IAQF Research:
Impact of Liquidity During de-peg Timeline

Financial context and motivation (including regulatory background): During March 11, 2023, there was a de-peg USDC losing dollar peg below $1 emphasizing the stresses in the liquidity. During the news of Silicon Valley Bank (SVB), the 3.3 billion dollars of reserves were tied that collapsed causing a sell of USDC at a high trades evident in the graph below starting 5:00 am. Interestingly though, although the sells were happening right after the news hit around 5:00 am, we also see a liquidity in trades after 9:00am that has a solid buy and sell movements higher than the normal days. So USDC tends to be liquid in a sense that there is a comeback to the depeg relationship. During this time, the confidence of the stablecoin dropped and the price fell below $1.

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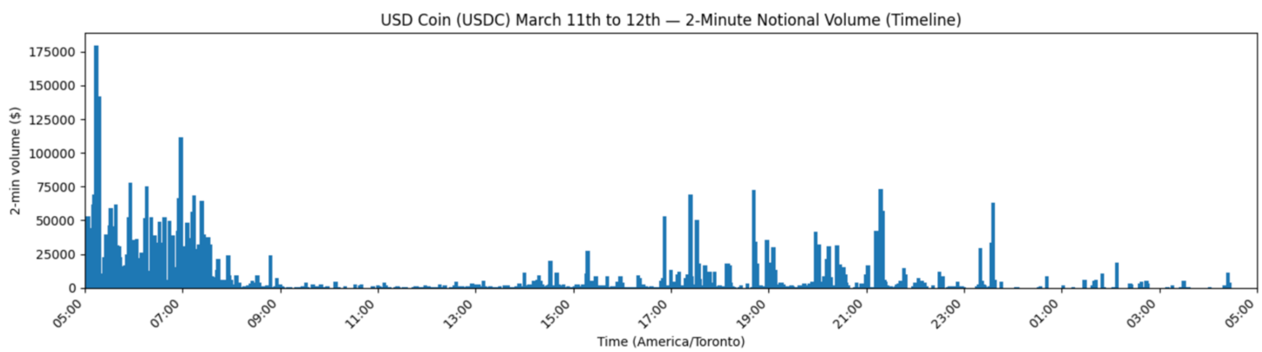
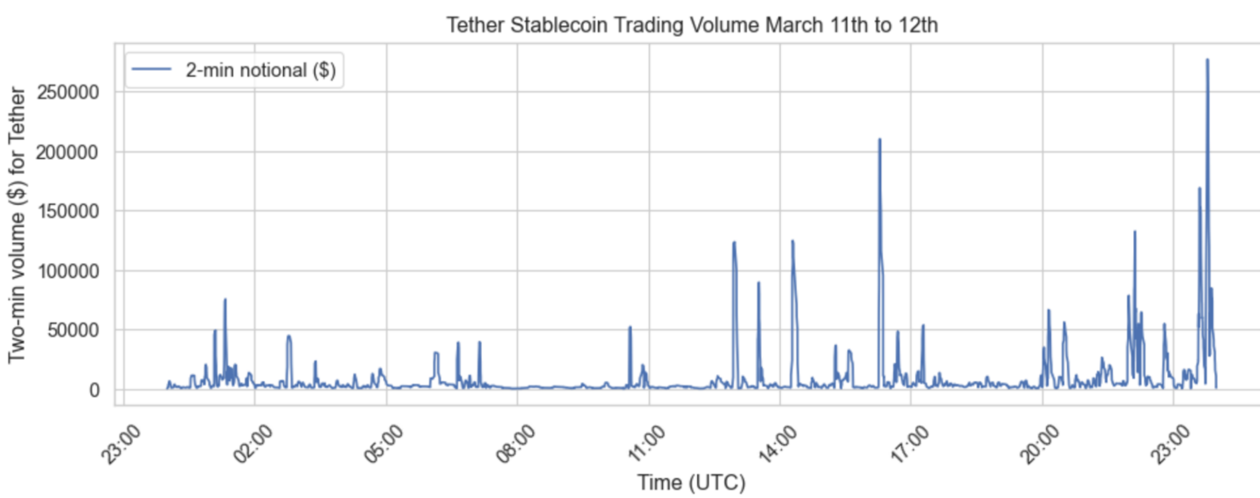
The financial background behind is that on March 10th, USD Coin (USDC) fell as huge asset of 3.3 billion of USDC reserves were withheld at Silicon Valley Bank.

Interestingly though, although the sells were happening right after the news hit around 5:00 am, we also see a liquidity in trades after 9:00am that has a solid buy and sell movements higher than the normal days as evident in USD Coin. So USDC tends to be liquid in a sense that there is a comeback to the depeg relationship.





While we noticed massive activity in the morning for USD coin, Tether was not reacting to the news but rather acting as a capital flow went into the market after the news at 23:00 pm. This is given the context that March 11st of Depeg was on Saturday, where U.S. Banks were closed. So the transfers were not operating at the functional timeline. Therefore, there was a friction-driven capital migration where USD Coin traded traded down to ~$0.87. Surprisingly, Tether traded at a premium (~$1.01–$1.02) given that Tether (USDT) is a globally liquid asset. Since Tether had no direct investments to SVB, a move of asset from one stablecoin USD Coin to another preserved the liquidity of the stable coin through liquidity transfer evident in the graphs above with transfer in Volumes. Through this liquidity movements, the preservation was possible and public trusted the stablecoin assets.

Data description and methodology

During this time, we want to test the moments specifically when de-peg existed in USD Coin to validate whether the moments of high peak in trade broke the structures of the market regime temporarily or permanently. In order to test the liquidity, we design OFE-ABS model which is used to test how much the price moved per unit under the directional pressure based on using the equation. Due to this context, the question of whether liquidity is sustainable has been tested. This real-world regulatory of institutional payment method's liquidity can be tested is not relevant for payments and institutional infrastructure. So we design liquidity testing strategy to see how much price moved per unit of market order flow.

$$\text{OFE-ABS}_t = |\Delta \log_{P_t}| \ / \ |\text{Signed Flow}_t|$$

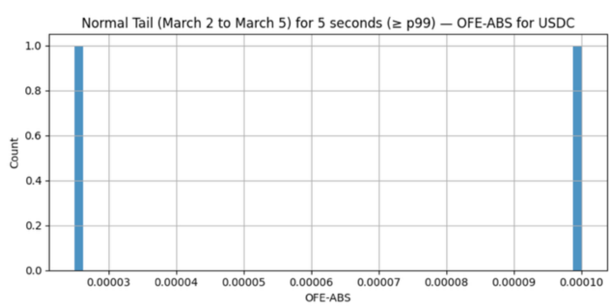
Where we have $\Delta\log\ P_t$= log price change over your rolling window that has Signed Flow that is a net aggressive notional = net aggressive notional (buy − sell) in that window. Sothis measures "How much did price move per unit of directional pressure?" Further, given this, we know that high liquidity means large value means small flow caused by price movement, causing a think liquidity. Also, Small value means large flow caused by small price movements with deep liquidity.

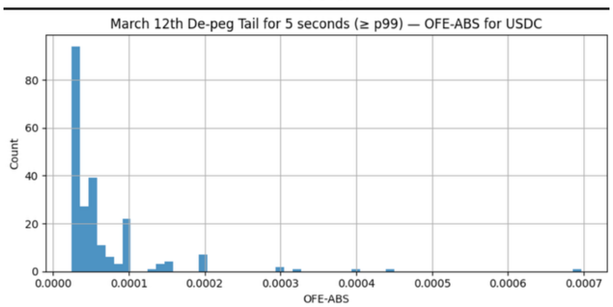
So during this computation process, OFE-ABS Value measures "how much price moved per unit of net aggressive trading pressure". When we have a small value of OFE-ABS result, this means that compared to the large amounts of selling, the price movement was low and so the liquidity is stable and deep. On the other hand, if large OFE-ABS exists, then there is a small selling amounts that cause high price impact so the thin and fragile liquidity exists.

An OFE-ABS value tells you how sensitive price was to directional trading pressure during that minute — higher values indicate weaker liquidity. Next, once we have the list of the values for OFE-ABS for both normal period and de-peg period, we count to see how many OFE-ABS values exceed the normal p99 threshold for the de-peg periods see the distribution. We dig into the microstructure moments of the extreme P-99.9 moments when the looking at the top 0.1% microstructure movements capturing the rare minutes during the de-peg. As a result, we have:

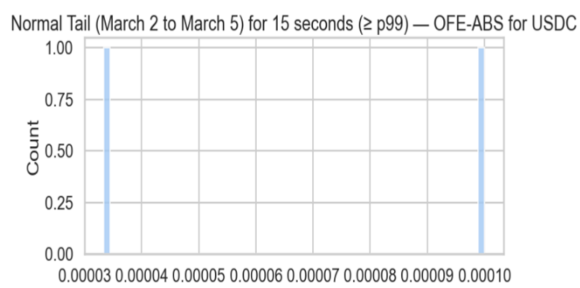
During this time the normal period, we see that the values were clustered tightly, not spread out evenly indicating that in normal periods, liquidity is not extremely dispersed. On the other hand, we see the De-peg Tail where values are higher yet spread out. During the de-peg, extreme liquidity was more volatile and concentrated.

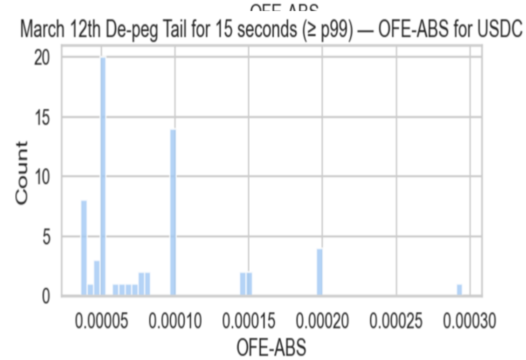
5 seconds window timeline





15 seconds window timeline





In terms of the graph, we see that for 5 seconds window, there is a clear regime collapse. This could be due to the fact that convexity exist in pricing relationship with flow of trades as a liquidity collapse happened in microstructure seconds. "Price impact became state-dependent and increasingly sensitive as liquidity thinned." On the other hand, for 15 seconds window, the distribution of OFE-ABS count is distributed evenly indicating that orderbook depth vanishes at an instantons moment where liquidity providers pull quotes rapidly. Then, "Count" = number of 1-minute windows that exceeded the normal p99 liquidity threshold. Furthermore, this indicates that most of the time, So after we design the threshold, we count how many OFE ABS values exceed this 99% normal minutes that are below threshold. Then, The answer depends on the time horizon that you look into. If you zoom into 5 seconds, we see that the OFE-ABS smaller than 0.0001 actually jumps up to more than 80 counts, and the distribution is also concentrated and not spread out evenly. As it captures more spikes and higher sensitivity to bid-ask bounce. (figure). It is the 5 seconds of microstructure moments that have breaking liquidity. The 15-second aggregation smooths high-frequency liquidity shocks, so it under-detects microstructure fragility due to the aggregation methods.

To further go into the microstructure behind the scene, we desin **CUSUM, cumulative sum,** accumulates deviations of OFE-ABS from its normal baseline and triggers an alarm only when those deviations persist long enough to indicate a temporary liquidity regime shift. We use CUSUM because it detects sustained deviations in liquidity conditions relative to a normal baseline, allowing us to distinguish structural liquidity stress from isolated microstructure noise.

Whenever there is an upward detection,

$$\boldsymbol{S_t = \max\,(0,\, S_{t-1} + (z_t - k))}$$

such that,

- S_t= CUSUM statistic
- k= drift parameter (small tolerance)
- h= alarm threshold

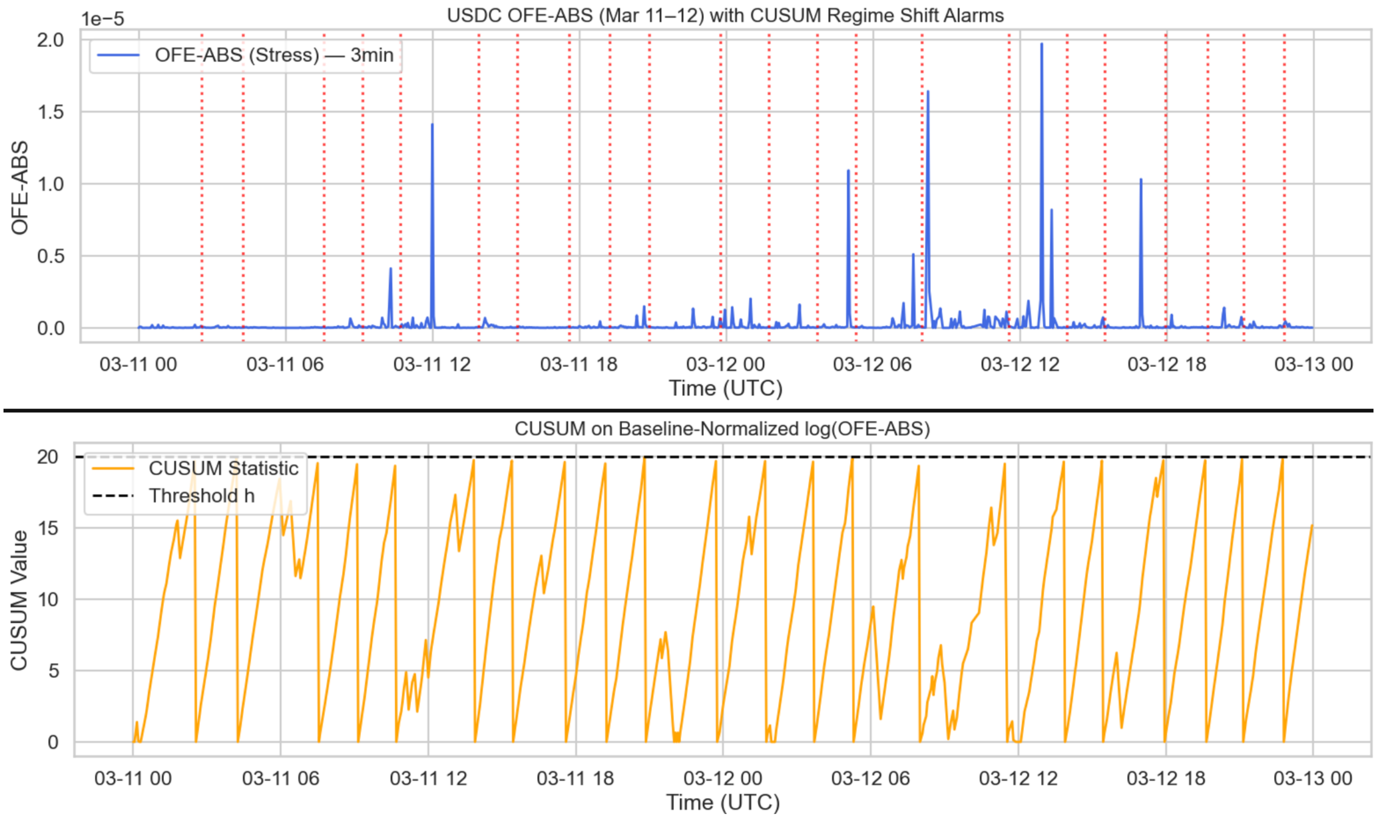
And alarm happens when

$$S_t > h$$

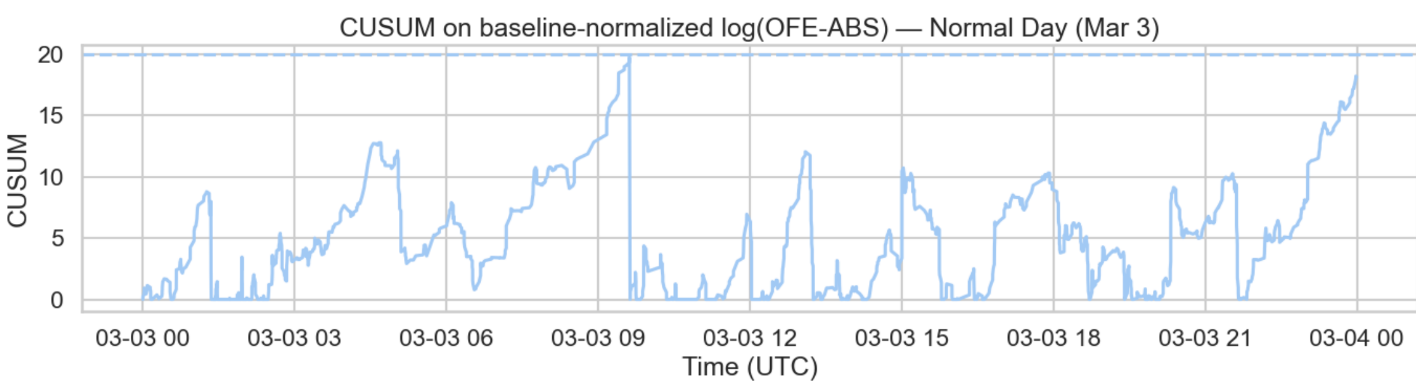
If such case is true,
Alarm triggers
Reset $S_t = 0$

Then accumulation starts again as well. In this way, price impact has stayed above normal levels long enough to indicate a temporary liquidity regime shift.

Empirical results on cross-currency pricing and liquidity



The graph indicates that during March 11–12, USDC experienced repeated episodes of elevated liquidity stress rather than a single permanent breakdown. While the top panel shows occasional spikes in OFE-ABS—reflecting moments when price moved sharply relative to signed order flow—the lower CUSUM panel reveals something more important: these elevated impact levels persisted for several consecutive 3-minute windows before reverting. Each upward ramp in the CUSUM statistic represents a sustained period in which price sensitivity to order flow remained above its normal baseline (defined using March 2–5), implying temporarily thinner depth and slower liquidity replenishment. However, the repeated resets of the CUSUM statistic indicate that these stress regimes were episodic and mean-reverting rather than structural. In liquidity terms, the de-peg was characterized by intermittent fragility—waves of reduced resilience and higher impact—rather than a permanent impairment of market functioning.



The CUSUM analysis for the normal trading day (March 3) indicates that liquidity conditions remained stable relative to the baseline period. Although OFE-ABS occasionally deviated above its normal level, these deviations were short-lived and did not persist long enough to trigger repeated structural alarms. The CUSUM statistic exhibits gradual oscillations and only breaches the detection threshold once throughout the day, suggesting that temporary fluctuations in price impact were quickly absorbed by the market. In microstructure terms, this implies that order book depth and resiliency were largely intact, and that elevated price sensitivity to order flow did not sustain long enough to signal a liquidity regime shift. Overall, the normal-day behavior reflects a well-functioning and mean-reverting liquidity environment.

Next, we design strengthening methodology using MRR (Madhavan–Richardson–Roomans) Modelling which states that Prices move because trades contain information; market makers set spreads to compensate for the expected impact of trades designing the following spread methods.

$$\boxed{s_{\mathrm{MRR}} = \frac{2R(1)}{1 - C(1)}}$$

MRR tells you whether trades cause structural movement, Whether order flow is toxic, or Whether spread widening is rational. During this step, we design the spread such that the response and correlation satisfy such that $R(1)=E[\varepsilon_t(m_{t+1}-m_t)]$ indicating "How much price moves one trade later, in the direction of the trade". $R(\tau)=\mathrm{Cov}(\varepsilon t, mt+\tau-mt)$ = is a signed covariance between trade sign and future price change. R tells you how informative trades are. / C tells you how clustered trades are.

Market makers earn half the spread per trade based on Revenue per trade = s/2. But they lose money if trades are toxic:

$$\text{Adverse selection loss} = R(1)$$

Then we have such that,

$$\frac{s}{2}(1 - C(1)) = R(1)$$

Our final output is:

$$s = \frac{2R(1)}{1 - C(1)}$$

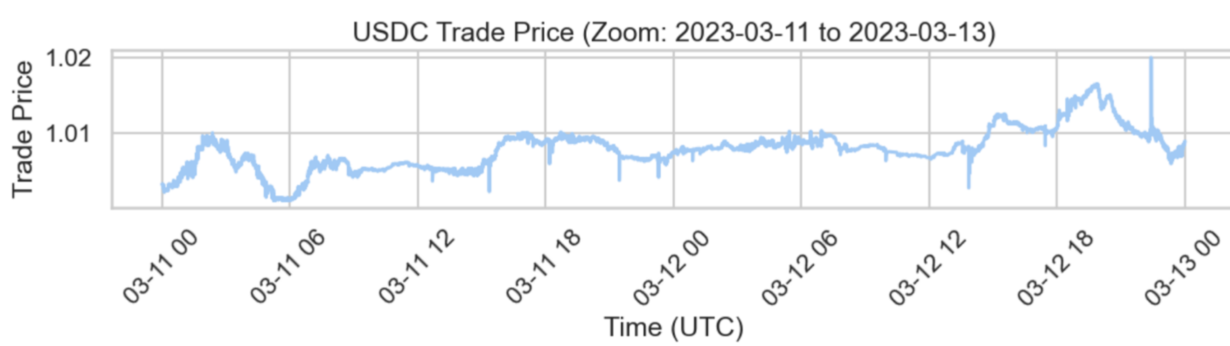
$R(\tau)$ in this case is the Response / Impact where R(1)=adverse selection cost per trade

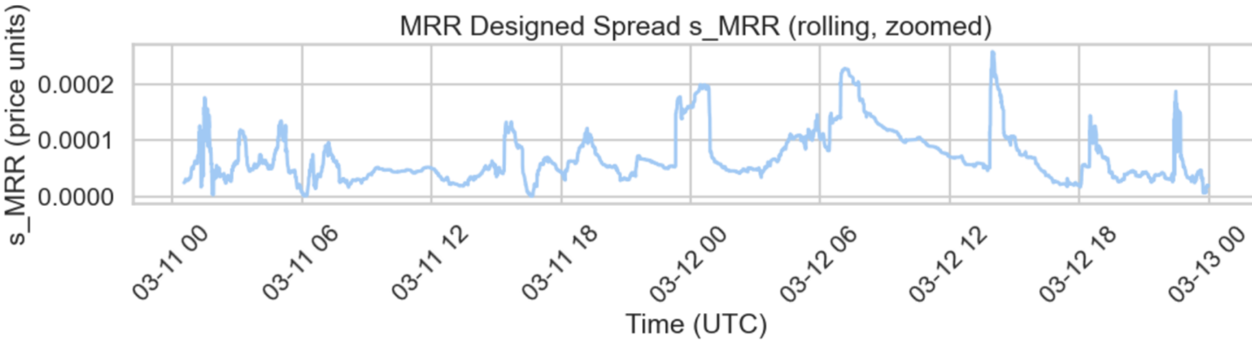
We design C(1) as Order-Flow Autocorrelation. In summary,

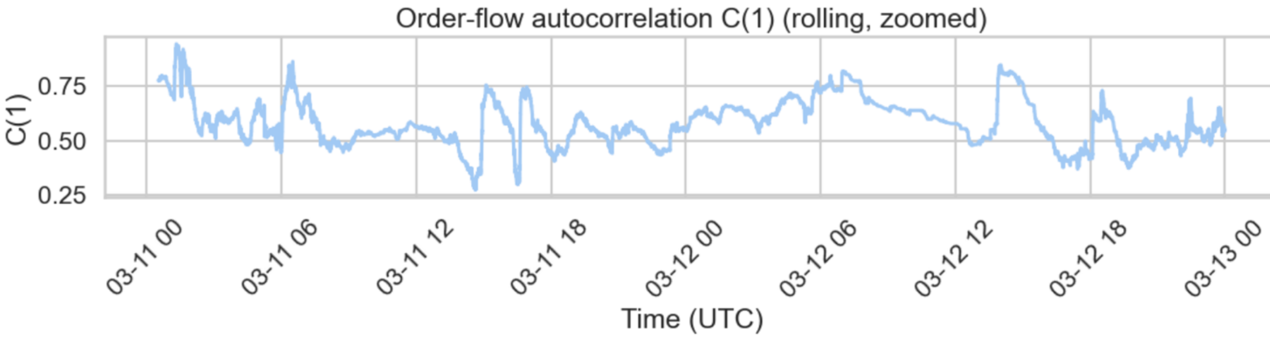
- $R(1)$ is how much price moves because of trades in market scenario.
- $C(1)$= how predictable and persistent trades are based on trades.

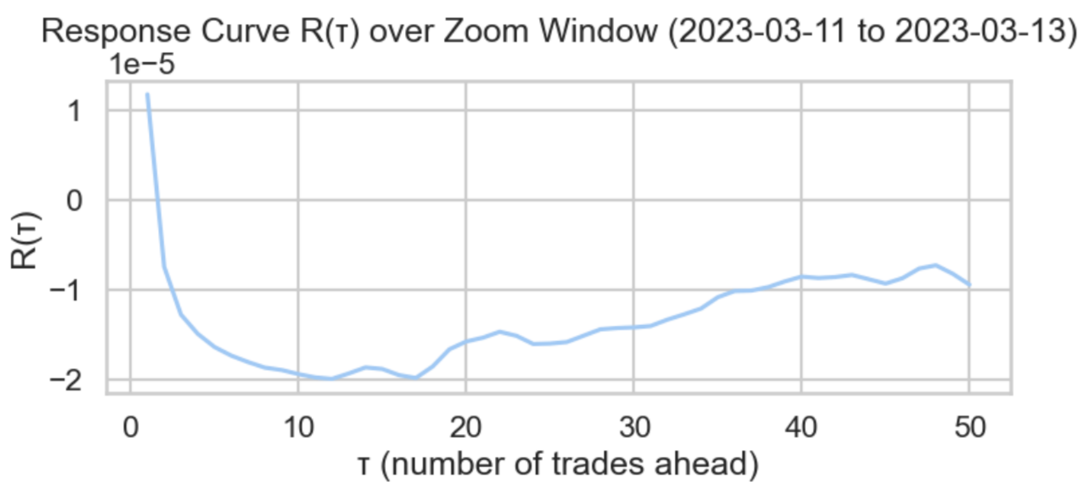
Then spread must satisfy. Because makers need to earn enough spread to offset. When Cov(sign, future price) increases implies higher hit to the liquidity.

Empirical Results

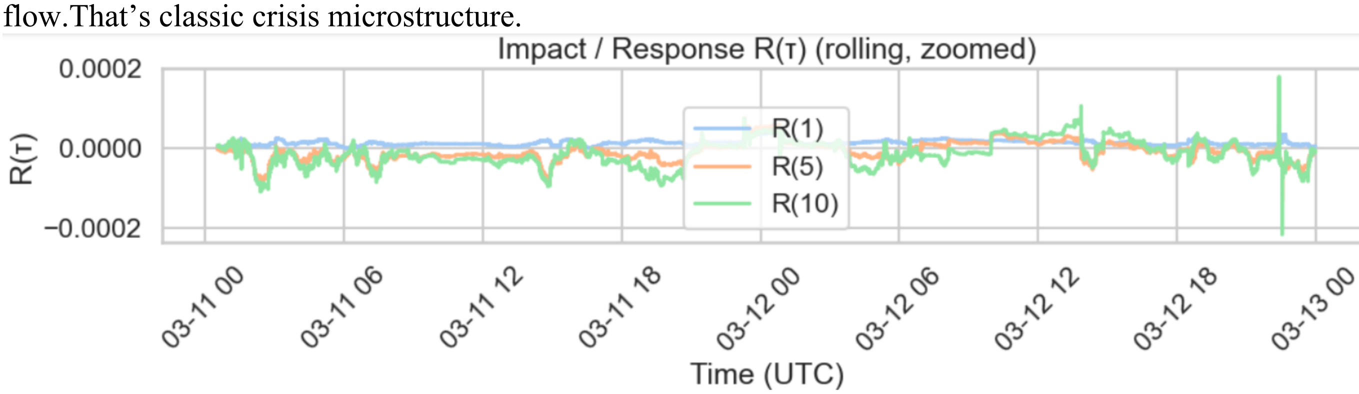








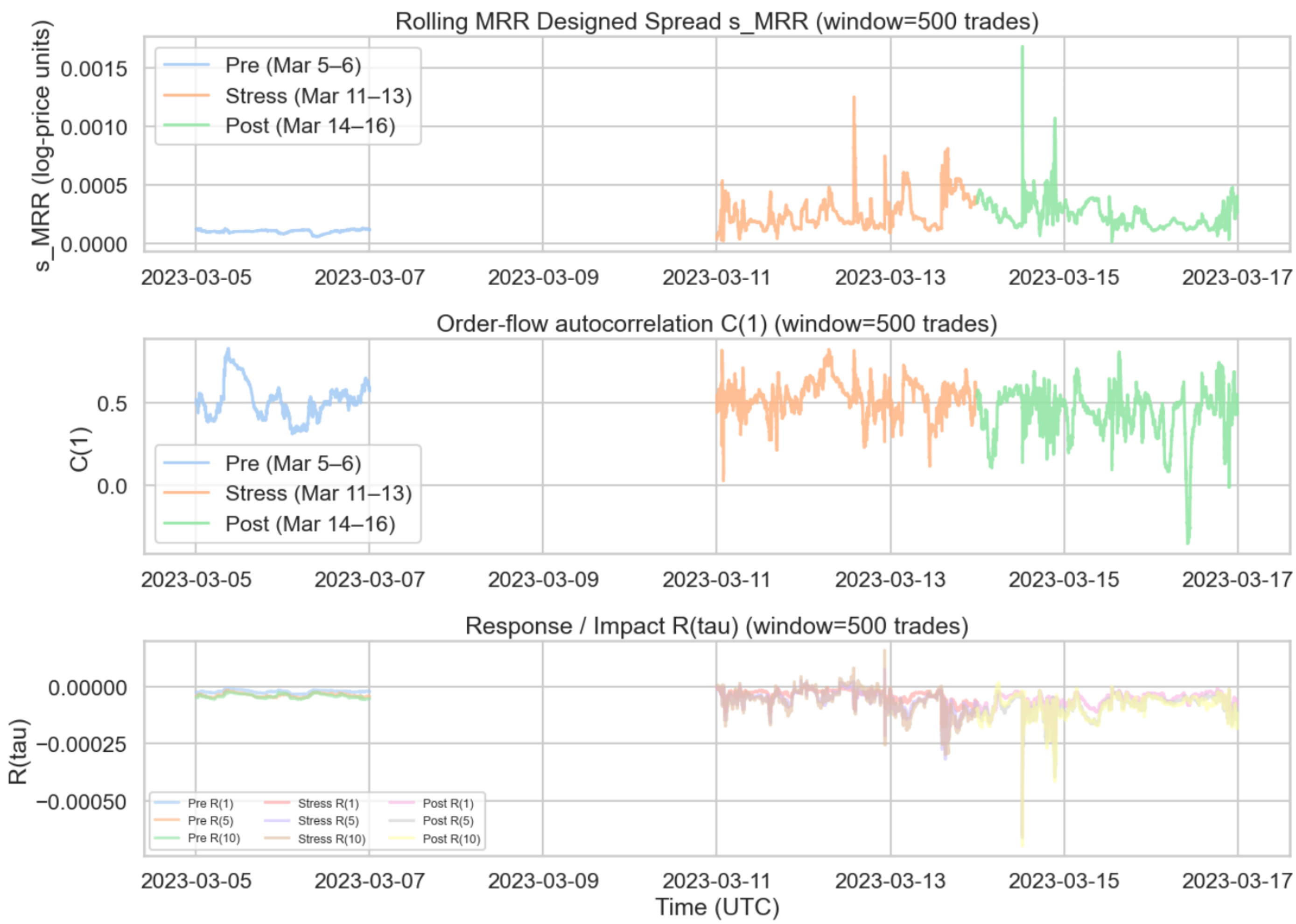
Based on the result, spread is mostly small, Spread mostly small computed as the moving window of 500 trades that is not a fixed time interval. Spread rises when Impact R(1) increases, Order flow persistence C(1) increases Or both. Order-flow autocorrelation C(1) during normal regime is considered as C(1) ≈ 0.5–0.6 (typical for crypto) but C(1) spikes to ~0.75–0.85, Meaning we see either consecutive trades of buys or sells, representing metaorder flow that is a structural break in liquidity. So this indicates apersistent directional flow.That's classic crisis microstructure.



To analyze the result, R(τ) measures the signed price impact such that R(1) is small but nonzero, R(5) is slightly larger, R(10) is larger at certain moments. In this context, τ is measured in number of trades**,** not seconds or minutes. In terms of the insights, the impact was not purely mechanical, Order flow had persistence and liquidity providers were absorbing stress. This indicate it is not a full breakdown, but a real stress. As a result, this means that Impact increase with higher τ. The price keeps drifting in the direction of the trade. Indeed, this is classic crisis microstructure.

Spread Tightening Afterwards. Yes — and this is crucial. After March 12 peak => MRR declines, C(1) moderates, R(τ) flattens**.** That means: Adverse selection risk decreased, Inventory risk decreased, Makers could quote tighter spreads again

That is exactly what liquidity resilience looks like during the depeg period. C(1) spike during peak stress, Then gradually decline toward normal levels as well.



During March 11-13th, MRR jumps significantly, large spikes, and becomes much more volatile. However, interestingly looking at March 15–17, permanent price impact remained elevated and Market makers likely still pricing in risk. Liquidity providers had not fully restored depth and Confidence had not fully returned.

During Post March 14th to 16th, MRR stays elevated, Even larger spikes at some points, Does NOT return to pre levels. Liquidity impairment persisted after price stabilized. That means that Repeg in price $\neq$ liquidity normalization and Confidence did not instantly return. In fact, this is a very important nuance since

While CUSUM earlier suggested stress was episodic, MRR now suggests even after episodic spikes, the average impact level remained structurally higher. So the system may have recovered from panic volatility, the combined result says that but not from liquidity fragility.

So CUSUM resets while MRR stays elevated. This is because bursts not long enough to create huge long-run mean shift creating CUSUM episodic. However, bursts frequent enough and flow persistent enough to raise rolling estimates that MRR elevated. That's the mathematical reason the two can diverge. CUSUM resets because the OFE-ABS "high" periods are not continuous. It's detecting *episodes of persistence* above baseline, and your implementation likely resets after alarms.

MRR stays elevated because microstructure structure stays worse *on average*, even outside the most extreme minutes.

Metric	Pre	Stress	Post	Late
s_MRR_median	9.74123E-05	0.000140311	0.000233475	0.000146035
s_MRR_p95	0.000108723	0.0004253	0.000507551	0.000204357
s_MRR_n	7128	40355	46119	8292
C1_median	0.516484	0.514954	0.447923	0.462202
C1_p95	0.767628	0.698333	0.639372	0.553565
C1_n	7128	40355	46119	8292
R1_median	-2.29975E-05	-3.32931E-05	-6.38834E-05	-3.82591E-05
R1_p95	-1.11988E-05	-1.26777E-05	-2.47696E-05	-2.77322E-05
R1_n	7128	40355	46119	8292
R5_median	-3.87957E-05	-5.45319E-05	-9.13618E-05	-6.02366E-05
R5_p95	-2.1199E-05	-9.32994E-06	-3.33396E-05	-3.99331E-05
R5_n	7128	40355	46119	8292
R10_median	-4.3597E-05	-5.98577E-05	-9.35056E-05	-6.64162E-05
R10_p95	-2.71981E-05	-1.99333E-06	-3.30229E-05	-3.98409E-05
R10_n	7128	40355	46119	8292

Trade impact and order-flow persistence increased, requiring wider break-even spreads. MRR strategy estimates the spread required to compensate for trade impact and order-flow persistence, allowing you to test whether market liquidity was healthy, stressed, or breaking down. After de-peg events, there were Metaorder behavior large informed flow broken into pieces with slower inventory absorption where makers cannot quickly neutralize risk with remaining widened spread. The March 12 de-peg episode triggered a sharp rise in order-flow persistence and multi-step price impact, leading to a doubling of the MRR-implied break-even spread. The subsequent normalization of both impact and autocorrelation indicates that liquidity providers adapted rather than withdrew, demonstrating short-lived liquidity stress rather than structural failure.

Pricing implications:

The findings suggest meaningful trading implications because they indicate that liquidity during the USDC de-peg was not merely volatile but intermittently fragile. The repeated CUSUM alarms imply that price impact sensitivity remained elevated for sustained multi-minute intervals, meaning that market depth was temporarily thinner and order flow moved prices more aggressively than under normal conditions. For market makers, this would justify widening spreads, reducing quote size, and tightening inventory controls during stress blocks. For execution strategies, it implies that slicing orders passively may not sufficiently reduce impact during these episodes, as liquidity replenishment is slower and slippage risk is higher. More broadly, the analysis distinguishes between simple volatility spikes and true liquidity regime deterioration, providing a practical framework for adapting position sizing, risk management, and execution tactics during periods of market stress..

Empirical Results on Cross-Currency Pricing and Liquidity

The empirical analysis reveals that the March USDC depeg episode generated a sharp but short-lived price dislocation, followed by a more persistent deterioration in liquidity conditions. While the stablecoin price re-pegged relatively quickly, microstructure measures indicate that effective transaction costs and price impact remained elevated for several days thereafter. The rolling MRR-designed spread increased significantly during the stress window, and trade impact measures ($R(\tau)$) became more negative, indicating that individual trades moved prices more than under normal conditions. Although extreme order-flow imbalances were episodic—as detected by CUSUM-based stress signals—the overall liquidity regime remained structurally impaired, with spreads and impact measures statistically higher than pre-crisis benchmarks even by March 20. These findings suggest that cross-currency parity enforcement and arbitrage mechanisms were temporarily constrained, leading to reduced market depth and increased trading frictions despite apparent price stabilization.

Regulation and Market Structure Implications.
The observed patterns highlight the importance of regulatory credibility and market structure in stablecoin ecosystems. Unlike traditional FX markets, stablecoin liquidity depends on redemption mechanisms, reserve transparency, and fragmented exchange-based trading venues. When reserve backing or banking relationships are questioned, liquidity providers incorporate higher adverse selection and inventory risk into pricing, widening effective spreads and increasing impact costs. The persistence of elevated microstructure frictions after the nominal re-peg indicates that confidence restoration lags behind price correction. This suggests that stronger regulatory clarity, reserve transparency, and more integrated liquidity infrastructure could mitigate the duration and severity of liquidity impairments during stress events. Overall, the results underscore that stablecoin market stability is not solely a function of price parity but also of the robustness of its underlying liquidity and institutional structure.

Citation:

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Bouchaud, Jean-Philippe, et al. *Trades, Quotes and Prices: Financial Markets Under the Microscope*. Cambridge University Press, 2018.