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Information Surprises and Cross-Border Capital Flows: Evidence from Foreign Exchange, Gold, and Digital Asset Markets

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Abstract*—This paper examines how extreme information shocks influence post-event price dynamics across eight internationally traded instruments: five major foreign exchange pairs (EURUSD, USDJPY, GBPUSD, USDCNY, and USDINR), gold, Bitcoin, and Ethereum. Using daily data from February 2018 through December 2025, information surprises are identified through a rolling-volatility standardized return approach, and cumulative abnormal returns (CARs) are tracked over a 30-day post-shock window. The empirical design extends the event-study logic of Bush, Mehdian, and Perry (2010) to a cross-asset international finance setting and evaluates post-shock adjustment patterns against three theoretical benchmarks: the Efficient Market Hypothesis, the overreaction hypothesis, and the Uncertain Information Hypothesis. Results indicate that informational efficiency is conditional rather than uniform across asset classes. Major foreign exchange pairs, particularly EURUSD, display relatively muted post-shock CARs consistent with faster information absorption. Gold behaves as an uncertainty-sensitive asset, with post-shock dynamics more consistent with gradual investor repositioning than immediate price discovery. Digital assets show the largest and least stable post-shock adjustments, with Bitcoin exhibiting statistically significant delayed positive drift following positive shocks and Ethereum showing early-window reversal behavior following positive shocks, though several Ethereum and Bitcoin results do not achieve conventional significance levels. These findings suggest that information shocks propagate differently across traditional currency channels, safe-haven assets, and cryptocurrency markets, with implications for portfolio management, risk hedging, and the assessment of market efficiency in globally integrated financial systems.*

Keywords*—capital flows; cumulative abnormal returns; digital assets; event study; foreign exchange markets; information shocks; market efficiency; safe-haven assets*

I. INTRODUCTION

Global financial markets have become increasingly interconnected as technological innovation, financial liberalization, international trade expansion, and cross-border capital mobility have accelerated the integration of national financial systems. Information generated in one region can now influence foreign exchange markets, commodity markets, and digital asset markets almost immediately as investors revise expectations and reallocate portfolios. In such an environment, understanding how quickly and efficiently financial markets incorporate unexpected information is central to evaluating capital mobility, the pricing of risk, and the stability of globally integrated markets.

The Efficient Market Hypothesis (EMH) provides the foundational framework for evaluating informational efficiency. In its semi-strong form, EMH proposes that asset prices rapidly reflect publicly available information, implying that unexpected information shocks should produce immediate price adjustments and leave little opportunity for predictable abnormal returns after the event (Fama, 1970, 1991). If this proposition holds, then the arrival of extreme new information should be followed by little or no systematic drift in post-event returns. Yet decades of empirical evidence have shown that financial markets do not always behave in a manner consistent with instantaneous and fully rational adjustment.

One prominent explanation for such deviations is the overreaction hypothesis, which suggests that investors may respond excessively to dramatic information events and that prices subsequently reverse as the initial overreaction dissipates (De Bondt & Thaler, 1985). A second explanation is provided by the Uncertain Information Hypothesis (UIH), which argues that unexpected information initially increases perceived risk and uncertainty,

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causing investors to respond cautiously and thereby generating a gradual price adjustment process as uncertainty is resolved (Brown et al., 1988). These competing perspectives imply distinct post-event return patterns and therefore provide a useful framework for interpreting cumulative abnormal return behavior following identified information shocks.

This study examines how extreme information shocks influence asset price dynamics across a set of globally traded instruments that differ substantially in institutional structure, liquidity, and investor composition. Specifically, the analysis focuses on five foreign exchange pairs, gold, Bitcoin, and Ethereum. The empirical design follows the logic of an event study by identifying extreme standardized return shocks using rolling volatility estimates and then measuring post-shock cumulative abnormal returns over a 30-day window. This framework makes it possible to compare the speed and direction of post-event adjustment across traditional cross-border capital flow channels, safe-haven assets, and major digital assets. It should be noted that the paper infers capital flow dynamics from price behavior rather than measuring capital flows directly; the foreign exchange setting provides a natural proxy because exchange rate adjustments reflect the cross-border reallocation of capital in response to information.

The contribution of the paper is threefold. First, it extends information-surprise analysis beyond the equity-market setting to a unified cross-asset framework that is well aligned with questions of international finance and capital mobility. Second, it evaluates whether informational efficiency differs systematically across foreign exchange markets, gold, and digital assets. Third, it provides evidence on how unexpected information may propagate through globally integrated markets in a period characterized by trade tensions, pandemic disruption, inflation shocks, tightening monetary policy, and growing institutional participation in digital assets. In doing so, the paper contributes to the literature on market efficiency, uncertainty, and cross-border capital flows.

II. LITERATURE REVIEW

The question of how financial markets process new information lies at the center of modern financial economics. The Efficient Market Hypothesis (EMH), most closely associated with Fama (1970), provides the foundational theoretical framework for understanding the relationship between information and asset prices. In its semi-strong interpretation, EMH suggests that prices fully and instantaneously reflect available information, rendering abnormal profit opportunities unsustainable once information becomes public. Fama's framework distinguished among weak, semi-strong, and strong forms of market efficiency and thereby provided a conceptual structure for evaluating what kinds of information should already be incorporated into market prices. Later work emphasized that empirical tests of efficiency are joint tests of both informational efficiency and the asset-pricing model used to measure abnormal returns (Fama, 1991).

Support for the efficient markets paradigm also emerged from the random walk literature. Samuelson (1965) demonstrated that if prices properly anticipate future information, price changes should be random and unpredictable. In a similar vein, Malkiel (2003) argued that the broad empirical tendency for prices to behave in an approximately random manner provided substantial support for the proposition that active attempts to exploit public information should not systematically outperform the market. Together, the EMH and random walk literature established the benchmark expectation that abnormal returns following public information releases should be minimal or short-lived in well-functioning markets.

At the same time, a large and influential body of work has documented patterns that appear inconsistent with strict forms of market efficiency. De Bondt and Thaler (1985) showed that extreme stock price movements are often followed by reversals over subsequent periods. Their results suggested that investors may overreact to unexpected information, temporarily pushing prices away from fundamental values. Subsequent behavioral finance research linked such anomalies to psychological biases, heuristic decision making, and limits to arbitrage, all of which may allow price deviations to persist beyond the initial event (Shiller, 2003; Tversky & Kahneman, 1974).

An alternative explanation for post-event return drift is the Uncertain Information Hypothesis (UIH) developed by Brown et al. (1988). Rather than arguing that investors systematically overreact, the UIH proposes that unexpected information initially increases uncertainty and perceived risk. Because investors are risk averse and uncertain about the full implications of new information, prices may initially under-adjust, with subsequent positive abnormal returns appearing as uncertainty dissipates and the market gradually converges toward a new equilibrium. This framework is particularly relevant for large macroeconomic, policy, or geopolitical shocks, where interpretation of the information may not be immediate even in highly liquid markets.Event-study methodology has become one of the primary empirical tools used to evaluate how markets respond to information events. Brown and Warner (1985) demonstrated that event studies using daily returns are generally well specified and sufficiently powerful to detect abnormal performance around events. MacKinlay (1997) further developed the econometric foundations of event-study analysis and formalized the use of abnormal returns and cumulative abnormal returns (CARs) to evaluate how quickly prices adjust after information events. Binder (1998) later summarized how event studies had become one of the standard methodologies in economics and finance precisely because they provide a transparent way to connect theory about information incorporation to observed price behavior.

A more specific strand of literature has focused on the response of returns to extreme or surprise information events. The earlier Bush, Mehdian, and Perry (2010) study examined investor reaction to information surprises across NASDAQ sector indexes and used a post-event CAR framework to distinguish among EMH, overreaction, and uncertain-information interpretations. That study found mixed evidence across sectors and highlighted the possibility that investor response to information is not uniform across different market segments. The present study extends that logic to a broader set of internationally traded assets, allowing comparison across foreign exchange markets, commodities, and digital assets.

Foreign exchange markets provide a particularly important setting for tests of informational efficiency because of their depth, global participation, and central role in cross-border capital allocation. Exchange rates absorb information about monetary policy, inflation expectations, trade prospects, geopolitical risk, and relative macroeconomic performance. Traditional international finance research often treats major currency markets as among the most informationally efficient financial markets because of their liquidity and continuous trading. However, empirical work has also shown that exchange-rate behavior can display departures from simple efficiency benchmarks, especially during periods of market stress, policy intervention, or rapid shifts in macroeconomic expectations. Narayan (2020) provided direct evidence of this phenomenon by showing that the COVID-19 shock altered exchange rate resistance to information shocks, highlighting how structural breaks and crisis episodes can reshape the efficiency properties of currency markets.

The foreign exchange literature also provides a strong rationale for connecting informational efficiency to cross-border capital flows. Exchange rates do not simply respond to news in isolation; they are a mechanism through which capital reallocation takes place internationally. Changes in expectations regarding relative growth, inflation, or policy rates can alter currency demand, hedging behavior, and international portfolio allocation. As a result, studying post-shock adjustment in FX markets offers insight into the speed with which global investors interpret and act on new information that affects international capital movements. This study uses five major FX pairs to represent cross-border capital-flow channels and to test whether currency markets display the rapid adjustment that their liquidity and depth would imply.

Gold markets add an important dimension to this inquiry because gold has long been viewed as both a hedge and a safe-haven asset. Baur and Lucey (2010) distinguish between a hedge, which is uncorrelated or negatively correlated with another asset on average, and a safe haven, which retains those properties specifically during periods of market stress. Baur and McDermott (2010) provide international evidence that gold may serve as a safe haven in some markets and episodes but not universally. This distinction matters for the present study because gold's response to information shocks may differ from the response of currencies if investors treat gold as a destination for capital during periods of heightened uncertainty.

Related work has also emphasized that gold's role is state dependent. Gold may react not only to inflation and interest-rate news but also to geopolitical risk, financial instability, and broad uncertainty about the credibility of monetary and fiscal regimes. Because the sample includes trade tensions, the COVID period, inflation shocks, and aggressive monetary tightening, gold provides a natural benchmark for examining whether post-event return dynamics reflect safe-haven demand and uncertainty resolution rather than immediate equilibrium pricing. The inclusion of gold in this study therefore tests whether uncertainty-driven behavior, as distinct from rational price discovery, can be identified in post-shock CAR patterns.

The emergence of digital asset markets has added a new layer to the literature on informational efficiency. Bitcoin, introduced by Nakamoto (2008), created a decentralized asset class operating outside traditional monetary institutions. Early empirical work often found that Bitcoin markets were characterized by substantial inefficiencies, pronounced volatility, and limited maturity. Urquhart (2016), for example, reported evidence inconsistent with weak-form efficiency in Bitcoin returns, while Bariviera (2017) showed that efficiency may change over time as the market evolves. Nadarajah and Chu (2017) revisited the efficiency question and argued that certain findings of inefficiency are sensitive to methodology, suggesting that the Bitcoin market may be more efficient than some earlier results implied. Cheah and Fry (2015) provided additional context by documenting evidence of speculative bubbles in Bitcoin markets, suggesting that prices can deviate substantially from fundamental values over extended periods.

Research on cryptocurrency pricing has also focused on volatility, return drivers, and the integration of digital assets into broader financial systems. Katsiampa (2019) documented substantial time-varying volatility and co-movement between Bitcoin and Ether, underscoring the importance of volatility-aware methods when identifying extreme events in cryptocurrency data. Liu and Tsyvinski (2021) argued that cryptocurrency returns display distinctive risk-return characteristics not fully explained by traditional asset-pricing factors. Corbet et al. (2019) examined the financial market effects of cryptocurrency energy usage, finding that Bitcoin's price volatility and mining dynamics affect energy sector performance, a result that underscores the growing interconnection between digital asset and broader financial markets. Kristoufek (2015) examined the main drivers of Bitcoin prices using wavelet coherence analysis and found that investor attention and speculative trading play a significant role alongside fundamental factors. Caporale et al. (2018) further documented persistence in cryptocurrency returns, providing evidence of long-memory behavior that is inconsistent with weak-form efficiency. Zhang et al. (2018) also characterized the distributional and stylized-fact properties of cryptocurrency returns, noting fat tails, volatility clustering, and long-range dependence as features that distinguish digital assets from traditional financial instruments.

Comparative studies between cryptocurrencies and traditional assets have yielded particularly relevant insights for the present paper. Dyhrberg (2016) argued that Bitcoin exhibits characteristics that overlap with both gold and the U.S. dollar, suggesting that digital assets may play hybrid roles as speculative instruments, alternative stores of value, and portfolio diversifiers. Bouri et al. (2017) further examined whether Bitcoin behaves as a hedge or safe haven and found that its safe-haven properties are conditional rather than universal. These results suggest that digital asset responses to information shocks may differ materially from those of traditional currencies or gold, especially when the

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informational event triggers shift in speculative sentiment or uncertainty.

Methodologically, the move from equity-sector analysis to a cross-asset event-study design introduces several advantages. First, it allows the empirical comparison of markets with different microstructures, trading regimes, and investor bases within a unified framework. Second, it makes it possible to evaluate whether similar information events generate different post-shock adjustment dynamics across asset classes. Third, the use of rolling-volatility standardized returns provides a practical way to identify extreme events while accounting for time-varying volatility, a particularly important consideration in cryptocurrency and commodity markets.

Taken together, the literature supports three core propositions that motivate the present study. First, EMH remains the primary benchmark for evaluating whether public information is rapidly reflected in prices. Second, the overreaction hypothesis and the Uncertain Information Hypothesis provide theoretically distinct alternatives when post-event drift appears. Third, the increasing integration of foreign exchange, commodity, and digital asset markets makes cross-asset comparison both feasible and important. By examining post-shock CAR behavior across currencies, gold, Bitcoin, and Ethereum, the present paper extends the information-surprise literature into a modern international finance setting and provides new evidence on how unexpected information influences cross-border capital flows in globally integrated markets.

III. DATA AND METHODOLOGY

This study uses daily log returns for eight internationally traded instruments from February 2018 through December 2025. The instrument set includes five foreign exchange pairs (EURUSD, USDJPY, GBPUSD, USDCNY, and USDINR), gold (XAUUSD), and two major digital assets (BTCUSD and ETHUSD). Daily closing price data were obtained from Investing.com historical price data for each instrument, including foreign exchange pairs (spot rates), spot gold (XAU/USD), Bitcoin (Bitfinex), and Ethereum (Binance), and converted into daily log returns for analysis. The sample period is intentionally broad enough to capture several major global regimes, including the late post-financial-crisis expansion, the COVID-19 shock, the inflation and monetary tightening cycle, and the increasing institutional relevance of digital assets. The inclusion of foreign exchange, gold, and cryptocurrencies allows the analysis to compare price adjustment across assets that play distinct roles in global capital allocation, including currency-based capital-flow channels, safe-haven behavior, and digital-asset risk-return dynamics (Baur & Lucey, 2010; Baur & McDermott, 2010; Liu & Tsyvinski, 2021).

Daily continuously compounded returns are used because they are standard in event-study and market-efficiency research and because they allow returns to be aggregated over post-event windows (Brown & Warner, 1985; MacKinlay, 1997). For each instrument, the daily log return is defined as:

$$r(t) = \ln[P(t) / P(t - 1)]$$

where P(t) represents the closing price of the instrument on day t. The use of log returns also helps ensure that foreign exchange, gold, and digital asset return series are analyzed in a consistent form.

A. Shock Identification

Information surprises are identified using a rolling-volatility standardized return approach. The purpose of standardization is to determine whether a return is unusually large relative to the recent volatility of that same instrument rather than unusually large in absolute terms. This is especially important in a cross-asset design because the normal volatility of EURUSD is materially different from the normal volatility of Bitcoin or Ethereum.

For each instrument, rolling standard deviations are calculated using 60-day and 90-day windows. The standardized return is then calculated as:

$$z(t) = r(t) / \text{rolling volatility}(t)$$

where r(t) is the daily log return and rolling volatility(t) is the rolling standard deviation of returns over the selected window.

A positive information shock is identified when z(t) is greater than or equal to +2.5. A negative

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information shock is identified when z(t) is less than or equal to -2.5. The ±2.5 threshold is used because it identifies materially unusual price movements while preserving a sufficient number of events for post-shock analysis. It also maintains methodological continuity with prior information-surprise research using standardized shocks, including the earlier Bush, Mehdian, and Perry (2010) event-study framework. Standardized-return thresholds in the range of ±2 to ±3 standard deviations are commonly used to identify extreme events in market-efficiency and event-study research (Brown & Warner, 1985; MacKinlay, 1997).

The 60-day rolling window is used as the primary specification because it is responsive to recent changes in volatility while still smoothing short-lived noise. The 90-day rolling window is used as a robustness check because it provides a somewhat more conservative volatility estimate. If the main conclusions remain similar across the two windows, the findings are less likely to be driven by an arbitrary volatility-window assumption.

B. Event-Study Design and Abnormal Returns

After identifying positive and negative shock days, the analysis follows an event-study structure. For each shock event, day 0 is the shock day and the post-event period is measured from day 1 through day 30. The 30-day window is long enough to detect delayed adjustment or reversal while short enough to remain connected to the original information shock. This design follows the general logic of the event-study literature in which abnormal returns are tracked after information events to evaluate whether prices adjust immediately or continue to drift.

Abnormal returns are calculated by subtracting the mean non-event return for the relevant instrument from the observed post-event return, where the mean non-event return is estimated over the full sample period excluding all identified event windows. To avoid contamination, post-event windows that overlap with a subsequent shock event are excluded from the analysis. The variance of abnormal returns used to construct the t-statistics is estimated from the time-series standard deviation of abnormal returns across non-overlapping event observations for each instrument, following the approach described in Brown and Warner (1985). Cumulative abnormal returns (CARs) are then calculated by summing abnormal returns over the post-event window:

CAR(i,K) = AR(i,t+1) + AR(i,t+2) + ...

+ AR(i,t+K)

where AR(i,t+k) is the abnormal return for instrument i on post-event day k and K is the event horizon. The reported tables focus on selected CAR checkpoints at days 1, 5, 10, 20, and 30. The figures display the full 30-day CAR path following positive and negative shocks. The interpretation of each CAR path is guided by three theoretical benchmarks: immediate adjustment consistent with the EMH, reversal consistent with overreaction, and gradual post-event drift consistent with the Uncertain Information Hypothesis.

C. Methodological Rationale and Alternatives

The rolling-volatility standardized event-study approach was selected because it balances rigor, transparency, and cross-market comparability. A GARCH-based approach could also be used to estimate conditional volatility, and such models are common in financial econometrics. However, GARCH estimation adds model complexity and can introduce specification risk when applied across heterogeneous asset classes with very different volatility structures. Because the central research question is whether post-shock adjustment differs across instruments, a transparent standardized-return approach is more easily interpreted and replicated across markets.

An intraday event-study design is another possible alternative, especially for research focused on scheduled macroeconomic announcements and real-time price discovery. However, this study is concerned with the broader post-shock adjustment process across foreign exchange, gold, and digital assets over a 30-day horizon. Daily returns are therefore appropriate for evaluating whether shock effects dissipate quickly, drift gradually, or reverse over time. The chosen approach also avoids imposing identical intraday trading-session assumptions on assets that trade under different market structures. The following section presents

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the empirical results, beginning with shock-frequency counts and then turning to post-shock CAR patterns for each instrument and shock direction.

IV. EMPIRICAL RESULTS

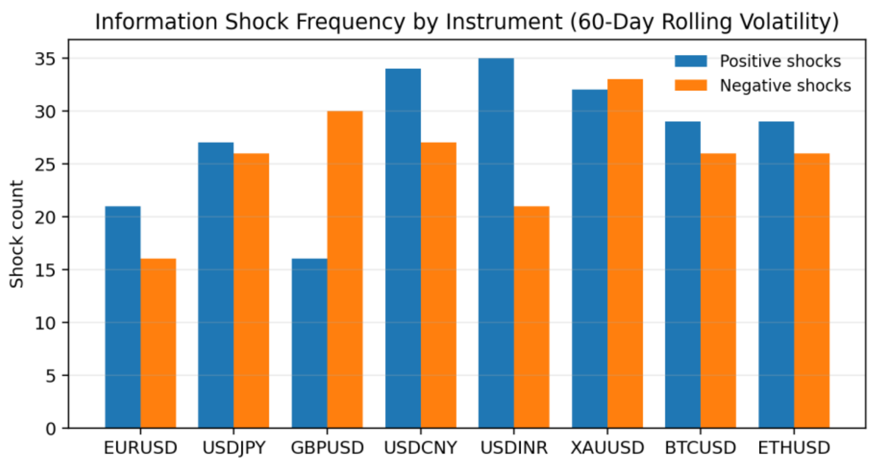
A. Shock Frequency

The shock-frequency results indicate that the rolling-volatility approach identifies a meaningful number of positive and negative events across all instruments. Using the 60-day rolling window, total shock counts range from 37 for EURUSD to 65 for XAUUSD (Table 1). The remaining instruments produce event counts that are sufficient for post-shock comparison: USDJPY generates 53 shocks, GBPUSD generates 46, USDCNY generates 61, USDINR generates 56, BTCUSD generates 55, and ETHUSD generates 55. This distribution suggests that the shock-identification procedure does not simply isolate events in the most volatile assets; once returns are standardized by recent volatility, both traditional and digital assets produce meaningful information-shock observations.

Table 1 Information Shock Frequency by Instrument: 60-Day Rolling-Volatility Standardization

Instrument	Positive shocks ($z >= +2.5$)	Negative shocks ($z <= -2.5$)	Total shocks	Shock rate (%)
EURUSD	21	16	37	1.84
USDJPY	27	26	53	2.64
GBPUSD	16	30	46	2.29
USDCNY	34	27	61	3.04
USDINR	35	21	56	2.79
XAUUSD	32	33	65	3.24
BTCUSD	29	26	55	2.74
ETHUSD	29	26	55	2.74

Figure 1 Information Shock Frequency by Instrument: 60-Day Window



Note. The figure reports positive and negative shock-event counts by instrument using the 60-day rolling-volatility standardization window.

The 90-day rolling window produces similar shock patterns, which provides support for the robustness of the event-identification procedure. Under the 90-day specification, EURUSD produces 32 shocks (Table 2), USDJPY 53, GBPUSD 48, USDCNY 56, USDINR 55, XAUUSD 63, BTCUSD 60, and ETHUSD 52. The similarity between the 60-day and 90-day shock counts suggests that the event-identification procedure is not highly sensitive to the volatility window selected. It should be noted that the CAR analysis is reported only for the 60-day primary specification; the 90-day window serves as a robustness check for shock identification rather than a full parallel CAR estimation.

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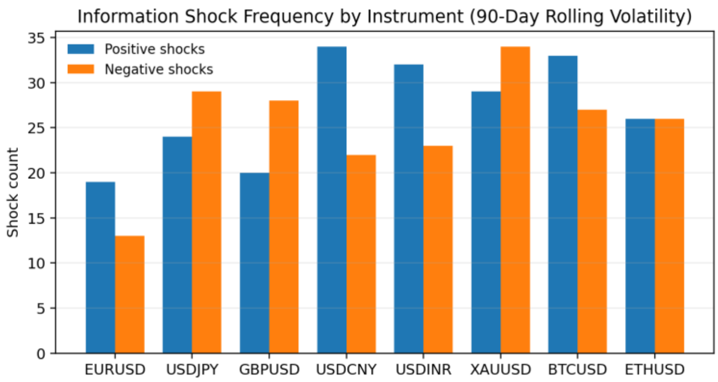
Table 2 Information Shock Frequency by Instrument: 90-Day Rolling-Volatility Standardization

Instrument	Positive shocks (z >= +2.5)	Negative shocks (z <= -2.5)	Total shocks	Shock rate (%)
EURUSD	19	13	32	1.62
USDJPY	24	29	53	2.68
GBPUSD	20	28	48	2.43
USDCNY	34	22	56	2.83
USDINR	32	23	55	2.78
XAUUSD	29	34	63	3.19
BTCUSD	33	27	60	3.04
ETHUSD	26	26	52	2.63

Figure 2 Information Shock Frequency by Instrument: 90-Day Window



Note. The figure reports positive and negative shock-event counts by instrument using the 90-day rolling-volatility standardization window.

B. Post-Shock CAR Patterns Following Positive Shocks

The positive-shock CAR results show substantial variation across instruments (Table 3; Figure 3). Among the foreign exchange pairs, EURUSD has a relatively muted 30-day CAR of approximately 0.49%, which is broadly consistent with faster information absorption, though the Day 5 CAR of +0.78% ($t = 2.64$, $p < .01$) is statistically significant, indicating a short-lived positive drift that dissipates by Day 30. USDJPY displays a consistently negative CAR path following positive shocks, ending at approximately -0.50% at Day 30, though none of these checkpoints achieve statistical significance, a pattern consistent with near-efficient adjustment. GBPUSD shows statistically significant positive drift, with CARs of +1.31% ($p<.01$) at Day 20 and +1.79% ($p<.01$) at Day 30, a pattern consistent with gradual post-shock adjustment in line with the Uncertain Information Hypothesis, while USDCNY shows statistically significant positive CARs at Days 5, 10, 20, and 30 (ranging from ** to ***), making it the most consistently significant FX pair in positive shocks, with a 30-day CAR of approximately 0.52%. USDINR shows a smaller positive 30-day CAR of approximately 0.24%, with no checkpoints reaching significance.

Table 3 Selected Cumulative Abnormal Returns Following Positive Information Shocks: 60-Day Window

Instrument	Day 1 CAR (%) [t]	Day 5 CAR (%) [t]	Day 10 CAR (%) [t]	Day 20 CAR (%) [t]	Day 30 CAR (%) [t]
EURUSD	0.15 [1.00]	0.78*** [2.64]	0.28 [0.54]	-0.10 [-0.20]	0.49 [0.74]
USDJPY	-0.22 [-1.55]	-0.33 [-1.19]	-0.45 [-1.12]	-0.42 [-0.81]	-0.50 [-0.81]

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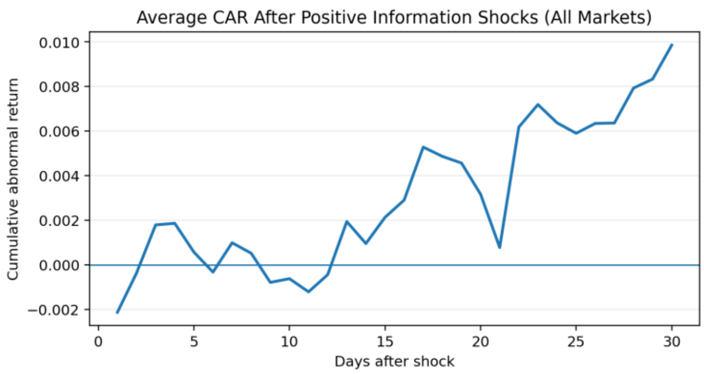
GBPUSD	0.15 [0.67]	0.44 [1.20]	0.70 [1.61]	1.31*** [2.91]	1.79*** [3.00]
USDCNY	-0.05 [-0.62]	0.30** [2.03]	0.53*** [2.72]	0.56** [2.11]	0.52* [1.71]
USDINR	-0.00 [-0.03]	0.01 [0.06]	0.13 [0.72]	0.38 [1.42]	0.24 [0.93]
XAUUSD	0.03 [0.12]	0.40 [0.59]	-0.30 [-0.42]	-0.16 [-0.20]	0.33 [0.43]
BTCUSD	-0.97 [-1.36]	0.11 [0.08]	1.43 [0.70]	5.10* [1.74]	8.17*** [2.63]
ETHUSD	-0.80 [-0.88]	-1.26 [-0.81]	-2.82* [-1.89]	-4.13 [-1.38]	-3.14 [-0.86]

Figure 3 Average Cumulative Abnormal Return After Positive Information Shocks: All Markets



Note. The figure displays average cumulative abnormal returns (CARs) in percentage terms over the 30-day post-shock event window following positive information shocks.

Gold exhibits a modest positive 30-day CAR of approximately 0.33% after positive shocks, but its path is less straightforward because the intermediate CAR values fluctuate across the post-event window. The most pronounced positive-shock result is observed in Bitcoin, which moves from a negative day-1 CAR to a 30-day CAR of approximately 8.17%. This large, delayed movement is difficult to reconcile with immediate adjustment and is more consistent with gradual information absorption or momentum-like investor behavior. Ethereum behaves differently from Bitcoin: following positive shocks, ETHUSD shows a statistically significant Day 10 CAR of -2.82% ($t = -1.89$, $p < .10$), the only significant Ethereum result in positive shocks. The 30-day CAR of approximately -3.14% is in the same negative direction but does not achieve statistical significance ($t = -0.86$), suggesting early-window reversal that does not persist robustly to month-end.

Positive Shock CAR Paths: Figures 5–8

Figure 5. EURUSD: Positive Shock CAR Path

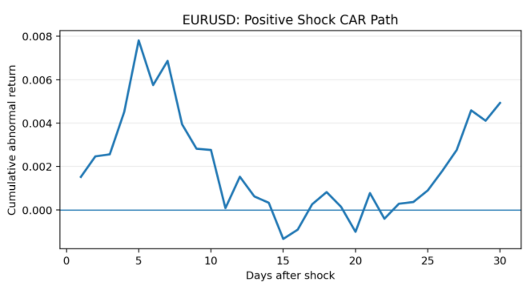


Figure 6. USDJPY: Positive Shock CAR Path

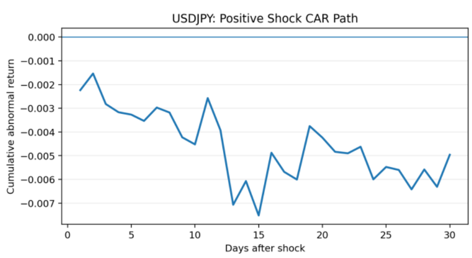


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Figure 7. GBPUSD: Positive Shock CAR Path

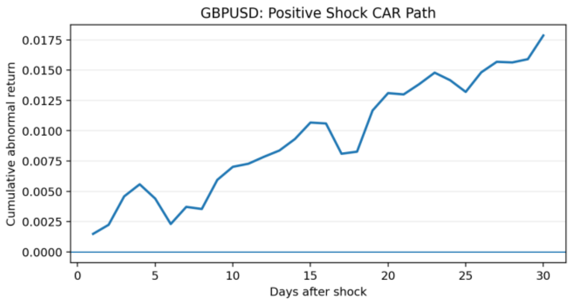
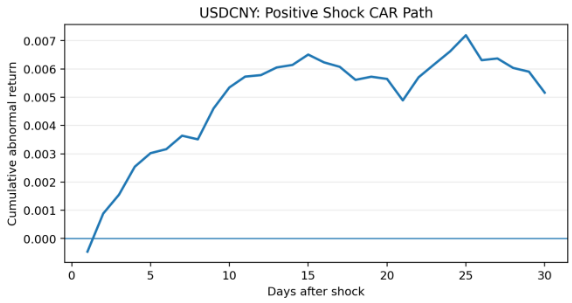


Figure 8. USDCNY: Positive Shock CAR Path



Note. Figures display average CAR (%) over the 30-day post-shock event window. Shocks are identified using the 60-day rolling-volatility standardized return threshold (|z| ≥ 2.5).

Positive Shock CAR Paths: Figures 9–12

Figure 9. USDINR: Positive Shock CAR Path

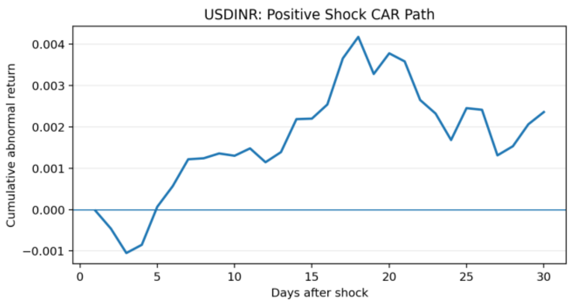


Figure 10. XAUUSD: Positive Shock CAR Path

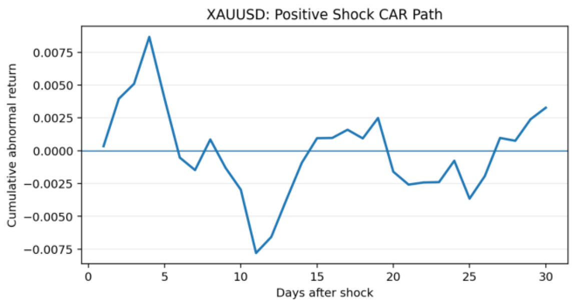


Figure 11. BTCUSD: Positive Shock CAR Path

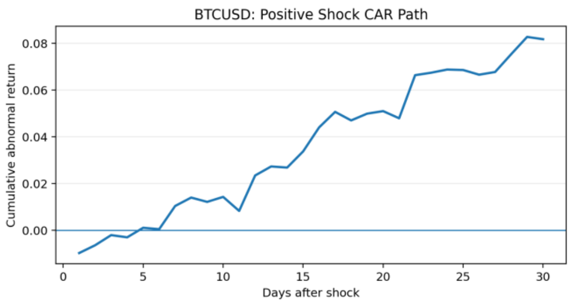
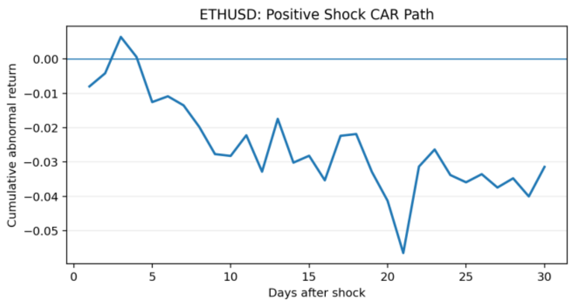


Figure 12. ETHUSD: Positive Shock CAR Path



Note. Figures display average CAR (%) over the 30-day post-shock event window. Shocks are identified using the 60-day rolling-volatility standardized return threshold (|z| ≥ 2.5).

C. Post-Shock CAR Patterns Following Negative Shocks

The negative shock results are particularly important because adverse shocks appear to produce more persistent and differentiated responses across markets (Table 4; Figure 4). EURUSD again shows relatively muted behavior, with a 30-day CAR of approximately -0.16%, making it the cleanest example of near-efficient adjustment among the included instruments. USDJPY shows statistically significant and progressively deepening negative drift, with significant CARs at Day 5 (−0.48%, p<.10), Day 20 (−0.81%, p<.10), and Day 30 (−1.35%, p<.05), a pattern consistent with gradual information absorption rather than immediate

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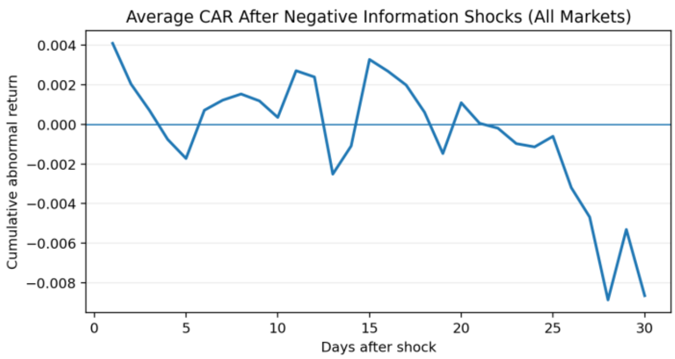
adjustment. GBPUSD shows a statistically significant initial decline of -0.37% at Day 1 (t = -2.14, p < .05), but the subsequent reversal to +0.10% at Day 30 (t = 0.20) does not achieve statistical significance, meaning the overreaction interpretation should be treated as tentative rather than confirmed.

Table 4 Selected Cumulative Abnormal Returns Following Negative Information Shocks: 60-Day Window

Instrument	Day 1 CAR (%) [t]	Day 5 CAR (%) [t]	Day 10 CAR (%) [t]	Day 20 CAR (%) [t]	Day 30 CAR (%) [t]
EURUSD	-0.00 [-0.03]	-0.12 [-0.33]	-0.24 [-0.56]	-0.08 [-0.17]	-0.16 [-0.30]
USDJPY	-0.06 [-0.35]	-0.48* [-1.71]	-0.33 [-0.74]	-0.81* [-1.68]	-1.35** [-2.28]
GBPUSD	-0.37** [-2.14]	-0.74 [-1.57]	-0.31 [-0.55]	0.18 [0.36]	0.10 [0.20]
USDCNY	0.11* [1.65]	0.06 [0.45]	-0.03 [-0.25]	-0.50*** [-3.07]	-0.99*** [-4.23]
USDINR	0.17** [2.36]	0.29 [1.48]	0.56*** [2.68]	0.38 [1.35]	0.42 [1.54]
XAUUSD	-0.30 [-1.51]	-0.47 [-1.00]	-0.62 [-1.25]	-0.45 [-0.76]	-1.30* [-1.78]
BTCUSD	1.74 [1.51]	-0.08 [-0.04]	1.19 [0.44]	3.30 [0.78]	4.09 [0.80]
ETHUSD	1.98 [1.22]	0.18 [0.06]	0.07 [0.02]	-1.13 [-0.22]	-7.75 [-1.14]

Figure 4 Average Cumulative Abnormal Return After Negative Information Shocks: All Markets



Note. The figure displays average cumulative abnormal returns (CARs) in percentage terms over the 30-day post-shock event window following negative information shocks.

Negative Shock CAR Paths: Figures 13–16

Figure 13. EURUSD: Negative Shock CAR Path

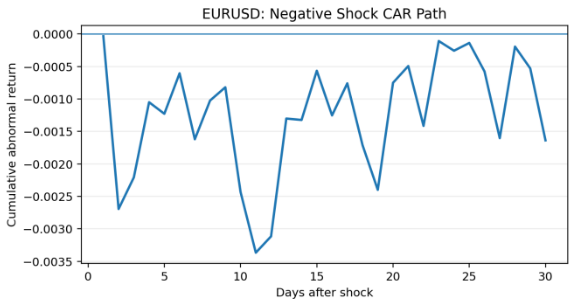


Figure 14. USDJPY: Negative Shock CAR Path

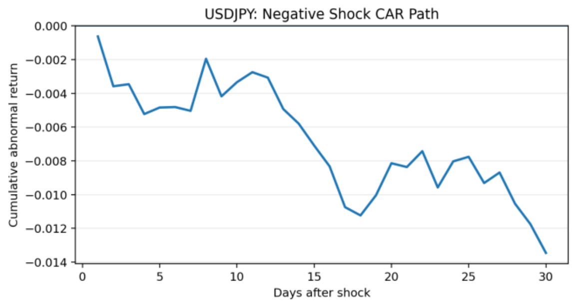


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Figure 15. GBPUSD: Negative Shock CAR Path

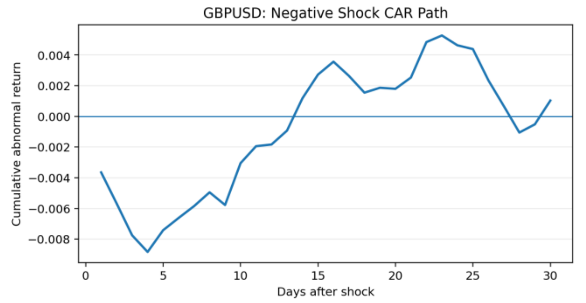
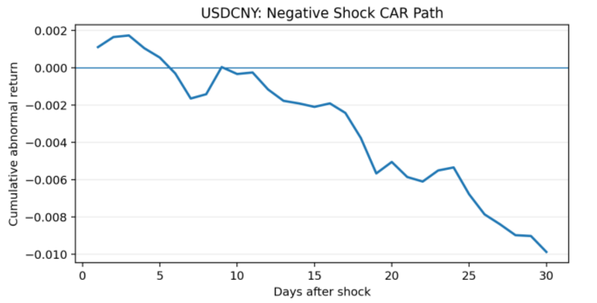


Figure 16. USDCNY: Negative Shock CAR Path



Note. Figures display average CAR (%) over the 30-day post-shock event window. Shocks are identified using the 60-day rolling-volatility standardized return threshold (|z| ≥ 2.5).

Negative Shock CAR Paths: Figures 17–20

Figure 17. USDINR: Negative Shock CAR Path

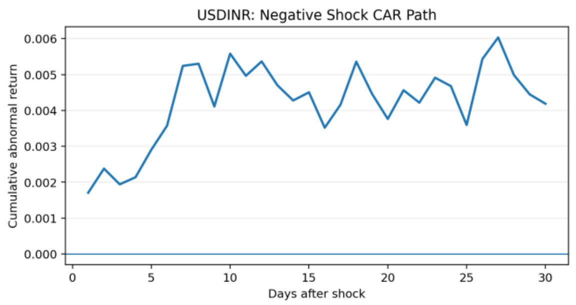


Figure 18. XAUUSD: Negative Shock CAR Path

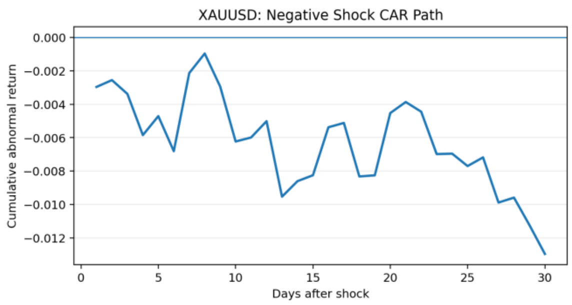


Figure 19. BTCUSD: Negative Shock CAR Path

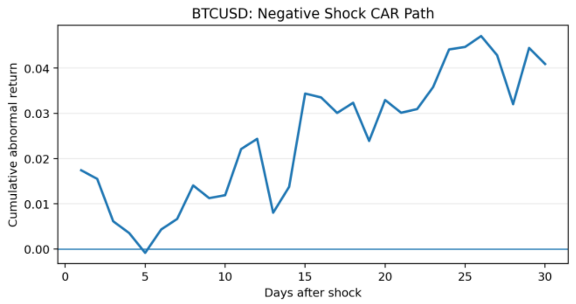
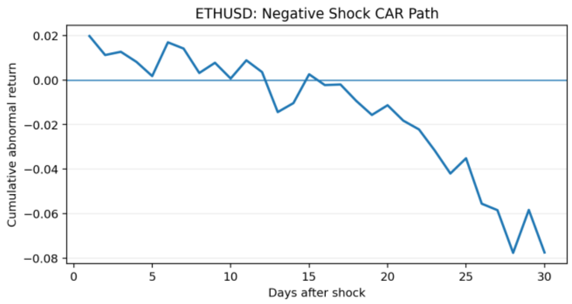


Figure 20. ETHUSD: Negative Shock CAR Path



Note. Figures display average CAR (%) over the 30-day post-shock event window. Shocks are identified using the 60-day rolling-volatility standardized return threshold (|z| ≥ 2.5).

USDCNY shows persistent negative drift following negative shocks, ending with a 30-day CAR of approximately -0.99%, while USDINR produces a statistically significant positive CAR of +0.56% at Day 10 (p<.01), the strongest early-window FX result in negative shocks, suggesting a rapid counter-directional move that may reflect the managed-float nature of the rupee and the tendency of the Reserve Bank of India to intervene following large exchange rate movements. The Day 30 CAR of +0.42% is in the same direction but does not achieve significance (t = 1.54). Gold has a statistically significant 30-day CAR of −1.30% (p<.10) after negative shocks — the only significant gold result in either table — which is consistent with the interpretation that gold's post-shock behavior reflects uncertainty resolution and investor repositioning rather than immediate and complete price discovery. Bitcoin produces a 30-day CAR of approximately 4.09% after negative shocks, a direction consistent with the overreaction hypothesis, though this result does not achieve statistical significance (t = 0.80). The pattern is suggestive but should be interpreted cautiously given the high volatility of Bitcoin returns and the relatively small number of negative shock events. Ethereum shows a 30-day CAR of approximately -7.75% following negative shocks — the largest magnitude in either table — but this result does not achieve statistical significance (t = -1.14), reflecting the high variance of Ethereum returns combined with the limited number of negative shock events (n = 26). The magnitude is notable but cannot be statistically distinguished from zero.

D. Cross-Asset Interpretation

The empirical results suggest that market efficiency is conditional rather than uniform across asset classes. Major foreign exchange markets, particularly EURUSD, appear closest to the EMH benchmark because their post-shock CAR paths are relatively muted compared with gold and digital assets. However, the FX evidence is not uniform. GBPUSD, USDJPY, USDCNY, and USDINR each show some combination of asymmetry, drift, or reversal, suggesting that informational efficiency is stronger in some currency channels than others.

Gold behaves differently from the FX group. Rather than serving as a simple efficient-pricing benchmark, gold appears to operate as an uncertainty-sensitive asset. Its negative-shock CAR path is consistent with an uncertainty or safe-haven interpretation in which post-shock behavior reflects investor risk positioning and the gradual resolution of uncertainty. This is consistent with the literature describing gold as a hedge or safe haven whose performance depends on market conditions.

The digital asset results are the least consistent with immediate efficiency. Bitcoin and Ethereum show larger and less stable CAR paths than the major FX pairs. Bitcoin displays statistically significant delayed positive drift after positive shocks (Day 20: +5.10%, $p<.10$; Day 30: +8.17%, $p<.01$). Bitcoin's positive CAR following negative shocks (+4.09%) is directionally consistent with overreaction but does not achieve significance. Ethereum's only statistically significant result is an early-window decline of −2.82% at Day 10 following positive shocks ($p<.10$); the large late-window CARs in both shock directions do not achieve significance, limiting the inferences that can be drawn. These results are consistent with the view that digital asset markets remain more sentiment-driven, more volatile, and less immediately efficient than major foreign exchange markets.

V. DISCUSSION

The results support the view that global market integration does not imply identical information processing across asset classes. Foreign exchange, gold, and digital assets are all part of the global capital-market ecosystem, but the speed, direction, and stability of post-shock adjustment differ materially across the instruments examined. This finding is important because it suggests that the relationship between information shocks and cross-border capital flows depends on the market channel through which the shock is transmitted.

The strongest evidence consistent with semi-strong market efficiency appears in the major foreign exchange segment, especially EURUSD. The relatively muted EURUSD CAR paths suggest that deep and liquid currency markets incorporate large, standardized shocks more quickly than other assets in the sample. This does not mean that all FX markets are fully efficient, but it does suggest that the most liquid currency pairs may provide the clearest example of rapid public-information absorption.

The gold and digital asset results point to a more complex adjustment process. Gold's statistically significant negative-shock CAR (Day 30: −1.30%, $p<.10$) provides the clearest support for the uncertainty-channel interpretation. Gold’s behavior is consistent with its role as an uncertainty-sensitive asset. It may not simply reflect immediate price discovery; rather, it may reflect investor repositioning, hedging demand, and safe-haven allocation as uncertainty evolves. Digital assets, by contrast, show stronger evidence of delayed movement and instability. This suggests that post-shock price dynamics in Bitcoin and Ethereum may be influenced by sentiment, liquidity, speculative behavior, and slower information absorption.

The theoretical interpretation is therefore mixed, which is itself a meaningful contribution. The EMH appears most applicable to the most liquid FX markets. The Uncertain Information Hypothesis helps explain gradual drift where prices continue moving after the shock rather than immediately settling into a new equilibrium. The overreaction hypothesis is relevant where prices initially move in one direction and then reverse over the event window. The key academic implication is that market efficiency should be treated as conditional on the asset class, market structure, and direction of the shock. Taken together, the EMH benchmark is most applicable to EURUSD and the most liquid FX pairs; the Uncertain Information Hypothesis best describes the gradual adjustment observed in gold and managed-float currencies; and the overreaction hypothesis finds its clearest support in the statistically significant Day 1 decline for GBPUSD following negative shocks (−0.37%, $p<.05$) and in the significant positive drift for GBPUSD following positive shocks. The directional evidence from Ethereum and Bitcoin's negative-shock rebound is consistent with overreaction but does not achieve statistical significance and should be treated as suggestive rather than confirmatory.

VI. CONCLUSION AND RECOMMENDATIONS

The empirical findings of this paper reveal that globally connected markets do not process major information shocks in the same way. Although FX, gold, and cryptocurrencies all participate in global capital allocation, the post-shock CAR paths reveal meaningful differences in speed of adjustment, direction of drift, and stability of response.

The evidence does not fully reject the Efficient Market Hypothesis, but it also does not support a simple conclusion that all markets adjust instantly to information shocks. Major FX pairs, particularly EURUSD, appear closest to efficient adjustment. Gold behaves more like an uncertainty channel, especially after negative shocks. Bitcoin shows statistically significant delayed positive drift following positive shocks, consistent with gradual information absorption. Ethereum and Bitcoin's negative-shock patterns are directionally suggestive of inefficiency but are not statistically significant, warranting caution in interpreting them as confirmed evidence of delayed adjustment.

For investors and risk managers, the practical implication is that information shocks should not be treated uniformly across markets. A shock in EURUSD may be absorbed relatively quickly. Statistically significant post-shock drift in gold (negative shocks) and Bitcoin (positive shocks) suggests these assets may continue to adjust over days or weeks. For Ethereum, the magnitude of post-shock movements is large but the statistical evidence is weaker, and claims about adjustment persistence should be treated with appropriate caution. This distinction matters for hedging, portfolio allocation, trading strategy, and reserve-management decisions. For policymakers and researchers, the findings suggest that digital assets may operate as a distinct and potentially less stable channel through which information shocks propagate in modern capital markets.

Several limitations should be acknowledged. First, the study identifies information shocks statistically through standardized return movements rather than linking each shock to a specific news announcement. This approach is useful for identifying extreme market events consistently across asset classes, but future work could classify shocks by source, including monetary policy announcements, inflation news, geopolitical events, crisis episodes, or trade-policy developments.

Second, the rolling-volatility approach is transparent and replicable, but alternative volatility models could be used as robustness checks. Future research could compare the rolling-volatility method with GARCH-based standardized residuals, stochastic volatility models, or realized-volatility measures. Intraday data could also be used to study the timing of adjustment more precisely, particularly around scheduled macroeconomic announcements.

Third, the asset universe could be expanded. Future studies could include additional currency pairs, sovereign bonds, equity indexes, oil, industrial metals, stablecoins, or other digital assets. A broader

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asset set would make it possible to examine spillovers and contagion more formally across global capital markets. Finally, future research could incorporate measures of investor sentiment, market liquidity, and policy uncertainty to test whether behavioral and uncertainty channels explain post-shock drift more directly.

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