# EXPLORING LIQUIDITY IN CRYPTO MARKET : A JOURNEY INTO MICROSTRUCTURAL UNDERSTANDING

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# 1/ Introduction

In financial markets, *liquidity* is often cited as a central determinant of efficiency, stability, and trading cost. Yet despite its ubiquity in market discourse, liquidity remains a multifaceted and sometimes elusive concept—particularly within the rapidly evolving ecosystem of cryptoassets. A concise and practical definition states that **liquidity is how easily and quickly one can buy or sell an asset without significantly changing its price**. This definition captures the essential intuition behind the phenomenon: a liquid market is one where transactions are executed smoothly, at low cost, and with minimal price slippage, while an illiquid one imposes frictions that shape both trading behavior and price dynamics.

Traditional financial markets—equities, futures, foreign exchange—have long been studied through the lens of market microstructure, a field dedicated to understanding how trading mechanisms, order-flow dynamics, and the behavior of liquidity providers collectively determine liquidity and price formation. Crypto markets, however, challenge conventional microstructure assumptions. Operating around the clock, fragmented across dozens of venues, influenced by retail flows, algorithmic strategies, and varying degrees of transparency, they exhibit unique patterns of liquidity provision and consumption. These characteristics make crypto an exceptional laboratory for studying microstructure phenomena that are often masked or stabilized in mature markets.

This paper aims to **explore liquidity in crypto markets through a microstructural perspective**, connecting theoretical constructs with empirical analysis. By studying order flow, price impact, trade sign dynamics, and the behavior of liquidity providers, we seek to uncover the forces that shape market quality in cryptocurrencies. Using high-frequency trade data and microstructure tools such as price response functions, concavity analysis, and trade sign autocorrelation, we examine how liquidity manifests in practice—how it varies across assets, responds to shifts in market conditions, and reveals the presence of informed or uninformed trading activity.

Ultimately, this work positions liquidity not as a static property of the market, but as a dynamic outcome of the continuous interaction between buyers, sellers, and the structure of the trading environment. Understanding these interactions is not only essential for traders, market makers, and algorithm designers, but also for researchers seeking to characterize what makes crypto markets both uniquely challenging and uniquely revealing.

# 2/Abstract

Liquidity is a fundamental aspect of market quality, typically defined as the ease and speed with which an asset can be traded without significantly affecting its price. While traditional financial markets have been extensively studied through the lens of market microstructure, crypto markets remain comparatively underexplored despite their growing economic relevance and unique structural features. This paper investigates liquidity in major cryptocurrencies using high-frequency trading data and a suite of microstructure tools, including price response functions, volume–impact concavity analysis, trade sign autocorrelation, and order-flow imbalance measures. Our results reveal clear distinctions between mature assets such as Bitcoin—characterized by shallow trade impact, rapid liquidity replenishment, and nearly memoryless order flow—and more volatile altcoins, which exhibit persistent order-flow dynamics, stronger concave impact patterns, and evidence of informed trading. These findings demonstrate that liquidity in the crypto ecosystem is highly heterogeneous, shaped by the interaction of market design, participant behavior, and asset-specific microstructure. By situating crypto liquidity within established microstructure frameworks, this study provides a deeper understanding of how these markets function and highlights the importance of microstructural analysis for traders, market makers, and researchers.

# 3/Find a clear measurement of liquidity

Finding a clear measurement of liquidity is something very complex because it covers bid/ask spread, depth of the order book, volume…

But if we go straight to the definition, liquidity is simply the ability of buy or sell an asset without changing significatively its price. Then, the goal is to measure the price impact, and try to understand it. This framework has been use many time in TradeFi.

At the beginning, most people thought it was a square root impact, before discovering it's more following a logarithmic curve. I found an article that explores it well, here we will try to go deeper and give more structured analysis (More statistical properties of order books and price impact - ScienceDirect)

Price impact is logarithmic :

$$R(V,\tau) = R(\tau) \times \ln(V)$$

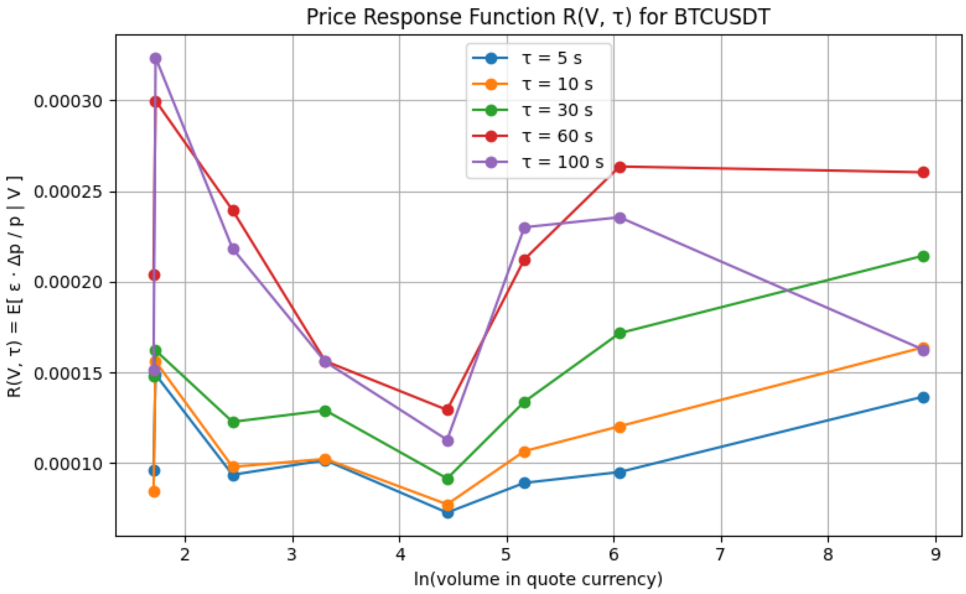
With V the volume and τ the time observation.

The response function is defined like :

$$R(\tau) = \mathbb{E}\left[\frac{\varepsilon_t\big(p(t+\tau) - p(t)\big)}{p(t)}\right]$$

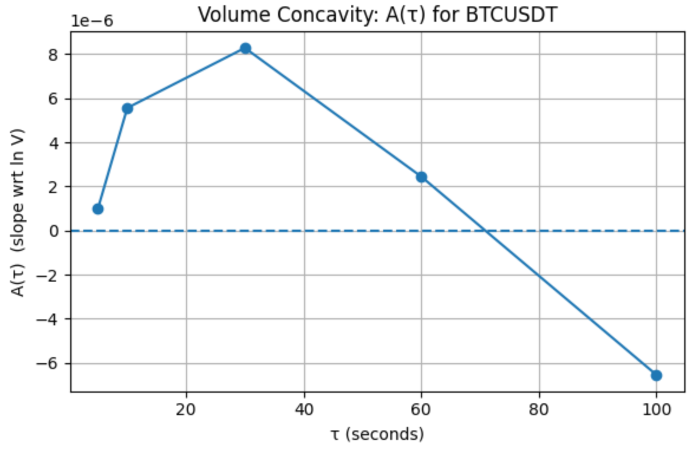
With ε sign of the trade, p(t) the price at the moment of the trade t, p(t+τ) the price at τ seconds after the trade.

Now, it's possible to draw price impact, for a given ln(V) :




For the pair BTC/USDT, liquiditiy is really high, from 0.01% to 0.03%, it shows the order book is deep and really well arbitraged. All positives values showed that buy order cause slight upward drift and the inverse for short. We can see volume does not really impact the market (for this scale of course).

We can also see the concavity of volume A(τ) :

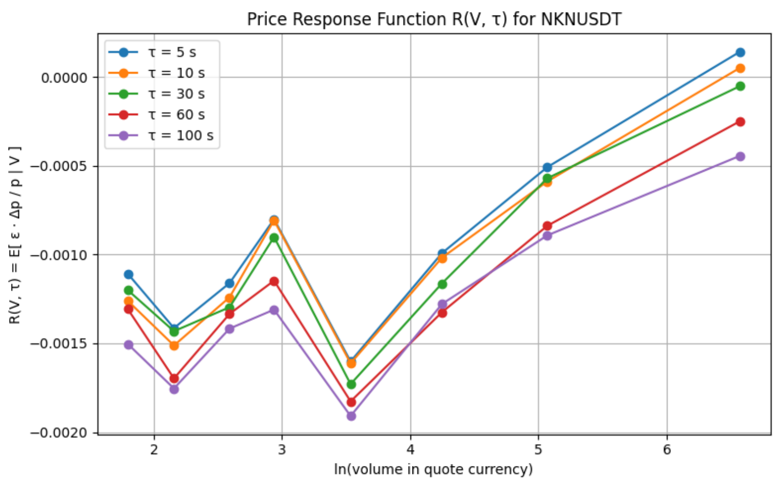



A(τ) is the slope of the regression :

$$R(V, \tau) \approx A(\tau) \times \ln(V) + B(\tau)$$

Something interesting to analyse is the mean reverting aspect of biggest trade, in a 100s timeframe, it's arbitraged really quickly by market makers (we will talk about market making perspective in the next part).

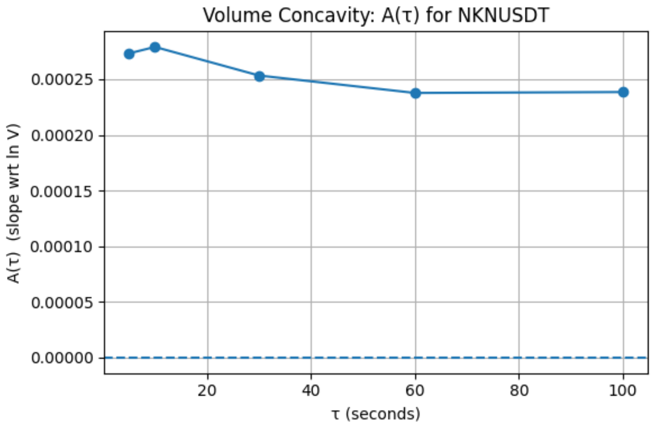
If we take another example to compare, for example NKN/USDT, we can see results are quite different




NKN is the #991 cryptocurrency in coin market capitalization, and then it's really insightful. In Bitcoin, arbitrage and market making opportunities are less obvious, because you need huge amount to market make bitcoin. BUT if we focus on lower pair, like NKN/USDT with $11.2M of market capitalization.

As we can see, flow is not stable, the asset is illiquid. We can see price impact is negative, it means trades are mostly noise random and retail driven. We can observe some volumes have more impact, but generally, the more the volume, the more the impact.

A(τ) is higher than BTC, biggest trading flows impact the market in their own direction :




So liquidity can be defined in really short term, you can't measure liquidity of an asset like we measure the volume. The volume is defined daily, liquidity is shown in seconds, because it moves at a really high speed. Using the fundamental definition of the liquidity can be define and use in crypto, for simple fundamental analysis of an asset of for market making.

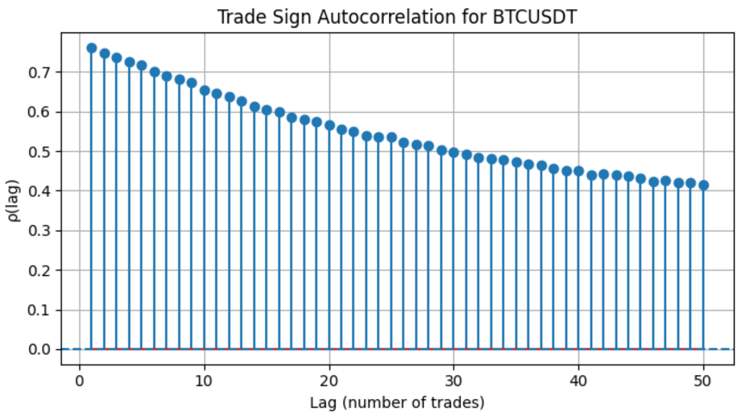
# 4/ Liquidity, microstructure & market making perspective

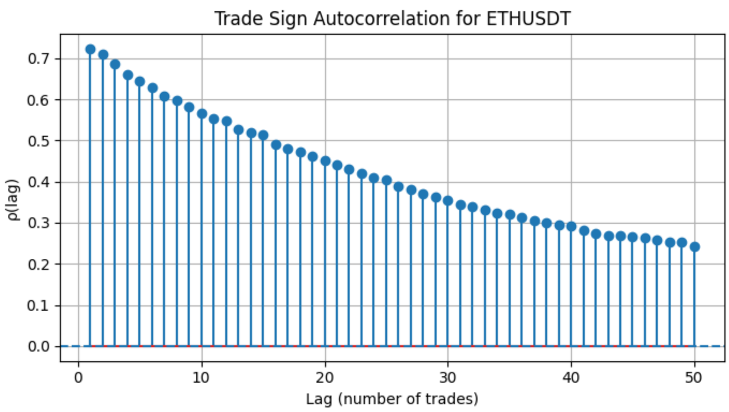
4.1- Liquidity & Microstructure :

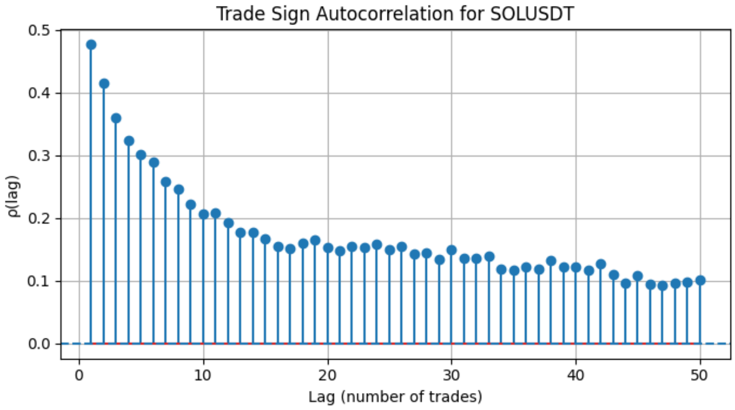
Now, we can get a visual of microstructure of a given asset by using autocorrelation concept, by finding :

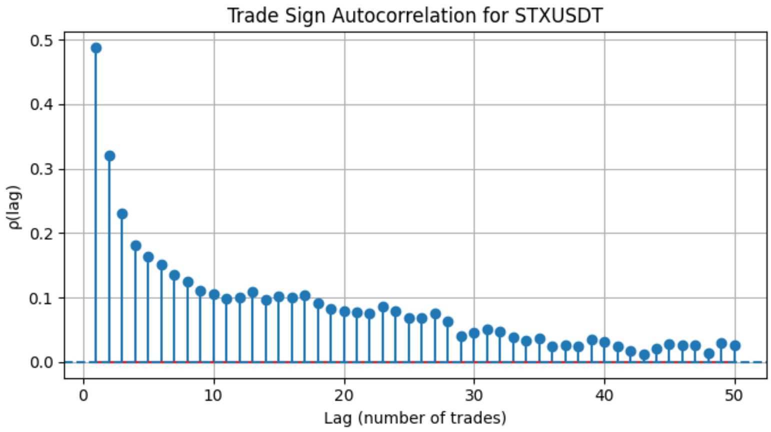
$$\rho(l) = Corr(\epsilon_t, \epsilon_{t+l})$$

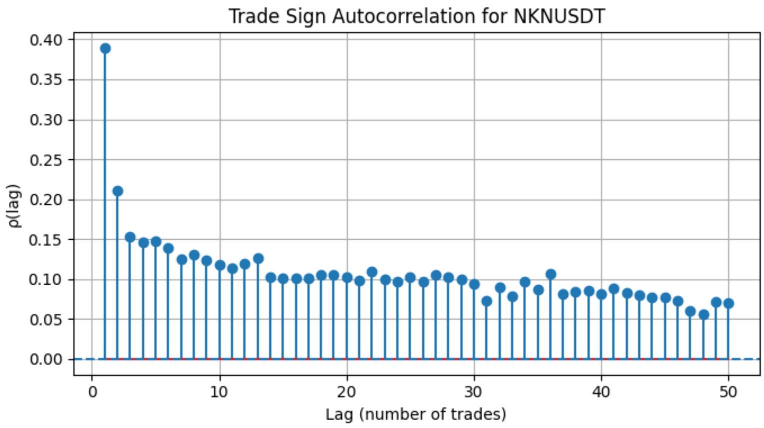
ε is the sign of the trade, + if long and – if short. Autocorrelation enable us to find the correlation of the trading sign and the previous trading sign. We can see with that indicator if the asset is liquid and if people are more following the trend. And we can observe high difference between coins :






As we can see, more illiquid assets have lower autocorrelation and it goes down rapidly. BTC is very strong and trend following, and NKN is very illiquid and trades are more chaotic and random. It can be interesting to market make NKN to bring liquidity, and stabilize the market (in ups and downs).

Before starting market make or trade a coin, you really need to deeply understand microstructure and liquidity.

4.2- Market Making perspectives :

The first MM (Market Making) strategy perspective is that the $R(V,\tau)$ can show how the price will move against you if you take a position after a time $\tau$, this is the definition of adverse selection. If $R(V,\tau)>0$, it means we are more in a conditionnal price drift, if $R(V,\tau)<0$, order flow is uninform and mean reverting (opposite of a trade) and if $R(V,\tau) \approx 0$, order flow is noisy.

We can analyse concavity to see lifetime of a trade. But a MM can use autocorrelation to see how predictable the order flow is, how strong is the market memory.

I think it can be possible to build indicators based on those research, it something that can be backtested.

## 5/Conclusion

This study provides a detailed quantitative exploration of liquidity and price formation in cryptocurrency markets through the lens of modern market microstructure. By analyzing the price response function $R(V, \tau)$, the concavity of impact with respect to trade size, and the autocorrelation structure of trade signs, we uncover the fundamental mechanisms that drive short-term price dynamics across assets of varying liquidity profiles.

Our results show that the microstructure of crypto markets is highly heterogeneous. Large-cap assets such as BTC exhibit minimal and rapidly decaying impact, with a near-flat relationship between volume and price response. This reflects a deep and highly efficient market in which order flow is dominated by algorithmic execution and hedged arbitrage strategies. In such environments, market makers face limited adverse selection risk, and liquidity replenishes almost instantaneously.

In contrast, mid-cap and small-cap assets exhibit markedly different behavior. The response functions of these assets display stronger size dependence, hump-shaped concavity curves, and clear patterns of transient impact followed by mean reversion. Smaller assets also show pronounced negative long-horizon slopes $A(\tau)$, indicating that large trades are often uninformed liquidity shocks that market makers quickly fade. Their high trade-sign autocorrelation reveals persistent, directional order flow, likely driven by metaorders or clusters of retail activity. These conditions create both risks and opportunities for liquidity providers: order-flow predictability increases inventory risk, yet strong mean reversion allows market makers to profit from fading uninformed pressure.

Across all assets, the interplay of immediate mechanical impact, impact decay, and order-flow persistence provides a coherent explanation for the observed dynamics. Crypto markets exhibit both universal features predicted by microstructure theory—such as concave impact, transient responses, and autocorrelated order flow—and asset-specific behaviors tied to depth, participation, and market-maker competition. The methodological framework developed in this study offers a systematic way to quantify these effects using publicly available trade data, making it applicable to a wide range of digital assets and market conditions.

Overall, this research highlights that liquidity in cryptocurrency markets is not a static property, but a multi-dimensional phenomenon shaped by trade size, order-flow structure, and the strategic behavior of liquidity providers. Understanding these microstructural dynamics is essential for traders, market makers, and researchers seeking to navigate or model these rapidly evolving digital markets.

# **SOURCES :**

- Binance API for data
- More statistical properties of order books and price impact - ScienceDirect
- Cryptocurrency Prices, Charts And Market Capitalizations | CoinMarketCap