Liquidity Fragility and Asymmetric Price Discovery in Crypto-Asset Markets: An Event-Based Microstructure Analysis

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Abstract

This study investigates the relation between trade imbalance, volatility, and liquidity costs in the BTC/USDT market by utilizing high-frequency Level 2 (L2) tick data. Through implementation of an event-based aggregation framework (Clark, 1973; Lopez de Prado, 2018), we partition market activity into "eras" of 50,000 trades to normalize for intraday seasonality and non-linear information arrival. The empirical results indicate that net signed trade imbalance is a substantial driver of price discovery, therefore explaining 42.9% to 47.1% of price variance (R^2) across different scales. Furthermore, we identify a statistically significant widening of bid-ask spreads during high-volatility regimes, consistent with adverse selection models (Glosten & Milgrom, 1985). Finally, we provide exploratory evidence of structural asymmetry: at a 100,000-trade scale, the magnitude of sell-side price impact exceeds buy-side impact by $30.46. This downward fragility provides empirical support for the Financial Accelerator and Margin Spiral frameworks, suggesting that automated liquidations and risk-mitigation by market makers create a non-linear "loss spiral" unique to the digital asset microstructure.

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1 Introduction

Bitcoin evolving from a retail experiment to a high frequency institutional asset has fundamentally altered its market microstructure. Currently, the BTC/USDT pair operates on a globally distributed limit order book dominated by High Frequency Trading (HFT) and algorithmic execution. The crypto market and Bitcoin operate 24/7/365 which results in asynchronous waves of global liquidity with continuous price discovery. These circumstances necessitate a rigorous empirical examination of how liquidity and price impact interact under varying regimes of volatility.

A major challenge in analyzing cryptocurrency microstructure is relying on chronological, time based sampling. Due to information arriving in decentralized markets non-linearly, time bars (e.g., 10 minute internals) suffer from inconsistent information density. A period of dormancy in a market is weighted equivalently to that of an extreme downward price discovery, introducing heteroscedasticity and statistical noise. Consequently, traditional time series analysis often shadows the true velocity of market shocks.

This study addresses these limitations through use of event based aggregation. Using level 2 tick data from the Bybit exchange, the data is split into fixed-count eras of 50,000 trades. This methodology subordinates chronological time to trade frequency, normalizing for intraday seasonality to ensure a more Gaussian distribution of returns. This paper is primarily descriptive rather than causal; it seeks to quantify the empirical relationships between net signed trade imbalance, bid-ask spreads, and directional price impact.

We isolate extreme market states by classifying eras into volatility and imbalance tertiles in order to test for structural asymmetries. More precisely, this analysis therefore seeks to establish whether the response of the market in terms of liquidity to aggressive selling is fundamentally different from its response to aggressive buying, thereby depicting the inherent downward fragility of crypto-asset liquidity.

The remainder of this paper is organized as follows: Section 2 reviews foundational literature in market microstructure and adverse selection; Section 3 describes the data acquisition from Bybit and the construction of event-based eras; Section 4 presents the empirical results; Section 5 discusses the findings within a Financial Accelerator framework; and Section 6 provides concluding remarks.

2 Literature Review

2.1 Information and Price Discovery

Understanding the relationship between trades and the price of an asset is central to this paper. There are many theories available discussing the relationship between these two though we will focus on the theory that prices move due to “informed traders”. This theory is presented in Continuous Auctions and Insider Trading (Kyle 1985) which talks about the idea that the net signed volume (trade imbalance) is the main driver of price. Kyle discusses how if the lambda, representing the cost of liquidity, is high then a small order will change the price significantly whereas if the lambda is low then large orders can be fulfilled with little to no price impact. He additionally adds that prices are efficient in how they reflect the total available public trade information but you can only see the information from the insider over time. Lastly he discusses how in order to detect insider trading you must find patterns in the order flow of how they are splitting up their orders.

2.2 Adverse Selection and Liquidity Costs

Another important theory to understand is the theory of adverse selection. This theory is discussed greatly throughout Bid, ask and transaction prices in a specialist market with heterogeneously informed traders (Glosten and Milgrom 1985). First off, there are two different types of buyers in a market, insiders, who only trade when it is profitable for them due to external information, and liquidity traders, who only have public information about the trades (uninformed). One thing to note is that market makers can not tell the difference between the insider and liquidity trader. Insiders have more information than the market makers which allows them to place orders right before an asset drops significantly in price. This then causes a spread between the asks and bids due to the fact that market makers must make back the losses they obtained from the insiders. Spread increases when insiders have better info and when there are more insiders than liquidity traders in the market because every time someone buys, there is a greater chance they have more info than the market makers. Spread decreases when liquidity traders are more eager to trade as market makers take on less risk due to the lower probability of a trader being an insider.

2.3 Market Fragility and Asymmetric Impact

One of the key insights to this paper is understanding market asymmetry and how selling has a larger impact on the price of an asset than buying does. The Financial Accelerator (Bernanke, Gertler, and Gilchrist 1998) explains this theory though it is easiest to understand through example. Let's say a portfolio has capital split into two different groups, Internal funds (the traders money) and External funds (borrowed money [lenders, banks etc.]). The Financial Accelerator argues that the less you have in your internal fund, the more you will be charged for your external funds. Now when the price of an asset decreases, you will lose part of your internal funds which means it will then cost you more to get money for your external funds. So when a small sell happens and the price of an asset drops, your net worth declines as your assets are valued lower than they were, as lenders think you are a greater risk so your interest rates are increased (credit becomes more restrictive when it is needed most), at some point borrowing will be too expensive and you will no longer be able to hold your positions which causes forced selling to meet margin calls which then pushes the price down even lower dropping your net worth even more (thus restarting this cycle). An additional factor that causes selling to have a larger impact on an asset's price is due to the fact that market making firms are generally net long in the market so their capital is more vulnerable to market declines. Market Liquidity and Funding Liquidity (Brunnermeier and Pedersen, 2009) discusses two different spirals economically, the loss spiral and the margin spiral. The loss spiral occurs when a shock causes people to sell their positions which then causes a price drop which causes more losses which force more selling, and so on. The margin spiral occurs when selling pressure causes volatility to increase which then causes financiers to raise margin requirements which forces traders to sell positions to pay for this (creating a feedback loop of price decrease).

2.4 Time vs Event based aggregation

Traditionally, financial econometrics has used time based aggregations, such as 1 or 5 minute candles, to analyze price action. Though Lopez de Prado (2018) states that time these time based bars demonstrate insufficient statistical properties, particularly heteroscedasticity and non-normality. Due to the fact that markets do not process information at a rate constant to time, trading activity is rather clustered during times of importance which results in time based bars commonly over sampling quiet periods and undersampling periods of high activity. This has caused researchers to instead use event based aggregations. This debate between time and event based aggregation is not new though. Papers dating as far back as Clark (1973), recognize that information arriving in a market does not follow a chronological timeline but instead rather an ‘economic clock’, which is dictated by trading activity. Clark's theory of Subordinate Exchange Time argues that price changes are more likely to follow a normal distribution if they are split into groups of n, an arbitrary number, transactions than if they were split into groups of n minutes. The industry however gravitated towards time based bars for simplicity sake in charting. Lopez de Prado reintroduces event based sampling in Advances in Financial Machine Learning (Wiley, 2018) with advanced “information bars” (volume or dollar imbalance bars), proving that traditional time based bars suffer from short term seasonal volatility (such as market open or lunch time) which is a problem trade count bars can efficiently normalize. These are even more distinct in crypto as they are open for trade 24/7/365 meaning that people from different parts of the world will be trading at different times which can introduce cultural differences in trading as well.

3 Methodology

3.1 Data Acquisition and Pre-processing

The empirical analysis uses high-frequency level 2, L2, tick data for the BTC/USDT pair, directly extracted from the Bybit exchange. The sample period covers 3 months from September 1, 2025, to November 30, 2025, covering a wide range of volatility regimes.

The raw data was synthesized by synchronizing the limit order book snapshots with the public trade feed. Pre-processing involved the removal of crossed-book anomalies (where Bid ≥ Ask), duplicated trade IDs, and flash outliers resulting from API latency. Calculating the Bid-Ask Spread (S) was done by the absolute difference between the best offer (A) and the best bid (B):

$$S = A - B$$

This metric serves as our primary proxy for immediate liquidity costs and market maker risk-aversion.

3.2 Fixed-Count Era Construction

To counter this heteroscedasticity common in time series data, this study breaks down the tick data into a series of eras consisting of a fixed number of trades, which is 50,000. As compared to time bars, eras based on events ensure normalizing activity and eliminate intra-day seasonality as well as the so-called “quiet period” associated with worldwide trading. It gives a common sample size (n = 50,000) for each observation unit, which makes employing ANOVA and OLS tests more reliable as each bar will contain equal information.

3.3 Metric Definitions

Four primary variables are calculated for each era:

- Mid Price (M): Calculated as the arithmetic mean of the best bid and ask at the time of each trade:

$$M = \frac{A + B}{2}$$

- Net Signed Impact (I): This represents the aggressive trade classification. Trades are signed as +1 (buyer initiated) or -1 (seller initiated) based on the exchange-reported side. I is the volume-weighted sum of these trades:

$$I = \Sigma(Side_i \times Volume_i)$$

- Price Impact (ΔP): Defined as the net change in mid-price from the inception (Mstart) to the conclusion (Mend) of an era:

$$\Delta P = M_{end} - M_{start}$$

- Volatility (σ): Measured as the standard deviation of the mid-price within the 50,000-trade window.

3.4 Statistical Framework

- Linear Association (R^2): This represents the Coefficient of Determination, which measures the proportion of price displacement that is predictable based on net aggressive order flow. It is derived by squaring the Pearson correlation coefficient (R) between Net Signed Impact (I) and Nominal Price Impact (ΔP):

$$R^2 = \left[\frac{\sum (I_i - \overline{I})(\Delta P_i - \overline{\Delta P})}{\sqrt{\sum (I_i - \overline{I})^2 \sum (\Delta P_i - \overline{\Delta P})^2}} \right]^2$$

3.5 Regime Classification

Eras are categorized into tertiles based on their distribution within the 3-month sample:

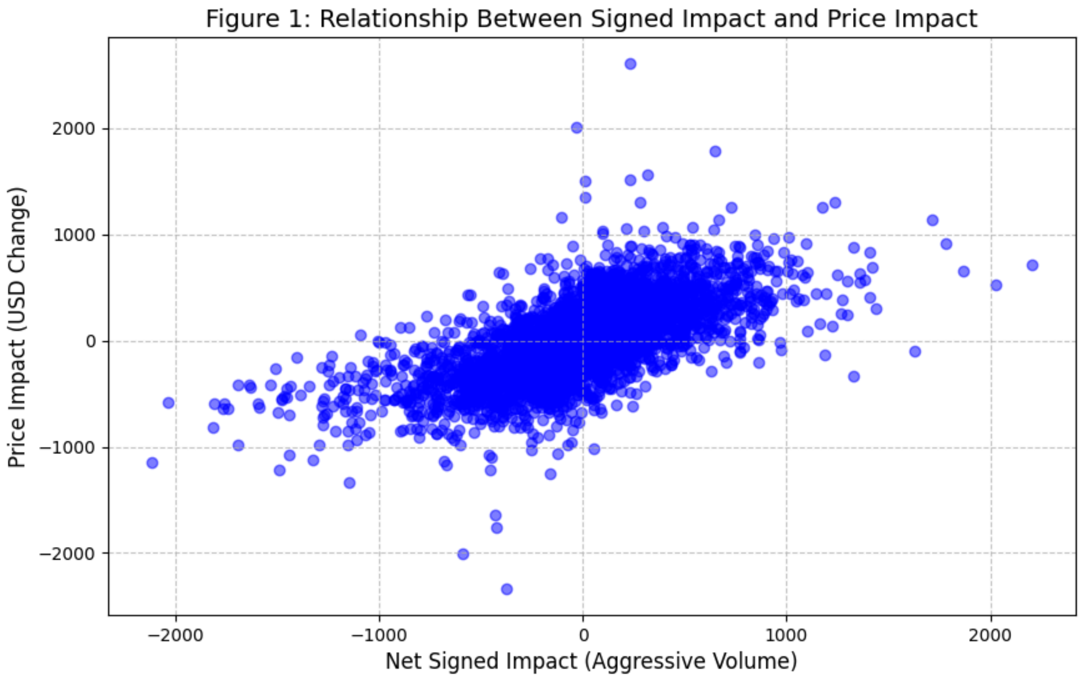
- Volatility Regimes: Low, Neutral, High (33.3% split)
- Imbalance Regimes: High_Sell, Neutral, High_Buy (33.3% split). This classification allows for a comparison of liquidity behavior during average versus extreme market states.

4 Empirical Results

This section provides the statistical findings of our study. The analysis is centered around the eras with 50,000 trades per era as the primary unit of observation, to show a middle range perspective. To ensure that our results are robust we compare our findings across three distinct scales: 10,000 (Micro), 50,000 (Baseline), and 100,000 (Macro) trades per era.

4.1 Trade Imbalance and Price Impact Correlation

The primary intention was to determine the extent at which trade imbalance, signed volume, predicts price movement.



As shown in Figure 1, a moderate positive correlation exists between the Net Signed Impact and Price Impact. The analysis of the baseline, 50,000 trades, yielded an R^2 value of 0.4293 indicating approximately 42.93% of the variance in price displacement is attributable to trade imbalance.

The correlation was tested across multiple scales to strengthen the rigor of this analysis:

- 10,000 Trades (Micro): Yielded an R^2 of 0.2720. At this high frequency scale, external noise and microstructure friction account for a larger portion of variation in price.
- 100,000 Trades (Macro): Yielded an R^2 of 0.4717. As the observation window expands, short term noise dissipates, revealing that trade imbalance becomes an increasingly presiding driver of price trends.

4.2 Volatility Regimes and Liquidity (Bid-Ask Spreads)

Next we examined how market makers adjust the cost of liquidity in response to perceived risk.

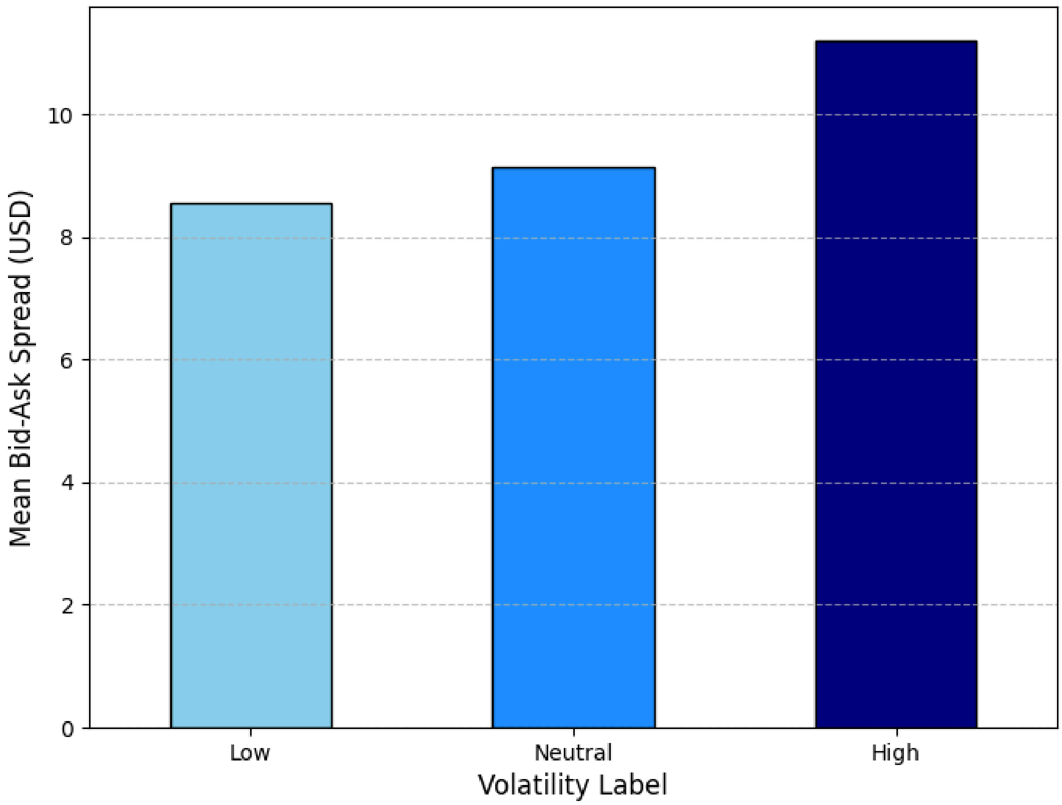


Figure 2: Average Bid-Ask Spread by Volatility Regime

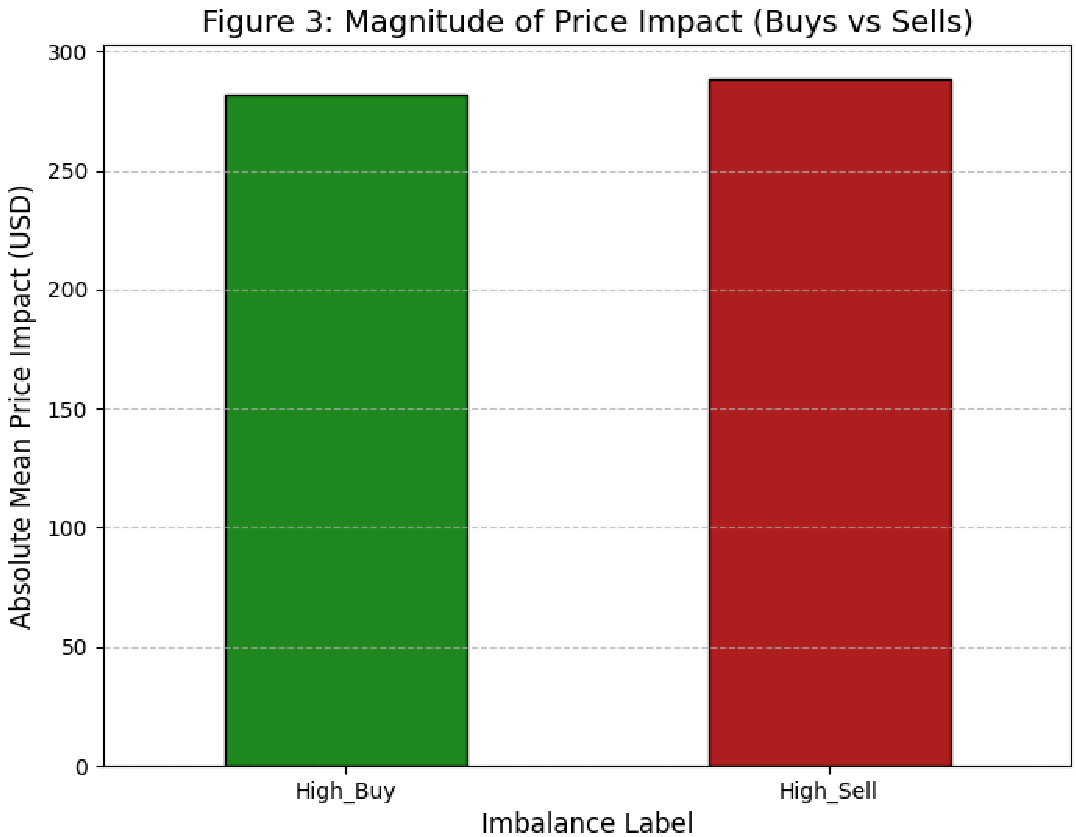
The data depicts a “staircase effect” where the mean spread widens as volatility increases.

- Low volatility eras: Mean spread of $8.56
- High volatility eras: Mean spread of $11.21

To ensure these results were not due to stochastic noise, a one-way ANOVA test was carried out, resulting in an F-statistic of 56.86 and a p-value of 4.6026e-25. A direct t-test comparing Low versus High volatility regimes produced a p-value 1.696e-19. Due to the fact that both p-values are well below 0.01, the results are statistically significant at the 1% level.

4.3 Directional Effects (Exploratory)

This subsection inspects the presence of structural asymmetry via comparing the magnitude of price during aggressive buying versus aggressive selling.



In the 50,000 trade baseline, the average price impact in High Buy eras was $282.07, while High Sell eras showed an absolute shift of $288.40 (a magnitude difference of $6.33). While this difference is marginal at smaller scales, the asymmetry scales significantly with trade volume:

- 10,000-Trade Scale: The magnitude difference is minor at $0.37.
- 100,000-Trade Scale: The magnitude difference expands to $30.46.

This trend suggests that while the "economic clock" progresses toward a macro level, sell side liquidity becomes more fragile compared to that of the buy side. These findings provide empirical evidence for the Financial Accelerator Theory, suggesting that downward price discovery is subject to a "loss spiral" effect that is less extensive during upward trends.

5 Discussion

5.1 The Information Content of Trades

The finding that trade imbalance explains between 43% and 47% of price movement gives rise to what makes up the remaining variance. There are many factors that make up this remaining portion including exogenous information such as news, social media, and macro events. Additionally limit order book changes such as people canceling or simply moving their orders are also within this portion. The scaling analysis reveals as the observation window expands from 10,000 to 100,000 trades, the R^2 value increases. This suggests that while high frequency noise may dominate shorter intervals, trade imbalance is the predominant driver of price discovery as the “economic clock” progresses.

5.2 Adverse Selection and Market Maker Risk

The substantial increase in the bid-ask spread from $8.56 to $11.21 during periods of high volatility is consistent with the Adverse Selection theories of Glosten & Milgrom (1985). During periods of high volatility, market makers are at a higher risk of trading with asymmetrically informed market participants. In order to mitigate this risk associated with harmful order flow, trading with asymmetrically informed market participants, market makers increase the bid-ask spread to offset potential losses. Empirical evidence here confirms that in the BTC/USDT market, liquidity is a dynamic process rather than a constant process because it adjusts to risk perceptions based on information asymmetry.

5.3 The Financial Accelerator & Liquidity Fragility

The $30.46 asymmetry at the 100,000 trade scale insinuates a structural bias in Bitcoins’s liquidity depth. Whereas upside price discovery appears relatively linear, downwards movements display characteristics of “forced” selling. This observation is coherent with that of the Financial Accelerator and Margin Spiral theories, in which price declines trigger automated liquidations and stop loss executions that further exhaust the available bid-side liquidity. The magnitude of this asymmetry at macro scales insinuates that the market's "floor" is more fragile than its "ceiling" at a structural level-a consequence, perhaps, of the nature of leveraged liquidations in crypto markets.

5.4 Practical and Regulatory Implications

- Execution Strategy: For institutional participants, the non linear increase in price impact at larger scales suggests that the execution algorithms should favor smaller, randomized orders to minimize the liquidity penalty associated with large scale selling.
- Market Design: The ANOVA results confirm that during high volatility the cost of trading becomes higher which may discourage trading when liquidity is needed to stabilize the market. While widening spread during times of high volatility is a reasonable risk mitigation strategy for market makers, it creates a challenge for exchange designers seeking to maintain orderly markets during volatility shocks.

5.5 Limitations

- Chronological Horizon: Having a sample period of three months provides a very high resolution picture, which might neither capture macro-economic changes nor the crypto cycles.
- Hidden Liquidity: A major drawback of L2 trade data is the presence of "iceberg" orders. Because of the lack of visibility of hidden orders in the limit order book, there could be a tendency to overstate the bid-ask spread if marketmakers are engaged in hidden levels.
- Exchange Specificity: The results obtained above are specific to the Bybit BTC/USDT market. Other assets with lower liquidity may give different results as the effect of price impact and market asymmetry is likely to be more significant.

5.6 Avenues for Future Research

Future studies could make use of more innovative “Information Bars,” such as Volume or Dollar Imbalance Bars, discussed in Lopez de Prado (2018). In contrast to eras based on fixed trade volumes, these bars account for the actual amount of exchanged value, which may offer a more detailed perspective of the “Information Clock.” Moreover, it should be investigated through cross-exchange analysis that whether the detected $30.46 imbalance is an event specifically occurring in Bybit or is it an intrinsic characteristic of the Bitcoin market structure.

6 Conclusion

This study successfully moved away from the deceptive nature of time based aggregation. Through use of the “Economic Clock” (Clark, 1973), the results of this study follow a more Gaussian distribution, which makes statistical tests (ANOVA and T-tests in this case) more reliable than if time based bars were used.

We split our eras into groups of 50,000 trades each which serves as a middle ground between short and long term intraday trading. Trade imbalance holding an R^2 value of ~0.43 goes to show that informed traders make up a significant amount of the price movement. This is due to the fact that market makers must protect themselves from these traders so they widen bid ask spreads during high volatile regimes. The differences in magnitude show that this protective behavior is much more aggressive during sell offs than rallies. This study was repeated 2 more times with eras made up of 10,000 and 100,000 trades which provided results following our hypothesis.

The sell side fragility shown is empirical proof of the loss and margin spirals (Brunnermeier & Pedersen). Due to the fact that Bitcoin operates 24/7 with high leverage, small price drops can trigger forced liquidations, which “accelerate” the crash because market makers have widened the spread and stepped away.

While the use of fixed trade bars is better than that of time based bars, future studies could look at Dollar Imbalance Bars (Lopez de Prado) to see if the value of the trades changes the asymmetry even more. Additionally as more institutional ETFs enter the market we might see this asymmetry decrease, as liquidity gets deeper, or increase, as more bots use the same stop loss levels. While Bitcoin has achieved institutional legitimacy, its underlying microstructure remains inherently fragile; understanding these asymmetric liquidity drains is not nearly an exercise for academia though rather a prerequisite for navigating the future era of digital finance.

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