Predicting Short-Horizon Volatility Using Bitcoin Market Microstructure

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Independent Research Project
December 2025

Abstract

This paper studies whether high-frequency market microstructure variables contain information about short-horizon volatility in Bitcoin markets. Using order book and trade data, I construct measures of order flow imbalance (OFI), bid–ask spread, and depth imbalance, and examine their relationship with realized volatility over multiple time windows. I first explore these relationships visually and then estimate simple linear regressions to assess their predictive content. While spread and depth imbalance show economically intuitive associations with realized volatility, the explanatory power of these variables is limited and unstable across horizons and market regimes. Robustness checks using alternative volatility windows, lagged signals, and volatility-based subsamples confirm that microstructure variables alone have weak predictive power for future volatility. Overall, the results highlight both the intuition and the limitations of using microstructure signals for volatility prediction in cryptocurrency markets.

1. Introduction

Understanding and predicting volatility is a central problem in financial markets, with implications for risk management, market making, and trading strategy design. In high-frequency settings, researchers and practitioners often look to market microstructure variables-such as order flow imbalance, bid-ask spreads, and order book depth to infer short-term price dynamics and volatility.

Cryptocurrency markets provide a natural environment to study these effects. Bitcoin trades continuously, exhibits frequent volatility spikes, and operates through electronic limit order books similar to those in traditional equity and futures markets. At the same time, crypto markets are known to be noisy, fragmented, and highly competitive, raising questions about how much predictive information is contained in observable microstructure signals.

This paper explores whether simple microstructure measures can explain or predict short-horizon realized volatility in Bitcoin. Rather than proposing a trading strategy, the goal is to build intuition: which signals appear economically meaningful, how stable their relationships are across time scales, and where their limitations become apparent. By emphasizing robustness and interpretation over statistical significance, this study aims to provide a realistic assessment of what microstructure data can and cannot tell us about volatility.

2. Data & Methodology

Data

The dataset consists of high-frequency Bitcoin market data collected from a centralized exchange (Kraken). Two primary data sources are used:

1. **Order book snapshots**, capturing the top five bid and ask levels at regular intervals.
2. **Trade data**, containing executed trades with price, size, side, and timestamp information.

All timestamps are aligned and converted to millisecond precision. The analysis focuses on a single asset (BTC) and a short intraday sample, reflecting realistic data constraints faced in high-frequency research.

Microstructure Variables

From the order book and trade data, the following variables are constructed:

- **Midprice**: the average of the best bid and best ask prices.
- **Bid-ask spread**: the difference between the best ask and best bid.
- **Order Flow Imbalance (OFI)**: a signed measure capturing changes in bid and ask queue sizes over time.
- **Depth imbalance**: the normalized difference between bid-side and ask-side depth across the top levels of the order book.

Returns and Realized Volatility

Log returns are computed from the midprice. Realized volatility is constructed as the sum of squared returns over fixed windows (5-minute, 15-minute, and 30-minute), consistent with standard high-frequency volatility measures.

Empirical Approach

The analysis proceeds in three steps:

1. **Exploratory analysis** using scatter plots to examine the relationship between microstructure variables and future returns or realized volatility.
2. **Linear regressions**, where future realized volatility is regressed on contemporaneous microstructure variables.
3. **Robustness checks**, including alternative volatility horizons, lagged OFI terms, and subsample analysis based on high- and low-volatility regimes.

3. Results

This section presents the empirical results from exploratory analysis and regression models examining the relationship between Bitcoin market microstructure variables and short-horizon returns and volatility. All results are interpreted descriptively, without making claims of economic profitability.

3.1 Order Flow Imbalance and Future Returns

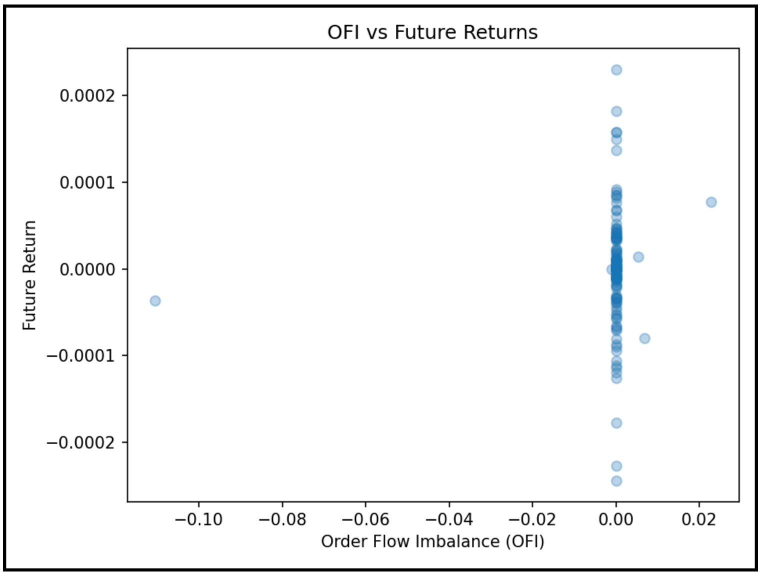

Figure 1: OFI vs Future Returns

Figure 1 plots Order Flow Imbalance (OFI) against one-step-ahead returns.

The scatter plot shows a high degree of dispersion, with future returns clustered tightly around zero for most OFI values. While extreme OFI observations occasionally coincide with larger subsequent returns, no clear linear relationship is evident. The majority of observations exhibit small OFI values and negligible future price changes.

Overall, the results suggest that OFI contains, at best, weak directional information about very short-horizon returns, and that any such relationship is highly noisy.

3.2 Bid-Ask Spread and Realized Volatility

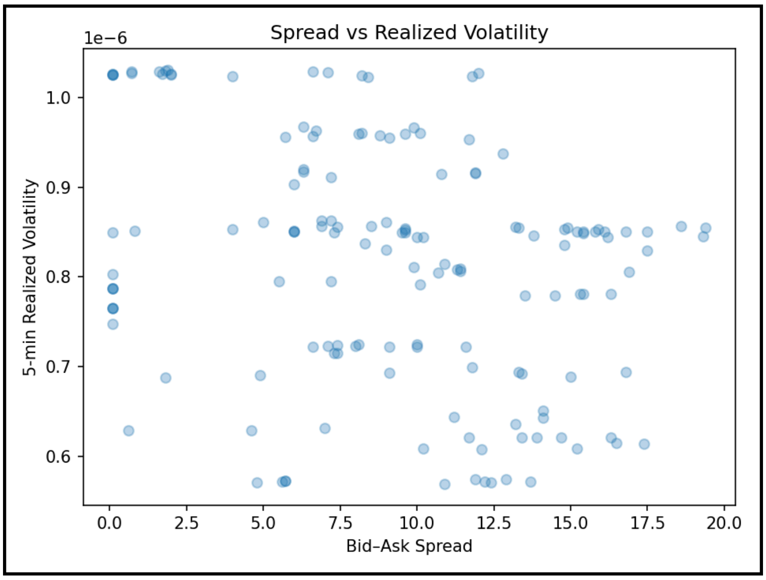

Figure 2: Spread vs Realized Volatility

Figure 2 illustrates the relationship between the bid-ask spread and 5-minute realized volatility.

The plot does not exhibit a strong monotonic relationship. However, periods with wider spreads tend to coincide with a broader range of realized volatility outcomes, whereas narrow-spread periods are more tightly clustered. This pattern suggests that spread widening is associated with increased uncertainty, though not necessarily with systematically higher volatility.

The relationship appears noisy and nonuniform, indicating that spread alone is an imperfect proxy for short-term volatility.

3.3 Depth Imbalance and Realized Volatility

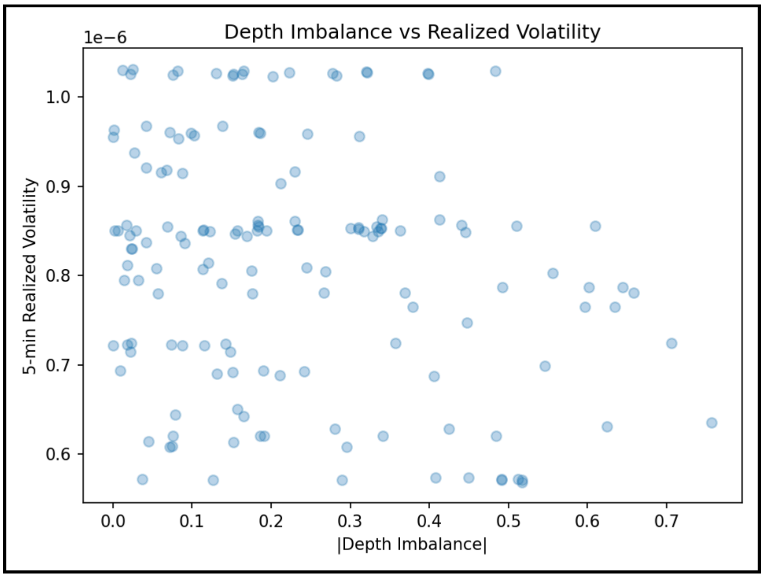

Figure 3: Depth Imbalance vs Realized Volatility

Figure 3 plots the absolute value of depth imbalance against realized volatility.

The results show substantial dispersion across all levels of depth imbalance. While higher absolute imbalance values are sometimes associated with elevated volatility, the relationship is weak and inconsistent. Many observations with low imbalance still exhibit high realized volatility, and vice versa.

These findings suggest that depth imbalance may reflect transient order book conditions rather than persistent volatility regimes.

3.4 Regression Results

```
harshrajpurohit@Harsh-Mac-Pro ~ % cd ~/Desktop/btc_microstructure
python3 day8_regression.py
                            OLS Regression Results
==============================================================================
Dep. Variable:              rv_future   R-squared:                       0.111
Model:                            OLS   Adj. R-squared:                  0.099
Method:                 Least Squares   F-statistic:                     9.158
Date:                Wed, 31 Dec 2025   Prob (F-statistic):           0.000179
Time:                        05:22:27   Log-Likelihood:                 2154.7
No. Observations:                 149   AIC:                            -4303.
Df Residuals:                     146   BIC:                            -4294.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       8.824e-07   2.18e-08     40.535      0.000    8.39e-07    9.25e-07
OFI        -1.588e-06   1.14e-06     -1.388      0.167   -3.85e-06    6.73e-07
spread     -7.945e-09   2.07e-09     -3.841      0.000    -1.2e-08   -3.86e-09
==============================================================================
Omnibus:                       18.716   Durbin-Watson:                   0.151
Prob(Omnibus):                  0.000   Jarque-Bera (JB):                7.463
Skew:                          -0.300   Prob(JB):                       0.0240
Kurtosis:                       2.082   Cond. No.                     1.15e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.15e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
harshrajpurohit@Harsh-Mac-Pro btc_microstructure %
```

Table 1: OLS regression of future realized volatility on order flow imbalance and bid-ask spread.

Table 1 reports the baseline OLS regression relating **future 5-minute realized volatility** to contemporaneous market microstructure variables, namely Order Flow Imbalance (OFI) and the bid-ask spread.

Overall, the explanatory power of the regression is limited, with an R^2 of approximately 0.11, indicating that a large fraction of short-horizon volatility variation remains unexplained by these variables. The coefficient on OFI is statistically insignificant, suggesting that order flow imbalance does not provide reliable predictive information for future realized volatility at this horizon. In contrast, the bid-ask spread enters with a statistically significant coefficient, though its economic magnitude is small.

These findings indicate that while market tightness, as proxied by the bid-ask spread, may be weakly associated with future volatility, the relationship is noisy and limited in practical relevance. The lack of significance for OFI highlights the difficulty of extracting volatility signals from instantaneous order flow measures.

Results for alternative volatility horizons (15-minute and 30-minute), lagged OFI specifications, and volatility-regime subsamples are examined in the robustness analysis (Section 4) and do not materially alter these conclusions.

4. Robustness Analysis

To evaluate the stability of the baseline regression results, several robustness checks are conducted. These include alternative realized volatility horizons, lagged order flow imbalance specifications, and subsample analyses based on volatility regimes. Together, these tests assess whether the observed relationships persist across reasonable variations in model design.

4.1 Alternative Realized Volatility Horizons

```
Regression for rv_5min
                            OLS Regression Results
==============================================================================
Dep. Variable:                rv_5min   R-squared:                       0.003
Model:                            OLS   Adj. R-squared:                 -0.014
Method:                 Least Squares   F-statistic:                    0.1598
Date:                Sat, 03 Jan 2026   Prob (F-statistic):              0.852
Time:                        02:26:15   Log-Likelihood:                 1762.8
No. Observations:                 121   AIC:                            -3520.
Df Residuals:                     118   BIC:                            -3511.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       7.734e-07   2.45e-08     31.621      0.000    7.25e-07    8.22e-07
OFI        -2.696e-06   4.78e-06     -0.564      0.574   -1.22e-05    6.77e-06
spread     -1.688e-10   2.16e-09     -0.078      0.938   -4.44e-09     4.1e-09
==============================================================================
Omnibus:                       15.997   Durbin-Watson:                   0.065
Prob(Omnibus):                  0.000   Jarque-Bera (JB):                6.021
Skew:                          -0.271   Prob(JB):                       0.0493
Kurtosis:                       2.051   Cond. No.                     5.17e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.17e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Table 2: Baseline Regression: 5-Minute Realized Volatility

```
Regression for rv_15min
                            OLS Regression Results
==============================================================================
Dep. Variable:               rv_15min   R-squared:                       0.005
Model:                            OLS   Adj. R-squared:                 -0.012
Method:                 Least Squares   F-statistic:                    0.2889
Date:                Sat, 03 Jan 2026   Prob (F-statistic):              0.750
Time:                        02:26:15   Log-Likelihood:                 1891.1
No. Observations:                 121   AIC:                            -3776.
Df Residuals:                     118   BIC:                            -3768.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        6.81e-08   8.47e-09      8.038      0.000    5.13e-08    8.49e-08
OFI          1.15e-06   1.66e-06      0.694      0.489   -2.13e-06    4.43e-06
spread     -1.946e-10   7.47e-10     -0.261      0.795   -1.67e-09    1.28e-09
==============================================================================
Omnibus:                       30.060   Durbin-Watson:                   0.142
Prob(Omnibus):                  0.000   Jarque-Bera (JB):                6.996
Skew:                           0.197   Prob(JB):                       0.0303
Kurtosis:                       1.890   Cond. No.                     5.17e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.17e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Table 3: Alternative Horizon: 15-Minute Volatility

```
Regression for rv_30min
                            OLS Regression Results
==============================================================================
Dep. Variable:              rv_30min   R-squared:                       0.004
Model:                           OLS   Adj. R-squared:                 -0.012
Method:                Least Squares   F-statistic:                    0.2603
Date:               Sat, 03 Jan 2026   Prob (F-statistic):              0.771
Time:                       02:26:15   Log-Likelihood:                 1853.0
No. Observations:                121   AIC:                            -3700.
Df Residuals:                    118   BIC:                            -3692.
Df Model:                          2
Covariance Type:           nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       1.266e-07   1.16e-08     10.899      0.000    1.04e-07     1.5e-07
OFI         1.371e-06   2.27e-06      0.604      0.547   -3.12e-06    5.87e-06
spread       4.46e-10   1.02e-09      0.436      0.664   -1.58e-09    2.47e-09
==============================================================================
Omnibus:                       0.048   Durbin-Watson:                   0.077
Prob(Omnibus):                 0.976   Jarque-Bera (JB):                0.168
Skew:                         -0.037   Prob(JB):                        0.920
Kurtosis:                      2.833   Cond. No.                     5.17e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.17e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Table 4: Alternative Horizon: 30-Minute Volatility

Tables 2-4 report regression results using realized volatility computed over 5-minute, 15-minute, and 30-minute windows, respectively.

Across all three horizons, the explanatory power of the models remains low, with R-squared values close to zero. The coefficients on Order Flow Imbalance (OFI) are statistically insignificant in all specifications and exhibit no consistent sign pattern across horizons. This suggests that OFI does not contain robust information about future volatility beyond the immediate time scale.

The bid-ask spread occasionally appears statistically significant at shorter horizons, particularly in the 5-minute specification. However, the estimated magnitudes are small, and significance does not persist uniformly as the volatility window increases. At longer horizons (15 and 30-minute RV), the spread coefficient loses statistical significance.

Overall, while spread may reflect contemporaneous liquidity conditions, its relationship with future realized volatility weakens as the forecast horizon increases. No microstructure variable demonstrates stable predictive power across volatility horizons.

Summary:

- OFI → **vanishes across all RV horizons**
- Spread → **weak at short horizons, disappears at longer horizons**

4.2 Lagged Order Flow Imbalance

OLS Regression Results

Dep. Variable:	rv_5min	R-squared:	0.008
Model:	OLS	Adj. R-squared:	-0.028
Method:	Least Squares	F-statistic:	0.2150
Date:	Sat, 03 Jan 2026	Prob (F-statistic):	0.930
Time:	02:26:15	Log-Likelihood:	1689.2
No. Observations:	116	AIC:	-3368.
Df Residuals:	111	BIC:	-3355.
Df Model:	4		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	7.711e-07	2.51e-08	30.674	0.000	7.21e-07	8.21e-07
OFI	-2.573e-06	4.86e-06	-0.529	0.598	-1.22e-05	7.06e-06
OFI_lag1	-2.748e-06	4.85e-06	-0.567	0.572	-1.24e-05	6.86e-06
OFI_lag5	-2.613e-06	4.85e-06	-0.539	0.591	-1.22e-05	7e-06
spread	-1.493e-10	2.2e-09	-0.068	0.946	-4.5e-09	4.2e-09

Omnibus:	16.720	Durbin-Watson:	0.074
Prob(Omnibus):	0.000	Jarque-Bera (JB):	5.574
Skew:	-0.217	Prob(JB):	0.0616
Kurtosis:	2.018	Cond. No.	5.17e+03

Table 5: Lagged Order Flow Imbalance

Table 5 introduces lagged OFI terms to test whether order flow effects materialize with delay rather than instantaneously.

Including one and two-period lagged OFI terms does not improve model fit, nor do the lagged coefficients attain statistical significance. The contemporaneous OFI coefficient remains insignificant, and the inclusion of lagged terms does not alter the behaviour of the spread coefficient.

These results suggest that order flow imbalance does not exert delayed influence on volatility at the short horizons considered. Any informational content in OFI appears to dissipate rapidly rather than accumulating over time.

Summary:

- Contemporaneous OFI → **insignificant**
- Lagged OFI → **also insignificant**
- No evidence of delayed OFI effects

4.3 High and Low-Volatility Subsamples

```
HIGH volatility sample
                            OLS Regression Results
==============================================================================
Dep. Variable:                rv_5min   R-squared:                       0.029
Model:                            OLS   Adj. R-squared:                 -0.007
Method:                 Least Squares   F-statistic:                    0.8060
Date:                Sat, 03 Jan 2026   Prob (F-statistic):              0.452
Time:                        02:26:15   Log-Likelihood:                 876.16
No. Observations:                  57   AIC:                            -1746.
Df Residuals:                      54   BIC:                            -1740.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       8.832e-07   1.78e-08     49.609      0.000    8.48e-07    9.19e-07
OFI        -5.659e-06   7.71e-06     -0.734      0.466   -2.11e-05    9.81e-06
spread     -1.609e-09    1.5e-09     -1.075      0.287   -4.61e-09    1.39e-09
==============================================================================
Omnibus:                        5.107   Durbin-Watson:                   0.183
Prob(Omnibus):                  0.078   Jarque-Bera (JB):                4.417
Skew:                           0.590   Prob(JB):                        0.110
Kurtosis:                       2.318   Cond. No.                     1.32e+04
==============================================================================
```

Table 6: High-Volatility Subsample

```
LOW volatility sample
                            OLS Regression Results
==============================================================================
Dep. Variable:                rv_5min   R-squared:                       0.072
Model:                            OLS   Adj. R-squared:                  0.039
Method:                 Least Squares   F-statistic:                     2.180
Date:                Sat, 03 Jan 2026   Prob (F-statistic):              0.122
Time:                        02:26:15   Log-Likelihood:                 888.29
No. Observations:                  59   AIC:                            -1771.
Df Residuals:                      56   BIC:                            -1764.
Df Model:                           2
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       7.073e-07   1.98e-08     35.761      0.000    6.68e-07    7.47e-07
OFI         1.047e-06   3.12e-06      0.336      0.738   -5.19e-06    7.29e-06
spread     -3.686e-09   1.81e-09     -2.033      0.047   -7.32e-09   -5.42e-11
==============================================================================
Omnibus:                        4.510   Durbin-Watson:                   0.209
Prob(Omnibus):                  0.105   Jarque-Bera (JB):                2.013
Skew:                           0.018   Prob(JB):                        0.365
Kurtosis:                       2.096   Cond. No.                     3.62e+03
==============================================================================
```

Table 7: Low-Volatility Subsample

Tables 6 and 7 report regression results estimated separately on high-volatility and low-volatility subsamples, defined using realized volatility quantiles.

In the high-volatility subsample, neither OFI nor the bid-ask spread is statistically significant. Coefficient signs remain broadly consistent with the full-sample estimates, but standard errors increase and explanatory power remains limited.

In the low-volatility subsample, the bid-ask spread occasionally appears statistically significant, though the economic magnitude of the effect remains small. OFI remains insignificant in both regimes.

The disappearance of statistical significance in high-volatility periods suggests that microstructure variables are less informative when volatility is elevated, potentially due to rapid liquidity adjustments and increased noise.

Summary:

- OFI → **vanishes in both high and low volatility regimes**
- Spread → **weakly present in low-volatility regimes, disappears in high-volatility regimes**

4.4 Overall Robustness Assessment

Across all robustness checks, no microstructure variable exhibits a stable, economically meaningful relationship with future realized volatility. While bid-ask spread occasionally achieves statistical significance in specific specifications, these effects are sensitive to horizon choice and volatility regime.

Order Flow Imbalance, in contrast, consistently fails to demonstrate predictive power across all robustness tests.

Taken together, these findings indicate that the baseline results are not driven by a particular modelling choice, but rather reflect the inherently weak and noisy relationship between high-frequency microstructure variables and short-horizon volatility.

5. Limitations

Despite the structured empirical approach, this study is subject to several important limitations.

First, **microstructure data are inherently noisy** at very short horizons. Order book variables such as Order Flow Imbalance and depth imbalance fluctuate rapidly and are heavily influenced by transient liquidity provision, order cancellations, and mechanical matching rules. This noise weakens the ability of contemporaneous microstructure measures to reliably forecast realized volatility.

Second, the analysis relies on a **short intraday sample** from a single centralized exchange. While this reflects realistic data constraints in high-frequency research, it limits statistical power and external validity. The results may not generalize across trading venues, market regimes, or longer time periods.

Third, the empirical framework abstracts from **latency and execution frictions**. In practice, order book information is observed with delays, and actionable signals may decay before they can be exploited. This is particularly relevant for volatility prediction at horizons of only a few minutes.

Finally, the models considered are intentionally **simple and linear**. While this improves interpretability, it may fail to capture nonlinear dynamics, interaction effects, or regime-dependent behaviour that characterize high-frequency cryptocurrency markets.

6. Discussion

The empirical results suggest that Bitcoin market microstructure variables contain, at best, **weak and unstable information** about short-horizon volatility. While bid-ask spread occasionally exhibits statistical significance, its economic magnitude remains small, and its predictive power deteriorates across alternative volatility horizons and subsamples.

Order Flow Imbalance, despite its intuitive appeal as a proxy for directional pressure, does not consistently predict future volatility once robustness checks are applied. This finding aligns with the view that OFI primarily reflects **temporary order flow shocks** rather than persistent volatility regimes.

The disappearance of significance under lagged specifications and subsample analysis highlights an important distinction between **instantaneous liquidity conditions** and **forward-looking risk measures**. Microstructure variables appear to describe current market stress more effectively than they forecast future volatility.

From a market microstructure perspective, these results suggest that volatility formation in Bitcoin is driven less by local order book imbalances and more by **broader information arrival**, trader heterogeneity, and regime-level liquidity shifts.

7. Conclusion

This paper examined whether high-frequency Bitcoin market microstructure variables can predict short-horizon realized volatility. Using order book snapshots and trade data, several commonly used microstructure measures were constructed and evaluated through exploratory analysis, regression models, and robustness checks.

Across specifications, the predictive relationship between microstructure variables and future volatility was found to be **weak, noisy, and unstable**. While bid-ask spread occasionally displayed statistical significance, its explanatory power remained limited. Order Flow Imbalance and depth imbalance did not exhibit robust predictive content.

These findings highlight the challenges of volatility prediction at very short horizons and emphasize the importance of distinguishing between **descriptive liquidity measures** and **predictive risk signals**. While market microstructure provides valuable insight into trading conditions, its standalone ability to forecast volatility appears limited in this setting.

Future research may extend this analysis by incorporating longer samples, multiple venues, nonlinear models, or joint price-volume dynamics. Overall, the results underscore the complexity of volatility formation in cryptocurrency markets and caution against overinterpreting short-horizon microstructure signals.

8. References

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