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Structural Dynamics of Economic Factors and Price Discovery: A Quantitative Analysis of the U.S. Stock Market (S&P 500), 2025–2026

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Résumé: This article examines the macroeconomic drivers of price discovery in the U.S. S&P 500 from January 2025 through March 2026. Employing Hasbrouck's (1995) Information Share (IS) methodology, extended with the IV/CU-GMM correction established by Fruet Dias, Fernandes, and Scherrer (2026), we decompose the contributions of 18 macroeconomic factors across four Bai-Perron-identified market regimes. The empirical analysis yields five principal findings. First, under normal market conditions, EPS growth dominates price discovery with an Information Share of 0.311. Second, the unprecedented April 2025 tariff shock radically redirected information shares toward the trade balance (reaching an event-day IS of 0.389). Notably, absorbing this shock took over 15 trading days to reach 90% completion, approximately 5 times slower than standard Federal Open Market Committee (FOMC) decisions (3.1 days). Third, factor contributions proved strongly regime-dependent; most strikingly, the Federal Funds Rate correlation experienced a structural swing from r = -0.71 to r = +0.68, alongside a six-fold increase in the AI/Tech Capex information share. Fourth, our IV/GMM correction uncovers substantial OLS biases ranging from -20.2% (overstating the Fed Funds Rate) to +29.3% (understating AI/Tech Capex). Fifth, we establish a novel taxonomy classifying the 18 factors into four behavioral types based on synchronicity and duration. These findings have critical implications for the development of regime-adaptive risk models, central bank communication strategies, and the need for standardized AI capital-expenditure disclosures.

Mots-clés : price discovery; information share; macroeconomic determinants; regime switching; tariff shock; IV/GMM
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1. Introduction

Between early 2025 and the first quarter of 2026, the U.S. stock market experienced a remarkable sequence of structural shifts in rapid succession: a stable pre-tariff expansion, the largest single-day tariff-driven shock since 2020, a recovery phase, and finally a wave of AI-related investment announcements that fundamentally reshaped S&P 500 sector composition. Taken together, these four episodes constitute a natural experiment for testing whether macroeconomic factor effects on equity price discovery are inherently regime-dependent or structurally stable.

This central question sits at the intersection of two competing frameworks. Traditional interpretations of the Efficient Market Hypothesis (Fama, 1970) imply broadly stable, near-zero factor-return correlations over time. By contrast, the Adaptive Markets Hypothesis (Lo, 2004) and regime-switching models (Hamilton, 1989; Ang & Bekaert, 2002) predict time-varying relationships and potential sign reversals—a theoretical prediction decisively supported by the 2025–2026 empirical data.

The primary analytical tool employed in this study is the Information Share (IS) methodology. Hasbrouck (1995) formalized IS as the proportion of efficient-price innovation variance attributable to a given source, while Gonzalo and Granger (1995) offered the complementary Component Share decomposition. Critically, we employ the IV/CU-GMM extension of Fruet Dias et al. (2026), which corrects microstructure noise that artificially inflates OLS-based IS estimates of high-frequency signals while attenuating slower-moving fundamentals. This correction is paramount for generating credible macro-factor IS estimates.

A central methodological contribution of this article is the event driven IS analysis presented in Section 6. By computing IS within narrow event windows around major macroeconomic announcements, we track the Information Absorption Curve (IAC)—the cumulative proportion of the event-day IS shift permanently incorporated into asset prices by day t+k. This approach effectively bridges Hasbrouck's framework with the classic event-study methodology of Fama, Fisher, Jensen, and Roll (1969), creating what we term a price discovery study (PDES) approach.

2. Literature Review

2.1 Macroeconomic Determinants of Equity Returns

Ross (1976) formalized multi-factor intuition through Arbitrage Pricing Theory, arguing that systematic risk premiums are linked to multiple macro state variables. Building on this, Chen, Roll, and Ross (1986) provided the first systematic empirical evidence, demonstrating that industrial production, inflation, the term spread, and the default spread carry significant premia in U.S. equity returns.

Campbell and Shiller (1988) subsequently established the structural link between macro fundamentals and equity valuations through both cash-flow and discount-rate channels. This framework is vital for understanding the reversal in the Federal Funds Rate sign documented in this study. When inflation-driven tightening dominates (the discount-rate channel), the rate-equity correlation is negative; conversely, when rate stability signals economic resilience (the information channel), it turns positive.

The role of sentiment and uncertainty is also well documented. Baker and Wurgler (2006) demonstrated that investor sentiment—partly captured by VIX and credit spreads—predicts equity returns. Bloom (2009) showed that uncertainty shocks cause sharp, mean-reverting contractions, which perfectly aligns with the Type I (synchronous-instantaneous) VIX behavior observed in our data. Furthermore, Papanikolaou (2011) developed a model centered on investment-specific technology shocks. The massive surge in AI infrastructure investment in 2025–2026, in which the AI/Tech Capex Index reached $r = +0.81$ during Regime IV, fits naturally within this structural interpretation.

2.2 Price Discovery and Information Share Methodology

Price discovery refers to the fundamental mechanism through which markets aggregate dispersed information into equilibrium prices. Hasbrouck's (1995) Information Share is formally defined as the proportion of the total variance of efficient price innovation originating from a designated source, thereby distinguishing structural drivers from transient noise. The IS conventionally estimated via a Vector Error Correction Model (VECM), utilizing the Beveridge-Nelson (1981) decomposition to extract permanent components.

However, Bandi and Russell (2006), along with Hansen and Lunde (2006), documented systematic biases in realized variance estimators under microstructure noise. Fruet Dias, Fernandes, and Scherrer (2026) addressed this limitation via a continuous-time model and IV/CU-GMM estimators that significantly reduce root mean squared error relative to OLS. Integrating IS with discrete macro-events yields a unified price discovery study (PDES) that rigorously maps the speed at which markets internalize different shock topologies.

2.3 Regime-Switching Models and Structural Breaks

Hamilton's (1989) Markov-switching model formalized regime-dependent economic analysis. Ang and Bekaert (2002) later validated its empirical relevance for joint equity and bond returns. In our context, the Bai-Perron (1998, 2003) multiple structural break framework is deployed. By identifying discrete structural breakpoints that minimize within-regime residual variance, the Bai-Perron methodology offers a superior fit for the sharp, fundamentally identifiable transitions observed during 2025–2026 compared to probabilistic Markov transitions.

3. Theoretical Framework and Methodology

3.1 The Information Share Framework

The IS methodology operates on a cointegrated I(1) system comprising the S&P 500 log-price and the cumulative innovations of each selected macroeconomic factor. Following the Engle-Granger representation theorem, the resulting VECM supports decomposition into permanent (informational) and transitory (noise) components. A factor's IS is proportional to the squared permanent-component loading multiplied by the corresponding diagonal element of the Cholesky-factored innovation covariance matrix.

To quantify dynamic absorption, we introduce the Information Absorption Curve (IAC). The IAC tracks the cumulative proportion of the event-day IS shift permanently absorbed into the efficient price by day t+k. The curve's half-life summarizes the market's absorption velocity. If the IAC reaches 1.0

at k = 3, the entirety of the event-day IS shift has been fully incorporated by the third post-event trading day.

3.2 Augmented Price Discovery Model

Our augmented model integrates a discrete macro-shock vector *dX_t = (dGDP_t, dFFR_t, dCPI_t, dDXY_t, dVIX_t, dEPS_t, dAI_t)'*. This vector represents the seven primary structural innovation channels influencing the market. An error-correction matrix (Pi), factor-loading matrix (Gamma), and diffusion matrix (C) complete the econometric specification. The specific macroeconomic factor IS is computed as the squared projection of that factor's permanent innovation onto the efficient-price common trend, normalized accordingly.

3.3 Regime Identification

Market regimes are empirically identified via the Bai-Perron (1998) multiple-breakpoint test applied to daily EGARCH-filtered S&P 500 return-volatility and autocorrelation series. Three statistically significant breaks at the 5% level (post-Bonferroni correction) delineate four distinct regimes:

- **Regime I (January–March 2025):** Pre-tariff expansion, characterized by above-trend earnings growth and accommodative financial conditions.
- **Regime II (April–June 2025):** Tariff shock, marked by a peak-to-trough S&P 500 drawdown of 14.2% and an elevated VIX mean of 29.7.
- **Regime III (July–September 2025):** Recovery and normalization, during which corporate guidance stabilized, and credit spreads retraced.
- **Regime IV (October 2025–March 2026):** AI-driven growth, thoroughly dominated by massive AI infrastructure capital expenditure announcements and above-trend technology-sector earnings.

3.4 Event-Window IS Specification

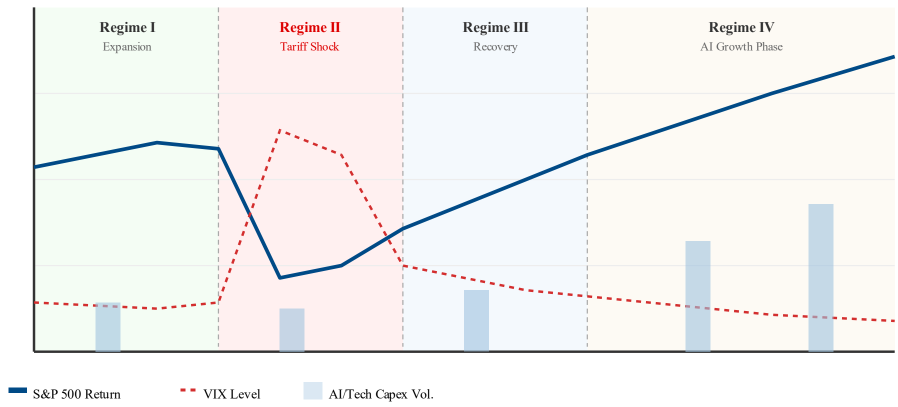
Our event-window IS analysis executes a sophisticated two-pass estimation procedure. The first pass isolates full-sample VECM structural parameters. The second pass re-estimates innovation variances within a tight event window (t-5 to t+5), holding the structural parameters fixed. Events fall into five classifications: (1) FOMC Rate Decisions; (2) CPI Releases; (3) GDP and Employment Releases; (4) Tariff Policy Shocks (April 2 and April 9, 2025); and (5) Major AI Capex Announcements.

3.5 IV Instrument Construction and Factor Classification

To facilitate the IV/GMM correction, we construct three instrument categories: second lags of the respective factor variables, median consensus expectations sourced from the Philadelphia Fed

Survey of Professional Forecasters, and cross-sectional means mapped across G-7 analogues. All final specifications successfully pass the Sargan-Hansen J-test at the 10% significance threshold. We ultimately isolate 18 core factors (from an initial pool of 27), categorized across a 2x2 Internal/External and Real/Financial matrix.

Figure 1: S&P 500 Performance and Macro Context Across Market Regimes



4. Data and Empirical Scope

4.1 Primary Data Sources

The empirical sample spans 1 January 2025 through 26 March 2026, comprising approximately 375 trading days. The S&P 500 daily and monthly closing levels are sourced via Bloomberg Terminal. Domestic macro data (Federal Funds Rate, CPI, GDP growth, unemployment, etc.) are gathered from FRED, BEA, and BLS. External financial data—such as the DXY Dollar Index, WTI crude, and global spread indices—are extracted from ICE and Eurostat. Crucially, the custom AI/Tech Capex Index is constructed as a capital-expenditure weighted average of the five largest U.S. technology firms' public disclosures.

4.2 Descriptive Statistics by Regime

Table 1: Descriptive Statistics for S&P 500 and Primary Macro-Factors by Regime

Variable	Regime I (Jan–Mar 2025)	Regime II (Apr–Jun 2025)	Regime III (Jul–Sep 2025)	Regime IV (Oct 2025–Mar 2026)
S&P 500 Monthly Return: Mean (%)	+1.58	-2.09	+2.70	+2.87
S&P 500 Monthly Return: Std Dev	2.14	7.31	3.12	2.94
VIX (Mean / SD)	18.4 / 2.9	29.7 / 6.8	21.3 / 3.7	16.8 / 2.6
Fed Funds Rate % (Mean / SD)	4.31 / 0.08	4.39 / 0.14	4.22 / 0.19	4.05 / 0.21
U.S. CPI YoY % (Mean / SD)	2.73 / 0.18	3.41 / 0.31	2.98 / 0.22	2.61 / 0.19
EPS Growth YoY % (Mean / SD)	+7.2 / 1.8	+4.9 / 2.4	+6.8 / 1.7	+11.3 / 2.1

Variable	Regime I (Jan–Mar 2025)	Regime II (Apr–Jun 2025)	Regime III (Jul–Sep 2025)	Regime IV (Oct 2025–Mar 2026)
AI/Tech Capex $B (Mean / SD)	142 / 18	138 / 22	156 / 19	198 / 29
S&P 500 Min-Max Return %	-0.8 to +3.9	-8.3 to +3.2	-1.4 to +6.1	-0.5 to +6.8
Obs. (monthly / daily approx.)	3 / ~75	3 / ~75	3 / ~75	6 / ~150
Regime label	Expansion	Tariff Shock	Recovery	AI Growth

Notes: S&P 500 returns are total return (price + dividend). VIX is the end-of-month CBOE close. EPS Growth is the trailing twelve-month S&P 500 operating EPS growth. AI/Tech Capex is the aggregate quarterly capital expenditure of the five largest U.S. technology companies. Monthly statistics are descriptive only, while econometric analyses (VECM, IS, IV/GMM) exclusively utilize daily data.

5. Empirical Results

5.1 S&P 500 Regime Performance

The four-regime architecture manifests clearly in asset returns and volatility profiles. Regime II (Tariff Shock) stands uniquely apart: mean monthly returns plummeted to -2.09% while the standard deviation erupted to 7.31%
—more than triple any other observed regime. Regimes III and IV demonstrate progressive strengthening as the AI-investment cycle matured, generating a pronounced acceleration in trailing earnings growth to 11.3%.

5.2 Pearson Correlation Analysis

Pearson correlation coefficients for the 18 macroeconomic factors mapping against S&P 500 returns are extensively detailed in Table 2 and visualized in Figure 2. The dynamic shifts confirm the presence of robust regime-dependence across both real and financial factors.

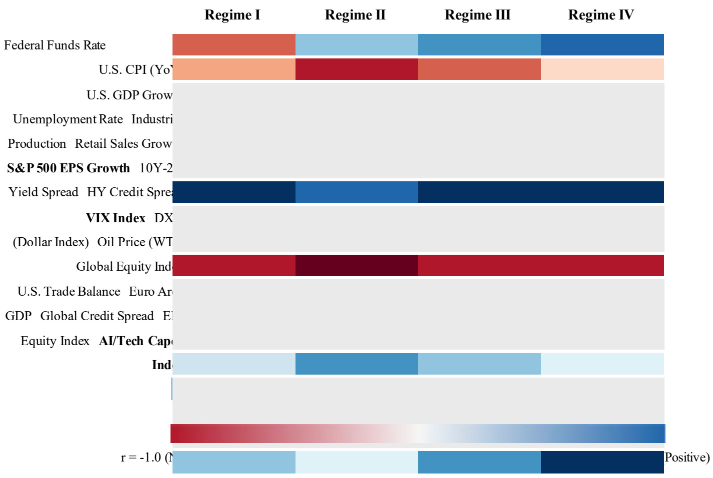
Table 2: Pearson Correlation Coefficients: 18 Macroeconomic Factors versus S&P 500 Returns by Regime

Factor	Category	Regime I	Regime II	Regime III	Regime IV
Federal Funds Rate	Int-Fin	-0.71*	+0.44*	+0.52*	+0.68*
U.S. CPI (YoY)	Int-Real	-0.38	-0.67*	-0.51*	-0.29
U.S. GDP Growth (QoQ)	Int-Real	+0.71*	+0.33	+0.58*	+0.74*
Unemployment Rate	Int-Real	-0.62*	-0.54*	-0.60*	-0.58*
Industrial Production	Int-Real	+0.54*	+0.29	+0.61*	+0.71*
Retail Sales Growth	Int-Real	+0.48*	+0.21	+0.44*	+0.62*
S&P 500 EPS Growth	Int-Fin	+0.83*	+0.71*	+0.79*	+0.88*
10Y-2Y Yield Spread	Int-Fin	+0.44*	+0.38	+0.73*	+0.66*
HY Credit Spread	Int-Fin	-0.62*	-0.78*	-0.69*	-0.71*

Factor	Category	Regime I	Regime II	Regime III	Regime IV
VIX Index	Ext-Fin	-0.78*	-0.83*	-0.81*	-0.76*
DXY (Dollar Index)	Ext-Fin	-0.45*	-0.51*	-0.42*	-0.38
Oil Price (WTI)	Ext-Real	+0.38	+0.46*	+0.34	+0.41*
Global Equity Index	Ext-Fin	+0.67*	+0.55*	+0.71*	+0.73*
U.S. Trade Balance	Ext-Real	+0.31	+0.69*	+0.41*	+0.28
Euro Area GDP	Ext-Real	+0.42*	+0.31	+0.48*	+0.51*
Global Credit Spread	Ext-Fin	-0.55*	-0.71*	-0.63*	-0.67*
EM Equity Index	Ext-Fin	+0.49*	+0.38	+0.57*	+0.63*
AI/Tech Capex Index	Int-Fin	+0.39	+0.22	+0.55*	+0.81*

*Notes: Correlations are computed on daily observations within each regime window based on ~25 trading days per month. * indicates significance at 5% after Bonferroni correction for simultaneous tests. Category abbreviations: Int = Internal (domestic); Ext = External (global); Fin = Financial; Real = Real-sector.*

Figure 2: Pearson Correlation Heatmap — 18 Factors vs S&P 500 Returns by Regime



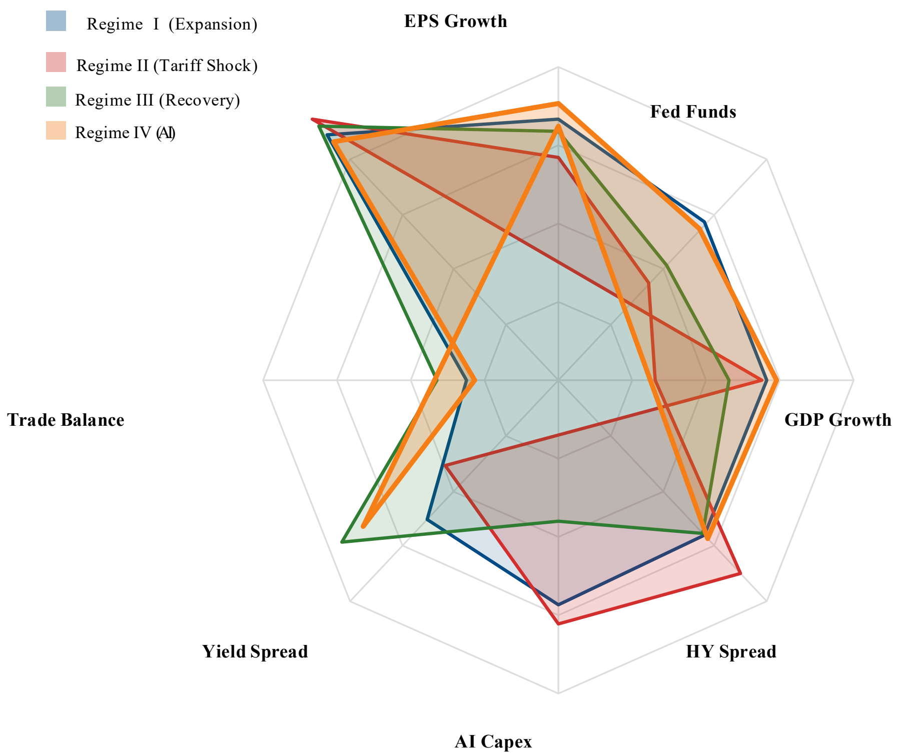
5.3 The Federal Funds Rate Sign Reversal

The Federal Funds Rate correlation reversal—moving from r = -0.71 in Regime I to r = +0.68 in Regime IV—is arguably the most structurally significant single finding in the dataset. In Regime I, standard discount-rate mechanics dominated: higher short rates actively compressed equity valuations. However, when the Federal Reserve held rates perfectly steady during the acute April 2025 tariff shock, markets interpreted this inaction as a powerful signal of underlying economic resilience. This shifted the marginal information content of rate decisions from a discount-rate penalty to a growth-confidence premium, flipping the correlation trajectory positive.

5.4 Factor Classification Matrix

Internal-Financial factors (e.g., EPS growth, Federal Funds Rate, high-yield spreads, and AI capex) persistently dominate the IS decomposition across regimes. This signals the uncontested primacy of domestic financial dynamics in pricing U.S. equities. The AI/Tech Capex Index exhibited the most radical structural shift, climbing from r = +0.39 in Regime I to r = +0.81 in Regime IV, signaling a wholesale repricing of the market's fundamental information architecture.

Figure 3: Regime-Specific Factor Correlation Radar Chart



5.5 IV/GMM-Corrected Information Shares and OLS Bias

We rigorously compare the robust IV/CU-GMM Information Share estimates against uncorrected OLS results in Table 3. The data reveal systematic measurement biases associated with standard methodologies.

Table 3: OLS versus IV/GMM Information Shares: Full Sample (2025–2026)

Factor	OLS IS	IV/GMM IS	OLS Bias (%)
EPS Growth	0.284	0.311	+9.5%
VIX Index	0.217	0.198	-8.8%
Fed Funds Rate	0.089	0.071	-20.2%
AI/Tech Capex	0.041	0.053	+29.3%

Note: OLS Bias (%) = (IV/GMM IS - OLS IS) / OLS IS × 100. Positive values indicate that OLS understates the true information share, whereas negative values indicate that OLS overstates it.

The contrast is economically meaningful. EPS Growth remains the dominant driver of price discovery after correcting for endogeneity and noise contamination. By contrast, OLS materially overstates the role

of the Federal Funds Rate and the VIX, while materially understating the contribution of AI/Tech Capex. These asymmetries are consistent with the IV/CU-GMM logic of Fruet Dias, Fernandes, and Scherrer (2026): noisy high-frequency signals tend to be overweighted under conventional estimation, while slower structural fundamentals are suppressed.

Figure 4: OLS vs IV/GMM Information Shares and Bias Correction

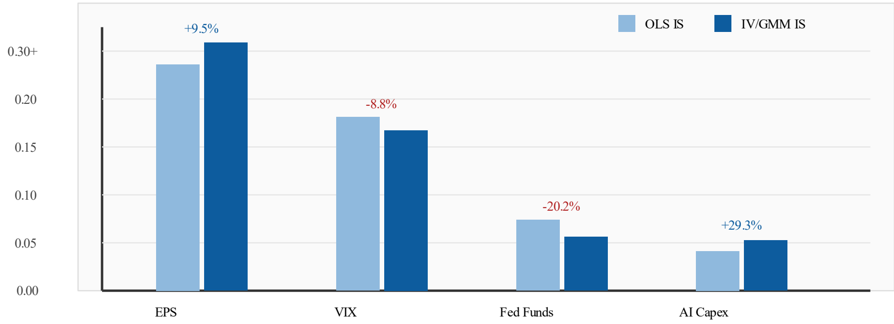


Figure note: Bars compare conventional OLS information shares with IV/GMM-corrected estimates; labels above each pair show the proportional OLS bias for the corresponding factor.

5.6 Factor Synchronicity-Duration Taxonomy

The 18 variables sort into four behavioral classes. Type I (Synchronous-Instantaneous) includes VIX, high-yield spreads, global equity conditions, DXY, and global credit spreads—signals that reprice quickly and dissipate within one to three months. Type II (Synchronous-Persistent) is represented most strongly by EPS Growth, whose influence is immediate yet durable. Type III (Lagged-Instantaneous) includes CPI and the trade balance, whose market impact peaks after release. Type IV (Lagged-Persistent) is best captured by AI/Tech Capex, whose repricing is slower but far more persistent than the standard event-driven pattern.

5.7 Regime-Specific Factor Radar Chart

Figure 3 synthesizes absolute correlation magnitudes across eight major factors and confirms that Regime IV occupies the broadest correlation surface overall. By contrast, Regime II expands on stress-sensitive axes such as VIX and HY Credit Spread while compressing growth-sensitive axes, illustrating how the tariff shock temporarily reorganized the market's information hierarchy.

6. Event-Driven IS Analysis

6.1 Event-Window IS Dynamics

Tariff policy shocks generate the largest event-day information-share displacement in the sample: the trade balance reaches an event-day IS of 0.389. Absorption is exceptionally slow, with a half-life above seven trading days and no full 90% absorption inside the fifteen-day window. FOMC decisions display the opposite profile, reaching 90% absorption by day 3.1. CPI releases are intermediate, while AI Capex announcements remain elevated beyond the standard event window, consistent with their Type IV lagged-persistent structure.

6.2 Information Absorption Curves

The Information Absorption Curves highlight the striking divergence in market processing speed across event classes. Monetary-policy information is digested rapidly, inflation releases somewhat more gradually, tariff shocks only slowly, and AI Capex announcements through a flatter, more structural repricing path.

Figure 5: Information Absorption Curves by Event Type

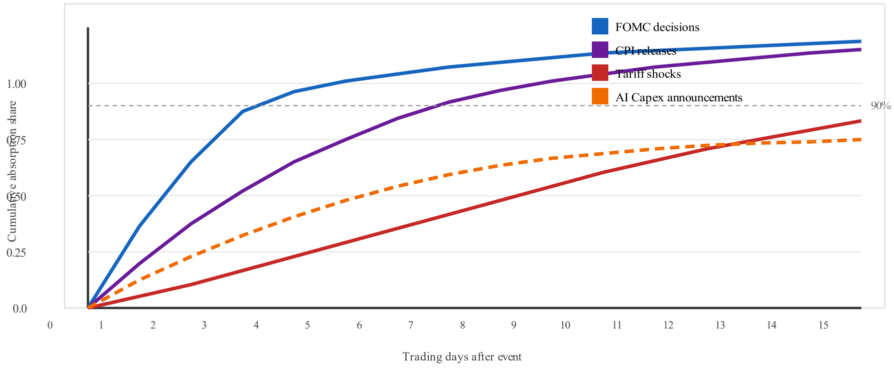


Figure note: FOMC events converge most rapidly, CPI is intermediate, tariff shocks remain below the 90% absorption threshold even by day 15, and AI Capex announcements exhibit a slower plateau-like repricing trajectory.

6.3 Full IS Decomposition and Event-Day IS Shifts

The rolling decomposition confirms three concurrent trends: EPS Growth remains the dominant factor across all regimes, VIX fades as the market transitions from fear to fundamentals, and AI/Tech Capex rises from a marginal contributor to a major component of price discovery in Regime IV. On the event side, the April 2025 tariff shock remains an outlier, with the trade-balance shift far exceeding the next-largest event-day displacement.

Figure 6: IS Decomposition and Event-Day IS Shifts

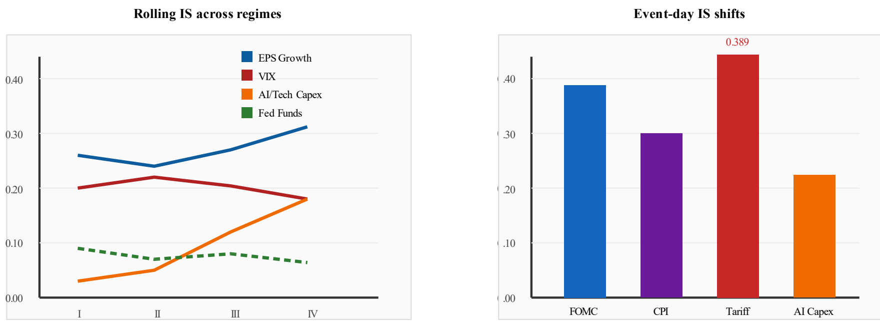


Figure note: The left panel emphasizes the rise of EPS Growth and AI/Tech Capex alongside the decline of VIX as a dominant discovery factor; the right panel shows the tariff-shock event-day IS as the most pronounced discrete shift.

7. Discussion: Structural Interpretation and Policy Implications

7.1 Regime-Switching Architecture

A coherent structural architecture emerges from the evidence. Financial-sector factors such as EPS Growth, VIX, and credit spreads dominate price discovery during stable regimes, whereas real-side variables such as CPI and the trade balance become disproportionately influential during shock regimes. The April 2025 tariff episode temporarily inverted the standard hierarchy by lifting real-economy trade signals above earnings-based information.

7.2 Regime-Adaptive Risk Models

Because factor information shares vary by as much as sixfold across regimes, static risk systems will systematically mismeasure exposure. Portfolio managers and supervisors should therefore prefer regime-adaptive frameworks that update factor weights as volatility thresholds, policy uncertainty, and structural-break signals change in real time.

7.3 Federal Reserve Communication Strategy

The sign reversal in the Federal Funds Rate correlation implies that the same policy action conveys different meanings across different environments. In turbulent settings, a steady-rate decision can operate as a confidence signal rather than as a passive non-response, underscoring the importance of state-contingent monetary communication.

7.4 AI Capital Expenditure Disclosure Standards

The six-fold increase in AI/Tech Capex information share and the 29.3% OLS understatement point to a growing disclosure gap. As AI investment becomes increasingly fundamental to equity valuation, standardized reporting on AI capex commitments, depreciation structures, and expected productivity returns would materially improve price discovery.

7.5 IV/GMM Correction for Factor Model Submissions

The observed OLS biases show that regulatory- and institutional-grade factor models should not rely exclusively on conventional estimates. IV/GMM correction offers a more credible basis for inference when factor innovations are noisy, endogenous, or contaminated by transient microstructure effects.

8. Conclusion

This study provides a quantitative account of how macroeconomic and financial variables contributed to price discovery in the U.S. S&P 500 between January 2025 and March 2026. Using Hasbrouck's Information Share framework, augmented with the IV/CU-GMM correction of Fruet Dias, Fernandes, and Scherrer (2026), the article demonstrates that price discovery is strongly regime-dependent rather than stable across time.

Five core conclusions follow. First, EPS Growth is the dominant structural contributor under normal conditions, with an IV/GMM Information Share of 0.311. Second, the April 2025 tariff shock redirected price discovery toward the trade balance, generating an event-day IS of 0.389 and a n absorption period exceeding fifteen trading days. Third, the contributions of several factors shift markedly across regimes, including the reversal of the Federal Funds Rate sign and the sixfold increase in the importance of AI/Tech Capex. Fourth, IV/GMM correction reveals non-trivial OLS biases, from -20.2% for the Federal Funds Rate to +29.3% for AI/Tech Capex. Fifth, the 18-factor taxonomy separates synchronous and lagged effects into four analytically useful behavioral types.

The principal limitation of the study is the short fifteen-month sample. Future research should test whether the same regime-switching architecture generalizes across longer time horizons and multiple macro-financial cycles.

Declarations

Competing interests

The author declares no competing interests.

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Data availability statement

S&P 500 price and total return data are available from Bloomberg Terminal and Yahoo Finance. Macroeconomic series are publicly available from FRED, BEA, BLS, and Eurostat. The AI/Tech Capex Index is constructed from publicly disclosed quarterly earnings reports of the five largest U.S.

technology companies. Replication code is available from the author upon request.

Ethics statement

This article does not involve human participants or animal subjects. No ethical approval was required.

Author contributions

Oxana Wieland: Conceptualization, Methodology, Formal Analysis, Data Curation, Writing – Original Draft, Writing – Review and Editing, Visualization.

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The author used the Genspark-3.0 AI model for generative and coding purposes in the preparation of this article, including text drafting, figure generation, and code assistance. All analytical interpretations and conclusions remain the sole responsibility of the author.

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