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NUMBERS AND NARRATIVES: AN EVALUATION FRAMEWORK FOR CRYPTO LIQUIDITY

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OVERVIEW

Selecting the right market maker is critical for any project, as their strategies can significantly impact token performance and ecosystem growth. However, some firms engage in questionable practices under the guise of "market making," posing challenges for a project's associated token(s). Market makers lacking experience or operating with ill intentions may make unrealistic commitments to reach specific price or volume targets, which can be considered unethical and impractical in a properly functioning market. Some clients may also engage with market makers without a clear understanding of their needs, only to then realize the mismatch in services.

To avoid such pitfalls, clients must understand the importance of liquidity in crypto markets and the market maker's role within a partnership. They should differentiate between bad actors and quality market makers, conduct thorough due diligence, and prioritize criteria such as track record, liquidity provision capabilities, and client service quality. Clarifying expectations and setting clear boundaries in the partnership agreement are also crucial to ensure an alignment of interests. With the right partnership, a market maker can provide lasting benefits to a project.

This report will start with a quantitative analysis of liquidity in crypto markets, examining its impact on price volatility across different geographies and assets. It will highlight the significance of robust liquidity in diverse markets for project success. Case studies will illustrate how market makers' liquidity provision has positively influenced clients, such as by reducing price volatility, or spread.

A more comprehensive assessment of broader market maker criteria will be presented in the subsequent report, complementing this focused examination of liquidity provision.

PART 1:

LIQUIDITY IN CRYPTO MARKETS

1.1 IMPORTANCE OF LIQUIDITY IN CRYPTO MARKETS

Market makers play a crucial role in the crypto market due to its unique challenges, such as increased volatility and liquidity fragmentation. These factors can make efficient trade execution difficult for traders. Market makers help mitigate these challenges and enhance market efficiency by maintaining deep order books ensuring sufficient liquidity, reducing the price impact of large orders and preventing manipulation. Consistent price quoting indicates active markets where prices quickly reflect new information, allowing traders to promptly adjust their positions. This fosters efficient price formation, aligning with true supply and demand dynamics.

Market makers absorb large volumes and ensure constant counterparty availability, facilitating easier entries and exits for traders. This reduces slippage on large trades and promotes fair and uniform pricing across exchanges. Without market makers, executing trades, especially for less popular assets with lower liquidity, would become challenging. Their presence attracts traders and investors, contributing to both market growth and price stability, mainly via:

- **Spread Reduction:** Spread reduction narrows the gap between bid and ask prices, encouraging trading activity. A tighter spread lowers trading costs, making trading more efficient.
- **Order Book Optimization:** Order book optimization involves managing limit buy/sell orders to enhance market depth and minimize market impact. A deep market, with high order quantities at various prices, indicates high liquidity. Market makers use real-time data to maintain a balanced and deep order book, which can absorb large trades without significant price shocks.
- **Price Stabilization:** Market makers stabilize prices by maintaining deep order books and ensuring liquidity. During market stress or sudden supply and demand

shifts, they adjust quotes and facilitate increased trading activity to manage price impacts. This approach helps foster trader confidence and enhances market attractiveness / reliability.
- **Price Harmonization:** Market makers harmonize prices across different trading venues through arbitrage, using price differences to generate profit and improve market efficiency. This reduces price discrepancies, like the 'kimchi premium' in isolated markets. By ensuring uniform asset values across platforms, market makers help participants access fair prices.
- **Efficient Price Discovery:** Price discovery is the process where buyers and sellers agree on an asset's fair price. Market makers play a crucial role, especially for new assets. By engaging across exchanges, they help establish market values, contributing to price discovery.

In summary, market makers are crucial for providing liquidity, enabling assets to be easily bought or sold without significantly affecting prices. Their consistent buy and sell orders help maintain a stable trading environment, reducing the risk of sudden price fluctuations. The trading stability achieved through liquidity provision encourages greater market participation, leading to higher trading volumes and improved price discovery. While market makers are essential for the constant liquidity they provide, the broader implications for market participants and ecosystem growth are worth noting as well.

If a project is building a tokenized economy, the team’s go-to-market strategy is crucial for the successful adoption of the product or service. In the cryptocurrency market, trust is vital for user engagement. Many market participants have noted that if people cannot sell an asset easily shortly after purchasing it, they lose trust in the product and could feel trapped. For instance, if a user buys an asset at a specific price and later needs to sell it, only to face a 20% slippage, the trade becomes costly and experience - frustrating. This underscores the importance of constant liquidity provision, which is achieved through market makers' tight spreads and uninterrupted uptime.

Moreover, if a user wants to acquire a large quantity of tokens and the market cannot handle this demand without significant slippage, trust erodes even further. Without entities providing liquidity, a project's go-to-market strategy faces significant challenges. Ensuring liquidity is crucial not only to maintain user trust but also to facilitate smooth and efficient trading experiences.

With reliable liquidity, a project's go-to-market strategy becomes more manageable and attractive to a larger user base. Increased user activity on exchanges drives higher trading volumes, which can draw the attention of larger exchanges to list the project's token, further boosting adoption. Higher liquidity means that users can buy and sell tokens with minimal price impact, leading to a more stable and reliable trading environment.

Additionally, in crypto markets, an asset's price often reflects adoption. A higher number of buyers and sellers indicates that people are satisfied with the product experience and want to engage with it further, driving up the price. Solid liquidity correlates with the usability of assets, leading to increased engagement and, ultimately, higher prices. In essence, market makers play a pivotal role in fostering a trustworthy and liquid market, which is fundamental for the growth and success of a tokenized economy.

1.2 QUANTITATIVE ANALYSIS METHODOLOGY

To provide empirical proof of the importance of market makers in digital asset markets, we have analyzed variables such as spread, volatility, price impact, price stability, and market efficiency over 23 different token pairs on major centralized exchanges (Binance, Coinbase, Kraken, OKX, Crypto.com HTX, Bitget etc.). The study's hypotheses propose that market makers reduce quoted, effective, and realized spreads, as well as overall volatility. Their presence lowers price volatility and dislocations, which might coincide with improving the token's price performance by ensuring sufficient liquidity. The null

hypothesis is that no significant change occurs in these metrics.

Over the course of our analysis, we had to first use a proxy to detect the presence of market makers; To do this, we identified dates when on-chain addresses associated with known market makers acquired significant amounts of assets and started providing liquidity to major CEXs. To identify market makers on-chain addresses we used Arkham Intelligence. This on-chain proxy has a fair amount of limitations, as some market maker addresses might be missed; not all market making activity is facilitated on-chain; or the adresses were being used for non-liquidity provision purposes. Nevertheless, this approach is consistent over a significant timeline and across a wide set of tokens and markets. We selected 23 [token]–USD trading pairs for analysis. These tokens come from the Global Market Crypto Intelligence (GMCI) baskets, ensuring representation of established projects across various sectors of the crypto industry.

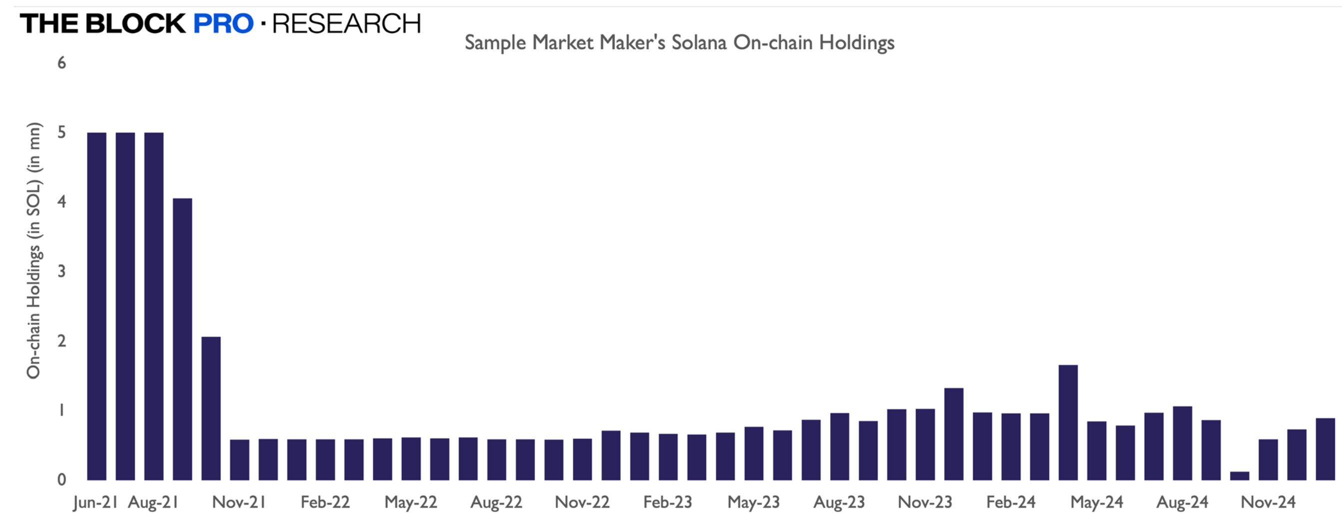

Figure 1: Sample of a Market Maker's On-chain SOL Balance

We determined the date of a market maker's entry by analyzing on-chain data (see Figure 1). For example, Arkham Intelligence data shows a market maker acquiring a significant amount of Solana in June 2021, which we interpret as the start of its market-making activity for SOL. If those tokens were subsequently deposited to exchanges, we treated that as evidence that active liquidity provision had begun. Based on each market maker's entry date, we split the analysis into two periods: (1) from the token's inception up to the market maker's acquisition date, and (2) from the market maker's entry (acquisition date) to Dec 31, 2024. The same steps were repeated for each market maker in the scope of our analysis. After gathering information about dates of market makers' entry, we gathered OHLC (Open, High, Low, Close) and orderbook data to perform the statistical analysis of the target variables (spreads, volatility and others) before a market maker's entrance and after. The main goal of the analysis is to test out the hypothesis: "The presence of a market maker leads to a reduction in spreads, volatility, price impact, price stability, and market efficiency." Meanwhile, the null hypothesis is that the presence of a market maker led to no significant change". These metrics represent the overall state of trading conditions, while the assumption of the analysis is that the presence of market makers affects them positively.

1.3 LIQUIDITY IMPACT ON ECOSYSTEM GROWTH

Building upon the premise that the active provision of liquidity by market makers (MMs) may enhance trading conditions and, by extension, broader ecosystem growth, we examined how on-chain transaction behaviour changes before and after a market maker's entry.

The core of this analysis involved comparing on-chain transaction count and average transaction amount over a 60-day window before and after professional liquidity-provision desks began supporting a given token. To reduce noise from post-TGE "hype" phases, we excluded instances where the MM entrance occurred within 90 days of a token-generation event.

From a dataset comprising 16 tokens (1INCH, BONK, COMP, CRV, CVX, LDO, LINK, LRC, MASK, MKR, OP, QNT, SAND, SUSHI, YFI, and ZRX), two key patterns emerged.

60%
OF THE OBSERVED SCENARIOS RECORDED AN INCREASE IN TRANSACTION COUNT AFTER THE ENTRANCE OF A MARKET MAKER.

In contrast, only 46% of the scenarios recorded an increase in average transaction amount, hinting that MM-driven liquidity primarily encourages more-frequent, smaller-sized trades. Furthermore, an aggregated correlation analysis did not reveal a strong linear relationship between changes in transaction count and changes in average transaction amounts: increases in the former did not systematically translate into higher or lower values of the latter.

Across all providers studied, the mean change in transaction count stood at approximately +17%, with individual instances ranging from about -7% to +45 %. The mean change in average transaction amount was noticeably lower, at roughly +6%, and exhibited a similar dispersion, from -11% to just over +15% once an extreme BONK-related outlier was removed. In other words, while most MMs were associated with modest upticks in activity, the magnitude of that effect varied widely from token to token and from desk to desk.

Taken together, these findings suggest that the narrower spreads and deeper books typically supplied by MMs tend to broaden participation, manifesting as a higher volume of smaller transactions, while exerting a weaker and more ambiguous influence on average transaction size. It is important to note that the sample size was relatively small and that single-token outliers, for instance, BONK's 446% surge in average transaction amount following MM onboarding, could skew headline figures. Nonetheless, even after excluding such extremes, the general picture holds: professional liquidity providers as a group appear to drive a modest but discernible increase in on-chain activity, with their primary contribution lying in the stimulation of trade frequency rather than in the consistent enlargement of trade size.

1.4 PROJECT DEVELOPMENT IMPACT ON ECOSYSTEM GROWTH

In parallel to liquidity-oriented considerations, the analysis of development intensity offers another critical angle on ecosystem growth. Here, we explored whether heightened GitHub commit activity correlates with an increase in token transaction counts or average transaction amounts. We computed both Pearson and Spearman correlation coefficients on a weekly basis for 22 tokens of actively developed protocols (1INCH, AAVE, ARB, COMP, CRV, GRT, IMX, LDO, LINK, LPT, LRC, MASK, MKR, OP, SAND, SNX, SUSHI, UNI, WLD, YFI, ZETA, and ZRX).

Aggregating these correlations across all tokens revealed a generally weak overall relationship. The mean Pearson coefficient for commit activity against transaction count was -0.06, while commit activity against average transaction amounts showed a similarly low -0.06, suggesting that high-intensity development weeks do not systematically align with more active or larger on-chain transactions. Moreover, certain tokens departed significantly from this near-neutral trend. For instance, CRV and MASK showed positive correlations, while AAVE displayed notably negative values.

In order to better contextualise these divergent behaviours, we clustered tokens by their overall correlation patterns (combining both Pearson and Spearman values for transaction count and average transaction amount). The clusters fell into four broad categories.

1. **Cluster 1 (MASK, UNI, WLD):** These tokens exhibited strong positive correlations with both transaction count (mean Pearson ~0.426) and average transaction amount (mean Pearson ~0.29). Heavier development periods for these projects seemed closely aligned with more on-chain engagement, possibly reflecting communities that respond quickly to feature releases or code updates.

2. **Cluster 2 (ARB, CRV, GRT, LPT, LRC, MKR, SAND, ZETA):** While correlations with transaction count were slightly positive (0.088 Pearson; 0.145 Spearman), correlations with average transaction amounts hovered near zero (-0.024 Pearson). Thus, bursts of development activity for these projects correspond modestly to higher user participation but not necessarily to larger trades.

3. **Cluster 3 (1INCH, AAVE, COMP, IMX, SAND, LRC):** Here, development intensity correlated moderately negatively with transaction count (-0.23 Pearson; -0.322 Spearman) yet remained near zero for average transaction amount. One interpretation is that developer efforts may ramp up when market-driven usage is comparatively lower, making the correlation appear negative or neutral.

4. **Cluster 4 (LDO, LINK, OP, SNX, SUSHI, YFI, ZRX):** These tokens saw a consistently negative relationship across both transaction count and average transaction amount (approximately -0.28 Pearson for each). This suggests that higher commit levels might coincide with periods of lower on-chain activity, potentially driven by broader market forces or the timing of project "build cycles" that do not immediately translate into active usage.

We also tested whether a delay (lag) exists between code commits and user behavior, specifically using a one-week and two-week lag. Across all 22 tokens, the average immediate (no-lag) Pearson correlation between commit activity and transaction count ranged between 0.25 and 0.30, but introducing a one-week lag raised it only by 0.02-0.04, while a two-week lag brought it closer to the original range again. The Spearman correlations shifted even less, generally by under 0.05 in either direction. Although a few tokens, including OP and WLD, showed a somewhat more pronounced uptick in correlation with a one-week lag, this was not a widespread effect. Overall, the data do not support the idea of a robust, systematic time-lagged "kick-in" for on-chain usage following code commits.

These findings collectively imply that there is no universal rule that a higher frequency of commits results in more token activity. In some ecosystems, such as MASK, UNI, and WLD, heavier development activity aligns with higher on-chain participation, potentially due to fast turnaround from commit to feature rollout or enthusiastic community engagement. Other tokens, however, appear to be driven by external catalysts, such as yield-farming releases for SUSHI or staking narratives around LDO, which overshadow normal development cycles. Meanwhile, projects might allocate periods of intense coding and security audits that boost commit counts without immediately translating to new user-facing features.

In summary, development intensity alone does not uniformly predict higher or lower on-chain activity. While a subset of tokens displays a meaningful positive correlation, the majority range from neutral to negative. Introducing short lags of one or two weeks similarly fails to reveal a broad, systematic pattern. Thus, the relationship between coding effort and ecosystem engagement is often moderated by external factors, release timelines, and the specific nature of each project's user base.

1.5 GEOGRAPHIC DISTRIBUTION OF LIQUIDITY

Due to the inherent decentralization of cryptocurrencies, different markets often exhibit slight price differences across exchanges due to their geographic user bases and liquidity providers. In our analysis, we focus on one specific pair – SOL/USDT – using aggregated daily orderbook data from exchanges categorized by primary userbase geography. Using Google Trends, we were able to gauge the relative geographical distribution of user bases. Understanding these geographic patterns is critical, as they influence liquidity fragmentation, price efficiency, and overall trading costs across different exchanges.

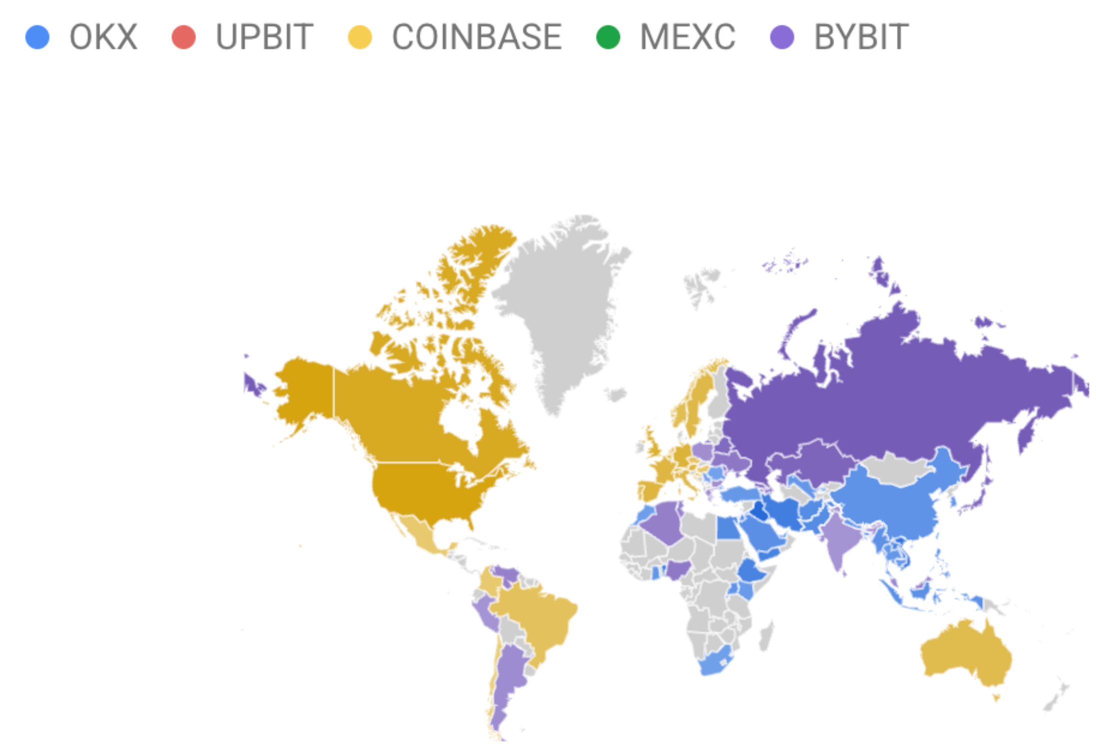

Figure 2: Search request distribution for major CEXs

Based on our analysis, we found that

- Coinbase mostly serves users from English-speaking countries and Western Europe,
- Bybit's audience is primarily focused on Eastern Europe and the Western Asia,
- OKX dominates in East/Southeast Asia and the Middle East,
- MEXC is popular among the users from Middle East and Turkey,
- UpBit is dominant in South Korea.

This regional split leads to distinct market dynamics. For instance, we can hypothesize a case when new information reaches Asian markets sooner than other regions, an asset's price on OKX might react the quickest because that is where the majority of traders receiving the news first are most active on, until cross-market traders neutralize the arbitrage opportunity. Such behavior demonstrates that exchanges can function as semi-independent micro-markets, emphasizing the critical role that global liquidity plays in maintaining price alignment.

Our data from five exchanges (OKX, UpBit, Coinbase, Mexc, and Bybit) in SOL/USDT trading pair on the March 1st, 2025, indicates significant variations in market microstructure, particularly in as bid/ask-spreads and mid-prices. Observing these exchanges, we see that spread on OKX, Mexc and Bybit is usually stable and is tightly centered around $0.01, this reflects efficient markets with consistent presence of market makers. Coinbase exhibits a spread which has both a higher mean and standard deviation, with usually being $0.05 but sometimes reaching $0.1. A different situation can be observed on UpBit, its average bid-ask spread is around $1 and reached a maximum of $10 during the trading day, suggesting periods of severe liquidity dislocation or pricing inefficiency. This observation highlights that despite Upbit's high trading volumes, the market can remain thin and prone to price dislocations if liquidity management is limited especially in a country with tighter capital control measures like South Korea, which limits nonresidents from opening bank accounts, accessing API tools, and depositing or withdrawing the South Korean won on crypto exchanges.

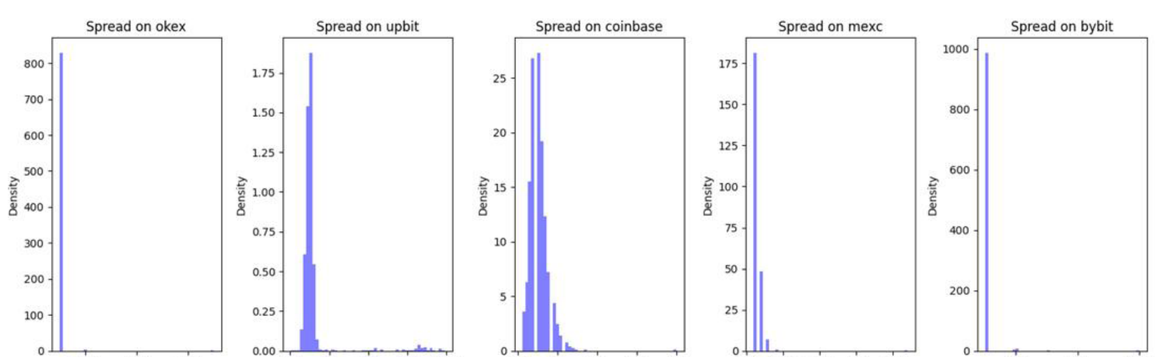

Figure 3: Spread distribution for major CEXs

When examining 5-minute rolling average prices across these exchanges, we observed that prices on OKX, Coinbase, MEXC, and Bybit remained consistently aligned throughout the 24-hour observation window. In contrast, Upbit consistently displayed a "kimchi premium", where prices traded materially higher than on other venues. Moreover, during periods of market stress — particularly between 10:00:00 and 16:30:00 — Upbit's prices showed erratic bursts of volatility, rapidly deviating from global benchmarks before re-converging. These divergences further illustrate how fragmented liquidity across regions can lead to local pricing anomalies, making global liquidity integration essential for maintaining stable and efficient crypto markets.

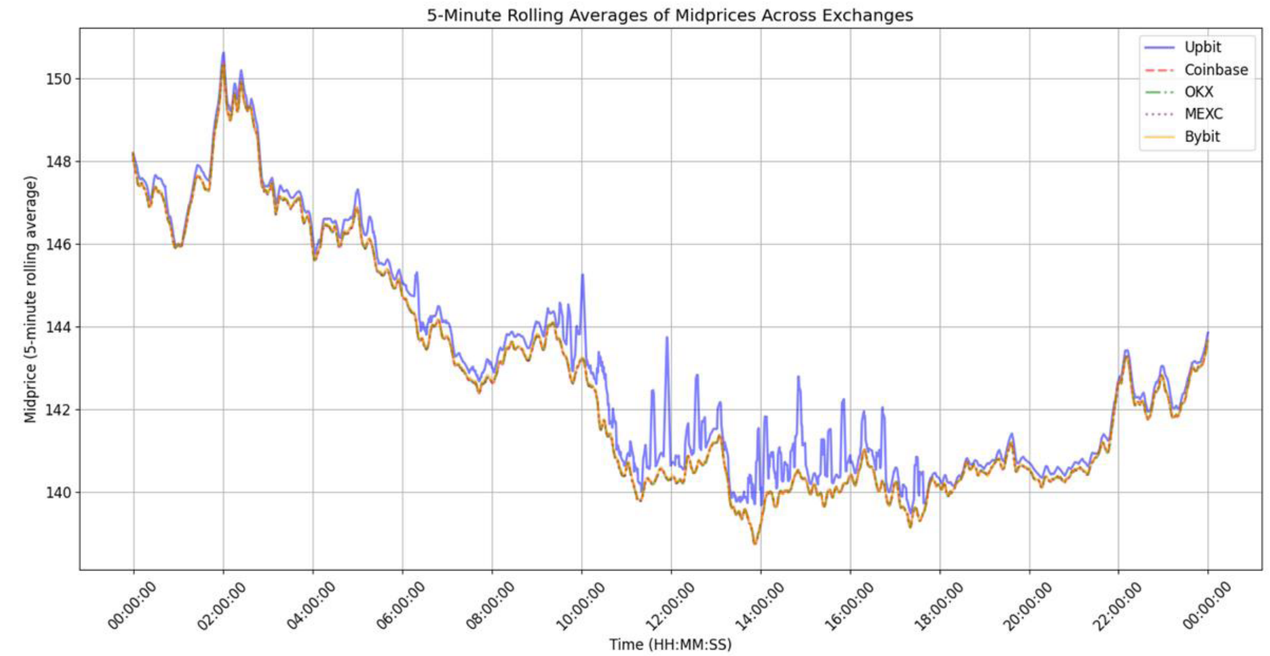

Figure 4: Mid-Price distribution for major CEXs

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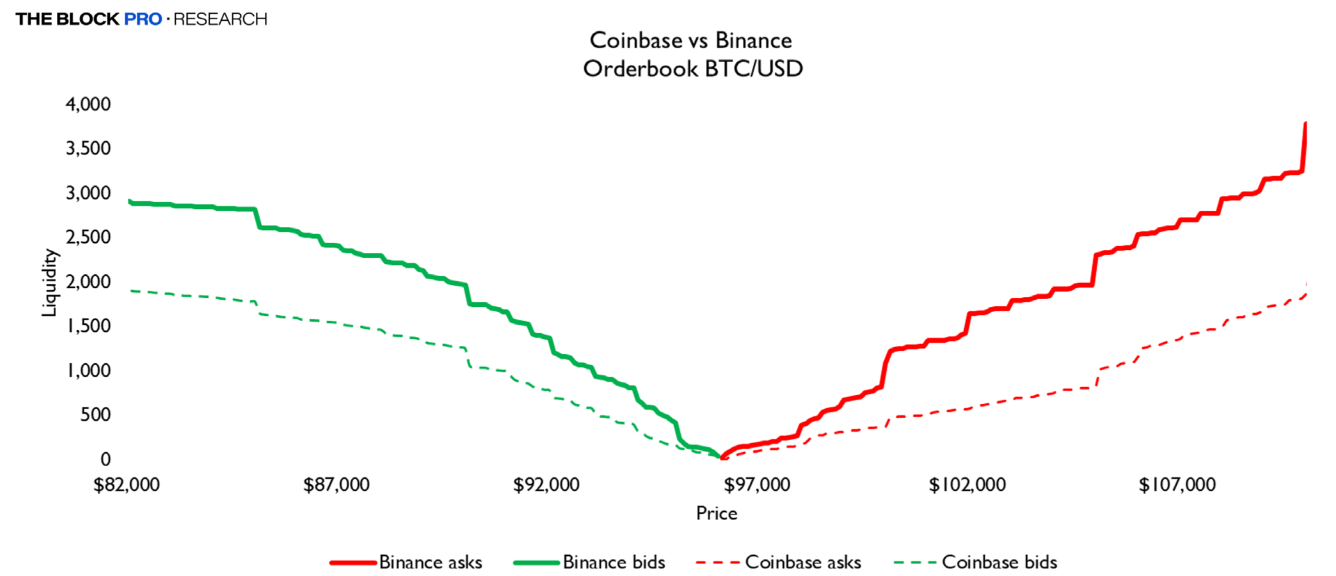
PART 2:

REALIZED, EFFECTIVE, AND QUOTED SPREADS

The bid/ask spread is the difference between the highest bid (buy price) and the lowest ask (sell price) and represents the trading costs for market participants. The lowest ask price at a certain time is always higher than the highest bid price. When estimating trading costs, order book depth must also be considered, as it dictates the effective bid/ask spread for large-size orders. For a sufficiently large order, the execution price will often move further into the order book, which leads to higher trading costs if the liquidity is thin.



2.2 ORDER EXECUTION IN ORDERBOOKS

In this snapshot, the highest bid is at $96,000 and the lowest ask is at $96,100, making the bid/ask spread $100. Summing across the six ask levels (96,100–96,600) gives a total of 589.45 BTC of sell-side liquidity, while the six bid levels (96,000–95,500) have 640.76 BTC on the buy side.

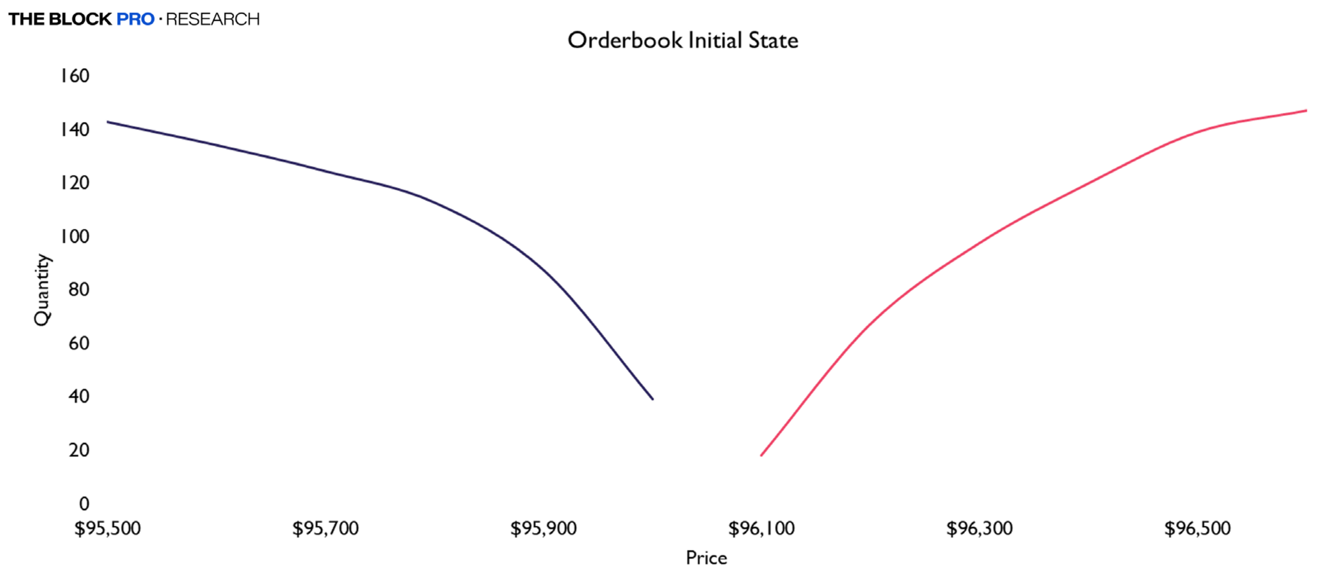


Figure 6: BTC Orderbook Snapshot

Price	Quantity	Type
$96,600	147.19	ASK
$96,500	139.14	ASK
$96,400	119.97	ASK
$96,300	97.62	ASK
$96,200	67.33	ASK
$96,100	18.20	ASK
$96,000	39.13	BID
$95,900	87.42	BID
$95,800	112.71	BID
$95,700	124.44	BID
$95,600	134.20	BID
$95,500	142.86	BID

Figure 7: BTC Orderbook Snapshot

Small Order Example: If a trader places a market buy for less than 18.20 BTC, it will be fully filled at the lowest ask ($96,100). The bid-ask spread remains unchanged because the order does not exhaust the lowest ask's volume.

Large Order Example: If the trader creates a market order buy for a quantity any larger than 18.20 BTC, for example - 100, then to fill the order exchange's execution engine will take out all the asks until filling the quantity ordered, being 100 BTC, here is how the order execution flow:

- Buy 18.20 BTC at $96,100 fully depleting the lowest ask order.
- Buy the remaining 49.13 BTC at $96,200 (out of 67.33 BTC originally available at this price level, 18.20 BTC was already filled at the previous level, leaving 49.13 BTC).
- Buy 30.29 BTC at $96,300, consuming all available liquidity at this price level.
- Buy 2.38 BTC at $96,400 to complete the 100 BTC order.

By executing against multiple price levels, the trader's average purchase price is $96,216.85 per BTC. As a result of removing these ask orders, the bid/ask spread widens from $100 (96,100 - 96,000) to $400 (96,400 - 96,000), altering the order book structure by reducing available liquidity and increasing spread.

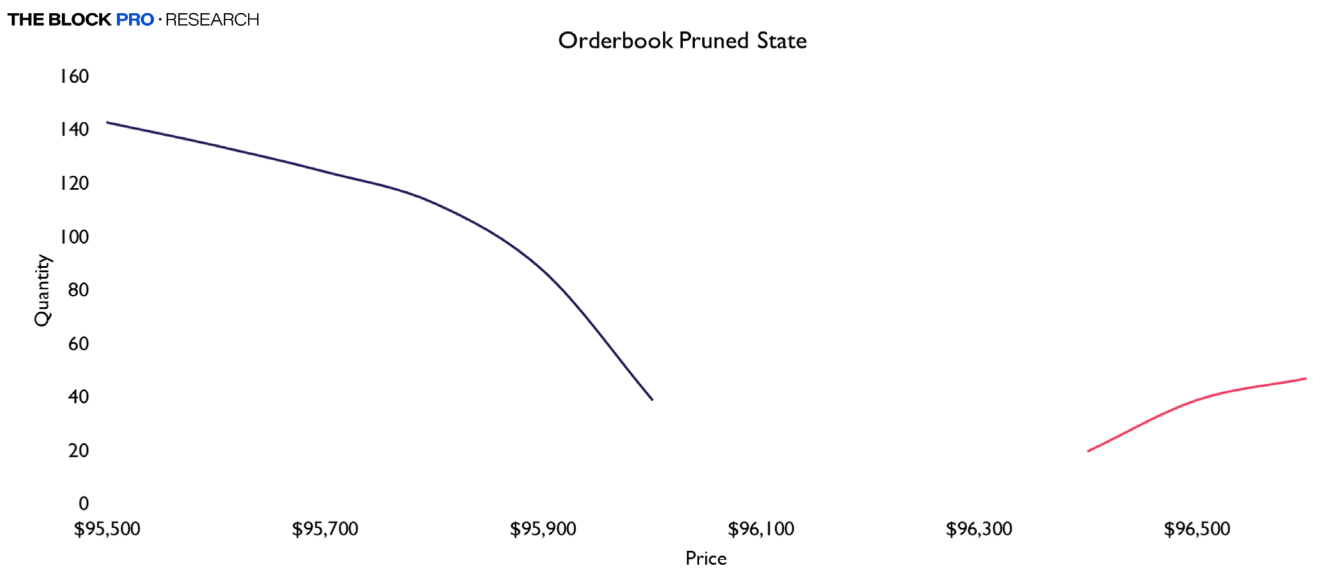


Figure 8: BTC Orderbook Snapshot (Pruned State)

Price	Quantity	Type
$96,600	47.19	ASK
$96,500	39.14	ASK
$96,400	19.97	ASK
$96,000	39.13	BID
$95,900	87.42	BID
$95,800	112.71	BID
$95,700	124.44	BID
$95,600	134.20	BID
$95,500	142.86	BID

Figure 9: BTC Orderbook Snapshot (Pruned State)

2.3 QUOTED AND RELATIVE SPREAD

Three types of spread are broadly recognized: Realized, effective, and quoted. Quoted spread is the difference between the best ask price (p_a) and the best bid price (p_b), in absolute terms.

$$\text{Quoted spread: } QS = p_a - p_b$$

$$\text{Relative spread: } \mathrm{RS} = \frac{\mathrm{QS}}{\hat{p}}$$

Taking the data from the initial state of orderbook quoted spread on the BTC-USD pair is: $68500\ p_a - 68400\ p_b = \$100$. The relative spread expressed this as a percentage of the mid-price, where mid-price is: $\hat{p} = \frac{p_a + p_b}{2}$. Following the previous example, the relative spread is:$\mathrm{RS} = \frac{100}{96050} = 0.10\%$.

2.4 EFFECTIVE SPREAD

Effective spread measures the real spread that occurs when a transaction is executed, better known as slippage. Effective spread compares the transaction price (p_t) with the mid-price ($\hat{p}$). The formula to calculate the effective spread in absolute terms is as follows:

$$\mathrm{ES} = d\left(p_t - \hat{p}\right)$$

Where d is the direction indicator. If the trade was buyer-initiated, the value of d is -1, and $+1$ otherwise. This way the effective spread remains a negative value, both absolute and relative, indicating extra trading costs. For illustrative purposes, let's imagine that the transaction got executed at the price of $68,475 per bitcoin ($p_t$) and the mid-price is $68,450 ($\hat{p}$). Since the p_t is higher than $\hat{p}$, the direction indicator will be -1.

Effective spread then is calculated: $-1(68475 - 68450) = -\$25$ per bitcoin, the transaction cost. On the contrary, if the execution price (p_t) is for example \$68,425 per bitcoin and the mid-price ($\hat{p}$) remains the same, the effective spread is: $+1(68425 - 68450) = -\$25$ per bitcoin.

For a practical illustration, we will reference the second example from the previous section. A trader purchased 100 bitcoins at an average price of \$96,216.85 per bitcoin, representing p_t. The mid-price before the execution was \$96,050. Since the order was initiated by a buyer, d is -1. Computing effective spread we can see that the trader lost \$166 on each bitcoin he purchased due to insufficient liquidity in the orderbook.

$$\mathrm{ES} = -1 \times (96216.85 - 96050) = -166$$

2.5 REALIZED SPREAD

Realized spread takes into consideration price impact, or in simple terms -- change in mid-price after trade execution. Realized spread also measures the profit or loss a trader makes after a certain period. The realized spread is calculated as follows:

Realized Spread: $\mathrm{RS} = \left|d\left(p_t - \hat{p}\right)\right| - \left(\hat{p}_{t+1} - \hat{p}\right)$

As outlined in the equation, $\left|d\left(p_t - \hat{p}\right)\right|$ is the absolute effective spread, and

($\hat{p}_{t+1} - \hat{p}$) is the difference between mid-price before and after trade execution. Referring to the example mentioned before we remember that a trader purchased 100 bitcoins at an average price of \$96,216.85 the execution of his order has wiped out multiple sell-side price levels (\$96,100, \$96,200, and \$96,300), which in turn changed the $\hat{p}_{t+1}$ and QS_{t+1}. Mid-price has shifted from \$96,050 (96,100 – 96,000) to \$96,250 (96,400 – 96,100), and the ES, which we have just computed in the previous subsection is -\$166. Hence,

$$\mathrm{RS} = -1(96216 - 96050) - (96250 - 96050) = 166 - 200 = -36$$

While the effective spread measured the immediate cost at execution, the realized spread shows the additional cost (or potential gain) after the market adjusts. A negative realized spread signals that after the market has adjusted to the price movement, the trader still realized a loss while executing the trade. The comparison between effective and realized spread in this case indicates that the new market conditions are slightly more favorable for our trader since the execution price is closer to the adjusted mid-price than initially expected. This suggests that while the trader still incurred a cost due to market impact, the final price movement mitigated some of the initial spread loss, reducing the overall impact of execution inefficiencies.

PART 3:

T-TEST ANALYSIS

3.1 VARIABLES

We hypothesize that the presence of market makers reduces both the relative spread. This metric will show how the percentage gap between the best bid and ask has changed over time. We have also analyzed the effect of market maker entry on orderbook liquidity in 0.5%, 1%, and 2% ranges from the mid-price. These specific thresholds are chosen for two main reasons:

1. Most trading activity is concentrated near the mid-price, making these ranges the most relevant for everyday traders.
2. One essential role of market makers is to ensure sufficient liquidity close to the mid-price so that larger trades can be executed efficiently (i.e., with minimal slippage).

3.2 TESTING PROCEDURE

For each token, we define two distinct time periods: One before MMs (market makers) are active ("pre-MM") and one after MMs have begun providing liquidity ("post-MM"). From each period, we select a single random date before computing the means and standard deviations of our target metrics over the complete orderbook data. Formally:

Null Hypothesis (H_0): The mean of the chosen metric (relative spread or liquidity) is the same across the pre-MM and post-MM periods, i.e. ($\mu_{\text{pre}} = \mu_{\text{post}}$).

Alternative Hypothesis (H_1): The means are not equal, specifically that the post-MM mean is either smaller for spreads or larger for liquidity (depending on which direction we expect improvement).

$$H_0 : \mu_{\text{pre}} = \mu_{\text{post}}$$

$$H_1 : \mu_{\text{pre}} \neq \mu_{\text{post}}$$

We then apply standard t-test methodology (e.g., a two-sample t-test) to determine whether the observed difference in means is statistically significant. A sufficiently low p-value allows us to reject H_0 and conclude that the presence of market makers likely contributed to a reduction in spreads and/or an improvement in order-book liquidity.

3.3 SPREAD T-TESTS RESULTS

We examined both relative and quoted spreads to assess how the distance between the best bid and ask changed pre versus post market maker entrance. Relative spread captures the difference as a percentage of the mid-price, whereas quoted spread measures the absolute difference in dollars.

1. **Strongly Negative T-Stats** (BNB, INCH, YFI, AVAX, BONK, SAND, MASK), These tokens recorded large negative t-values for both spread measures, indicating significantly tighter spreads post-MM. The reduction suggests that professional liquidity provision likely enhanced trading conditions and lowered execution costs.

2. **Notable Positive T-Stats** (COMP, SUSHI, LRC, JASMY, GALA), A handful of tokens saw increases in spreads despite MM activity. This may imply other market forces—such as volatility spikes or exchange-specific liquidity shifts—offset or outweighed the MM's impact, leading to wider average spreads in the post period.

3. **Neutral T-stats** (ZRX QNT, LDO, OP, CVX), These tokens showed either had an insignificant increase in relative spread or a sub 10% decline.

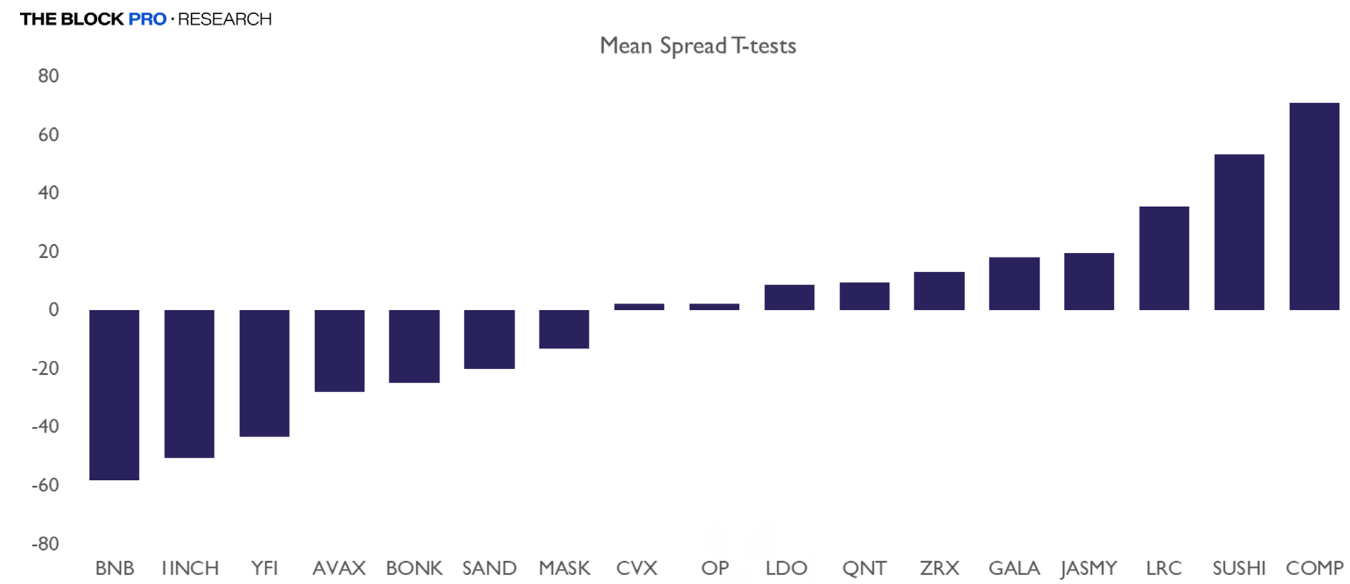


Figure 10: Spread T-tests

3.4 LIQUIDITY T-TESTS RESULTS

In the liquidity t-test results, a positive t-statistic means average posted liquidity increased after a market maker's entry, whereas a negative t-statistic means the order-book depth in that band decreased after a market maker began their activities.

1. AVAX and BONK stood out as having strongly **positive t-stats**, indicating substantial increases in posted liquidity after the entrance of a market maker. 1INCH had a similar occurrence, albeit the magnitude of its liquidity increase was different, as most of it was added to the 1% range of its mid-price.

2. A large share of tokens — including BNB, COMP, JASMY, LDO, LRC, OP, QNT, SAND, SUSHI and ZRX — showed **negative results** at all bands. This indicates that the net liquidity within 0.5%, 1% and 2% of mid-price was lower after the entrance of market makers. This counterintuitive result could have stemmed from several external factors – e.g., initial listing hype during the pre-MM period, or liquidity moving to other exchanges – and underscores that market makerpresence alone does not guarantee higher liquidity in every scenario.

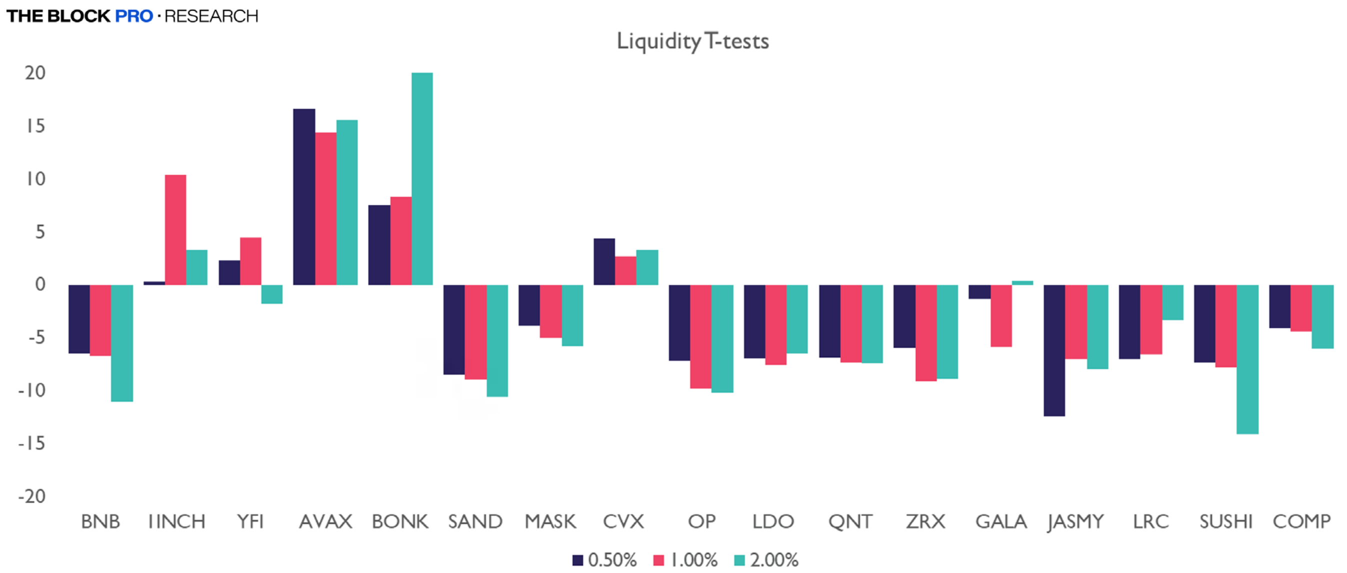


Figure 11: Liquidity T-tests

3.5 INTERPRETING RESULTS

While our t-tests suggest that market maker presence can correlate with narrower spreads and enhanced order-book depth, multiple **confounding factors** complicate the interpretation of the findings. Price volatility, for example, can overshadow liquidity provision by prompting market makers to widen spreads or reduce near-mid quotes to manage risk. Absolute token's price shifts might inflate or shrink perceived spread changes, distorting the real degree of improvement. Meanwhile, fluctuations in trading volume, often driven by external news or investor sentiment, can induce abrupt shifts in liquidity unrelated to market-making activity. Consequently, additional variable controls and broader data are needed to isolate true causal effects.

PART 4:

VOLATILITY ANALYSIS

Aside from liquidity and spreads, **price volatility** is another crucial aspect of market stability affected by market makers. Volatility quantifies the dispersion of an asset's price or returns over time, serving as a fundamental measure of market stability and risk. Higher volatility indicates greater price fluctuations, implying higher uncertainty and potential for rapid price swings. Conversely, lower volatility suggests higher price stability with movements concentrated around the mean. While volatility increases exposure to risk, it also creates opportunities for arbitrage and speculative profit, which are often taken advantage of by market makers and other market participants.

4.1 TYPES OF PRICE VOLATILITY

Volatility can be categorized into two primary types based on its temporal perspective:

- **Implied Volatility** (**IV**). Implied volatility is forward-looking metric derived from options prices under models such as Black–Scholes. By solving for the volatility that equates the theoretical option price to its market price - given strike price, time to maturity, underlying asset price, and risk-free rate—IV represents the market's expectation of future price fluctuations. While IV reflects market expectations via options prices, in practice, most tokens do not have their associated options markets, therefore our analysis will focus on historical volatility metrics.
- **Historical Volatility** (**HV**). Historical volatility is a retrospective measure of how much an asset's price has fluctuated over a specified timeframe. Typically expressed as the standard deviation of either prices, returns, or logarithmic returns, it captures the extent of average deviation from the mean. Rising historical volatility indicates growing uncertainty and higher potential for larger price swings, while a decline in HV signals the opposite.

4.2 ANALYSIS METHODOLOGY

In this section, we analyze how the presence of market makers impacts price volatility in cryptocurrency markets. The Garman-Klass volatility estimator was selected as our primary analytical tool due to its increased efficiency in capturing intraday price movements using high, low, open, and close price data.

$$\sigma_{\mathrm{GK}} = \sqrt{\frac{1}{2T} \sum \sum_{t=1}^{T} \left(\ln\left(\frac{h_t}{l_t}\right)\right)^2 - \frac{2\ln 2 - 1}{T} \sum_{t=1}^{T} \left(\ln\left(\frac{c_t}{o_t}\right)\right)^2}$$

Where:

- σ_{GK} is the Garman Klass volatility
- h_t, l_t, c_t, o_t are the values of high, low, close and open prices at day t

For each asset, we identified the specific date when a market maker entered the market and compared volatility metrics for equivalent time periods before and after this entry point. This allowed us to isolate the effect of market maker activity while controlling for temporal factors.

This analysis has several limitations, which can introduce certain biases in the analysis, its interpretations and results, including:

- Confounding Variables: While our methodology isolates pre- and post-market maker periods, we cannot fully control for concurrent market developments, regulatory changes or broader economic factors that may have influenced volatility.
- Market Maker Identification: Our approach identifies when market makers acquired significant token positions but cannot definitively determine when they began active market-making operations, and which exact exchanges were affected. The rough assumption is that if arbitrage opportunities exist, then market makers took advantage of them.

- Attribution Challenges: In cases where multiple market makers entered within short time frames, precisely attributing volatility effects to specific entities presents methodological challenges.
- Market Maturity Effects: Some volatility reductions may be attributable to general market maturation rather than specific market maker activity, particularly for newer assets that naturally stabilize over time

Despite these limitations, our analysis provides valuable insights into how market makers correlated with cryptocurrency price stability across different asset categories and market conditions.

4.3 IMPACT OF MARKET MAKERS ON VOLATILITY

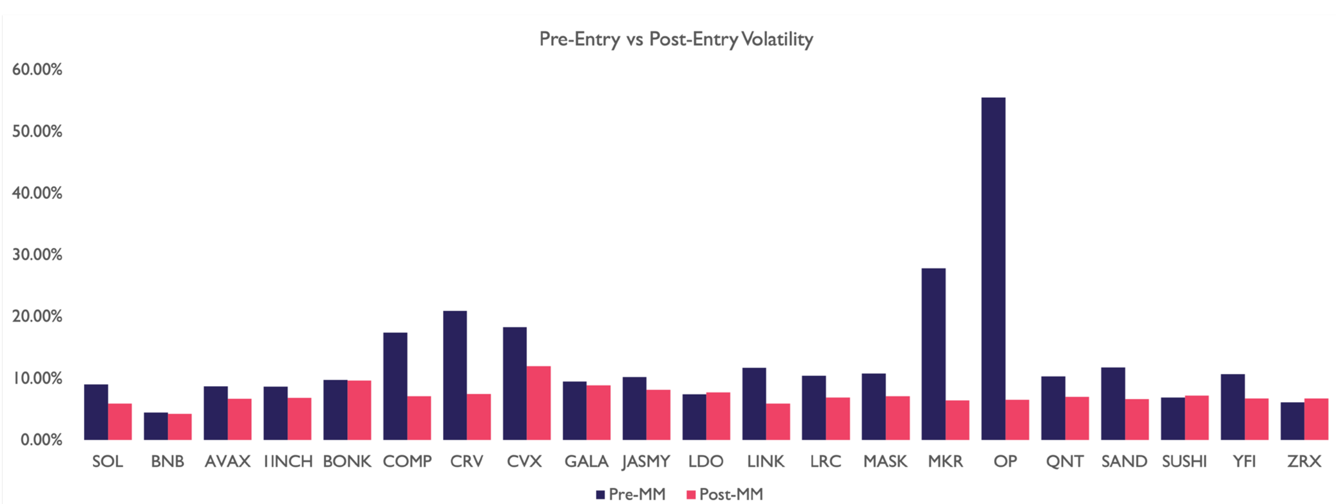


Figure 12: Pre-Entry vs Post-Entry Volatility

A comparative analysis of price volatility before and after market maker entry, using the Garman-Klass formula, indicates a notable reduction in volatility across most asset pairs.

-30%

ON AVERAGE, THE INTRODUCTION OF MARKET MAKERS WAS ASSOCIATED WITH A -30% DECREASE IN VOLATILITY,

with 20 out of 23 assets (87%) experiencing a decline. While market maker activity generally enhances liquidity and dampens price fluctuations, certain assets exhibited minor increased volatility after a market maker's entry, specifically, ZRX (0.61%), SUSHI (0.27%) and LDO (0.3%). These deviations may be attributed to underlying market conditions, differences in trading behavior or shifts in liquidity concentration.

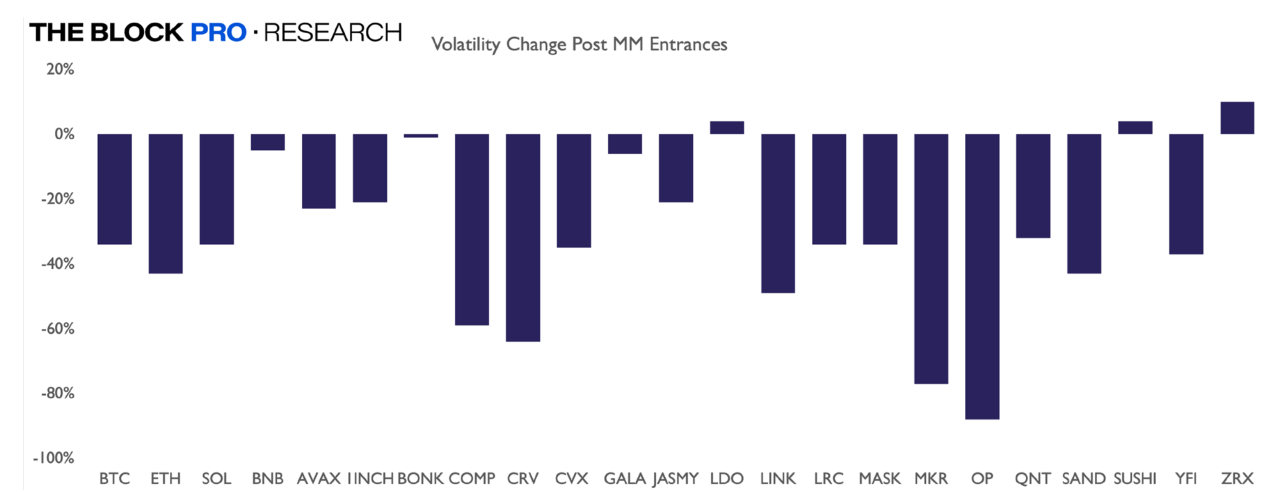


Figure 13: Average Volatility Change

4.4 VOLATILITY REDUCTION ACROSS CRYPTO SECTORS

The impact of market makers on volatility across different crypto subsectors is predominantly stabilizing, with reductions observed in nearly all categories.

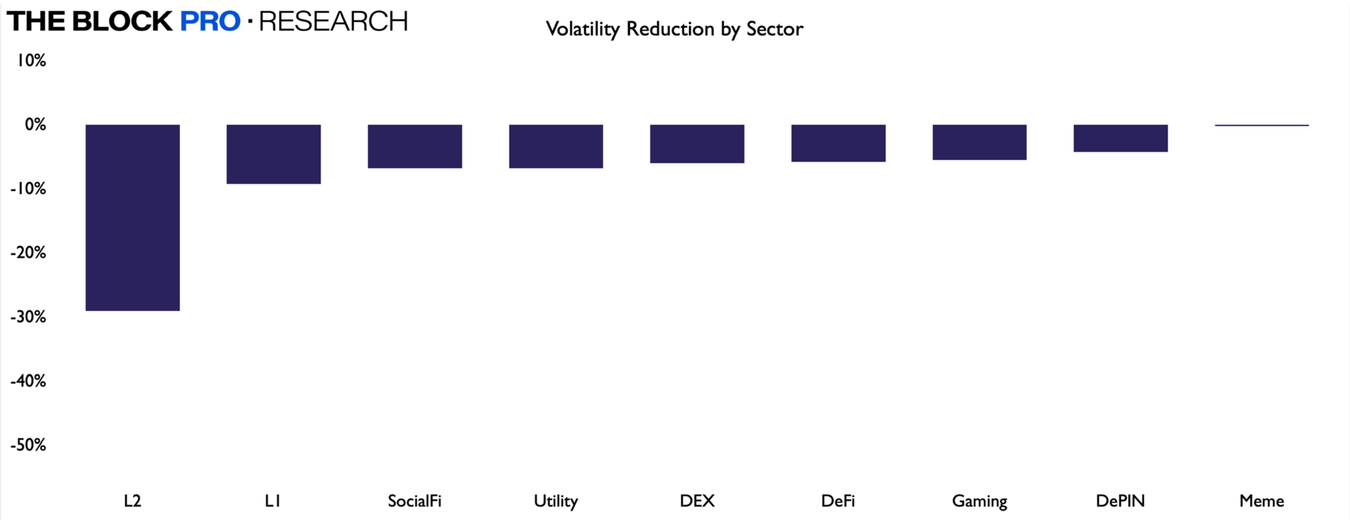


Figure 14: Volatility Reduction by Sector

- **Layer 2** (L2) tokens experienced the largest volatility reduction, averaging 29% post-market maker entry, with Optimism (OP) showing an 88% reduction. This effectiveness likely stems from enhanced liquidity depth and order book support that mitigates price swings in fragmented L2 ecosystems.
- **Layer 1** (L1) tokens benefited significantly from a single market maker's presence (-23%), while others have demonstrated more modest impact, indicating different strategic priorities.
- **SocialFi** tokens primarily saw improvements in volatility through one specific market maker (-34%), with no significant impact from others.
- **Memecoins** showed negligible volatility improvement across all market makers, suggesting either limited engagement with highly speculative assets or intrinsic

volatility characteristics resistant to traditional market-making approaches.

- **DEX, DeFi, Utility, DePIN** and **Gaming** tokens showed similar moderate improvements (-6% average), despite representing different functional components, suggesting market makers may approach these categories with similar strategies.

4.5 BRIEF SUMMARY

The overall effect of market makers on cryptocurrency volatility is predominantly positive, with an observed average volatility reduction of 30% across analyzed assets. This stabilization makes price movement magnitudes more predictable, enhancing market quality for traders and investors. The introduction of professional liquidity providers creates more orderly markets where extreme price swings are dampened, though not eliminated entirely.

Different cryptocurrency sectors benefit unevenly from market maker activity. L2 tokens show the most dramatic improvement (29% average reduction), while memecoins remain largely resistant to volatility reduction. This variance suggests that market structure, token economics and trading patterns significantly influence how effectively market makers can stabilize prices.

In the first part of this analysis, we examined 38 cryptocurrencies trading pairs and their interactions with major market makers. Our further analysis employs a scoring system that evaluates market making quality through four key components: Market efficiency, price stability, price impact and price average. This approach allows us to identify meaningful patterns in how market maker services affect market structure.

5.1 METHODOLOGY

Our approach to evaluating market making is to examine changes in four key metrics, each reflecting a distinct aspect of the trading experience. Four each analysis, we study a 60-day window — 30 days pre- and post-market maker entry, drawing on daily data.

1. **Market Efficiency** (**ME**): This metric corresponds to the following formula: $\mathrm{ME} = 1 - |\rho_1|$, where ρ_1 is the lag-1 autocorrelation coefficient of returns, calculated as:

$$\rho_1 = \frac{\sum_{t=2}^{T}\left(r_t - \bar{r}\right)\left(r_{t-1} - \bar{r}\right)}{\sum_{t=1}^{T}\left(r_t - \bar{r}\right)^2}$$

where $r_t, \bar{r}$ correspond to returns at period t and average returns over a period T. In simpler terms when if ρ_1 is high, then past returns, to a certain extent, predict future prices, hence the market is not efficient.

2. **Price Stability** (**PS**): Measures the consistency of price movements over time and is a direct indicator of market maker effectiveness in maintaining orderly markets, since it captures the magnitude of price fluctuations, with lower volatility indicating more stable pricing.

$$\mathrm{PS} = \frac{1}{\sigma_t}, \text{ where } \sigma_t = \sqrt{\frac{1}{T-1}\sum\sum_{t=1}^{T}\left(r_t - \bar{r}\right)^2}$$

3. **Price Impact** (**PI**): Quantifies the average size of returns in relation to a volatility-adjusted baseline, positing that price impact peaks when returns are substantial and rolling volatility is low. Utilizing a 5-day rolling volatility, this approach reveals how returns, on average, influence price movements over a defined period.

$$\mathrm{PI} = \frac{1}{T} \sum_{t=1}^{T} \frac{|r_t|}{\sigma_t}$$

4. **Price Average** (**PA**): PA represents the average return of the asset over the period, capturing the general price trend or drift.

$$\mathrm{PA} = \frac{1}{T} \sum_{t=1}^{T} r_t$$

5.2 METRIC CORRELATION ANALYSIS

The low correlation coefficients across most metric pairs indicate that each measure captures a distinct aspect of market performance, where dPA, dPI, dPS and dME represent reductions in respective metrics.

	dPA	dPI	dPS	dME
dPA	1.00	0.04	-0.14	-0.07
dPI	0.04	1.00	-0.07	-0.02
dPS	-0.14	-0.07	1.00	0.55
dME	-0.07	-0.02	0.55	1.00

Figure 15: Correlation Matrix

- Price Average (**PA**) difference, which measures the change in average price levels before and after a market maker's entry, shows minimal correlation with Price Impact (**PI**) at 0.04, suggesting that changes in overall price levels operate independently from improvements in trade execution costs, confirming that market makers' impact on price trajectory is separate from their ability to absorb large trades efficiently.

- The slight negative correlation between Price Average (**PA**) difference and Price Stability (**PS**) at -0.14 implies a weak inverse relationship. This could indicate that when market makers help stabilize price movements, there might be a modest dampening effect on price appreciation. This aligns with the understanding that excessive volatility can sometimes drive speculative price increases that become more controlled with professional market making.

- The most substantial correlation exists between Price Stability (**PS**) and Market Efficiency (**ME**) at 0.55, suggesting that as markets become more stable with reduced volatility, they also tend to exhibit more efficient price discovery. This relationship makes practical sense, as both metrics capture aspects of market maturity.

- Price Impact (**PI**) shows remarkably low correlations with all other metrics, indicating that a market maker's ability to minimize market impact from large trades operates through mechanisms distinct from those affecting other market quality metrics.

Overall, these low correlations validate our multi-factor approach to evaluating market making quality, confirming that no single metric adequately captures the full spectrum of market improvements. The relative independence of these factors suggests that market makers must balance multiple, sometimes competing, objectives in their operations, and that different tokens may benefit from different areas of emphasis, depending on their specific market characteristics.

5.3 TOKEN SPECIFIC RESULTS

Given the low correlations between different metrics of market making quality, we can make sense of how different specific tokens react to the entry of a market maker. In this section, we examine the average effects of a market maker's entry on the difference in PI, PS, and ME.

PI: Our analysis shows that on average, a18% increase coincides with the entry of a market maker. A stark example is MKR, which exhibited the highest positive average difference (184%), significantly outperforming other tokens in terms of reduced adverse price movements after a market maker entry. LPT (61%) and GRT (25%) followed with notable improvements. Conversely, YFI, LRC and SUSHI saw slight negative differences, implying negligible effects on their price impacts.

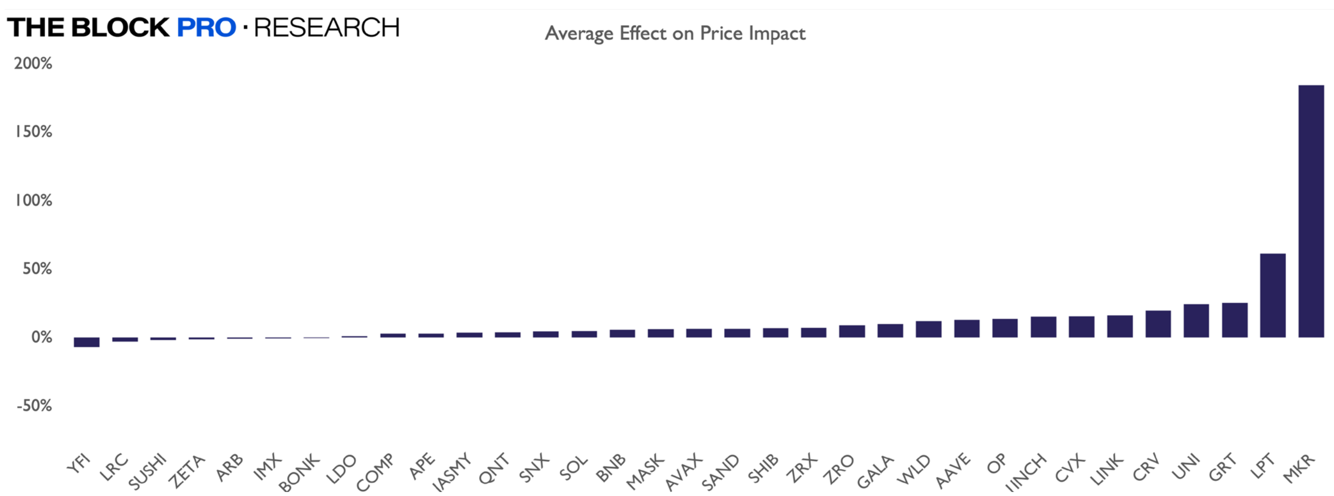


Figure 16: Average PI Change

PS: WLD displayed an exceptional improvement in price stability (491%), substantially exceeding other tokens. SHIB (288%) and CRV (152%) also significantly benefited from market maker presence, while, on average, tokens exhibited a 57% increase in price stability. On the downside, YFI (-49%), JASMY (-47%), and MKR (-40%) experienced decreased price stability, indicating either potential challenges with natural market dynamics or inadequate market making strategies for these tokens.

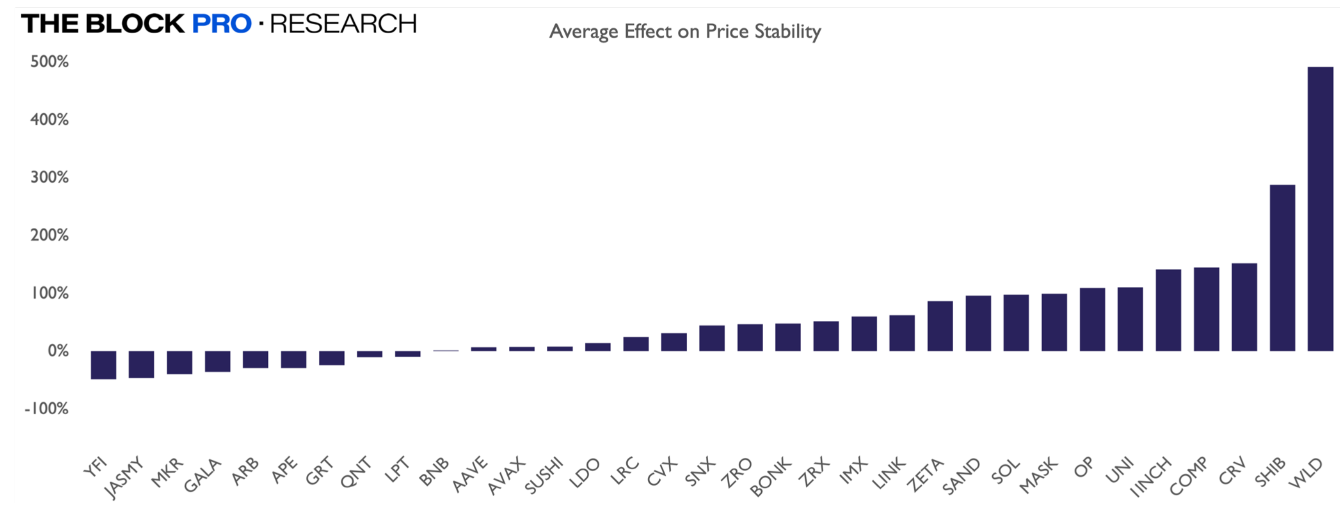


Figure 17: Average PS Change

ME: WLD again demonstrated outstanding results, markedly improving in market efficiency following market maker entry (389%). Other notable improvements include LPT (291%) and OP (251%). Tokens negatively impacted include MKR (-43%), SUSHI (-26%) and SHIB (-23%), suggesting a detrimental effect from market making activity or adverse external market conditions for these tokens.

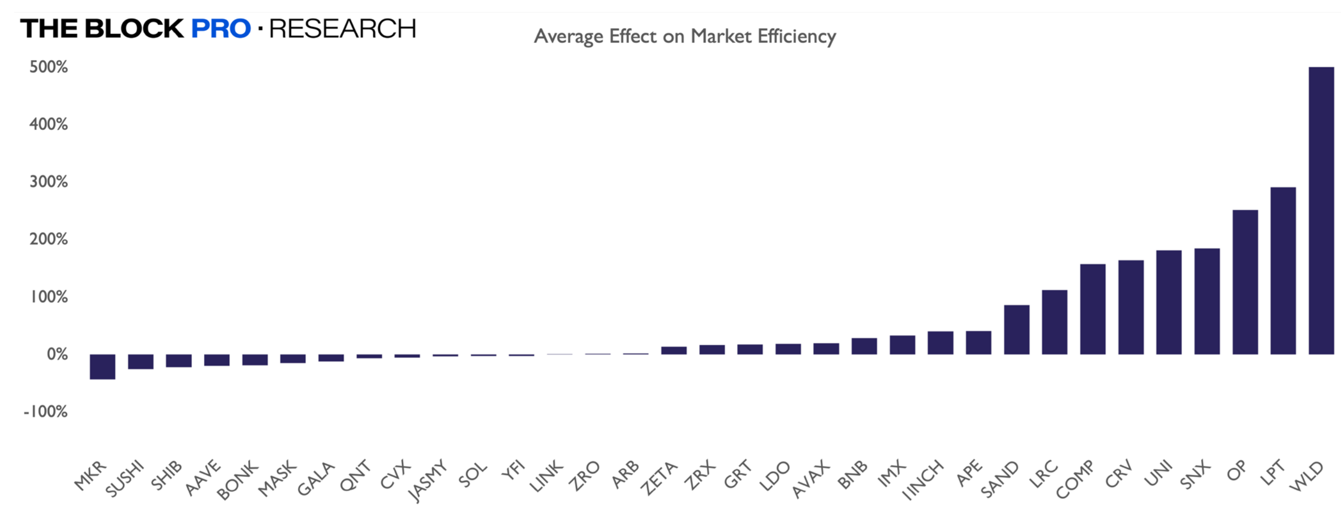


Figure 18: Average ME Change

5.4 MARKET MAKING EVOLUTION OVER TIME

Market making has witnessed considerable evolution from 2018 to 2024, driven by fluctuations in market conditions, technological advances and shifts in strategic emphasis among market makers. By analyzing yearly data, two distinct trends emerge: An initial exploratory phase from 2018 to 2020, and a subsequent period of accelerated market maturity from 2021 to 2024.

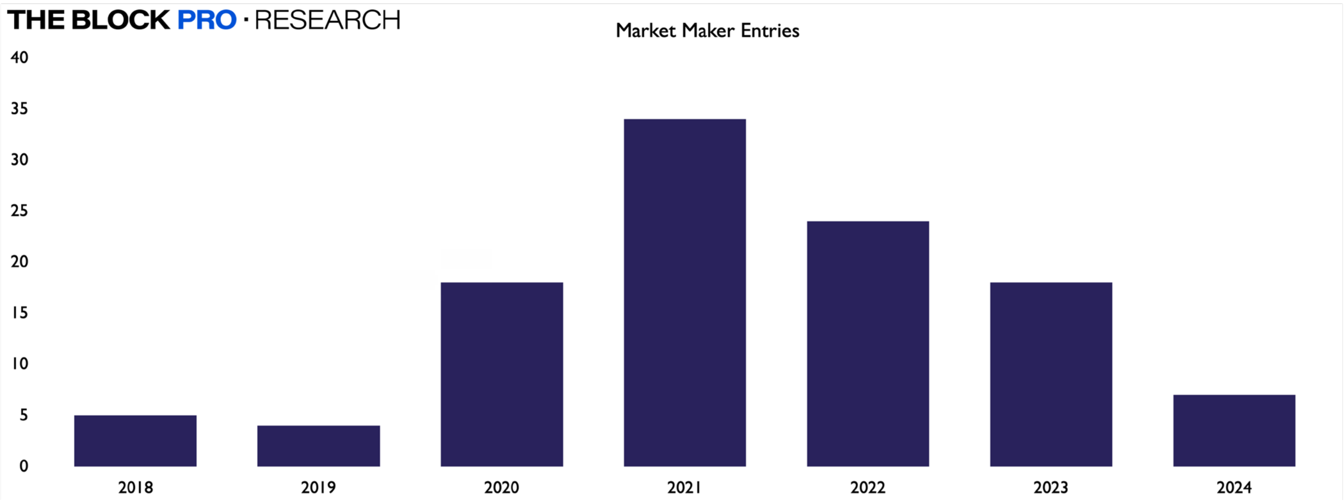


Figure 19: Market Maker Entries

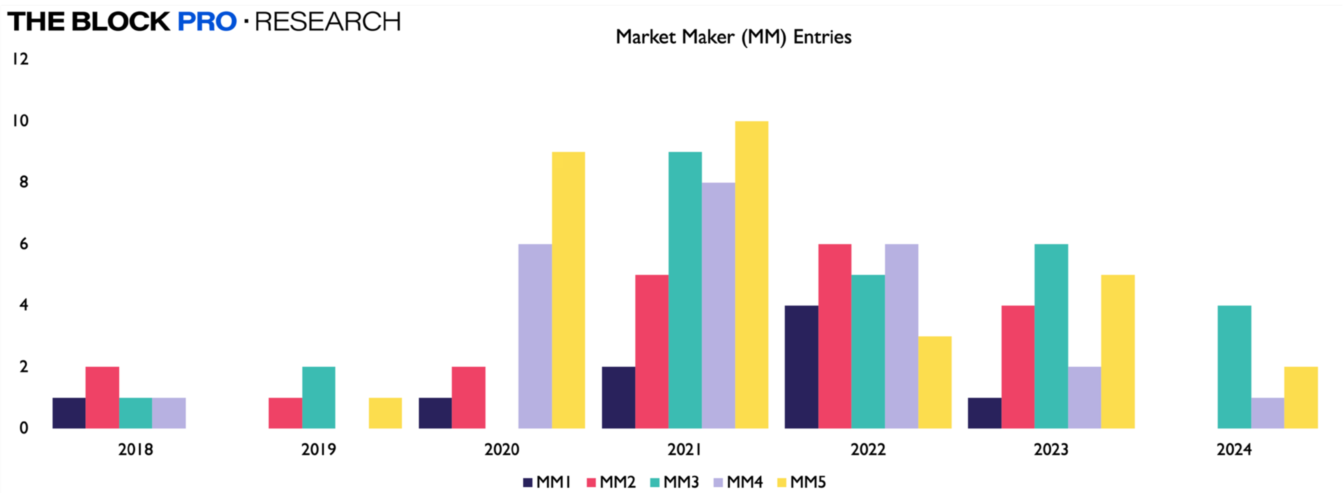


Figure 20: Market Maker Entries

From **2018** to **2020**, market-making strategies were nascent and primarily exploratory, characterized by limited infrastructure, cautious entry and basic liquidity provision. The modest metrics of Price Stability (32% in 2018) and Market Efficiency (1% in 2018) reflect initial cautious efforts and limited impact. The incremental improvements in 2019 (Price Impact at 25% and Market Efficiency deteriorating to -10%) demonstrate the initial volatility of market maker effectiveness amid turbulent market conditions.

However, **2020** marked a significant turning point, with substantial improvements across key metrics (Price Impact at 48%, Price Stability at 109%, and Market Efficiency at 164%). This period saw some market makers significantly expand their activities and strategic frameworks, reflecting increased confidence and technological investments.

From **2021** onwards, the environment shifted towards rapid growth and maturity, marked by a significant increase in the number of tokens receiving active market-making support. In **2021**, market makers maintained solid performance metrics, including Price Stability (60%) and moderate Market Efficiency (28%), indicating substantial engagement across numerous tokens (34).

However, **2022** presented new challenges, as broader economic uncertainties and regulatory pressures caused volatility, reflected in declining Price Stability (22%). Despite these conditions, market makers showed resilience and adaptability, continuing active operations with 24 tokens. In **2023**, market makers achieved remarkable gains, particularly in Market Efficiency (467%), possibly driven by the advanced integration of algorithmic strategies and improved liquidity management. By **2024**, the market-making landscape exhibited signs of stabilization, with moderate metrics (Price Stability at 46% and Market Efficiency at 11%). This most recent stage indicated market makers increased strategic selectivity, reflecting a more mature environment with increased competition and refined operational strategies.

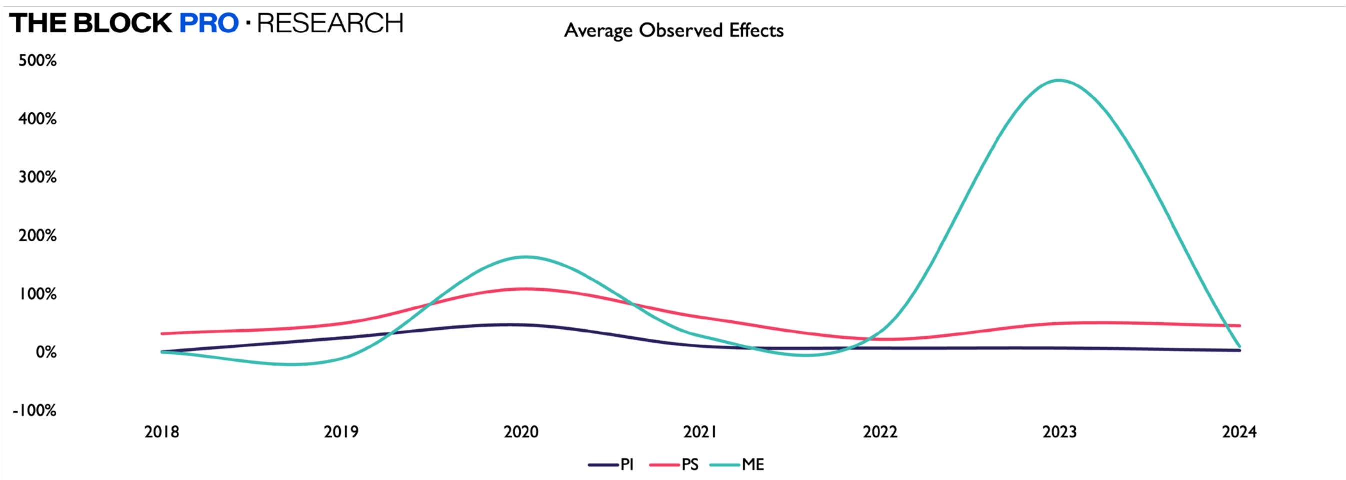


Figure 21: Average Observed Effects

Overall, this temporal analysis highlights how the early stage of market-making exhibited significant dispersion in results, reflecting immature markets and varying strategic capabilities. Conversely, the later period from 2021 onwards demonstrated convergence and stabilization, indicating a maturing industry characterized by refined strategies and decreased performance variability.

CONCLUDING NOTE

The analysis confirms that professional market makers play a vital role in the health and maturity of crypto markets. By continuously quoting buy and sell orders and maintaining deep order books, market makers enhance liquidity and dampen volatility. This leads to tighter bid-ask spreads and more stable prices, making trades easier to execute without a significant price impact. Such stability in turn fosters greater user trust and adoption – when market participants know that they can enter and exit positions at fair prices, confidence in the market grows. The result is a more efficient trading environment where price discovery aligns closely with supply and demand, and sudden price fluctuations or market manipulations are less likely to occur.

Our comparative review of major crypto liquidity providers further highlights the impact of professional market makers on stable trading environments. While all the firms studied generally contributed to more liquid and less volatile markets, the consistency and magnitude of their effectiveness varied. Factors influencing their varying performance include differences in strategic approaches, technological sophistication, and adaptability to changing market conditions. Additionally, the geographical distribution of liquidity and the ability of market makers to harmonize prices across exchanges through effective arbitrage play significant roles. Ultimately, selecting an experienced market maker that aligns strategically with a project's specific needs is crucial to fostering a sustainable and attractive marketplace, thereby promoting long-term token adoption and ecosystem growth.