

Orderbook Delta price reaction research

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Orderbook Delta definition

The orderbook delta is calculated by the difference between the sum of the bid and ask orders at a certain depth. Formula:

$$\Delta_{x\%} = \sum_{i=1}^{x\%} \Delta_i$$

- $\Delta_{x\%}$ is the sum of the orderbook delta for the last $x\%$ of the orderbook.
- Δ_i is the orderbook delta for the i -th level of the orderbook.

Outlier Detection Using Mean and Standard Deviation (Z-Score Based Outlier Detection)

Normal Range

What I want to test is how price reacts to anomalous orderbook delta movements, particularly in scenarios where unrealistic or clearly outlying values are detected. In cryptocurrency markets, such inefficiencies can be caused by various events, one example is liquidation events that interact with passive demand order stacked zones. During these events, the orderbook delta exhibits significant increases, providing a clear signal of market stress. This research will focus on understanding the relationship between rapid delta movements and how price reacts after these events.

My Hypothesis

- I expect realized volatility to increase after an outlier is detected.
- I expect a return to the mean after a strong outlier is detected.

Normal Range

$$\mu(\Delta) \pm 2\sigma(\Delta)$$

This means most data points (about 95% if normally distributed) are expected to lie within this range.

Outlier Condition

A value is considered an outlier if:

$$\Delta < \mu(\Delta) - 2\sigma(\Delta) \quad \text{or} \quad \Delta > \mu(\Delta) + 2\sigma(\Delta) \quad (1)$$

This is a simple Z-score based outlier detection.

- Δ - Orderbook Delta Depth with a certain depth I will test on: $\Delta_{1\%}$ $\Delta_{2.5\%}$ $\Delta_{5\%}$ from Coinbase (BTC/USD)
- This basically means we take a delta of the Bid and Ask orders which are in a range of x% from the current price.
- $\mu(\Delta)$ — Mean of the last 1440 values of Δ before time t
- $\sigma(\Delta)$ - Standard deviation over the last 1440 Δ values before time t

Idea behind

- This method assumes data is roughly normally distributed.
- Using 2σ captures approximately 95% of data points under a normal distribution.
- You can adjust the multiplier (e.g., 3σ) for stricter or looser thresholds.

Future Plans

- Test on more data
- use rolling windows (e.g. 1 day or 1 week) for local context.
- Compare sensitivity with $\pm 1.5\sigma$ or $\pm 2.5\sigma \rightarrow$ optimize for best results

Measuring Volatility After Price Outlier Detection

$$r_t = \frac{P_t - P_{t-1}}{P_{t-1}} \quad (2)$$

Dictionary of Terms

- P_t Asset price at time t .
- $r_t = \frac{P_t - P_{t-1}}{P_{t-1}}$ – 1-minute price return at time t .
- $\sigma_t^{(15)}$ – Realized volatility: the standard deviation of the next 15 one-minute returns,

$$\sigma_t^{(15)} = \sqrt{\frac{1}{14} \sum_{i=1}^{15} (r_{t+i} - \bar{r}_t)^2}, \quad \bar{r}_t = \frac{1}{15} \sum_{i=1}^{15} r_{t+i}. \quad (3)$$

aligned so that at time t it measures volatility over $t + 1$ to $t + 15$.

In Python code

```
import pandas as pd
df = pd.read_csv(file_path)
df.set_index('timestamp', inplace=True)
#Compute 1-min return of delta_5

df['r_t'] = df['price'].pct_change().fillna(0)

#compute rolling std of the future 15 min window

window = 15

#rolling on r_t, then shift forward so index t hold vol of t+1...t+15
df['future_vol_15'] = (
    df['r_t']
    .rolling(window=window)
    .std()
    .shift(-window)
)
```

Statistical evidence

Once an outlier is detected (1) inside of the Orderbook Δ , we calculate the 15-minute ahead realized volatility using Equation: (3)

if a Δ_t values is flagged as an outlier (1) we record

$$\sigma_t^{(15)} = \sqrt{\frac{1}{14} \sum_{i=1}^{15} (r_{t+i} - \bar{r}_t)^2},$$

We then form two samples over our full dataset which during this test includes 104 957 one minutes intervals of P and Orderbook Δ :

$$\mathcal{S}_{\text{out}} = \{\sigma_t^{(15)} : t \text{ is an outlier}\}, \quad \mathcal{S}_{\text{non}} = \{\sigma_t^{(15)} : t \text{ is not an outlier}\}.$$

Sample mean results:

$$\bar{\sigma}_{\text{out}}^{(15)} = 0.0006244, \quad \bar{\sigma}_{\text{non}}^{(15)} = 0.0005138,$$

This concludes an increase of r_t of roughly 21.5%

To check Statistical evidence

- a two-sample *t*-test (unequal variances), which yields

$$T = 24.72, \quad p = 4.79 \times 10^{-132},$$

- a Mann–Whitney *U*-test, which returns

$$p = 4.02 \times 10^{-157}.$$

Optimising for best Z-Score threshold for outliers

As state inside of (1) we use a Z-Score threshold of 2 to detect outliers. I now want to see if by any chance there is a better Threshold value

To compare the outliers Volatility with the non outliers volatility I will use the following formular:

$$U(z) = \frac{\overline{\sigma}_{\text{out}}^{(15)}}{\overline{\sigma}_{\text{non}}^{(15)}} \quad (4)$$

First I run an optimization for the thresholds of the Z-Score to find the best threshold value for the outliers on a 45 days dataset. After that I compare the result with a 107880 minutes dataset. Where I also run an optimization for the thresholds of the Z-Score to find the best threshold value for the outliers.

Top 3 z -values with largest volatility uplift 69811-minutes sample

z	N_{out}	$U(z)$ (%)	Mann-Whitney p
3.8	221	+58.36	1.913×10^{-51}
3.9	166	+61.99	4.227×10^{-41}
4.0	117	+58.36	8.228×10^{-28}

Same z -values on extended dataset 107880-minutes sample

z	N_{out}	$U(z)$ (%)	Mann-Whitney p
3.8	644	+51.73	2.549×10^{-77}
3.9	561	+53.28	6.150×10^{-88}
4.0	479	+50.90	5.517×10^{-59}

Top 3 z -values with largest volatility uplift 107880-minutes sample

z	N_{out}	$U(z)$ (%)	Mann-Whitney p
4.8	214	+65.10	6.475×10^{-33}
4.9	197	+66.81	3.693×10^{-29}
5.0	181	+70.53	6.599×10^{-28}

Measuring average return after price outlier detection

Formulas

Once a Δ_t Outlier is detected we calculate the 15-min forward return of BTC/USD price

$$\text{Ret}_t^{(15)} = \frac{P_{t+15} - P_t}{P_t} \quad (4)$$

We then differentiate between a bullish and a bearish outlier. Which is already defined (1)

$$\overline{\text{Ret}}_{\text{bull}}^{(15)} = \frac{1}{|\mathcal{T}_{\text{bull}}|} \sum_{t \in \mathcal{T}_{\text{bull}}} \text{Ret}_t^{(15)} \quad (7)$$

$$\overline{\text{Ret}}_{\text{bear}}^{(15)} = \frac{1}{|\mathcal{T}_{\text{bear}}|} \sum_{t \in \mathcal{T}_{\text{bear}}} \text{Ret}_t^{(15)} \quad (8)$$

Dictionary of Terms

- Price at a certain time: P_t
- 15-min forward return: $\text{Ret}_t^{(15)}$

#compute 15-min forward return of BTC/USD price

1 Combining indicators for strategy

Underlying strategy Bias

Every single parameter has to fight to be implemented into my strategy. To get some kind of filter since we are working with an asset which has clear trends and isn't stationary we need to do some trend identification. I'll call it the underlying bias. Some simple examples are for a bias are:

- $\Delta_{5\%} < 0$ (more passive demand than supply)
- $EMA_n > P_t$ (EMA is an exponential average of $P_t - n$, $P - T$ is the price at time t)
- $EMA_n > EMA_x$ (Crossing of two EMAs with different time periods n and x)

But I want to get some clear trend identification where we divide into the three different categories:

Ideas I want to test on:

- Market Structure definition (Higher Highs and Higher Lows)
- Relative strength index on Price and $\Delta_{x\%}$

Finding an edge

No clear path

Finding an edge is a very hard task. There is no clear path to success. You kinda have to try by trail and error every error could be a step further but also a potential path into a dead end.

Sources: TRDR This platform allow you to use different kind of metrics on different Timeseries datasets (BTC/USD Price, orderbookdelta and Open Interest

2 Comparison of Delta Indicators on 39,694-minute sample

Period	$N_{signals}$	$U(z)$ (%)	T-statistic p
Delta2.5 Strategy ($N_{total} = 9,182$)			
5m	9,182	+52.03	1.851×10^{-41}
60m	9,182	+55.94	3.537×10^{-4}
360m	9,182	+59.20	12.524×10^0
Delta5 Strategy ($N_{total} = 12,234$)			
5m	12,234	+51.38	3.382×10^{-7}
60m	12,234	+53.44	4.010×10^{-1}
360m	12,234	+57.04	13.617×10^0

Table 1: Comparison of Delta2.5 vs Delta5 strategies across different time periods

- $N_{signals}$ represents number of trading signals
- $U(z)$ represents positive return ratio
- T-statistic p represents statistical significance

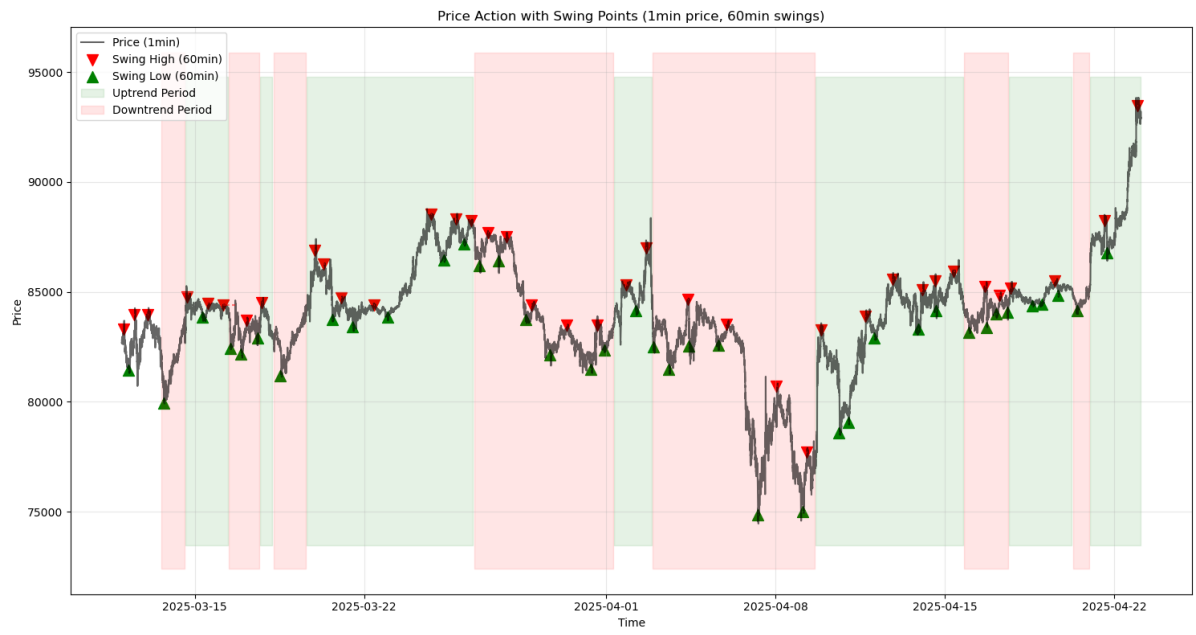


Figure 1: 1 min interval price with 60 min swing points and a n value of 8

Swing Point Bias Visualization

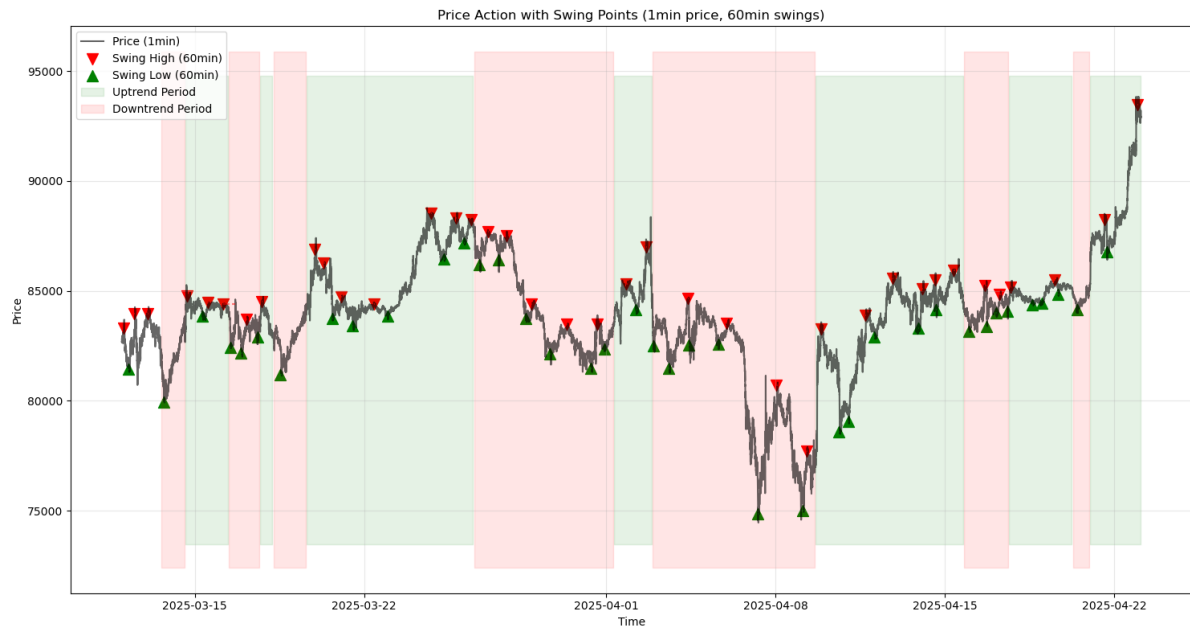


Figure 2: Price Action with Swing Points (1min price, 60min swings) showing trend periods

This visualization demonstrates how swing points are identified on a 1-minute price chart using a 60-minute window for swing point detection. The green and red shaded areas represent uptrend and downtrend periods respectively, while red triangles mark swing highs and green triangles mark swing lows.

Combining Indicators

Here I visulised the swing points, the EMA spread and the 100 outliers with the highest Z-Score in the same plot.

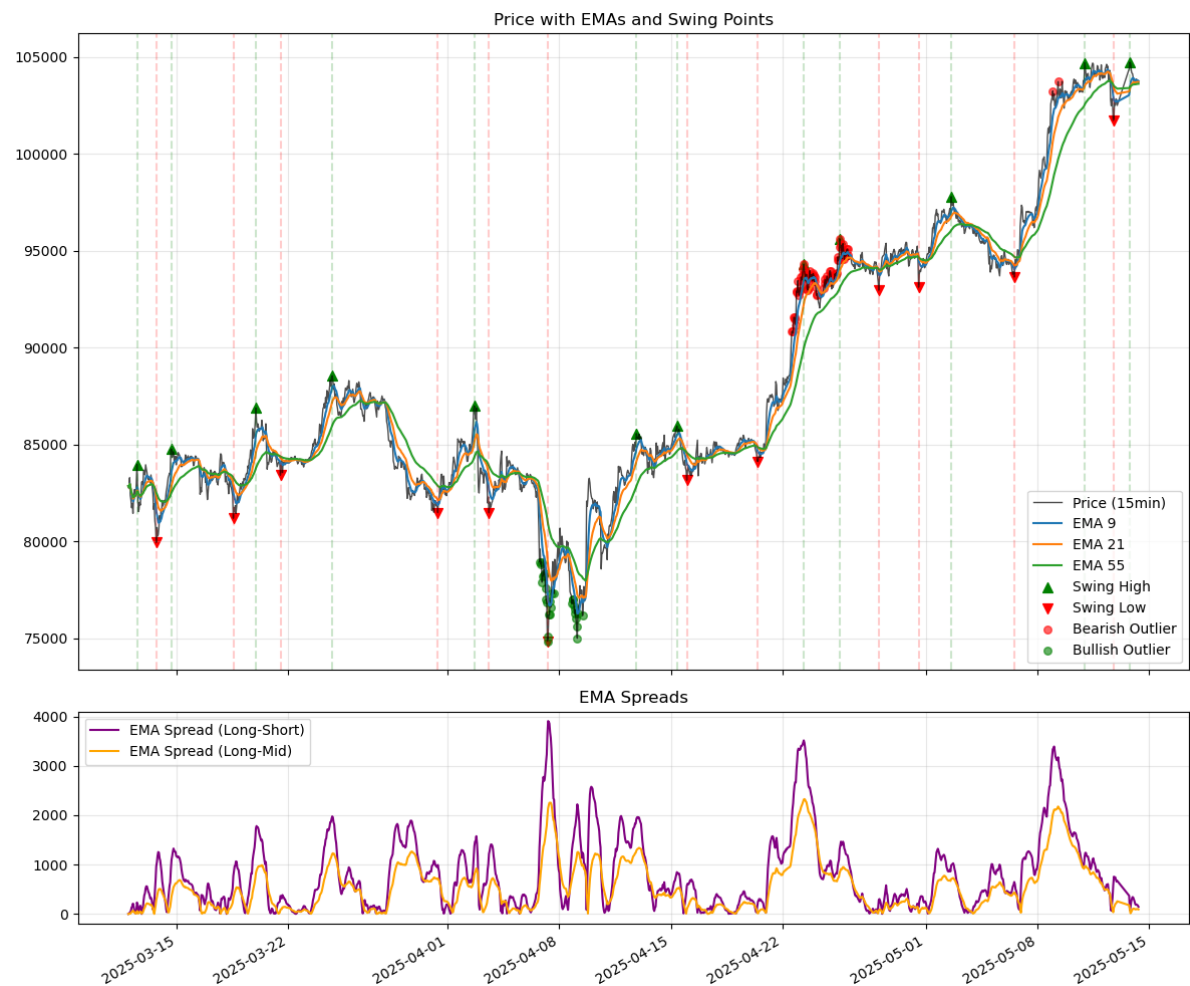


Figure 3: combined indicators png

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¹Chart made with Matplotlib and Seaborn

Mapping Orderbook delta EMA with standard deviation shifing

Formulars

$$EMA_t = \alpha \cdot \Delta_t + (1 - \alpha) \cdot EMA_{t-1} \quad (5)$$

Dictionary of Terms

- EMA_t - Exponential Moving Average at time t
- Δ_t - Orderbook delta at time t
- α - Smoothing factor
- $\alpha = \frac{2}{n+1}$ where n is the period of the EMA
- $\sigma(\Delta)$ - Standard deviation of the orderbook delta with a

We'll now shift the EMA by the standard deviation of the orderbook delta

From outliers to strategy

Progress description

I had a pretty hard time going from developing a logic for the outliers of the Delta. Finding that volatility increases after outliers was a good first find which didn't take long to find. But finding some a defenition condtion is meet directional bias was very difficult. By directional bias I mean a price direction which is not random after some kind of condition. It was pretty clear from the begging on that the outliers by there selfe won't offer any kind of directional bias

An outlier is defined as:

- (1). $\Delta < \mu(\Delta) - 2\sigma(\Delta)$ or $\Delta > \mu(\Delta) + 2\sigma(\Delta)$

Then since we Bitcoin clearly is not a stationary asset I needed to find some kind of trend identification. I found that the swing points are a good indicator for this. We determined a trend by using looking at swingpoints. A swing point is a local extrema of a certain period.

Where did I start my research

```
#compute swing points
swing_points = swing_points(df['price'], period=n)
```

Parameters of the swing_points function:

- n is the lookback period
- $df['price']$ is the price column of the dataframe (Which is a timeseries)
- P_t is a value of $df['price']$ at time t

We basically got through the time series dataset and look back n P_t values. The highest and lowest points inside of that specific lookback period are the swing points. After that we detetermine if price is making higher highs or lower lows. We check this by storeing the last swing points and wait till we are eighter making a higher high or a lower low.

Finding an edge

Developing a strategy

sources

How good or random is your trading

Testing 1000 strategies at the same time (via Monte Carlo)

A lot of my ideas come from thiy guys Tweets, to research into this