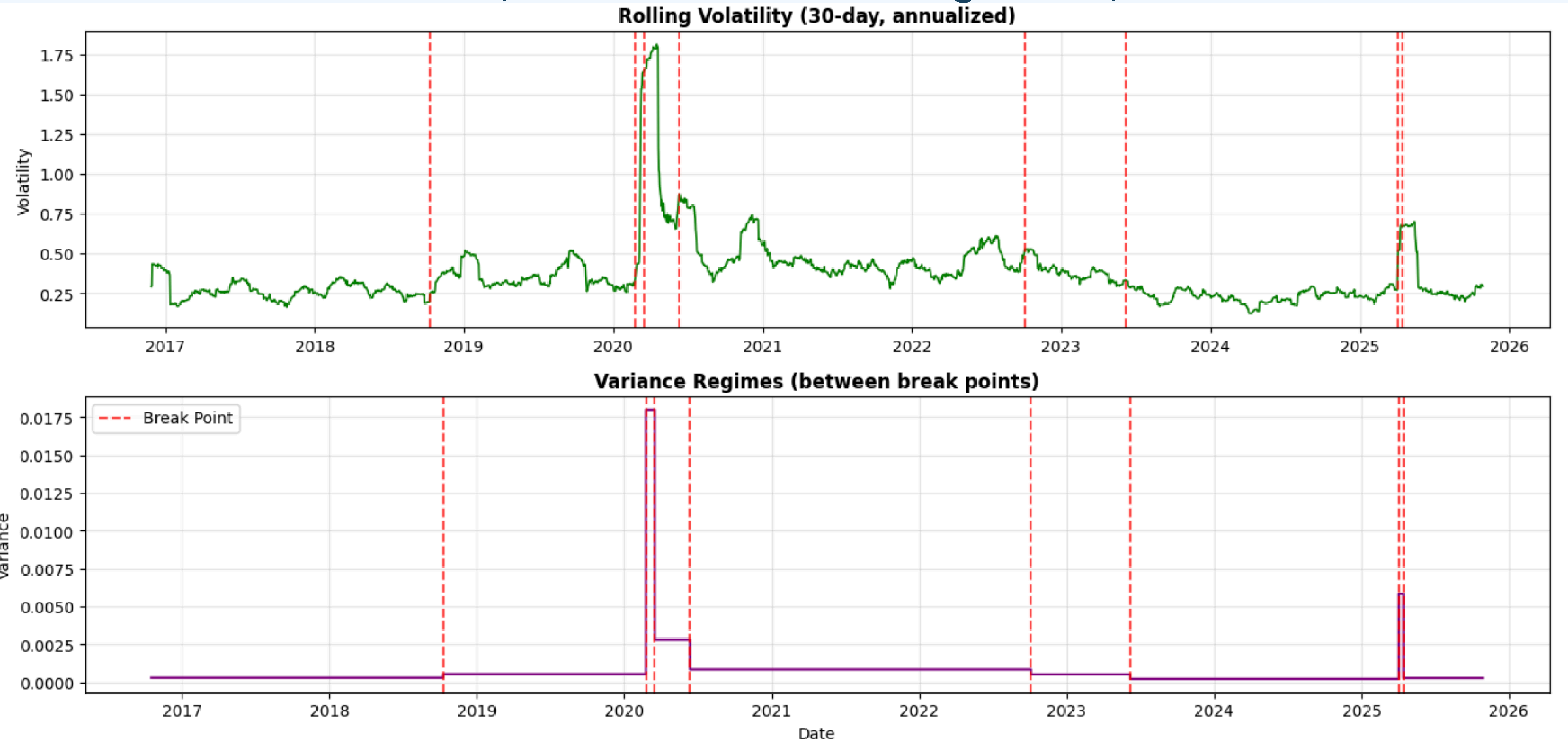
Garch(1,1) model(midstream)

$$r_t = 0.0735 + \varepsilon_t, \quad \varepsilon_t = z_t\sqrt{h_t}, \quad h_t = 0.0418 + 0.109\,\varepsilon_{t-1}^2 + 0.869\,h_{t-1}, \quad z_t \sim t(7.5)$$

```
                           AR - GARCH Model Results                           
==============================================================================
Dep. Variable:                mid_log_ret   R-squared:                  -0.010
Mean Model:                            AR   Adj. R-squared:             -0.013
Vol Model:                          GARCH   Log-Likelihood:           -3584.30
Distribution:      Standardized Student's t   AIC:                     7192.60
Method:                Maximum Likelihood   BIC:                       7261.31
                                            No. Observations:             2265
Date:                    Thu, Oct 30 2025   Df Residuals:                 2257
Time:                            16:52:56   Df Model:                        8
                                  Mean Model                                  
==============================================================================
                     coef    std err          t      P>|t|       95.0% Conf. Int.
------------------------------------------------------------------------------
Const              0.0735  2.218e-02      3.314  9.204e-04    [3.002e-02,  0.117]
mid_...ret[1]      0.0316  2.181e-02      1.447      0.148 [-1.118e-02,7.432e-02]
mid_...ret[2]     -0.0249  2.061e-02     -1.208      0.227 [-6.527e-02,1.550e-02]
mid_...ret[3]     -0.0264  2.215e-02     -1.192      0.233 [-6.983e-02,1.702e-02]
mid_...ret[4] -5.8096e-03  2.164e-02     -0.268      0.788 [-4.823e-02,3.661e-02]
mid_...ret[5]     -0.0177  2.071e-02     -0.856      0.392 [-5.832e-02,2.287e-02]
mid_...ret[6]  1.5152e-03  2.164e-02  7.002e-02      0.944 [-4.089e-02,4.392e-02]
mid_...ret[7]  2.7130e-05  2.180e-02  1.245e-03      0.999 [-4.269e-02,4.275e-02]
                              Volatility Model                              
============================================================================
                 coef    std err          t      P>|t|      95.0% Conf. Int.
----------------------------------------------------------------------------
omega          0.0418  1.220e-02      3.424  6.164e-04 [1.786e-02,6.568e-02]
alpha[1]       0.1090  1.943e-02      5.612  2.004e-08   [7.095e-02,  0.147]
beta[1]        0.8690  2.099e-02     41.397      0.000     [  0.828,  0.910]
                              Distribution                              
========================================================================
                 coef    std err          t      P>|t|  95.0% Conf. Int.
------------------------------------------------------------------------
nu             7.4944      1.219      6.151  7.722e-10 [  5.106,  9.883]
========================================================================

Covariance estimator: robust
```

Garch(1,1) model with structural breaks(upstream)

Detected Breaks(from Modified ICSS algorithm)



0	499	2018-10-10	3.089350
1	842	2020-02-24	8.543802
2	858	2020-03-17	2.692380
3	919	2020-06-12	7.077906
4	1502	2022-10-05	5.755426
5	1671	2023-06-08	3.597724
6	2127	2025-04-03	2.537316
7	2134	2025-04-14	4.371631

Garch(1,1) model with structural breaks(upstream)

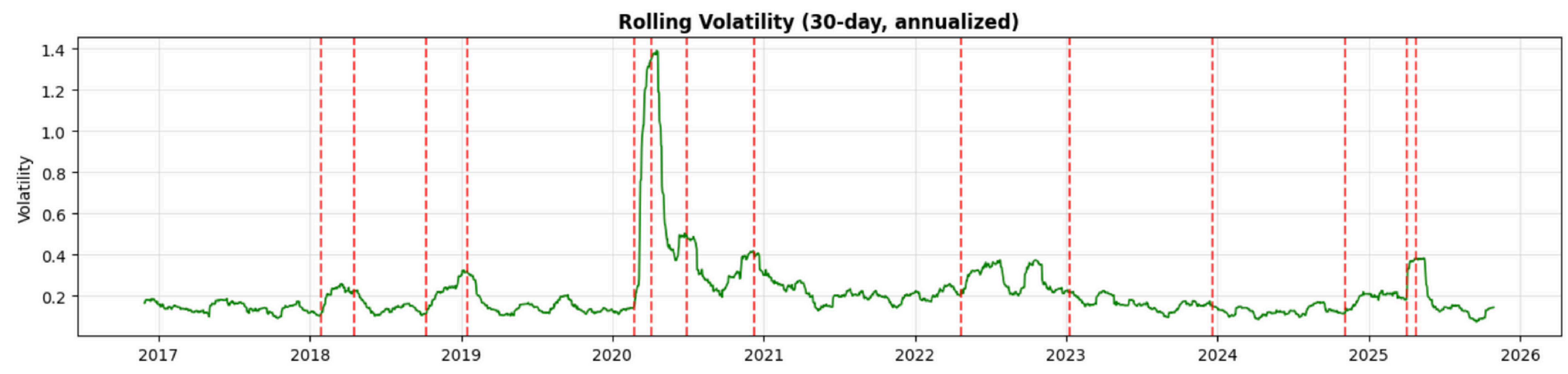
```
Estimating GARCH(1,1) with structural breaks...
Number of regimes: 9
Sample size: 2272

======================================================================
GARCH(1,1) MODEL WITH STRUCTURAL BREAKS – ESTIMATION RESULTS
======================================================================

Log–Likelihood: 5517.2441
Convergence: True

------------------------------------------------------------
GARCH PARAMETERS:
------------------------------------------------------------
Parameter        Estimate        Description
------------------------------------------------------------
mu                     0.000291  Mean return
omega              1.065750e-06  Constant term
alpha                  0.033387  ARCH effect
beta                   0.851172  GARCH effect
alpha+beta             0.884559  Persistence

------------------------------------------------------------
REGIME–SPECIFIC VARIANCE SHIFTS (δ_i):
------------------------------------------------------------
Regime     Period                         Delta (δ)
------------------------------------------------------------
0 (base)   2016–10–17 to 2018–10–10   3.228576e–05
1          2018–10–10 to 2020–02–24   6.104435e–05
2          2020–02–24 to 2020–03–17   2.641172e–03
3          2020–03–17 to 2020–06–12   2.742820e–04
4          2020–06–12 to 2022–10–05   9.445948e–05
5          2022–10–05 to 2023–06–08   5.737633e–05
6          2023–06–08 to 2025–04–03   2.342540e–05
7          2025–04–03 to 2025–04–14   9.616260e–04
8          2025–04–14 to 2025–10–29   2.826640e–05
======================================================================
```

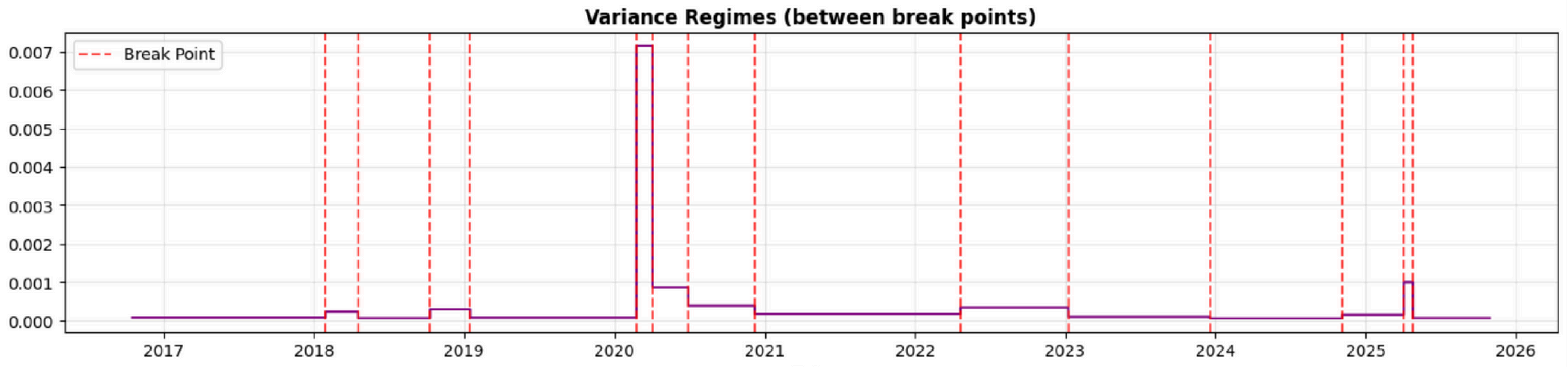
```
Mean equation:
 r_t = 0.000291 + ε_t

Variance equations by regime:
Regime 0:  h_t+1 = 3.33515100e–05 + 0.033387 * ε_t² + 0.851172 * h_t
Regime 1:  h_t+1 = 6.21001000e–05 + 0.033387 * ε_t² + 0.851172 * h_t
Regime 2:  h_t+1 = 2.64223800e–03 + 0.033387 * ε_t² + 0.851172 * h_t
Regime 3:  h_t+1 = 2.75347800e–04 + 0.033387 * ε_t² + 0.851172 * h_t
Regime 4:  h_t+1 = 9.55252300e–05 + 0.033387 * ε_t² + 0.851172 * h_t
Regime 5:  h_t+1 = 5.84420800e–05 + 0.033387 * ε_t² + 0.851172 * h_t
Regime 6:  h_t+1 = 2.44911500e–05 + 0.033387 * ε_t² + 0.851172 * h_t
Regime 7:  h_t+1 = 9.62691800e–04 + 0.033387 * ε_t² + 0.851172 * h_t
Regime 8:  h_t+1 = 2.93321500e–05 + 0.033387 * ε_t² + 0.851172 * h_t
```

Garch(1,1) model with structural breaks(Midstream)

Detected Breaks(from Modified ICSS algorithm)

	index	date	statistic	critical_value
0	322	2018-01-29	1.831282	1.63
1	377	2018-04-18	2.857660	1.63
2	499	2018-10-10	2.337362	1.63
3	565	2019-01-16	2.983560	1.63
4	842	2020-02-24	7.619899	1.63
5	871	2020-04-03	5.507251	1.63
6	930	2020-06-29	1.799501	1.63
7	1043	2020-12-08	12.821936	1.63
8	1388	2022-04-22	2.650515	1.63
9	1567	2023-01-09	4.620648	1.63
10	1805	2023-12-19	1.974780	1.63
11	2026	2024-11-05	3.223965	1.63
12	2127	2025-04-03	2.818083	1.63
13	2142	2025-04-25	3.414974	1.63





Garch(1,1) model with structural breaks(midstream)

```
Estimating GARCH(1,1) with structural breaks...
Number of regimes: 15
Sample size: 2272

======================================================================
GARCH(1,1) MODEL WITH STRUCTURAL BREAKS - ESTIMATION RESULTS
======================================================================

Log-Likelihood: 6856.5367
Convergence: True

------------------------------------------------
GARCH PARAMETERS:
------------------------------------------------
Parameter       Estimate        Description
------------------------------------------------
mu                    0.000570  Mean return
omega             1.000000e-06  Constant term
alpha                 0.079956  ARCH effect
beta                  0.899953  GARCH effect
alpha+beta            0.979910  Persistence

------------------------------------------------
REGIME-SPECIFIC VARIANCE SHIFTS (δ_i):
------------------------------------------------
Regime     Period                          Delta (δ)
------------------------------------------------
0 (base)   2016-10-17 to 2018-01-29   1.767418e-06
1          2018-01-29 to 2018-04-18   7.460303e-06
2          2018-04-18 to 2018-10-10   1.142992e-06
3          2018-10-10 to 2019-01-16   9.504071e-06
4          2019-01-16 to 2020-02-24   1.187751e-06
5          2020-02-24 to 2020-04-03   5.138227e-04
6          2020-04-03 to 2020-06-29   4.534735e-06
7          2020-06-29 to 2020-12-08   1.091884e-05
8          2020-12-08 to 2022-04-22   3.850745e-06
9          2022-04-22 to 2023-01-09   7.065962e-06
10         2023-01-09 to 2023-12-19   2.007273e-06
11         2023-12-19 to 2024-11-05   9.928397e-07
12         2024-11-05 to 2025-04-03   1.289128e-05
13         2025-04-03 to 2025-04-25  -2.610063e-05
14         2025-04-25 to 2025-10-29   6.855496e-07
======================================================================
```

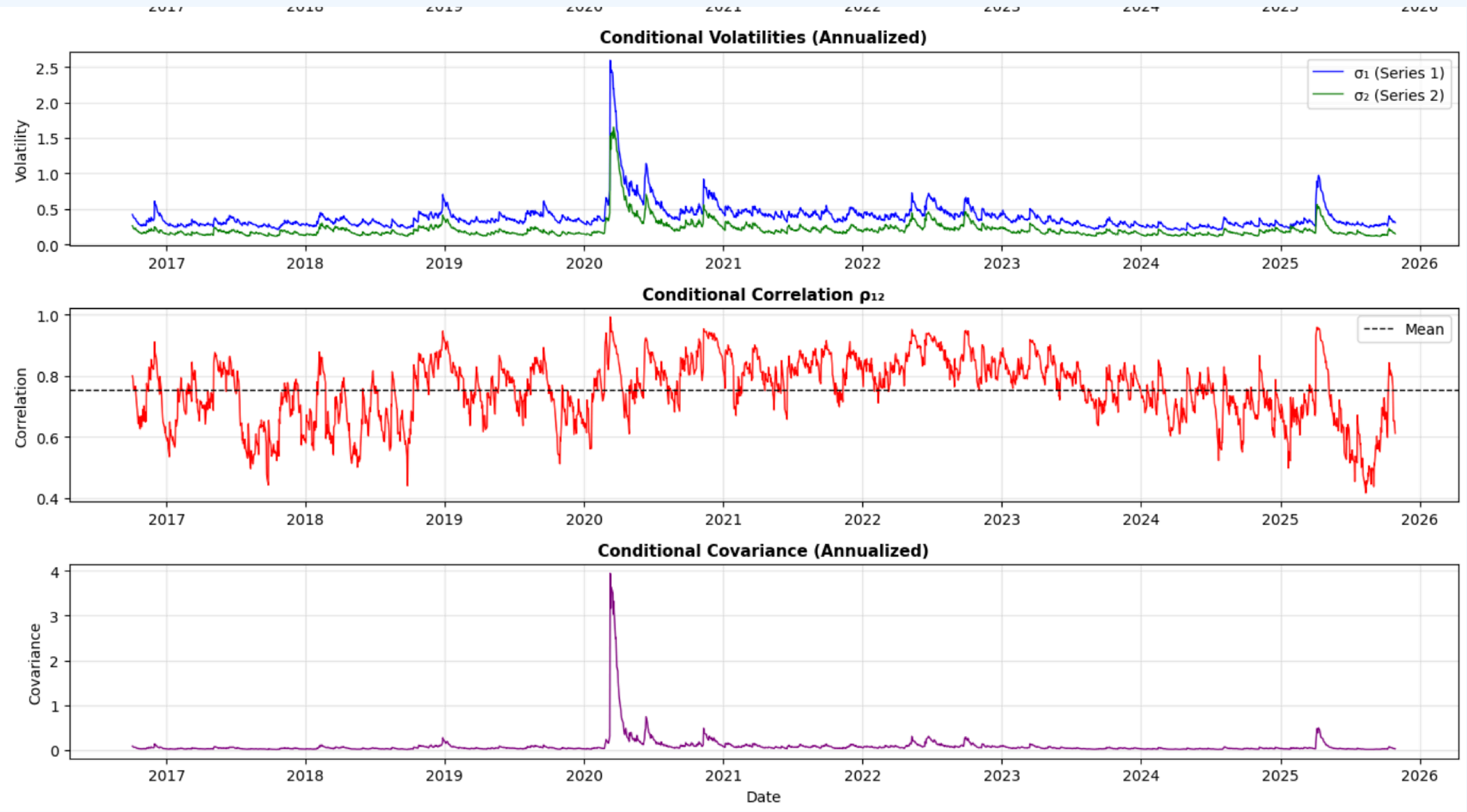
```
Regime 0:  h_t+1 = 2.76741800e-06 + 0.079956 * ε_t² + 0.899953 * h_t
Regime 1:  h_t+1 = 8.46030300e-06 + 0.079956 * ε_t² + 0.899953 * h_t
Regime 2:  h_t+1 = 2.14299200e-06 + 0.079956 * ε_t² + 0.899953 * h_t
Regime 3:  h_t+1 = 1.05040710e-05 + 0.079956 * ε_t² + 0.899953 * h_t
Regime 4:  h_t+1 = 2.18775100e-06 + 0.079956 * ε_t² + 0.899953 * h_t
Regime 5:  h_t+1 = 5.14822700e-04 + 0.079956 * ε_t² + 0.899953 * h_t
Regime 6:  h_t+1 = 5.53473500e-06 + 0.079956 * ε_t² + 0.899953 * h_t
Regime 7:  h_t+1 = 1.19188400e-05 + 0.079956 * ε_t² + 0.899953 * h_t
Regime 8:  h_t+1 = 4.85074500e-06 + 0.079956 * ε_t² + 0.899953 * h_t
Regime 9:  h_t+1 = 8.06596200e-06 + 0.079956 * ε_t² + 0.899953 * h_t
Regime 10:  h_t+1 = 3.00727300e-06 + 0.079956 * ε_t² + 0.899953 * h_t
Regime 11:  h_t+1 = 1.99283970e-06 + 0.079956 * ε_t² + 0.899953 * h_t
Regime 12:  h_t+1 = 1.38912800e-05 + 0.079956 * ε_t² + 0.899953 * h_t
Regime 13:  h_t+1 = -2.51006300e-05 + 0.079956 * ε_t² + 0.899953 * h_t
Regime 14:  h_t+1 = 1.68554960e-06 + 0.079956 * ε_t² + 0.899953 * h_t
```

Bivariate GARCH(1,1) model(BEKK)

```
============================================================
BEKK-GARCH ESTIMATION (FULL)
============================================================
Sample size: 2281
Date range: 2016-10-04 00:00:00 to 2025-10-29 00:00:00
Model type: full

Estimating 13 parameters...
This may take a few minutes...


============================================================
ESTIMATION RESULTS
============================================================
Log-Likelihood: 13304.3011
Convergence: True
Iterations: 414
AIC: -26582.60
BIC: -26508.08

------------------------------------------------------------
PARAMETERS:
------------------------------------------------------------
   mu1 =     0.000413
   mu2 =     0.000653
   c11 =     0.001755
   c21 =     0.002697
   c22 =     0.002160
   a11 =     0.260764
   a12 =     0.039855
   a21 =     0.149314
   a22 =     0.300000
   b11 =     0.963565
   b12 =    -0.006244
   b21 =    -0.055421
   b22 =     0.932076
```

```
------------------------------------------------------------
MATRICES:
------------------------------------------------------------
C matrix:
[[0.00175498 0.        ]
 [0.00269718 0.00216035]]

A matrix (ARCH effects):
[[0.26076395 0.03985477]
 [0.14931412 0.3       ]]

B matrix (GARCH effects):
[[ 0.96356503 -0.00624395]
 [-0.05542129  0.93207558]]


------------------------------------------------------------
VOLATILITY SUMMARY:
------------------------------------------------------------
Series 1 - Mean volatility: 0.024179
Series 1 - Volatility range: [0.012327, 0.163451]
Series 2 - Mean volatility: 0.013375
Series 2 - Volatility range: [0.006891, 0.104011]
Average correlation: 0.7543
Correlation range: [0.4156, 0.9929]
============================================================
```

Bivariate GARCH(1,1) model(BEKK)



Some Comments on Breaks

- 2018 Breaks: Trade tensions (US-China), OPEC production cuts, and oil price volatility impacted both upstream and midstream sectors.
- Early 2020 Breaks: COVID-19 pandemic onset and the historic oil price crash caused sharp disruptions in demand and operations, triggering multiple volatility breaks.
- 2022–2023 Breaks: Geopolitical tensions (notably Russia-Ukraine war), energy supply constraints, and infrastructure regulatory changes increased volatility, especially in midstream assets.
- 2025 Breaks: Evolving energy transition policies, global supply-demand uncertainties, and investment shifts created new volatility regimes affecting upstream and midstream differently.

Conclusions, Results and Findings

“Our Data Showed More Structural Breaks in Mid stream data than Upstream Data”

-

- Between 2016 and 2025, midstream oil and gas companies have exhibited a higher frequency of volatility breaks, reflecting evolving market fundamentals. Key drivers include regulatory changes, ESG-related pressures, infrastructure bottlenecks, and shifts in investor sentiment. Despite these disruptions, midstream volatility—once muted due to fee-based business models—has become noticeably more pronounced.

- Earlier studies covering 2013–2021 indicated that upstream companies (tracked by the XOP ETF) experienced more frequent volatility breaks due to their direct and highly sensitive exposure to fluctuating oil prices. In contrast, midstream firms displayed greater stability, characterized by fewer volatility regimes and more predictable earnings from contracted, fee-based cash flows.

- The paradigm shift reflects broader structural changes in the oil and gas sector, where midstream's risk profile is more dynamic, influenced by policy, capital expenditure trends, and energy transition factors, contrasting with their traditionally lower volatility role during earlier periods

Conclusions, Results and Findings

“Midstream volatility spills more into the upstream data than the opposite-Asymmetric Volatility Transmission”

```
A = [[0.260764, 0.039855],
     [0.149314, 0.300000]]
B = [[ 0.963565, -0.006244],
     [-0.055421,  0.932076]]
C'C (constant) ≈ [[1.0357e-05, 5.827e-06], [5.827e-06, 4.667e-06]]

Equations (symbolic form, with coefficients substituted):

h11_(t+1) = 1.0357e-05 + (0.260764*e1_t + 0.149314*e2_t)**2 + (0.963565**2)*h11_t + 2*(0.963565)*(-0.055421)*h12_t + (-0.055421**2)*h22_t

h22_(t+1) = 4.667e-06 + (0.039855*e1_t + 0.300000*e2_t)**2 + (-0.006244**2)*h11_t + 2*(-0.006244)*(0.932076)*h12_t + (0.932076**2)*h22_t
```

Notice that the Coefficient of $h_{22,t}$ in $h_{11,t+1}$ eqn is much greater than the coefficient of $h_{11,t}$ in $h_{22,t+1}$

This is in consistency with the previous literature.

“The stronger volatility spillover from midstream to upstream sectors can be explained by the critical role midstream plays as the infrastructure backbone for oil and gas production. Disruptions in midstream operations or regulatory changes affect pipeline capacity, storage, and transportation, directly constraining upstream production and increasing upstream firms' risk and uncertainty. Additionally, investors perceive midstream volatility as signaling fundamental supply chain risks, causing amplified repricing upstream. Conversely, upstream volatility driven mainly by commodity price changes tends to have a more isolated impact on midstream firms, whose stable contracts and infrastructure position buffer them from upstream shocks. This creates an asymmetric volatility transmission pattern, with midstream shocks exerting a stronger influence on upstream risk profiles than the reverse.”

Refrences

- Inclan, C., & Tiao, G.C. (1994). "Use of Cumulative Sums of Squares for Retrospective Detection of Changes of Variance." Journal of the American Statistical Association.
- Hillebrand, E. (2005). "Neglecting Parameter Changes in GARCH Models." Journal of Econometrics.
- Basher, S., & Sadorsky, P. (2006). Energy Economics.
- Broadstock, D.C., & Filis, G. (2014). Energy Economics.
- Swaray, R., & Salisu, A. A. (2018). A firm-level analysis of the upstream-downstream dichotomy in the oil-stock nexus. Global Finance Journal
- Engle, R., & Kroner, K. (1995). Multivariate simultaneous generalized ARCH. Econometric Theory
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Thank You