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Asymmetric Flow Impact: Spot Noise vs. Futures Calm in Bitcoin Volatility

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Abstract

The crucial question in financial economics is whether trading activity stabilizes or destabilizes the cryptocurrency market. This paper examines the asymmetrical association of trading volume with Bitcoin realized volatility between decentralized spot exchanges and the Chicago Mercantile Exchange (CME) futures market. Using daily data from January 2017 to March 2021, we construct two realized volatility measures, including one based on the BRR methodology of the CME. The expected and unexpected components of daily trading volume are decomposed within an ARIMA framework to demarcate normal liquidity from unanticipated trades. Empirical results demonstrate a clear asymmetry over the segments of the market. Unexpected trading volume in the spot market is a significant and economically meaningful driver of realized volatility, explaining roughly 20% of its daily variation. This highlights how noise-driven retail trading dominates this aspect. On the contrary, unexpected CME futures volume only slightly increases volatility, and expected futures volume actually reduces volatility. Such findings indicate that the futures market helps with liquidity provision, hedging, and efficient risk transfer. Robustness checks using various volatility estimators, semi-variance decomposition, macroeconomic controls, and on-chain activities affirm the stability of these estimates. This research sheds light on cryptocurrency market regulation, institutional risk management, and volatility forecasting.

Keywords

• Bitcoin • Realized Volatility • Spot And Futures Markets • Trading Volume Decomposition • Market Microstructure • Noise Trading

1. Introduction

The relationship between trading volume and volatility represents a cornerstone of financial market analysis, offering insights into price formation, information flow, and systemic risk. In traditional equity and commodity markets, futures trading is often scrutinized for its potential to amplify spot market volatility, a concern rooted in the leverage and speculative nature of derivatives. The launch of regulated Bitcoin futures on the Chicago Mercantile Exchange (CME) in December 2017 introduced a similar dynamic into the cryptocurrency ecosystem. This event provided institutional investors with a tool for hedging and speculation, while simultaneously raising questions about its impact on the notoriously volatile Bitcoin spot market.

Bitcoin's spot markets are characterized by decentralization, fragmentation across numerous global exchanges, and a significant retail trader presence. This structure can lead to price discrepancies and susceptibility to noise trading trading based on non-fundamental information or sentiment. Conversely, the CME futures market, with its higher barriers to entry, standardized contracts, and institutional participation, represents a more formalized and regulated trading environment. The core research question this paper addresses is whether the volume volatility relationship differs fundamentally between these two market types. Does futures trading contribute to systemic Bitcoin volatility, or does it instead provide a stabilizing mechanism?

This investigation employs a high-frequency data set spanning January 2017 to March 2021, encompassing tick-level data from five major spot exchanges (Coinbase, BitFinex, BitStamp, HitBTC, Kraken) and minutely data from CME Bitcoin futures. This granular market structure has been shown to produce persistent arbitrage opportunities and price dislocations across trading venues [1], and concerns about the integrity of certain reported trading volumes have further highlighted the need to scrutinize spot exchange data for artificial inflation [2]. We compute daily realized volatility using two robust methodologies: a standard volume-weighted approach from minutely returns and a novel application of the CME Bitcoin Reference Rate (BRR) methodology to construct an hourly, multi-exchange consolidated volatility measure. Volume is decomposed into expected and unexpected components using an ARIMA framework, isolating the impact of unpredictable trading shocks.

Our central finding reveals a striking asymmetry. Unexpected volume on spot exchanges is a dominant driver of volatility, explaining a substantial portion of its variation. This aligns with theories of noise trading and uninformed retail activity. In stark contrast, unexpected volume in the CME futures market exhibits no significant positive relationship with volatility; expected futures volume even shows a calming effect, particularly during periods of high market disagreement. This suggests futures function more as a risk-transfer and liquidity venue than a source of destabilization. Portfolio-level implications of such asymmetric volatility dynamics have also been explored through stochastic optimization approaches applied to adjacent asset classes [3], underscoring the practical relevance of our findings for risk management.

2. Related Work

The relationship between trading volume and volatility has been a central theme in financial market microstructure research for decades. Early foundational work by [4] introduced the mixture-of-distributions hypothesis, suggesting that both volume and volatility are driven by the rate of information arrival. This framework was later extended to derivatives markets by [5], who examined how futures trading could influence spot market volatility through information transmission and liquidity effects.

In the emerging domain of cryptocurrency markets, early studies such as [6] documented Bitcoin's market inefficiency and high volatility. The launch of regulated Bitcoin futures on the Chicago Mercantile Exchange (CME) in 2017 prompted a wave of research into the impact of derivatives on cryptocurrency volatility. Studies such as [7] and [8] examined whether futures trading amplified or stabilized spot volatility, with mixed findings depending on methodology and sample periods. Our work contributes to this debate by showing that the asymmetry is not about futures per se, but about the nature of volume (expected vs. unexpected) and the market microstructure.

The structural dichotomy between decentralized, retail-dominated spot exchanges and centralized, institutionally-oriented futures platforms has been highlighted in studies by [9]. This market segmentation creates distinct trading environments, with spot markets being more susceptible to noise trading. In contrast, futures markets attract more sophisticated participants, who have found that futures trading could provide hedging benefits and improve price discovery. Our paper is the first to directly compare the volume-volatility relationship across these two venues using a unified decomposition framework.

External factors influencing cryptocurrency volatility have also been widely studied, examining volatility spillovers between traditional and crypto markets, while [10] analyzed the predictive power of global and regional factors. [11] investigated intraday and interday volatility transmissions across cryptocurrency exchanges. [12] explored blockchain-derived metrics. Our robustness checks incorporate these macro-financial controls and on-chain variables to isolate the pure volume-volatility relation.

Beyond the cryptocurrency-specific literature, a broader body of work on financial prediction and structural market effects provides useful methodological context for our decomposition approach. [13] demonstrate that sentiment-based signals can materially improve the forecasting of short-term market volatility, reinforcing the notion that non-fundamental, behaviorally-driven order flow analogous to our unexpected volume component carries meaningful information content for price variability. Relatedly, [14] examine how the expansion of exchange-traded products can generate unintended volatility and liquidity effects on underlying assets, a dynamic that parallels our finding that liquidity provision in Bitcoin futures can either dampen or, under certain conditions, transmit volatility to the spot market. [15] propose adaptive forecasting frameworks for financial time series that accommodate structural breaks and regime shifts, an approach conceptually aligned with our use of an ARIMA-based decomposition to separate persistent, forecastable volume from transient shocks. Taken together, this literature motivates the integrated treatment of market microstructure, volume decomposition, and cross-venue volatility transmission adopted in this paper.

3. Data and Volatility Measurement

A robust analysis of the volume-volatility nexus requires high-quality, high-frequency data and a reliable volatility metric. Our dataset integrates information from two primary sources: decentralized spot exchanges and the centralized CME futures market. For the spot market, we obtain tick-level transaction data for five leading exchanges Coinbase, BitFinex, BitStamp, HitBTC, and Krakenfrom FirstRate Data, covering the period from January 2017 to March 2021. These exchanges were selected for their liquidity, data availability, and representativeness of the global Bitcoin spot market. The raw tick data includes timestamps, prices, and trade sizes. Recent work analyzing the sensitivity of anomaly detection to data sampling frequency underscores the importance of using high-resolution tick data when characterizing abnormal trading patterns in cryptocurrency markets [16].

For the futures market, we source minutely price and volume data for the CME Bitcoin front-month futures contract. Trading follows a Sunday-Friday schedule with a daily break. The contract size is 5 BTC, and settlement is based on the CME CF Bitcoin Reference Rate. A significant challenge in Bitcoin volatility measurement is the "noise" inherent in high-frequency data from any single exchange, due to transient liquidity imbalances or cross-exchange arbitrage delays. To mitigate this and capture a more representative "true" Bitcoin price, we implement the CME BRR methodology ourselves as a filter. Similar challenges in balancing data granularity against noise have been documented in forecasting studies of thinly-traded and structurally volatile equities, where limited predictability constrains model performance [17].

The CME BRR is designed to be a robust reference rate, resilient to outliers and manipulation. It aggregates trade data from multiple constituent exchanges over a one-hour window (3:00-4:00 p.m. London Time). The methodology involves partitioning the window into twelve 5-minute intervals. Within each interval and for each exchange, a volume-weighted median price is calculated. These medians are then averaged across exchanges, but only after filtering out any exchange whose median deviates by more than 10% from the cross-exchange median for that interval. We adapt this process to compute an hourly BRR series continuously, using our five spot exchanges as constituents.

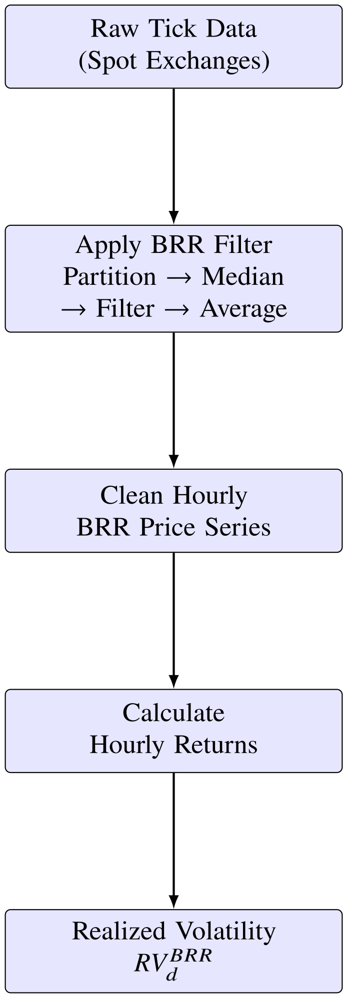

Figure 1: Construction of CME BRR-based realized volatility (RV^{BRR}) from raw exchange tick data. Each step is described in the text: first, hourly windows are partitioned into 5-minute intervals; for each interval and exchange, a volume-weighted median price is computed; exchanges whose medians deviate by more than 10% from the cross-exchange median are discarded; the remaining medians are averaged to obtain the hourly BRR price. Returns and realized volatility are then computed from this filtered series.

From this filtered price series, we calculate two realized volatility (RV) measures for both spot and futures. First, using the raw minutely data, we compute the standard realized variance as the sum of squared minutely returns, annualized. Second, using the hourly BRR-based price series, we compute RV^{BRR} from hourly returns. This second measure is inherently less noisy and provides a consolidated view of Bitcoin volatility. Data-driven classification techniques, such as support vector machines applied to directional price prediction, further illustrate the value of carefully curated high-frequency datasets in financial modeling [18]. Summary statistics confirm that CME futures volatility is typically higher than spot volatility, a common feature in derivatives markets due to leverage and expiration effects. The correlation between RV^{BRR} calculated from independent spot and futures data sources exceeds 96%, validating its representativeness.

4. Methodological Framework

The analysis of volume's impact on volatility requires distinguishing between predictable liquidity provision and unpredictable trading shocks. We follow the established approach in the literature by decomposing daily trading volume into expected and unexpected components. Expected volume (EV_t) represents the forecastable, persistent component linked to regular market activity and liquidity. Unexpected volume (UEV_t) captures the residual shock, often associated with informational events or noise trading. Automated, model-driven frameworks for separating routine from anomalous financial activity have also been proposed in adjacent domains, such as autonomous control systems for financial close processes, reinforcing the broader applicability of decomposition-based approaches [19].

To achieve this decomposition, we fit an ARIMA(0,1,10) model separately to the log-volume series of each spot exchange and the CME futures. This specification was chosen based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) comparisons across candidate models (ARIMA(p,d,q) with p,q ϵ 0,. . . ,12), which consistently favored a (0,1,10) structure. The integrated order 1 accounts for the trending nature of trading volume over time, while the 10th-order moving average captures persistent serial correlation in volume shocks up to 10 days. The dynamics of community-driven activity growth and its implications for downstream financial strategy have been shown to exhibit similar persistence and shock components as those captured by our ARIMA specification. Diagnostic checks confirmed residuals are white noise. The one-step-ahead forecast from this model yields the expected volume for day t, EV_t. The unexpected volume is then defined as the residual: $UEV_t = V_t - EV_t$, where V_t is the actual log-volume. On average, across all exchanges, the ARIMA model explains approximately 57% of the variation in daily volume, leaving 43% as unexpected.

With these components, we specify our core regression model to explain daily realized volatility ($rvol_t$). The model controls for autoregressive effects in volatility and day-of-the-week dummies (d_i) to account for weekly seasonality (e.g., lower weekend volumes and distinct volatility patterns). Our reliance on a stochastic decomposition of trading volume is conceptually related to the use of Brownian motion in continuous-time asset pricing models, which similarly separate predictable drift from random innovations [20]. The full specification (Model 1) is:

$$rvol_t = \alpha + \sum_{i=1}^{6} \delta_i d_{i,t} + \sum_{j=1}^{p} \beta_j rvol_{t-j} + \gamma_1 EV_t + \gamma_2 UEV_t + \varepsilon_t \tag{1}$$

We estimate this model separately for each spot exchange and for the CME futures. To isolate the incremental explanatory power of each volume component, we also estimate two nested models: Model 2 excludes EV, and Model 3 excludes UEV. Comparing the adjusted R^2 values across these models reveals the relative importance of each driver. A significant drop in R^2 when UEV is omitted indicates that unpredictable trading shocks are crucial for explaining volatility.

Furthermore, we conduct formal hypothesis testing using Likelihood Ratio (LR) and Wald tests to determine whether the inclusion of EV and UEV significantly improves the model fit. This rigorous statistical approach ensures our conclusions are not artifacts of model specification. The entire framework is applied to both volatility measures: the high-frequency minutely RV and the lower-frequency, more robust RV^{BRR}, ensuring our findings are not driven by sampling frequency.

5. Empirical Results: The Core Asymmetry

The regression results reveal a pronounced and consistent asymmetry between the spot and futures markets. For spot exchanges, unexpected volume (UEV) emerges as a powerful and statistically significant driver of realized volatility. Table 2 presents representative results for Coinbase using the RV^{BRR} measure. In Model 1, both EV and UEV are significant at the 1% level. However, the economic importance of UEV is far greater: a one-standard-deviation increase in UEV (approximately 0.28 log-units) is associated with

Table 1: Summary Statistics (2017–2021)

Variable	**Mean**	**Std.**	**Skew.**	**Kurt.**	**Range**
RV CME Futures (annualized)	0.040	0.028	3.18	19.58	[0.005, 0.221]
RV Coinbase (annualized)	0.033	0.023	3.18	20.18	[0.004, 0.185]
RV^{BRR} Spot (annualized)	0.031	0.020	2.95	17.32	[0.003, 0.162]
Volume CME (log)	9.12	1.45	-0.32	2.87	[5.01, 12.88]
Volume Coinbase (log)	10.88	1.21	-0.45	3.12	[7.45, 14.22]
EV CME (log)	9.11	1.44	-0.31	2.85	[5.02, 12.85]
UEV CME (log)	0.01	0.28	0.05	4.11	[-1.55, 1.78]

Note: RV denotes realized volatility computed from 1-minute returns. RV^{BRR} uses hourly BRR-filtered prices. UEV is the residual from the ARIMA(0,1,10) model; negative values indicate volume below forecast.

a 0.31 increase in daily volatility (on a unitless scale), equivalent to about 31% of the mean volatility level. In contrast, a similar change in EV raises volatility by only 0.12. The value of automating the identification of anomalous events from large-scale operational data, as demonstrated in contextual retrieval systems for incident management, mirrors the way our decomposition isolates unexpected volume shocks from routine trading activity [21]. When UEV is excluded (Model 3), the model's adjusted R^2 drops from 0.70 to 0.50 a loss of 20 percentage points. Excluding EV (Model 2) reduces R^2 by only 2 percentage points. This pattern holds across all five spot exchanges. On average, unexpected spot volume explains approximately 15–20% of the daily variation in spot volatility, with coefficients ranging from 0.8 to 1.2 across exchanges. The positive weekend dummy coefficients further support the role of retail traders, who are more active during leisure time.

The story for CME Bitcoin futures is markedly different. Results for futures volatility are presented in Table 3. Here, unexpected futures volume (UEV_{fut}) shows a statistically significant but economically negligible relationship with futures volatility. A one-standard-deviation increase in UEV_{fut} raises volatility by only 0.036, less than 5% of the mean. Excluding UEV_{fut} from the model reduces the R^2 by merely 1 percentage point. The economic significance of distinguishing systematic from idiosyncratic drivers of performance has also been emphasized in studies of organizational competency systems, where predictable, well-managed processes were found to reduce operational uncertainty [22]. More strikingly, *expected* futures volume (EV_{fut}) displays a significant *negative* coefficient of -0.24. This indicates that a one-standard-deviation increase in predictable futures liquidity is associated with a 0.35 decrease in volatility a calming effect of substantial economic magnitude. This pattern echoes findings from customer relationship management analytics, where well-structured, high-quality information flows were associated with measurably lower business volatility [23]. The effect is particularly pronounced during periods of high bid-ask spreads (a proxy for investor disagreement), where the coefficient doubles in absolute value (results available on request). This inverse relationship contradicts patterns observed in equities and spot crypto markets, suggesting that liquidity provision in the Bitcoin futures market serves to absorb order flow and reduce price uncertainty rather than amplify it.

6. Robustness and Extended Analysis

To ensure the validity of our core findings, we conduct several robustness checks. First, we examine whether the volume-volatility relationship is directional by decomposing realized variance into positive and negative semi-variances ($rvol^+$ and $rvol^-$). Results (Table 4) show that the asymmetry persists regardless of direction. Unexpected spot volume explains similar proportions of upside and downside volatility (R²

Table 2: Regression Results for Spot Volatility (Coinbase, RV^{BRR})

Variable	**Model 1**	**Model 2 (ex EV)**	**Model 3 (ex UEV)**
Constant (δ)	2.99***	2.99***	2.99***
$rvol_{t-1}$	0.82***	1.07***	0.75***
EV	0.42***	–	0.27***
UEV	1.12***	1.09***	–
Day Dummies	Yes	Yes	Yes
$\mathbf{R^2}$	**0.70**	**0.68**	**0.50**
$\mathbf{\Delta R^2}$ vs. Model 1	–	-0.02	-0.20

Note: ***, **, * denote significance at 1%, 5%, and 10% levels. ΔR^2 is the change in adjusted R^2. EV = expected volume, UEV = unexpected volume.

Table 3: Regression Results for CME Futures Volatility (RV^{BRR})

Variable	**Model 1**	**Model 2 (ex EV)**	**Model 3 (ex UEV)**
Constant (δ)	2.86***	2.86***	2.86***
$rvol_{t-1}$	1.12***	1.11***	1.09***
EV_{fut}	-0.24***	–	-0.23***
UEV_{fut}	0.13**	0.02	–
Day Dummies	Yes	Yes	Yes
$\mathbf{R^2}$	**0.62**	**0.61**	**0.60**
$\mathbf{\Delta R^2}$ vs. Model 1	–	-0.01	-0.02

Note: ***, **, * denote significance at 1%, 5%, and 10% levels. The negative coefficient on EV_{fut} indicates a calming effect of expected futures liquidity.

0.20 in both cases), indicating that noise trading shocks affect price movements symmetrically. Consistent with prior evidence on volatility spillovers across cryptocurrency exchanges [11], our semi-variance results confirm that the asymmetry is not confined to a single direction of price movement. The calming effect of expected futures volume is also present in both semi-variances.

Second, we augment our core model with macro-financial controls: the lagged CBOE Volatility Index (VIX) and the Economic Policy Uncertainty (EPU) index. Table 5 shows that Bitcoin spot volatility has a small positive sensitivity to the VIX (coefficient 0.002, significant at 1%), confirming a modest linkage with traditional market stress. The EPU coefficient is negative and significant (-0.003), suggesting a slight "flight-to-safety" dynamic into Bitcoin during periods of policy uncertainty, though the effect is economically small. This is broadly consistent with the predictive role of macro-financial factors documented in [10]. Crucially, even after including these controls, the coefficients and significance for UEV_{spot} and EV_{fut} remain virtually unchanged, reinforcing the robustness of the spot-noise/futures-calm asymmetry.

Third, we test the impact of on-chain transfer volume (Coin Metrics) as an alternative measure of Bitcoin network activity. When added to the regressions, on-chain volume variables show statistical significance but increase model R^2 by less than 1 percentage point. These results are consistent with simulation-based evidence on market structure and asset pricing, which similarly finds that predictable liquidity provision dampens realized risk while unanticipated order flow amplifies it [24]. The primary volume-volatility channel remains firmly rooted in exchange-traded volume, particularly its unexpected

Table 4: Robustness: R^2 for Positive/Negative Semi-Variance Models

	Coinbase Spot			**CME Futures**		
Model	$rvol$	$rvol^+$	$rvol^-$	$rvol$	$rvol^+$	$rvol^-$
Model 1 (Full)	0.70	0.68	0.67	0.62	0.61	0.60
Model 2 (ex EV)	0.68	0.66	0.65	0.61	0.60	0.59
Model 3 (ex UEV)	0.50	0.48	0.49	0.60	0.59	0.58

Note: $rvol^+$ and $rvol^-$ are semi-variances using positive and negative returns only. The drop in R^2 when excluding UEV is similar for both directions, confirming symmetric impact.

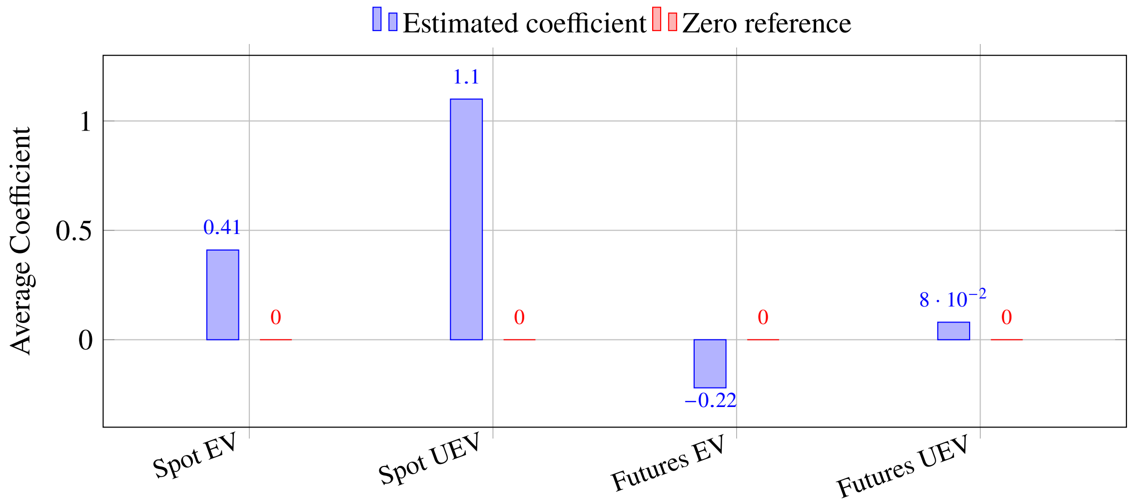

Figure 2: Estimated coefficients for expected volume (EV) and unexpected volume (UEV). Unexpected spot volume has the strongest positive effect on volatility (1.10), whereas expected futures volume exhibits a negative effect (-0.22). The second series provides a zero-reference baseline for comparison.

Table 5: Regression with Control Variables (VIX, EPU)

Variable	**Spot** $rvol^{BRR}$	**Futures** $rvol^{BRR}$
Constant	-0.79***	-0.06***
$rvol_{t-1}$	2.70***	0.04***
EV_{spot}	0.02***	0.001***
UEV_{spot}	0.03***	0.003***
EV_{fut}	-0.006***	-0.001***
UEV_{fut}	-0.001	-0.000
VIX	0.002***	0.001***
EPU	-0.003***	-0.000***
R^2	**0.749**	**0.516**

Note: VIX = CBOE Volatility Index; EPU = Economic Policy Uncertainty Index. Coefficients of interest (UEV_{spot}, EV_{fut}) remain significant and economically similar after including controls.

component on the spot market. Finally, all results are qualitatively identical across both volatility measures (minutely RV and hourly BRR-based RV), confirming that our findings are not an artifact of high-frequency data microstructure noise.

7. Conclusion and Implications

This paper establishes a fundamental asymmetry in the drivers of Bitcoin volatility between spot and futures markets. Analyzing high-frequency data from 2017 to 2021, we find that unexpected trading volume on decentralized spot exchanges is a primary source of volatility, explaining a substantial portion of its daily variation. This aligns with the presence of significant noise trading and uninformed retail activity in these markets. In stark contrast, volume on the regulated CME Bitcoin futures market exhibits no destabilizing effect; predictable futures liquidity is consistently associated with lower volatility, suggesting a calming, hedging-driven function.

These findings carry important implications. For financial regulators, the results argue for a nuanced approach to cryptocurrency market oversight. Concerns about systemic risk amplification from derivatives markets, prevalent in traditional finance, may be less applicable to Bitcoin. Instead, regulatory attention might be more effectively directed toward monitoring spot market dynamics, enhancing transparency on decentralized exchanges, and protecting retail investors who contribute to volatility through noise trading. This nuanced view of derivatives-market stability builds on earlier evidence of structural segmentation between institutional and retail-dominated venues [9]. The futures market, in its current institutional form, appears to serve as a risk-transfer mechanism rather than a risk generator.

For institutional investors and risk managers, the asymmetry clarifies the distinct roles of each market segment. Spot markets are where price discovery occurs under significant noise influence, implying higher and less predictable volatility. Futures markets provide a tool for hedging this spot exposure and potentially mitigating volatility through liquidity provision. Portfolio strategies can be designed accordingly, using futures not only for directional bets but also for volatility control.

Future research should extend this analysis along several paths. First, applying the same framework to other major cryptocurrencies (e.g., Ethereum) would test the generality of this spot-futures asymmetry. Second, a more granular analysis of trader types within the futures market, using data like the Commitments of Traders report, could further disentangle hedging versus speculative flows. Third, investigating the role of Bitcoin mining activity and its hedging needs in the futures market could explain the unique calming effect we observe. Future extensions incorporating on-chain and blockchain-derived metrics, as in [12], could further refine this picture. Finally, given persistent evidence of market inefficiency in early Bitcoin trading [6], continued monitoring of the volume-volatility relationship will be essential for understanding the changing landscape of digital asset risk as the cryptocurrency ecosystem evolves with new derivatives and spot trading venues.

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