Orderbook Delta price reaction research

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Orderbook Delta defenition

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

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

- $\Delta_{x\%}$ 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 expext realized volatility to increase after an outlier is detected.
- I expext 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:

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

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 +- 1.5σ or +-2.5σ $\rightarrow$ optimize for best results

Measuring Volatility After Price Outlier Detection

$$r_t = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{2}$$

Dictionary of Terms

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

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

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 the15-minute ahead realized volatility using Equation: (3)

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

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

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:

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

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 thresold for outliers

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

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

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

First I run an optimization for the thresholds of the Z-Score to find the best thresold 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 thresold 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 avearge return after price outlier detection

Formulars

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

$$\mathrm{Ret}_t^{(15)} \;=\; \frac{P_{t+15} - P_t}{P_t} \tag{4}$$

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

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

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

Dictionary of Terms

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

```
#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)
- $EMA_{\mathrm{n}} > P_t$ (EMA is an exponential average of $P_t - n$, $P - T$ is the price at time t)
- $EMA_{\mathrm{n}} > EMA_{\mathrm{x}}$ (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 defenition (Higher Highs and Higher Lows)
- Realtive strenght 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

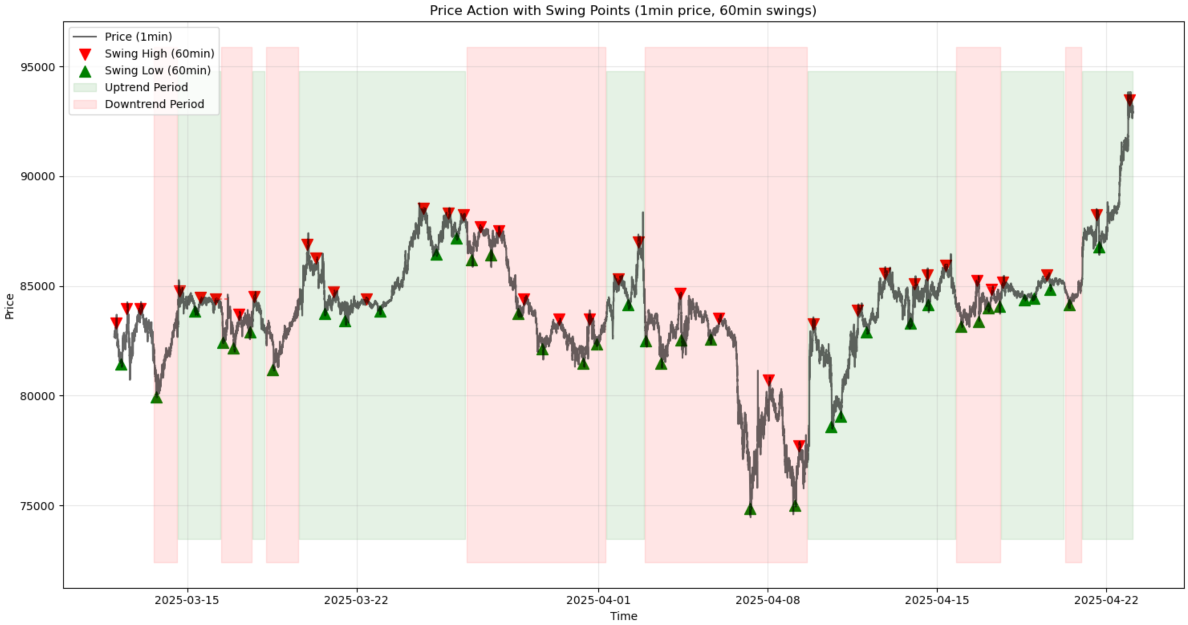

Figure 1: 1 min interval price with 60 min swing points and a n value of 8

Swing Point Bias Visualization

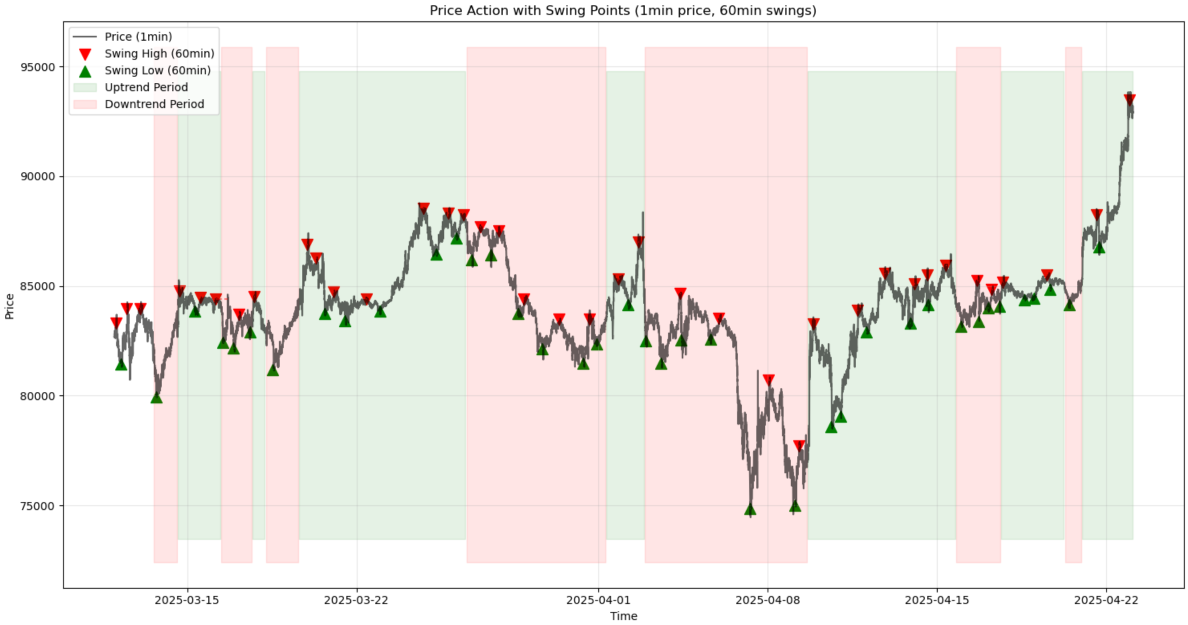

Figure 2: Price Action with Swing Points (1min price, 60min swings) showing trend periods

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.

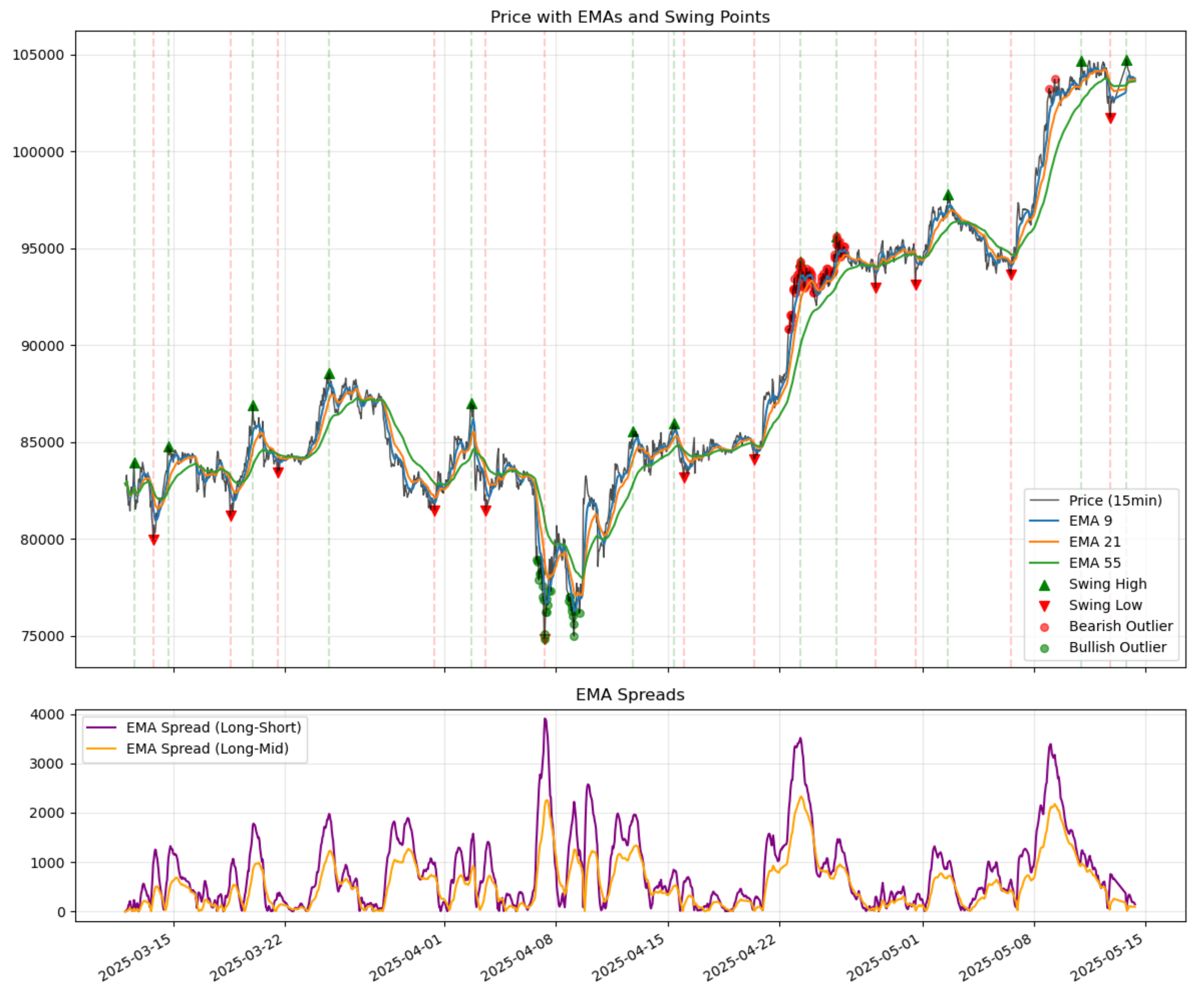

Figure 3: combined indicators png

1

[1]Chart made with Matplotlib and Seaborn

Mapping Orderbook delta EMA with standard deviation shifing

Formulars

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

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

sources

url: How good or random is your trading