Resilience in Fiery Seas

An analysis of liquidity resilience in the Centralized ETH/USDT and Decentralized WETH/USDT cryptocurrency market

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Abstract:

This paper investigates how liquidity reacts to pre-defined stress events on a specified decentralized and centralized exchange. We study the period, 2021 to 2025, and identify stress as the most volatile 10% hourly candles using ETH/USDT data from Binance and Uniswap V3. The liquidity resilience of the two venues post-stress is investigated through the vehicle of transaction cost, examining the unique constituents of this cost for each market structure, such as gas fees and slippage. We find that liquidity tends to deteriorate for both venues following market stress for different reasons. On the centralized venue, market volatility causes liquidity depth to evaporate and, in turn, increase slippage. On the decentralized venue, we find that gas price spikes explain the disproportionate liquidity degradation for smaller trade sizes relative to larger ones. Thereafter, we decompose gas prices into base and priority fees. From this, we derive the expected future liquidity resilience of the two venues by only accounting for the structural aspects of the decentralized venue, mainly through the priority fee of gas, as the mostly technologically dependent base fee component is observed to be trending towards a zero level. Furthermore, we establish a causal relationship, for specific trades sizes, between pre-stress volume and the improvement of slippage for the DEX relative to CEX following a stress event. These findings contribute to the existing literature by showcasing the long-run competitiveness of DEX accurately and expanding on the debate for why the beneficiaries of venue fees are relevant for liquidity degradation in cryptocurrency markets.

Keywords:

Cryptocurrency Exchanges, Liquidity Degradation, Automated Market Making, Gas Fees, Stress Events

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I. Introduction

Over the last two decades, disregarding any niche hybrids, two key cryptocurrency venues have bifurcated from the original motivations behind Bitcoin's inception. These include decentralized exchange (DEX) venues, such as the likes of Uniswap, PancakeSwap and Aerodome, and centralized exchange (CEX) venues like Binance and Kraken. These two cryptocurrency market structures contain many technical microstructural differences but are both relevant to a wide array of crypto traders today. From the way pricing is set with market makers through limit order book (LOB) in CEXs and automatic market makers (AMM)[1] protocols set in DEXs, it is clear to see why they are so intertwined with current and ongoing financial literature. In today's market climate, where volume may no longer be the best way to measure success in exchanges, a contributing analysis in the market or an exchange venue analyzed may be *how well they may fare during times of extreme market stress*. Currently, there is a large growing body of literature that reviews which venue type is safer and cheaper during varying market conditions, such as with Angeris, Kao, Chiang, Noyes and Chitra (2020).

Narrowing down, arguably, the most relevant aspect when evaluating how well these exchange venues fare during times of market stress is the cost of performing transactions on that venue, referred to as the transaction cost. In most CEXs, the components that are most relevant when analyzing transaction costs are the *price slippage*[2], which is influenced by the state of the LOB through the bid-ask spread, and the *fixed fee* of the specific venue. Although the approach for computing the components for transaction costs differ for AMMs, transaction costs for DEXs are also determined through the components of slippage and the fixed fee of the venue, with the addition of the on-chain settlement costs known as "gas fees". This represents a secondary stochastic variable for calculating the cost of transactions for DEX and, as their behavior is often governed by block-level demand [Koutmos (2023) and Karaivanov and Zarifian (2024)], this can make it problematic to know exactly what the optimal gas fees set for highest chance of inclusion in the next block[3].

Although research does not focus on the microstructural components of these reasons that gas fees will become fixed costs or zero in the future, this assumption often neglects the characteristic variability of gas fees and, therefore, does not represent them faithfully. Despite this, in their comprehensive study that examines a wide array of cryptocurrency venues and their qualitative attributes including transaction costs, Barbon and Ranaldo (2024), the main inspiration for exploring this subject, argue that DEX transaction costs are becoming better with time than CEX and will even eventually outperform current CEX venues; this is found to be especially true for smaller trade sizes. Their reasoning for this trend stems from a key assumption that gas fees will eventually reach a substantially lower value due to solely technological advancements made in the decentralized exchanges lowering the gas fees. In this study, we observe that, in the long term, a structural component to gas fees persists, which stems in large part from the priority fee, and is the

[1] "An automated market maker (AMM) is a type of decentralized exchange (DEX) protocol that allows users to buy and sell digital assets without the need for a third-party intermediary." (CoinMarketCap, 2025)
[2] Price slippage (AKA simply slippage) reflects the part of transaction costs that occurs when executing an order in a market where available depth cannot fully absorb the trade size at the quoted price.
[3] "A block is the fundamental unit of a blockchain that contains a set of validated transactions and cryptographic links to previous blocks, forming an immutable record in the blockchain network." (Investopedia, 2025)

main aspect as to how traders in DEXs can compete for block space[4] in the current block. As such, we believe that there is a gap remaining to exactly understand transaction costs during events of market stress in modern and expected future markets where gas fees will continue to vary and *cannot be assumed to be fixed or zero*. To clarify, this stress event-based study we propose in this paper would observe the change in transaction costs and would recognize this as a measure of liquidity resilience or, as we predict during market stress, *liquidity degradation*.

Following this, we chose to analyze one very specific cryptocurrency trading pair known as the ETH/USDT for CEXs or otherwise recognized as WETH/USDT for DEXs. The decision for choosing each token in this token pair is as follows: i) USDT is the most traded and stable digital tokens (otherwise known as stablecoins) in most cryptocurrency exchanges as of 2025 and ii) Ethereum (ETH), other than bitcoin, is also among the most traded and modernized crypto tokens. This ensures a focused and microstructural analysis of this token swap with ample data with regards to trade volume and less noise when it comes to potential speculative/noise trading. In addition, the Binance and Uniswap V3 fee tier 0.3% were selected as the key CEX and DEX venues for study, respectively, based on having high quantities of publicly available data that could be retrieved and analyzed. With this traded pair and the venues established for the CEX and DEX, the scope of this research paper is detailed by this research question:

"*How does liquidity resilience, or degradation, in the (W)ETH/USDT market in the Uniswap V3 0.3% fee tier pool and the Binance venue behave during periods of great market stress?*"

We define and analyze a "stress event" as the merged or individual 10% most volatile hourly candles in the period (09-11-2021:09-11-2025). Volatility for each candle is initially estimated using the Roger-Satchell volatility estimator for the purposes of identifying desired stress events which will predictably have a potentially non-zero drift component.

Briefly, the most significant methods with which we studied liquidity degradation in this market were derived by first simulating transaction costs for both venues for a variety of trade sizes ranging from 0.1 ETH to 100 ETH, taking inspiration from the methods used by Barbon and Ranaldo (2024). Thereafter, the statistical significance of the degradation of transaction costs, the vehicle for liquidity resilience in this study, was evaluated for these trade sizes to verify the discrepancies between small and large trade size transaction costs. On top of this, a panel regression and decomposition were performed to investigate whether smaller trade sizes are disproportionately affected in the DEX venue and if this is due to a change in gas, supporting the treatment of gas as a stochastic variable and, thus, staying consistent with the approach of Koutmos (2023). Thereafter, the priority fee and the base fee of gas were identified and decomposed and regressed on every 300th block number in the past 4 years to examine how the trends in these two components in the WETH/USDT market vary with time. It is important to note that this is an effective way of measuring each components' trends as block numbers are chronologically serialized in the Uniswap V3 DEX exchange to account for time. Further, this paper also employed a first-difference interaction regression model to examine how pre-stress trade volume impacts slippage through liquidity depth differently in the CEX and DEX venues, controlling for variables

[4] Block space is limited capacity in fitting transaction into a block on the blockchain. Because this space is scarce, users compete for it through gas fees, which determines how quickly their transactions are confirmed by validators.

such as price directionality and realized volatility outlined by Andersen, Bollerslev, Diebold, and Labys (2001). This concludes the scope of our exploration.

Through the results for these various tests, we effectively examine the liquidity resilience of the CEX and DEX venue, respectively, and evaluate the behavior of the (W)ETH/USDT market to stress, contributing to existing literature. Accordingly, we find that liquidity degradation for the DEX venue tends to disproportionately affect smaller trade sizes, while larger trade sizes tend to experience a liquidity degradation competitive with the studied CEX venue. In addition, we find that liquidity resilience on the DEX Uniswap V3 fee tier 0.3% pool for the WETH/USDT market is worse than CEX for small trade sizes and this difference converges to approximately zero for large trade sizes. However, after accounting only for the structural components of gas costs in the long run, we observe that the DEX venue becomes more resilient than the CEX for large trade sizes. While the liquidity equivalence point, defined as the trade size at which average liquidity degradation is equal across the two venues, shifts towards even smaller trade sizes, the DEX venue's liquidity resilience does not outperform the CEX venue's liquidity resilience across the full trade-size spectrum. Finally, following the framework employed by Heimbach, Schertenleib, and Wattenhofer (2022), we determine that, for some trade sizes, liquidity providers in the Uniswap V3 venue tend to concentrate their liquidity during stress to capture revenues from fees from increase in volume traded in the DEX venue, demonstrating that following a stress event the slippage in DEX tend to improve in comparison to CEX.

Due to the highly technical nature of this paper, we divide and attempt to compartmentalize our research. As such, following this introduction, this paper has been divided into 4 separate sections: Section II features Related literature and Hypotheses formation, Section III outlines Data procurement and Methods, Section IV presents our Empirical Findings and Section V details our Concluding Remarks.

II. Related literature and Hypotheses formation

This section starts off by examining the theories related to market microstructure, identifying what constitutes liquidity in different market structures, and the relevant factors that impact it. We then proceed to delve into the financial literature's perspective as to how liquidity is measured in DEXs and CEXs for cryptocurrency tokens. We conclude by grounding our research in the logic and justifications behind the formation our hypotheses.

A. Background: Market Microstructure theory

To analyze the liquidity resilience of both the CEX and DEX venues effectively, a fundamental understanding of slippage must be established before moving forward. Works from previous studies such as Glosten & Milgrom (1985) and Kyle (1985) have both been recognized for laying the groundwork for microstructure analysis in microstructure theory for central limit order books (LOB) exchanges, exploring both the explicit and implicit sources of slippage and, hence, transactional costs from different perspectives. These analyses are both relevant for the simulation of transaction costs for the Binance centralized exchange and the Uniswap V3 fee tier 0.3% explored for the (W)ETH/USDT market.

With regards to Glosten & Milgrom (1985), they explore the notion that market makers in exchanges, referred to as liquidity providers for the context of this paper, will tend to act rationally in an attempt to minimize their risk exposure from more informed traders; this effectively represents the problem of adverse selection due to information asymmetry. In turn, they argue that market makers will, in response, charge higher risk premiums to offset this risk and that this becomes far more pronounced during periods of market stress. This is in the form of increasing the range of the bidding price at which they offer liquidity for buyers and increasing their asking price to sell a financial asset for, today known as the *bid-ask spread*. This is relevant to our study's analysis as we use this concept to justify our hypotheses for much of the outcome for our testing.

In equal measure, Kyle (1985) has provided the foundational concepts of the implicit market cost components of slippage in central LOB markets. He achieves this by establishing a model focused on market depth and price impact that demonstrates that market liquidity is "finite" and directly derivative of the ratio of *noise trading*, the trade volume that is motivated by random and uninformed decisions that excludes insider trading, from traders to the volatility of the traded asset's fundamental value. He finds that market makers tend to adjust their prices in accordance with *order flow*, the difference between execution price set by efficient market makers and the expected execution price (for the insider acting as a monopolist calculating their own trade impact) of a transaction because it is a signal of private information. He concludes that the cost of executing a trade tends to increase as the volatility of the underlying asset increases.

For the purposes of this paper, the understanding behind these analyses is paramount as they are the source for liquidity degradation analysis in both the Binance and Uniswap V3 (W)ETH/USDT exchanges, and, as a result, we utilize this literature by verifying that this effect can be observed in both venue types.

B. Execution costs in DEX and CEX markets

The existing literature examining the cryptocurrency market has put heavy emphasis on CEX and DEX markets in general and not specifically delved into events that cause market breakdown. As previously referred to, the most relevant and comprehensive study that inspired the venture into this topic is by Barbon and Ranaldo (2024), where they examine the differences across a plethora of DEX and CEX venues for the top 20 most popular currency swap pairs, finding that DEX transactions tend to be impeded by the presence of gas fees and slower settlement times relative to CEX. With higher trade sizes, however, they find that transaction costs in DEXs become very competitive with CEXs and that, for some currency markets, they even tend to outperform them. To contribute, we add to the literature by observing if this competitive nature between a given CEX and DEX venue persists, even during market-stress sourced liquidity degradation.

To supplement their analysis, Barbon and Ranaldo (2024) further compare the DEX and CEX venues by removing gas prices in totality. This was justified on the basis that gas prices will, over time, fall to 0 as they are entirely assumed to be temporary technological hurdles of the DEX markets which will only shrink with time. Effectively, this removed the regressive characteristic of the DEX transaction costs as it was only made up of the specific protocol fee (venue pool for DEX) and the slippage. However, the assumption that gas costs converge to 0 is challenged by recent empirical studies. Specifically, Karaivanov and Zarifian (2024) research that in the post EIP-1559 protocol[5], users actively select their priority fees in response to network congestion, transaction type, and block-level demand conditions. Similarly, Koutmos (2023) shows that Ethereum gas prices are highly sensitive to network congestion, with changes in intraday transaction volume, block capacity (determined by the EIP-1559 protocol) and block time all being found to significantly explain changes in gas fees across the full distribution of gas-price movements. This shows that, while there might be a technological advancement in decreasing gas costs due to block capacity and similar advancements, the *priority fee component of gas remains highly sensitive to economic factors such as urgency and block utilization*. In reference to this, we contribute to the literature by isolating the technological and structural components of gas prices and determining how the structural and technological aspects of gas fees change over time during stress events and if it is justified to assume 0 invariant gas prices in the long term.

In reference to Uniswap V3, Heimbach et al. (2022) proposes a theoretical framework that models active liquidity providers' decision-making, explicitly accounting for both the fee revenues and the additional risks liquidity providers enjoy with concentrated liquidity, where liquidity providers (LPs) can set their own price ranges for which they provide liquidity for. This allows for complex, liquidity provider-determined liquidity distributions in the Uniswap V3 venue that vary greatly with price. In likeness to Glosten & Milgrom (1985), this study finds that liquidity providers face similar adverse selection issues in decentralized market structures in the form of impairment losses. However, it is important to note that in a DEX on Uniswap V3, liquidity providers make an earning on the volume traded, determined by the pool fee. The implication of this is that there is a return relationship where decisions need not only be made by what the expected loss due to gas prices and impairment is, but also on the potential profits. We contribute to the literature by

[5] Ethereum Improvement Proposal 1559 (EIP-1559) was an upgrade to Ethereum's fee system that introduced a base fee and a priority fee (tip). Before this Ethereum used a first-price auction for transaction fees.

examining whether DEX liquidity improves following a stress event in comparison to CEX when factoring in the determinants of LP behavior.

The literature reviewed in section A and B gives reasonable grounds to expect that the degradation of transaction costs during stress events will rise. This dissertation has attempted to investigate and verify whether this degradation applies to a specific crypto exchange in direct contribution to the existing body of literature.

C. Hypotheses formation

On the basis of the limit-order-book microstructure theory for centralized exchanges discussed in section A, and through evidence that gas fees and volatility increase execution costs on decentralized exchanges discussed in section B, the following first hypothesis can be investigated: *transaction costs on both CEXs and DEXs are higher on average during stressed market conditions than during normal periods, across all trade sizes.*

Complementing this, Koutmos (2023) argues that that gas fees react to network congestion. As aforementioned, during stress events in the cryptocurrency markets, competition for block space is at a high in the DEX market and, as such, gas fees in that period tend to hike, with transaction costs following in consequence. In combination with the fixed aspect of gas prices, Barbon and Ranaldo (2024), we hypothesize; *for smaller trade sizes, DEX transaction costs, tend to degrade worse during a stress period as opposed to a normal period, due to an increase in effective gas paid, while larger trade sizes are affected less.*

As reviewed briefly in section B, we examine gas costs with Barbon & Ranaldo's (2024) claim that there is a technological aspect to gas. This view is reasonable: lowering gas fees aligns with Ethereum's long-run design incentives, since cheaper transactions increase network usage and may ultimately increase the value of the underlying asset (ETH) (Butverin, 2020). This, in turn, strengthens their competitiveness as a network provider. Under this perspective, most of the gas price is driven by technological constraints such as the base fee, block capacity, and processing efficiency.

According to current research and in reference to the findings of Karaivanov and Zarifan (2024), a structural component of gas may persist under future technological improvements that will limit how much gas price can decrease in the Ethereum network. To clarify, on the blockchain, competition for inclusion in the current block can persist due to the presence of priority-fee bidding, making this a central aspect of how the blockchain can continue to function through incentivizing validators.[6] This characteristic of user urgency and valuation of the block space does, therefore, imply that a non-zero minimum priority fee may very well prevail, even if the technological aspects of gas (such as the base fee) may shrink to a zero or zero equivalent level. In addition to this, factors such as MEV dynamics[7] and imperfect gas-price estimation by user and bot traders alike further exemplify how priority fees contain an intrinsic aspect of the block space market as they guide the competitive forces of the space. Given this, the trends in base gas fee and

[6] Validators are the block producers, through a proof-of-stake system locking 32 ETH capital, they are given the opportunity select the transactions to be included in the next block. Their compensation is the priority fees of each transaction included.
[7] MEV: "Maximal extractable value (MEV) refers to the maximum value that can be extracted from block production in excess of the standard block reward and gas fees by including, excluding, and changing the order of transactions in a block." (Ethereum foundation, 2025)

priority fee will reflect if the literatures assumptions can be validated and justified. This train of thought enabled us to ask the following: *If it can be assumed that gas fees will reach an approximate zero value over time, do both the technological and structural components of gas fees trend downward at equally substantial rates with diminishing variance in time?*

A downward-trending and variance-shrinking base fee and priority fee would strengthen Barbon & Ranaldo (2024) claim, and provide basis for the third hypothesis; *Liquidity degradation for DEX is lower than CEX across all trade sizes when accounting for only the structural components of gas price*.

Although our study attempts to decompose gas price to identify technological and structural components, the results rely on assumptions that, while validated historically, are not immutable in the future. Thus, a potentially more interesting analysis would be to look at the component in transaction costs that both markets share, the slippage. In relation to their mentioned framework in section B, Heimbach et al. (2022), it is determined that liquidity providers may concentrate liquidity in the Uniswap V3 venue by either readjusting or adding reserves at the current price during a volatile event if they expect that the revenue from the increase in volume may outweigh the rise in gas prices coupled with the expected impairment loss from the price detection. By these means, the fourth hypothesis is derived: *for a disproportionate amount of stress events, DEX slippage will improve while CEX slippage degrades when the change in volume prior to the stress moment increases.*

III. Data procurement and Methods

Formally, the scope of this section is to isolate moments of market shock by identifying and segmenting the historical ETH/USDT market into both "stress" and "normal" regimes. In equal measure, this section will derive the relevant methods and their data to investigate the central research question. The ETH/USDT pair was selected due to being one of the most liquid crypto pairs globally, with both having daily traded volumes reaching tens of billions of dollars, making them among the top 4 most traded tokens across all markets; USDT is the more prominent of the two (CoinGecko, 2025). However, the rationale for this pair extends beyond this as USDT is a USD-pegged stable coin and its value is intentionally designed to remain close to one U.S. dollar, irrespective of broader market conditions on the Ethereum network. This makes USDT functionally equivalent to a stable unit of account within the markets. Because ETH is not ERC-20 compliant[8], DEXs wrap ETH into its ERC-20 equivalent (Wrapped-ETH or WETH) to allow it to interact with liquidity pools and smart contracts. Thus, for the DEX venue, the pair analyzed is WETH/USDT. Importantly, WETH is fully backed 1:1 by ETH and, therefore, it serves as the functional representation of ETH in the DEX. Due to dataset constraints and API query limits, only one market is analyzed as representable for the measurement of liquidity on both venues, despite the existence of other valid pairs. The DEX and CEX venues this paper explores are Uniswap V3 0.3% fee tier and Binance. The rationale behind Uniswap V3 comes from its ranking as the third most used DEX venue in terms of traded volume across all pairs (CoinGecko, 2025). However, more importantly, through inspection of the WETH/USDT pools in the top 2 venues, it is observed that Uniswap V3 has a greater total value lock (TVL)[9] for WETH/USDT 0.3% than PancakeSwap and Aerodrome Slipstream had for their highest TVL WETH/USDT pool ($11.7m vs $1.34m vs $200k) (PancakeSwap, 2025), (Aerodome Slipstream, 2025). Fee tier pool 0.3% was selected due to having the highest TVL among the fee tiers on Uniswap V3. The rationale for selecting Binance as the CEX representative venue is similar to Uniswap (CoinGecko, 2025).

To clarify the structure of the following sections: Section A. delves into the identification of our stress and normal periods, section B establishes the methodologies used to test for the hypotheses, and section C explores the methodologies regarding the data and its collection.

A. Specifying the Normal-to-Stress period sample

To procure the primary dataset on the historical hourly data for the ETH/USDT pair, Klines API from the Binance centralized exchange was selected and used for its popularity among users and volume (Binance, 2025). This allowed for a more representative picture of the CEX venue which many other competing venues strive to replicate. To this end, a four-year sample, spanning from November 9th, 2021, to 2025, of 1-hour candles was extracted as this was the time frame in which the Uniswap V3 venue had become an established and relevant venue for cryptocurrency traders and market makers. The variance of these data points was estimated using the popular Rogers-Satchell (RS) volatility estimator, as opposed to the commonly employed Garman-Klass estimator,

[8] ERC-20 compliant means that a token follows the ERC-20 standard. This standard is a set of rules on the Ethereum blockchain that defines how tokens should behave. ETH was created before ERC-20 came into effect; thus its new form became WETH on chain.

[9] TVL represents the total monetary value of the reserved tokens provided by the liquidity providers in this pool. A greater TVL often implies better liquidity assuming its normally distributed around price.

due to the particularly high frequency of the stress period data resulting in a definitive non-zero drift component. To justify, stress periods identified in our sample did not last more than 10 hours and were thus analyzed as events and not continuously. The use of the Garman-Klass estimator would, therefore, have been unfaithful due to its zero-drift assumption, as discussed by Shu and Zhang (2006). For every given hourly candle with open timestamp t, The RS volatility for each candle, σ_{RS}, was calculated as follows:

$$\sigma_{RS} = \sqrt{ln\left(\frac{H_t}{C_t}\right) ln\left(\frac{H_t}{O_t}\right) + ln\left(\frac{L_t}{C_t}\right) ln\left(\frac{L_t}{O_t}\right)} \quad (1)$$

Where O_t, H_t, L_t, and C_t represent the open, high, low and close (OHLC) prices at for the candle with open timestamp t for each candle, respectively. Through a percentile-based filtering process, stress and normal periods were identified in our dataset on the complete 4-year time series. Stress candles were defined as those that were at or beyond the 90th percentile of the total candle RS volatility distribution, while normal candles were at the bottom 50% of the distribution.

FIGURE 1 – Distribution of RS volatility (σ_{RS}) [%]

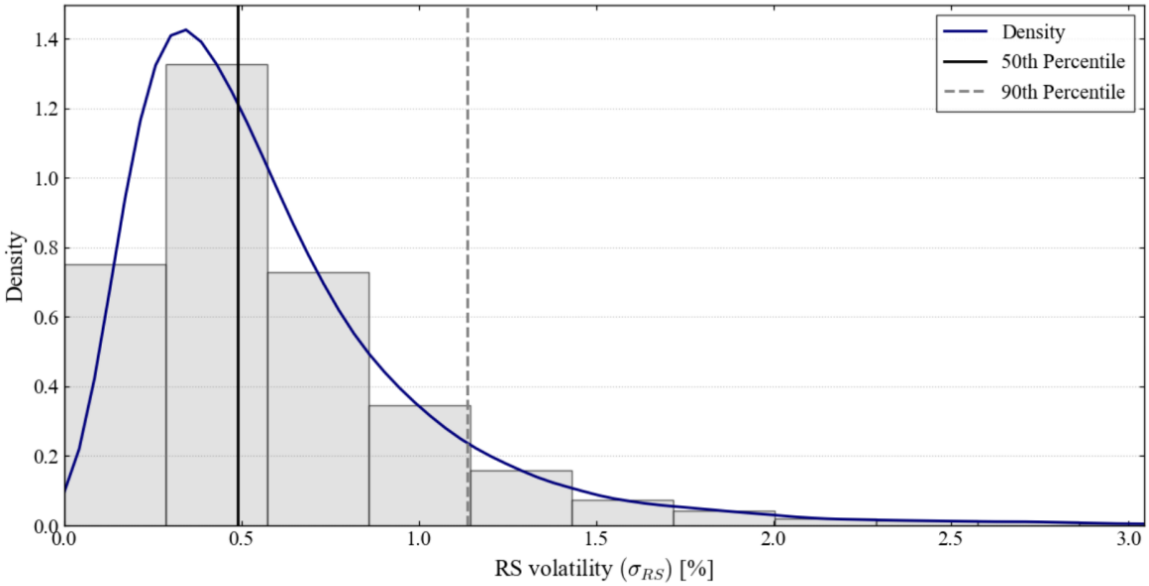


FIGURE 1. This figure shows the density of Roger–Satchell volatility, expressed in percent, computed from hourly ETH/USDT candles on Binance over our four-year period sample, 2021-11-09 to 2025-11-09. The solid black line marks the median (50th percentile), while the grey dashed line marks the 90th percentile. The histogram includes a kernel density estimate for smoothness (blue line).

Continuous stress candles were merged and sequences that did not have a normal-volatility period immediately before were removed. The rationale for this was to account for the lagged decay effect candles can have on future candles (Bouchaud, Farmer, & Lillo, 2009). With this, a data-based approach for determining normal and periods of market stress is derived. However, since volatile events can occur in a select few minutes within an hourly candle, further investigation on the volatility of the minute candles in the normal stress was conducted. To measure the short-horizon volatility of minute candles, the log of price return for ETH/USDT for each candle with a 1-minute difference (t) was computed. In addition, the realized volatility (RV) was also determined using a

rolling 10-period window, decided based on the robustness test results from Table 1, with t here representing the candle index in our normal-stress (normal or stress timestamp) period:

$$r_t = ln\left(\frac{P_t}{P_{t-1}}\right) \tag{2}$$

$$RV_{10}(t) = \sqrt{\sum_{i=t-9}^{t} r_t^2} \tag{3}$$

Examining realized volatility in such a manner follows the Andersen-Bollerslev-Diebold-Labys (ABDL) framework (Andersen et al., 2001) and is a noteworthy method for the purposes of selecting moments of liquidity degradation, both due to the immediate volatility, but also the delayed volatility effect from previous candles (Bouchaud, Farmer, & Lillo, 2009). To identify persistent normal and stress volatility states, the mean RV inside 35% windows throughout the entire normal-stress event was computed.

FIGURE 2 – Realized Volatility $\mathrm{RV}_{10}(t)$ and Timestamp Selection

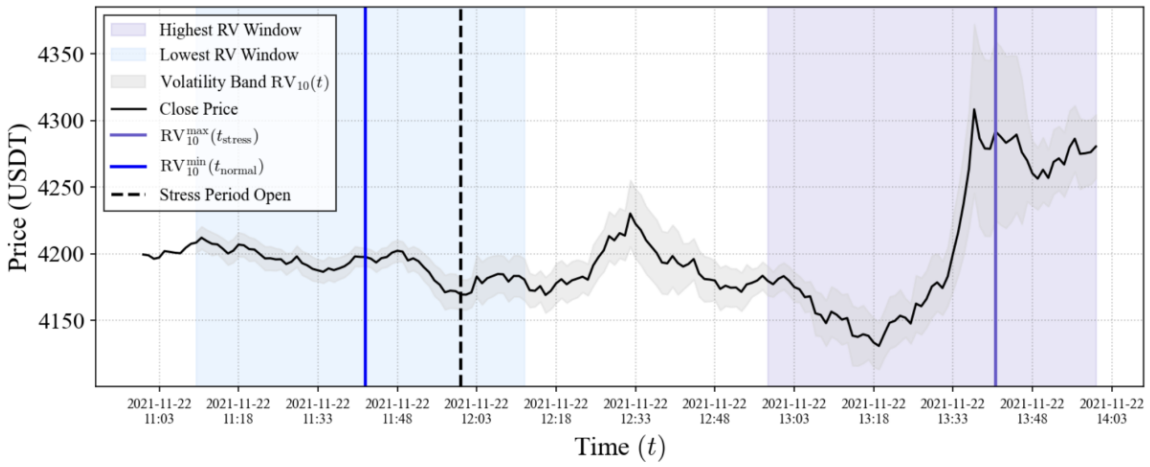


FIGURE 2. This figure displays the ETH/USDT close price and the realized volatility measure $\mathrm{RV}_{10}(t)$ together with the highest- and lowest-volatility 35% windows. The purple line marks the highest $\mathrm{RV}_{10}(t)$ in the purple 35% window, while the blue line marks the minimum $\mathrm{RV}_{10}(t)$ in the blue 35% window. The dashed black line marks the stress-period opening timestamp identified from the hourly RS-based analysis.

The highest and lowest points of RV were labelled, and, thereafter, the stress timestamp t_{stress} and normal timestamp t_{normal} were selected accordingly. These timestamps were then translated into block numbers for the DEX venue, which occurred at or immediately after t_{stress} and t_{normal}, formalized as: bl_{stress} and bl_{normal} (refer to Appendix B.1 and Figure 2). After removing continuous adjacent normal-stress events with gaps lasting less than 1 hour and where a stress event, i, has $t_{stress} < t_{normal}$ (refer to Appendix B.2), the final normal-stress event sample size was 417, with a timestamps/block for each t_{normal} and t_{stress}.

B. Variable construction for testing Hypotheses

To derive an empirical method for testing the hypotheses for the liquidity resilience/degradation of the Binance ETH/USDT market CEX venue and the Uniswap V3 fee tier 0.3% WETH/USDT DEX venue, transaction costs are utilized as the primary dependent variable for observing and comparing the market quality of the two analyzed venues. This variable summarizes the effective cost for a user executing a trade and is determined by the underlying mechanisms of the two venues, thus making it possible to investigate them through transaction cost components.

B.1 Computing Transaction costs

The total transaction cost (TC) for the identified normal and stress timestamps, t_{normal} and t_{stress}, was constructed as the main investigated dependent variable for both the Binance and Uniswap V3 venues for a range of standardized ETH (X). According to the following formula used by Barbon and Ranaldo (2024), the total transaction cost for a given trade size, Δx (ranging from 0.1 to 100ETH), traded to or from USDT (Y) at a given timestamp t (block number, bl, for DEX), for normal-stress period, i, on either the Binance or the Uniswap V3 fee tier 0.3% venue is defined as follows when accounting for the key cost components for the trading of CEX versus DEX:

$$TC_{XY,i}^{CEX}(\Delta x, t) = S_{XY,i}^{CEX}(\Delta x, t) + f_{venue}^{CEX} \tag{4}$$

$$TC_{XY,i}^{DEX}(\Delta x, bl) = S_{XY,i}^{DEX}(\Delta x, bl) + f_{venue}^{DEX} + \frac{g_i(bl)}{\Delta x} \tag{5}$$

For $TC_{XY,i}^{CEX}(\Delta x, t)$:

$S_{XY,i}^{CEX}(\Delta x, t)$ represents the spread-based measure of slippage, calculated as the difference between the volume-weighted ask and bid prices and normalized by their sum for a specific ETH order size, Δx, at time, t. This value measures the relative cost or market friction of executing an order of size Δx (refer to Appendix B.3 for further explanation). The f_{venue}^{CEX} is the fixed percentage fee of the venue for Binance, and, assuming the utilization of BNB[10], is fixed at 0.075%.

For $TC_{XY,i}^{DEX}(\Delta x, bl)$:

$S_{XY,i}^{DEX}(\Delta x, bl)$: the average of the slippage when buying (W)ETH and when selling (W)ETH. This method differs from the CEX venue, and a more detailed overview provided in Appendix B.4. f_{venue}^{DEX}: the fixed percentage fee of the Uniswap V3 venue, which is the pool fee tier of 0.3% in this case. $g(bl)_i$: represents the settlement cost of the on-chain gas fee required for users to validate their (W)ETH/USDT swap, exclusive to the DEX venue, and is the effective median gas price at block bl (See Appendix B.5 for more details).

[10] BNB is Binance's native utility token used to reduce trading fees and facilitate various services across the Binance ecosystem.

B.2 Testing for Hypotheses 1&2: Degradation in liquidity

For the measurement of degradation in liquidity of both venues, the change in transaction cost between the stress and normal time/block within the normal-stress event i is examined. For the CEX Binance venue, it is as follows:

$$\Delta TC_{XY}^{CEX}(\Delta x, i) = \Delta TC_{XY}^{CEX}(\Delta x, t_{stress}) - \Delta TC_{XY}^{CEX}(\Delta x, t_{normal}) \tag{6}$$

And for the Uniswap V3 DEX:

$$\Delta TC_{XY}^{DEX}(\Delta x, i) = \Delta TC_{XY}^{DEX}(\Delta x, bl_{stress}) - \Delta TC_{XY}^{DEX}(\Delta x, bl_{normal}) \tag{7}$$

After the degradation in liquidity for CEX and DEX are determined, a one-sided (right tail) t-test is performed to test if hypothesis 1 (refer to Hypotheses formation) is significant at the 5% level, allowing for the verification of whether or not the DEX and CEX venues do both, in fact, have higher transaction costs post-stress:

$$H_0: \overline{\Delta TC_{\Delta x}^{CEX/DEX}} \leq 0,\ H_1: \overline{\Delta TC_{\Delta x}^{CEX/DEX}} > 0 \tag{8}$$

With regards to hypothesis 2, this study has attempted to investigate whether smaller trades for a DEX degrade more than larger trades during stress and if this degradation becomes stronger when gas is removed. To test for this, a panel regression with an interaction term is performed. Using the natural log of the trade size (Δx) to linearize the inverse relationship in equation 5:

$$TC_{i,bl}^{DEX} = \beta_0 + \beta_1 Stress_{bl} + \beta_2 ln(\Delta x_i) + \beta_3 \big(Stress_{bl} \cdot ln(\Delta x_i)\big) + \varepsilon_{i,bl} \tag{9}$$

Where $Stress_{bl}$ is a dummy variable that takes on the values of 0 or 1 if the observed block is normal or stress, respectively; $Stress_{bl} \cdot ln(\Delta x_i)$ is the interaction term. Lastly, $\varepsilon_{i,bl}$ is the error term, or the unexplained variation of the regression due to omitted variable bias. This regression is re-ran excluding the gas component in the DEX transaction cost:

$$TC_{XY,i}^{DEX,no\ gas}(\Delta x, bl) = TC_{XY,i}^{DEX}(\Delta x, bl) - g_i(bl)$$

A positive and statistically significant β_1 would prove that the degradation in DEX liquidity after a stress event holds. A negative and statistically significant β_2 would signify that larger trades tend to have a lower relative liquidity degradation, consistent with the diminishing marginal slippage that is present at AMM pricing (Adams, Zinsmeister and Robinson 2020). The key parameter for our hypothesis is the coefficient β_3 which details whether market stress affects transaction costs differently. More profoundly, the comparison of this coefficient between $TC_{XY,i}^{DEX,no\ gas}$ and $TC_{XY,i}^{DEX}$ gives rise to a noteworthy relationship. If $\beta_3^{no\ gas}$ is less negative and statistically significant than β_3, this would imply that the disproportionate deterioration in liquidity observed for smaller trades is *caused* by the gas component of DEX execution costs. Namely, a reduction in the size of $\beta_3^{no\ gas}$ relative to β_3 would provide direct support for this paper's second hypothesis, shedding light to whether gas fees are a driver of weaker liquidity for small trade sizes during stress.

B.3 Testing for Hypothesis 3: Additive decomposition

To test for hypothesis 3, leading question on how the behavior of gas varies in the WETH/USDT market in the Uniswap V3 fee tier 0.3% venue over time must be addressed. Since gas fees constitute a core component of transaction costs in DEXs, understanding their historical long-run behavior is vital for assessing if the DEX venue's liquidity will converge towards being competitive with those on CEXs like Binance, as proposed by Barbon and Ranaldo (2024). Significantly, this examination would determine if there were a time effect that needs to be adjusted for in the gas fee component of transaction costs for, at least, the WETH/USDT market. Through an additive decomposition of the time series of gas prices, effective gas prices are deconstructed into two primary, non-overlapping components, following the design of EIP-1559: base fee, B, and the priority fee, Pr, for block, bl, and transaction number, tx. Consistent with the method in B.1, we use the median priority fee and the base fee for a given block, yielding a relation as follows:

$$G_{Total}(bl) = B(bl) + MPr(bl) \tag{10}$$

The aim with this is to observe the *time effect* of the base fee and the median priority fee. This is achieved by regressing the trend as follows:

$$B_\lambda = \alpha_B + \beta_B \lambda + \varepsilon_\lambda^B, \tag{11}$$

$$MPr_\lambda + \alpha_{MPr} + \beta_{MPr} \lambda + \varepsilon_\lambda^{MPr}, \tag{12}$$

$$\lambda = \frac{bl - bl_0}{\Delta bl}, \tag{13}$$

Where, λ represents every 300th incremental block (Δbl), from block number $bl_0 = 13623124$ to 238286124 ($\lambda_{max} = 34210$). For more information as to why this was done, please refer to section C.2. The squared residuals of the base fee and priority fee are then regressed:

$$\left(\widehat{\varepsilon_\lambda^B}\right)^2 = \gamma_B + \delta_B \lambda + u_\lambda^B \tag{14}$$

$$\left(\widehat{\varepsilon_\lambda^{MPr}}\right)^2 = \gamma_{MPr} + \delta_{MPr} \lambda + u_\lambda^{MPr} \tag{15}$$

All regressions listed above are estimated using ordinary least square (OLS) and the statistical significance of the trend coefficients is evaluated using two-sided t-tests; the conclusions drawn from them will provide the groundwork for the new construction for the gas component, referred to as adjusted gas $\left(g_i^{Adj}\right)$:

$$g_i^{Adj}(bl) = U_C \cdot \left(B^{Adj}(bl) + MPr^{Adj}(bl)\right) \tag{16}$$

We adjust the base, $B^{Adj}(bl)$, and median priority, $MPr^{Adj}(bl)$, gas fee components based on observations on the regression coefficients and their respective significance:

$$B^{Adj}(bl) = \begin{cases} 0 \; if: \hat{\beta}_B < 0 \; and \; p_{\hat{\beta}_B} < 0.05 \; and \; \hat{\delta}_B < 0 \; and \; p_{\hat{\delta}_B} < 0.05, \\ B_\lambda + \hat{\beta}_B(\lambda_{max} - \lambda) \; if: \hat{\beta}_B < 0 \; and \; p_{\hat{\beta}_B} < 0.05 \; and \; p_{\hat{\delta}_B} \geq 0.05, \\ B(\lambda) \; if: \; p_{\hat{\beta}_B} > 0.05 \; and \; p_{\hat{\delta}_B} > 0.05 \, . \end{cases}$$

$$MPr^{Adj}(bl) = \begin{cases} 0 \; if: \hat{\beta}_{MPr} < 0 \; and \; p_{\hat{\beta}_{MPr}} < 0.05 \; and \; \hat{\delta}_{MPr} < 0 \; and \; p_{\hat{\delta}_{MPr}} < 0.05, \\ MPr_\lambda + \hat{\beta}_{MPr}(\lambda_{max} - \lambda) \; if: \hat{\beta}_{MPr} < 0 \; and \; p_{\hat{\beta}_{MPr}} < 0.05 \; and \; p_{\hat{\delta}_{MPr}} \geq 0.05, \\ MPr(\lambda) \; if: \; p_{\hat{\beta}_{MPr}} > 0.05 \; and \; p_{\hat{\delta}_{MPr}} > 0.05 \, . \end{cases}$$

Where: bl is the block observed, bl_0 is block number 1362314 ($\lambda_0 = 0$), and $\Delta bl = 300$ is the incremental size for the trend data we retrieve. The expression for the second-row conditions preserves the fee level at the newest block and incrementally shifts earlier blocks. This adjustment removes the deterministic decline in fees over time while retaining idiosyncratic cycle-by-cycle variation that is economically relevant for transaction-cost formation for modern day analysis. Using these derived insights and in the pursuit of examining whether these gas fee trends will continue in the future, a new set of adjusted transaction costs for the DEX Uniswap V3 venue is obtained which better models the transaction cost that can be expected in future.

$$TC_{XY,i}^{DEX,Adj}(\Delta x, bl) = S_{XY,i}^{DEX}(\Delta x, bl) + f_{venue}^{DEX} + \frac{g_i^{Adj}(bl)}{\Delta x} \tag{17}$$

The difference in liquidity degradation between DEX and CEX, for a specific normal-stress event i, reusing equation 6 and adjusting equation 7 with the new $TC_{XY,i}^{DEX,Adj}$ is as follows:

$$D(\Delta x, i) = \Delta TC_{XY}^{DEX,Adj}(\Delta x, i) - \Delta TC_{XY}^{CEX}(\Delta x, i) \tag{18}$$

Where a one-sided (right tail) t-test for the mean of a trade size, Δx, across all normal-stress events is performed to test for hypothesis 3:

$$H_0: \overline{D_{\Delta x}} \geq 0, H1: \overline{D_{\Delta x}} < 0$$

B.4 Testing for Hypothesis 4: Explaining Improved Slippage on DEX

In this section, the empirical method for testing whether pre-stress volume has a differential impact on DEX and CEX slippage during volatile events is established, as formulated in our fourth hypothesis in Hypotheses formulation. To test for this, a first-difference interaction regression model is constructed that compares how DEX and CEX slippage react to changes in pre-stress volume. This model was chosen to control for omitted variable bias, allowing for the better isolation of the effect of the pre-stress volume on DEX and CEX slippages.

For each event, i, occurring in a venue (DEX / CEX), slippage is measured at stress (t_{stress} or bl_{stress}) and at normal (t_{normal} or bl_{normal}). The dependent variable is the change in slippages between these states,

$$\Delta S_{XY,i}^{venue}(\Delta x) = S_{XY,i}^{venue,stress}(\Delta x) - S_{XY,i}^{venue,normal}(\Delta x) \quad (19)$$

A positive and statistically significant value in the change in slippage signals worsened slippage following a stress event while a negative value would reflect an improvement. Trade volume activity *before* a stress timestamp occurs is examined as this is observable by liquidity providers. To quantify this activity, ETH/USDT transaction volume in two windows is compared: ten minutes prior to the stress timestamp, and ten minutes prior to the normal timestamp:

$$\Delta Volume_i = V_i^{stress} - V_i^{normal}$$

This denotes the change in volume or otherwise interpreted as volume pressure. Prior to our stress and normal timestamps, starting precisely at the 10-minute mark leading up, it is observed that the stress–normal difference in volume spikes sharply. This sudden and enduring increase in trading activity suggests that liquidity and order-flow conditions begin to shift meaningfully only within the final ten minutes before a stress event.

FIGURE 3 – Mean Difference in Pre-Event Volume Between Stress and Normal

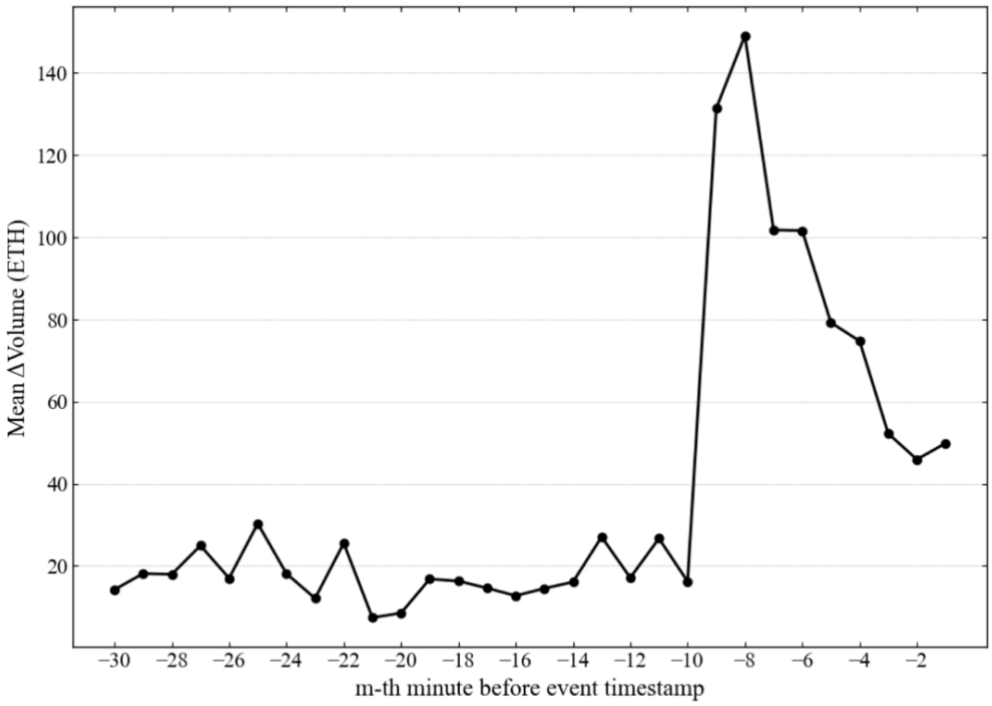


FIGURE 3. This figure shows the mean difference in average minute-by-minute trading volume between stress and normal events on Uniswap v3 (0.3% WETH/USDT) over a 30-minute pre-event window. The x-axis shows the m-th minute before the event timestamp, while the y-axis shows the mean change in trading volume, calculated as the average stress volume minus the average normal volume.

The following first-difference interaction model is derived from this information to test for whether this volume build up affects slippage differently between DEX and CEX:

$$\Delta S_{XY,i}^{venue}(\Delta x) = \alpha + \beta_1 \Delta Volume_i + \beta_2 \text{Market}_i + \beta_3(\Delta Volume_i \cdot \text{Market}_i) + \gamma X_i + \varepsilon_i^{venue} \quad (20)$$

Where Market_i is a dummy variable taking on the values of 0 or 1 if the observation is for either the Binance or Uniswap V3 venue, respectively. The main coefficient of interest is β_3, or the coefficient of the interaction term of the Market dummy variable and the volume pressure which captures the additional sensitivity of the Uniswap V3 slippage for the WETH/USDT pair to change in pre-event volume, relative to the Binance slippage for the ETH/USDT pair. A statistically significantly and negative value for this coefficient would support the hypothesis that increases in pre-stress trading activity disproportionately improve execution on the DEX.

To isolate the effect of when LPs withdraw reserves or stay passive during these events, we account for several control variables in the vector X_i. Firstly, realized volatility change between stress and normal is controlled for, as the change in realized volatility between the normal and stress timestamps controls for shifts in price variability. Secondly, price directionality (defined in equation 2) is included to control for directional price moves that generate impermanent-loss-driven liquidity changes. This allows for the determination of whether rising pre-stress volume improves DEX liquidity only when prices are not trending strongly. Thirdly, the change in effective gas price between the two timestamps is also included as a control as it is a viable proxy for examining blockchain congestion, which influences repositioning decisions by LPs. Finally, the asset price at the normal timestamp is used to control for the mechanical scale effect by which slippage increases with the level of the underlying asset.

C. Data for Hypothesis testing

To procure reliable results for the scope of this paper and to give a robust review of the hypotheses, certain data requirements need to be satisfied. Namely, data on liquidity depth, the gas fee components, and trade volume data must be retrieved for both the CEX and DEX venue to test for the four hypotheses established. As such, this section details exactly how and why we retrieve the data required and is formally to support choices made leading up to the empirical findings.

C.1 Collecting Data on liquidity depth

To capture liquidity conditions on the Binance venue, the identified timestamps t_{stress_i} and t_{normal_i} in section A were used to query CoinAPI in an attempt to fetch the snapshots of the historical limit orderbook (LOB) states for each normal-stress event, i, on the Binance venue and, in particular, the twenty best bid levels and the twenty best ask levels for ETH/USDT (CoinAPI, 2025):

$$B_i = \{(b_i, v_i) : I = 1, \dots, 20\},\ A_i = \{(a_j, v_j) : j = 1, \dots, 20\}$$

Because LOBs on the CEX venue are a form of continuous data, it is expensive to store the state of every timestamp. For this reason, many free APIs, such as CoinAPI, have gaps in their database (CoinAPI, 2025). As such, a tolerance window is needed to match event timestamps to the closest available book state. After different tolerance intervals were tested for, a ± 35 second time was selected as a reasonable time interval based on the logarithmic relationship between recovered events and window size. Orderbook states were retrieved in this interval and the closest ones to

their respective query timestamp were selected as the representable timestamps. However, due to missing data from CoinAPI, our main data extractor for the Binance venue, our sample of orderbook snapshots for Binance (CEX) was reduced to 294 events.

Unlike Binance, DEXs, such as Uniswap V3, do not organize liquidity in a LOB. Rather, price movements evolve *endogenously* based on how liquidity is distributed across price intervals (known as "ticks", an internal price measurement for Uniswap V3 smart contract), implying that slippage on DEXs is determined entirely by the current price in the liquidity curve at the exact block in which the trade is executed. Because Uniswap V3 operates on a public blockchain, all interactions with smart contracts are permanently recorded on-chain, including liquidity additions and removals to tick intervals and swap transactions by liquidity providers. From these raw events, free and commercial APIs, such as the Alchemy RPC endpoint, reconstruct the liquidity curve and store it as a snapshot (Alchemy, 2025). Using this, a $\pm$ 333 tick window around current price, P_0, of net liquidity, L_{net}[11], with its corresponding tick on the Uniswap V3 WETH/USDT 0.3% pool state for normal and stress blocks, b_{normal} and b_{stress}, for normal-stress event, i, were retrieved to observe the state of the liquidity distribution at the event observed and accounted for.

C.2: Setting up gas price data

Gas data was retrieved for two purposes: i) to investigate the technological components of gas, and ii) to identify the gas prices for our blocks, b_{stress} and b_{normal}. With this data, we can effectively use these gas components in the simulation for transaction costs in the DEX venue for testing our third hypothesis.

Formally, a time series of gas data (including base fee, median priority fee, etc) was retrieved from Alchemy API. Due to computational constraints, the fetched historical dataset contained the base fee and the median priority fee for every 300th block, λ, between block numbers 13,623,124 and 23,886,141 (15 Nov 2021 to 26 Nov 2025). This sampling approach provided a consistent and computationally efficient way to observe gas-market trends without the need to query every individual block on the blockchain. Thereafter, using Alchemy API once more, a dataset was retrieved specifically for the stress and normal blocks containing transaction-level gas data for every transaction in the block. (Alchemy, 2025)

C.3: Volume and Price directionality

To retrieve data capable of testing Hypothesis 4 (refer to section B.4), 30 minutes of decentralized-exchange swap events preceding each normal and stress timestamp was collected from the Uniswap V3 WETH/USDT 0.3% pool using the API endpoint "The Graph" (The Graph, 2025). For each normal and stress timestamp in event, i, all swaps occurring in the 30 minutes leading up to the timestamp were aggregated into minute-level volumes, yielding the vector:

$$(V_{t-30}, V_{t-29}, V_{t-28}, \ldots, V_{t-1}, V_t)$$

[11] Liquidity net is the change in active liquidity when the price crosses a tick boundary, reflecting how much liquidity is added or removed. It can be observed at every tick and essentially determines how the pool's total active liquidity updates as price moves through the tick grid.

V_{t-m} represents the total ETH-denominated trading volume executed in the m[th] minute before timestamp, t. This produced a consistent and aligned set of pre-event volume observations for both the normal and stress events to be used to examine whether increases in on-chain trading activity helped explain differences in slippage behavior between DEX and CEX during stress periods; effectively, it enabled the construction of the main explanatory variable testing for the fourth hypothesis. Once more, The Binance public API Klines was queried to fetch both a ten-minute lagged benchmark price and the current price for each of the stress and normal timestamps which is depicted by Figure 4 (Binance, 2025). This allowed for the construction of the price-directionality measure, the control variable for testing hypothesis 4.

FIGURE 4 – Price Directionality from t − 10 Minutes to Timestamp: Stress vs Normal

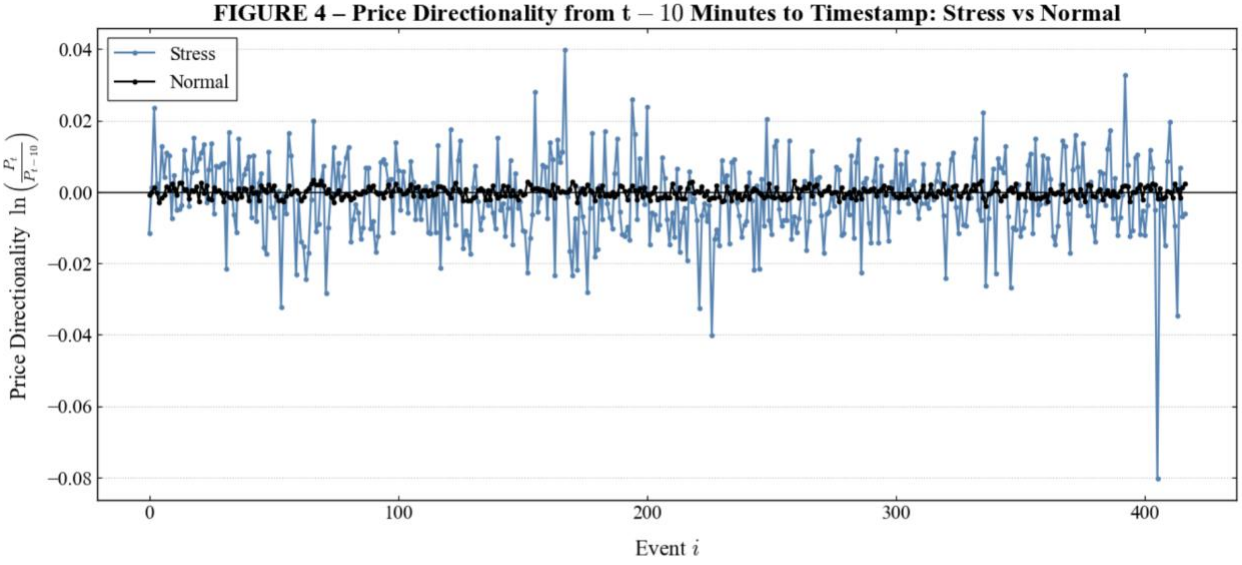


FIGURE 4. This figure shows the log price change $\ln\left(\frac{P_t}{P_{t-10}}\right)$ ten minutes before the timestamp under stress and normal conditions. The black points represent the log price change for normal events, while the blue points represent stress events. Positive values indicate upward price movement, while negative values reflect downward pressure.

IV. Empirical findings

This section presents the empirical results and descriptive statistics for testing hypotheses 1-4. We begin by examining how transaction cost changes in the DEX and CEX. We then turn to the estimates from the panel regression that assess the relationship between stress and the liquidity degradation across trade sizes for testing our second hypothesis. Thereafter, the gas fee trend over time and the tables featuring the estimates from the regressions for the main structural and technological components of gas are illustrated, setting the grounds for the results comparing the liquidity degradation in the DEX and CEX. Lastly, the regression on whether DEX liquidity, relative to CEX, can improve under stress by studying how pre-stress trading activity affects the outcome is shown.

A. Hypotheses Results

A.1 Results for Hypothesis 1

FIGURE 5 – Average Liquidity Degradation After a Stress Period in Binance (CEX) and Uniswap v3 (DEX)

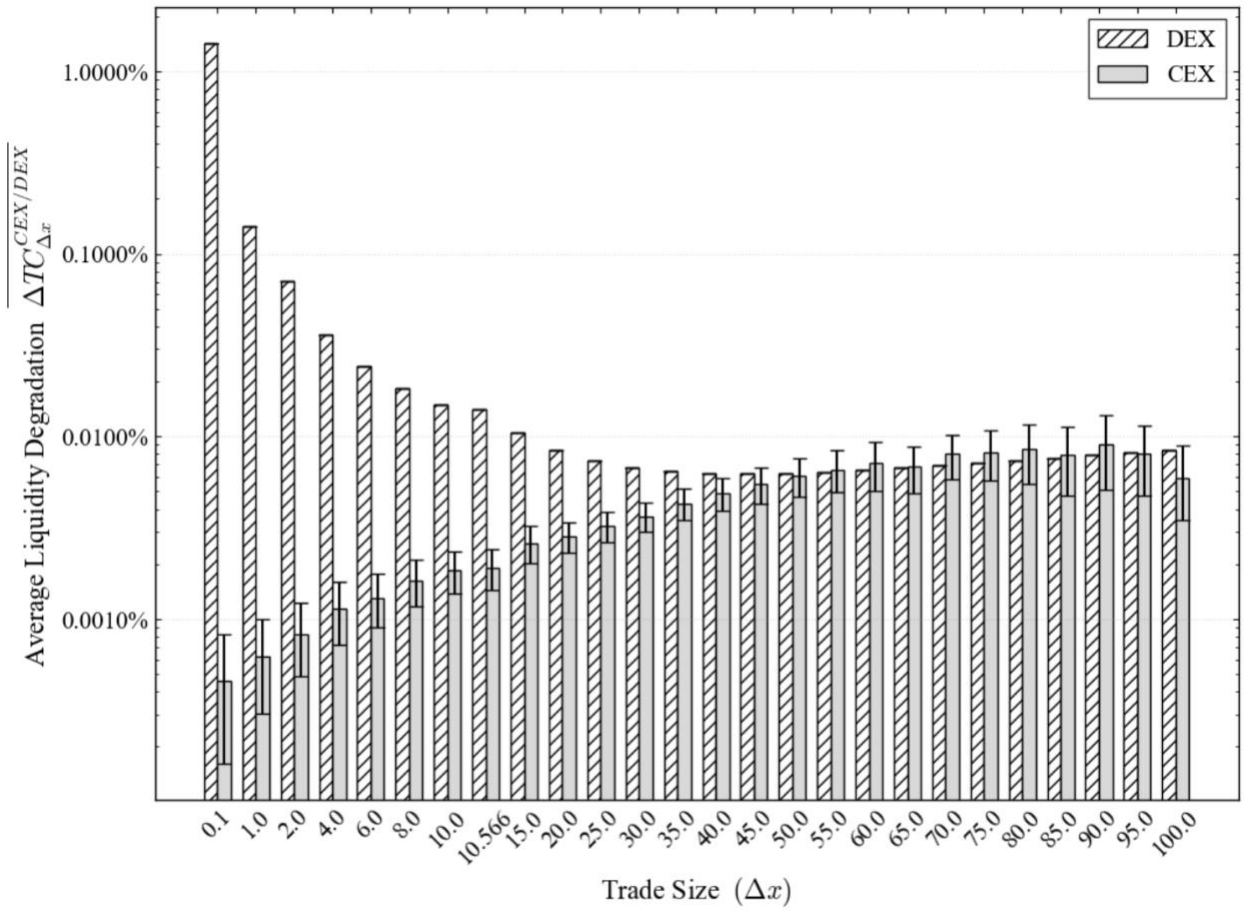


FIGURE 5. This figure displays the average change in Transaction Costs (TC) between stress and normal periods on a [%] log scale, across trade sizes (Δx). The CEX error bars represent 95% confidence intervals, using bootstrapping (n=10,000). This was done due to the missing data when queries were made to CoinAPI

Table 2: T-test results for Hypothesis 1 for the CEX and DEX of fee tier 0.3

Trade Size	N	Mean ΔTC [%]	t-stat
Panel A: CEX			
0.1	294	0.00046***	2.66
0.5	294	0.00053***	2.97
1.0	294	0.00062***	3.44
4.0	284	0.00114***	5.06
10.0	277	0.00184***	7.34
20.0	245	0.00283***	10.17
50.0	87	0.00605***	8.00
100.0	11	0.00592***	4.15
Panel B: DEX			
0.10	417	1.42308***	6.64
0.50	417	0.28465***	6.64
1.00	417	0.14237***	6.64
4.00	417	0.03583***	6.67
10.00	417	0.01488***	6.79
20.00	417	0.00844***	6.83
50.00	417	0.00629***	4.83
100.00	417	0.00846***	3.62

Note: This table presents the t-test results comparing liquidity degradation between the CEX Binance and DEX Uniswap V3 fee tier 0.3 venues at different trade sizes after a stress event in the ETH/USDT and WETH/USDT markets. Panel A reports results for the Binance exchange and Panel B reports results for the Uniswap V3 fee tier 0.3 venue. Δ TC represents the total variable impact (Spread + Gas + Venue fee for Uniswap V3, Spread + venue fee for Binance). Δ Spread represents the Bid-ask spread for the CEX and DEX venues. Δ Gas is the change in median effective gas price, defined by the sum of the median priority and base gas fees from each block number. Statistic significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Inspecting Table 2, it is observed that transaction costs statistically significantly increase following a stress event for both the Binance (CEX) and Uniswap V3 (DEX) venues. The mean change in transaction costs, the liquidity degradation, is positive across all trade sizes for both CEX and DEX and is statistically significant at the 1% level, except for CEX trade size 100 ETH which is only statistically significant at the 5% level. With increased trade size in CEX, the results become more unreliable due to insufficient data on liquidity depth and this is accounted for by applying a bootstrapping method for 10000 iterations, depicted by the error bars in Figure 5. In reference to this figure, on average, liquidity degradation occurs across both venues and there is a clear convergence between CEX and DEX as trade size increases. Both the DEX and CEX liquidity degradation trends show that, for larger trade sizes, the average liquidity degradation stabilizes. Overall, these results showcase that both venues experience a deterioration in market quality when volatility spikes.

A.2 Results for Hypothesis 2:

Table 3: Regression Results for testing Hypothesis 2: Total Transaction Cost [%] for the WETH/USDT Market in the Uniswap V3 Fee Tier 0.3 Venue (Including Gas)

Variable	Coeff. (β)	Std. Err.
Constant	1.1929***	0.057
Stress	0.3959***	0.060
$\ln(\Delta x)$	-0.2320***	0.016
Stress $\times$ $\ln(\Delta x)$	-0.1090***	0.017

Model Statistics		*Residual Diagnostics*	
Observations	22,518	Omnibus	42,637.1
R-squared	0.161	Prob(Omnibus)	0.000
Adj. R-squared	0.161	Skew	14.529
F-statistic	89.80	Kurtosis	333.359
Log-Likelihood	-35,368	Durbin-Watson	1.105
AIC	70,740	Jarque-Bera	1.03×10^8
BIC	70,780	Prob(JB)	0.00
		Cond. No.	18.3

Note: This table presents the total simulated transaction cost [in %] for all blocks gathered, both before and after a stress event in our sample. These transaction costs correspond to the WETH/USDT market in the Uniswap V3 fee tier 0.3 pool. Total transaction cost includes slippage, venue fee, and gas fees. Standard errors are clustered by event ID. The variable $\ln(\Delta x)$ represents the natural logarithm of the simulated trade size Δx. The interaction term Stress $\times$ $\ln(\Delta x)$ is used to test whether liquidity degradation worsens disproportionately for small trade sizes during stress (Hypothesis 2). Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: Regression Results for Testing Hypothesis 2: Total Transaction Cost for the WETH/USDT Market in the Uniswap V3 Fee Tier 0.3 Venue (Excluding Gas)

Variable	Coeff. (β)	Std. Err.
Constant	0.2946***	0.000
Stress	-0.0004***	0.000
$\ln(\Delta x)$	0.0176***	0.000
Stress $\times$ $\ln(\Delta x)$	0.0011***	0.000

Model Statistics		*Residual Diagnostics*	
Observations	22,518	Omnibus	16,488.0
R-squared	0.365	Prob(Omnibus)	0.000
Adj. R-squared	0.365	Skew	3.288
F-statistic	509.5	Kurtosis	22.541
Log-Likelihood	39,549	Durbin-Watson	0.398
AIC	-79,090	Jarque-Bera	3.99×10^5
BIC	-79,060	Prob(JB)	0.00
		Cond. No.	18.3

Note: This table presents the total simulated transaction cost [in %] for the WETH/USDT pair on Uniswap v3 0.3% fee tier pool during normal and stress conditions. The transaction costs does not include the gas fee component (determined by sum of the base fee of the block and the median priority fee). Standard errors are clustered by event ID. $\ln \Delta x$ denotes the natural logarithm of simulated trade size Δx. The Stress dummy variable indicates whether or not the observation is a transaction cost recorded during stress (1) or normal (0). The interaction term Stress $\times$ $\ln(\Delta x)$ is used to test Hypothesis 2 regarding whether liquidity deterioration during stress is more severe for small trades. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Furthermore, Table 3 showcases the results of the panel regression performed on the total transaction cost for each block in the WETH/USDT market that is studied during a stress event, i, with gas prices included for both the normal and the stress blocks. The regression features 2 key variables for testing hypothesis 2: i) a stress dummy, $Stress_{bl}$, taking on values of 0 or 1, and ii) natural logarithm of the trade size, $\ln(\Delta x_i)$. An interaction term between the two is also included to review whether transaction costs are lower for higher trade sizes. All the coefficients for these variables are found to be statistically significant at the 1% level.

Table 4 shows an identically setup panel regression as performed in Table 3 for the adjusted transaction cost (exclusion of effective gas prices) for each block for event, i. We observe that $\beta_1^{no\ gas}$ gas is negative, having the opposite sign from Table 2 regression. This implies that, for very small trade sizes, pure slippage is slightly lower during stress in the DEX venue. Similarly, we see a reverse in sign for $\beta_2^{no\ gas}$, where a relative size up in traded ETH (e.g doubling) has a positive effect on transaction costs, implying that without gas, transaction costs scale with trade size. Lastly, the coefficient of interest, $\beta_3^{no\ gas}$, shows also a reverse in sign, turning positive. This means that during a stress moment ($Stress = 1$) a relative increase in ETH traded (e.g. doubling) will increase transaction cost for DEX.

Table 5: Decomposition of Liquidity Degradation in the ETH/USDT Market for CEX and DEX (bps)

Δx (ETH)	$\overline{\Delta S_{XY}^{\text{venue}}}$	$\overline{\Delta g}$	Δf_{venue}	$\overline{\Delta TC_{XY}^{\text{venue}}}$	N
Panel A: DEX (Uniswap v3)					
0.1	0.0006	142.3072	0	142.3078	417
2.0	0.0129	7.1154	0	7.1283	417
10.0	0.0650	1.4231	0	1.4881	417
25.0	0.1673	0.5692	0	0.7365	417
50.0	0.3446	0.2846	0	0.6292	417
100.0	0.7038	0.1423	0	0.8461	417
Panel B: CEX (Binance)					
0.1	0.0459208	0.0000	0	0.0459208	294
2.0	0.0826946	0.0000	0	0.0826946	290
10.0	0.1836587	0.0000	0	0.1836587	277
25.0	0.3245859	0.0000	0	0.3245859	205
50.0	0.6047814	0.0000	0	0.6047814	87
100.0	0.5921527	0.0000	0	0.5921527	11

Note: This table presents the decomposition of liquidity degradation, measured as the change in total transaction cost between normal and stress periods, for different trade sizes Δx in the ETH/USDT (Binance) and WETH/USDT (Uniswap v3) pair. The notation $\overline{\Delta S_{XY}^{\text{venue}}}$ denotes the mean change in the spread-based measure of slippage, $\overline{\Delta g}$ denotes the mean change in effective gas cost, and Δf_{venue} represents the change in venue fee. The total change in transaction cost is given by $\overline{\Delta TC_{XY}^{\text{venue}}}$, which combines spread, gas, and venue fees for DEX venues and spread plus venue fee for CEX venues. The decreasing number of observations for the CEX at larger Δx reflects book–depth limitations but remains consistent with expected liquidity patterns.

Table 5 presents a decomposition panel for the transaction costs for the DEX and CEX venues of different trade sizes. It is observed that, on average across all events, for a small trade size such as 0.1 or 2 ETH, more than 99% of the average transaction cost increase is explained by the average change in gas fee. Meanwhile, by the time the trade size reaches 100 ETH, only 16.82% of the

transaction cost in DEX is explained by gas. These results prove our hypothesis 2, that gas disproportionally impacts liquidity degradation of smaller trades sizes.

A.3 Hypothesis 3: The gas component and adjusted Transaction cost

FIGURE 6 - Total Gas Fee Decomposition

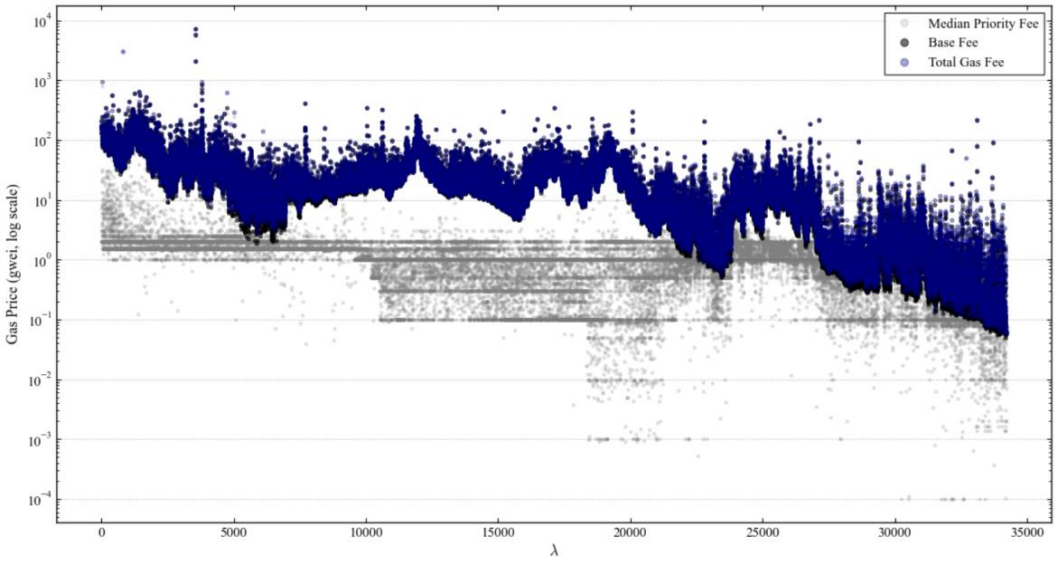


FIGURE 6. This figure reflects, in Gwei, the effective gas prices (blue) together with its components base fee (black) and median priority fee (grey), across observations indexed by λ. All values are plotted on a log scale to illustrate fluctuations across the full range of network conditions. The total gas price appears as the outer series, while the Base Fee and median Priority Fee are shown as separate underlying components.

FIGURE 7 - Median Priority Fee (Sampled Over Time)

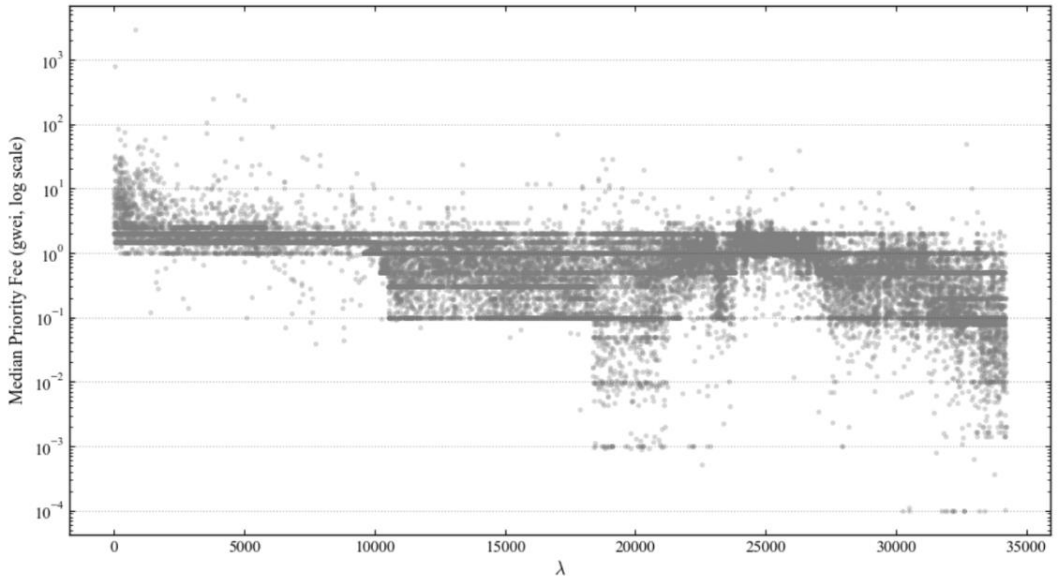


FIGURE 7. This figure displays the median priority fee, in Gwei, across observations indexed by λ which is the 300th block incremental from block number 13,623,124 to 23,886,141. The values are shown on a log scale to capture variation during both calm and congested periods. Each point corresponds to the median Priority Fee, in Gwei, recorded at a sampled block normalized to λ.

FIGURE 8 - Base Fee (Sampled Over Time)

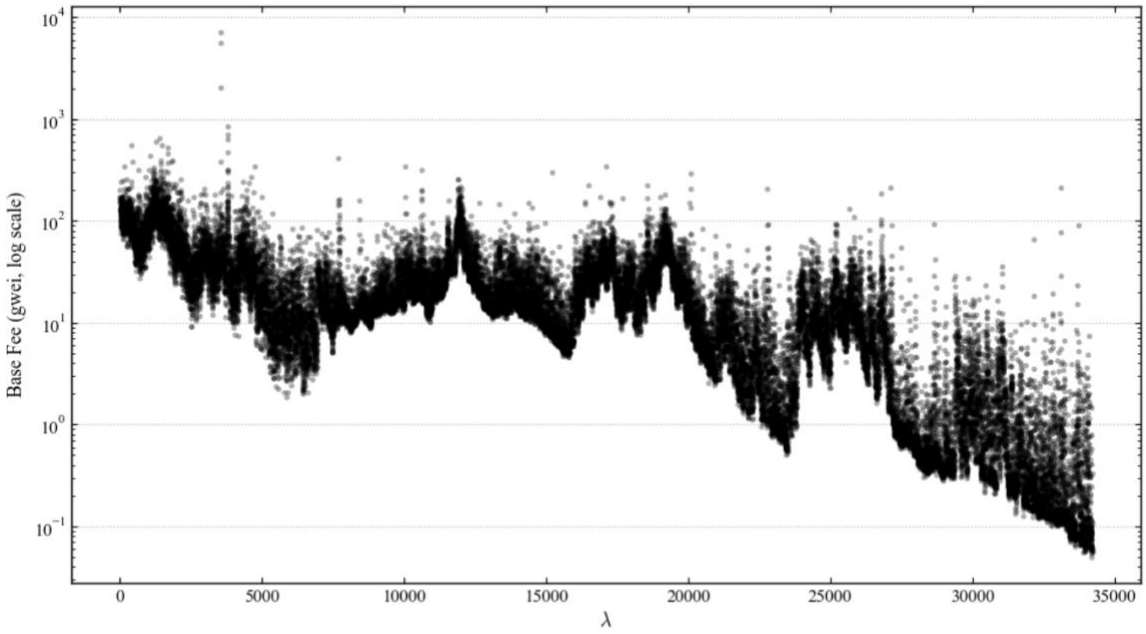


FIGURE 8. This figure shows the evolution of the Base Fee across consecutive observations, indexed by λ which is the 300th block incremental from block number 13,623,124 to 23,886,141. The Base Fee values are plotted on a log scale to display both low and high periods of network activity clearly. Each point represents the Base Fee, in Gwei, recorded at a sampled block normalized to λ.

All figures examine the relationship between the trend in the effective gas price, $G_{Total}(bl)$, or its constituents, $B(bl)$ or $MPr(bl)$, with time, represented by λ, tracked by every 300th chronological block number, indexed by λ, in the past 4 years (from 09-11-2021 to 09-11-2025). For the effective gas price, there is an apparent downward trend, often associated with an improvement in technological costs in existing literature (Barbon et al, 2024). Through the additive decomposition (III B.3), base gas fees show a clear downward trend with time in Figure 8. On the other hand, as observed in Figure 7, median priority fees tend to have much less downward pressure, with a more unambiguous trend revealed. Although both components experience large volatility over time, Median priority fee is much more constant over time than the base fee, revealed by the trend differences.

Table 6: Regression Analysis: Gwei Gas Fee Trends on the Ethereum Blockchain (09-11-2021:09-11-2025)

	Base Fee Trend (B)		Priority Fee Trend (MPr)	
Variable	**Coeff. (β)**	**Std. Err.**	**Coeff. (β)**	**Std. Err.**
Constant	55.8606***	0.620	2.6740***	0.180
Lambda (λ)	-0.0019***	3.14e-05	-7.89e-05***	9.10e-06
Model Statistics				
Observations	34,211		34,211	
R-squared	0.094		0.002	
F-Statistic	3,535.0***		75.18***	
Log-Likelihood	-1.871×10^5		-1.447×10^5	
AIC	3.742×10^5		2.894×10^5	
BIC	3.742×10^5		2.894×10^5	
Residual Diagnostics				
Omnibus	128,507.3		157,344.0	
Prob(Omnibus)	0.000		0.000	
Skew	84.007		161.596	
Kurtosis	9,466.3		27,919.7	
Durbin-Watson	0.710		1.995	
Jarque-Bera (JB)	1.28×10^{11}		1.11×10^{12}	
Prob(JB)	0.00		0.00	
Cond. No.	3.95×10^4		3.95×10^4	

Note: This table shows the OLS results for the gas fee (Gwei) trend components over time. λ is the normalized block number defined as $\lambda = \frac{bl - bl_0}{\Delta bl}$, where bl is the block number, $bl_0 = 13,623,124$, and the increment $\Delta bl = 300$. Gas fees, in Gwei, are the additional settlement cost for transactions to be processed and validated on the Ethereum blockchain, in which a decentralized exchange operates. Standard errors are non-robust. Significance levels: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7: Regression Analysis: Gwei Gas Fee Variance Trends on the Ethereum Blockchain (09-11-2021:09-11-2025)

	Base Fee Variance (ϵ_B^2)		Priority Fee Variance ($\epsilon_{\mathbf{MPr}}^2$)	
Variable	**Coeff. (β)**	**Std. Err.**	**Coeff. (β)**	**Std. Err.**
Constant	10,710***	3,462.8	1,061.3**	499.1
Block Number (λ)	-0.4336**	0.175	-0.0459*	0.025
Model Statistics				
Observations	34,211		34,211	
R-squared	0.000		0.000	
F-Statistic	6.116**		3.298*	
Log-Likelihood	-4.822×10^5		-4.160×10^5	
AIC	9.645×10^5		8.319×10^5	
BIC	9.645×10^5		8.320×10^5	
Residual Diagnostics				
Omnibus	150,271.2		163,294.1	
Prob(Omnibus)	0.000		0.000	
Skew	138.642		183.513	
Kurtosis	19,963.3		33,838.1	
Durbin-Watson	1.025		2.000	
Jarque-Bera (JB)	5.68×10^{11}		1.63×10^{12}	
Prob(JB)	0.00		0.00	
Cond. No.	3.95×10^4		3.95×10^4	

Note: OLS regression results for the trend in the squared residuals (variance) of gas fees in Gwei, over time. λ is the normalized block number defined as $\lambda = \frac{bl - bl_0}{\Delta bl}$, where bl is the block number, $bl_0 = 13,623,124$, and the increment $\Delta bl = 300$. Gas fees are the additional cost for transactions and activity to be processed and validated on the Ethereum blockchain, in which decentralized exchanges operate. Standard errors are non-robust. Significance levels: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6 is a regression performed (following equations 11 and 12) on the separate components of the effective gas fee in the WETH/USDT market from the Uniswap V3 pool, with one regression targeting the base gas fee, and the other the median priority fee trends over block numbers normalized to. The statistically significant base fee coefficient, β_B, has a negative value of 0.0019. This number suggests that for one increase in λ, which is 300 blocks (meaning every 25 minutes), the base fee has had a downward trend of 0.0019 Gwei, over the past 4 years. Similarly, we see a statistically significant β_{MPr} that is negative. Importantly, this value is much smaller than the magnitude of β_B.

In parallel to this, a divergence in the results between the estimated variance in base fee and median priority fee is observed. We observed a statistically significant and negative δ_B, implying that the variance of the base fee has decreased over time. In contrast, while δ_{MPr} takes on a negative value, it is not statistically significant with a p-value < 5%. Based on the conditions set in, section III B.3 and on the assumption that these observed results in trends will maintain in the future, we set $B^{Adj}(bl) = 0$, and $MPr^{Adj}(bl) = MPr_{\lambda} + \widehat{\beta_{MPr}}(\lambda_{max} - \lambda)$ thus obtaining a new adjusted transaction costs for DEX making for a better comparison between DEX and CEX.

FIGURE 9 – Average Liquidity Degradation ($\Delta TC^{CEX/DEX\text{-}adj}$) Across Trade Sizes ($\Delta x$) in Binance (CEX) and Uniswap v3 (DEX)

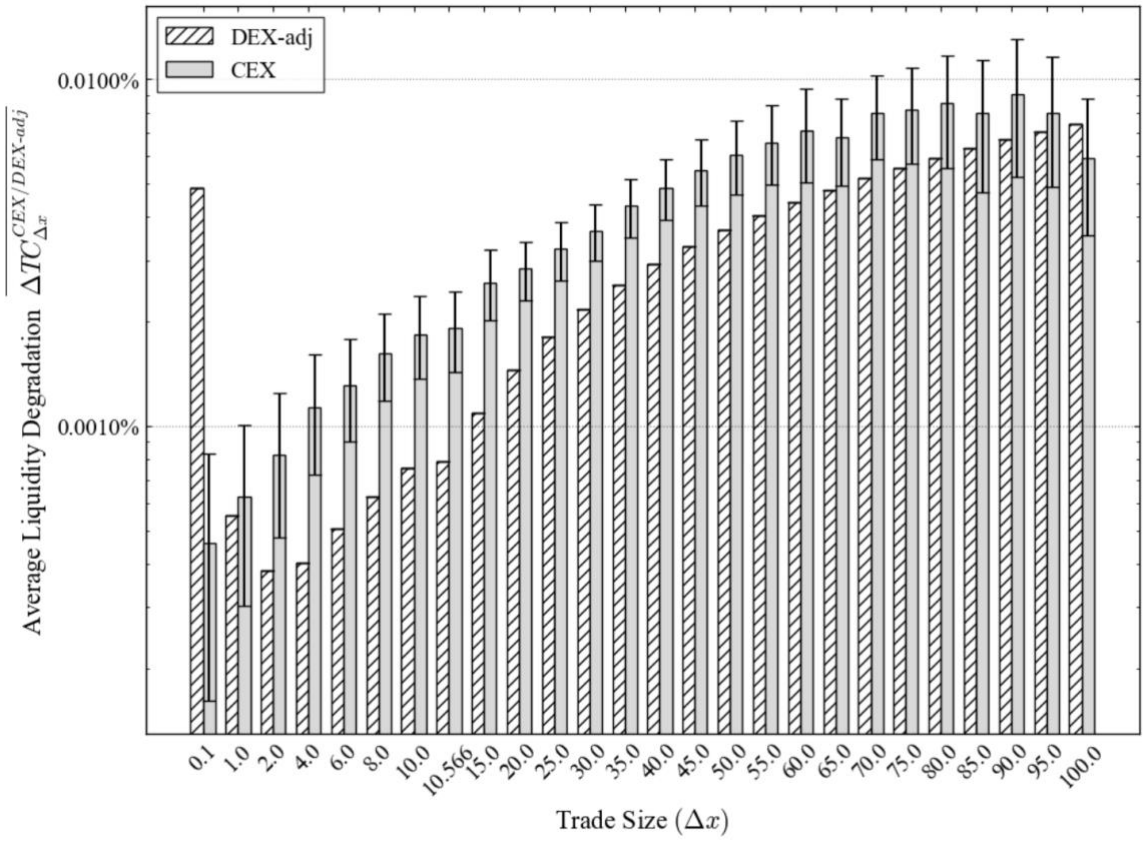


FIGURE 9. This figure displays the change in Transaction Costs (TC) between the stress and normal period for both DEX and CEX. However with DEX median priority fees adjusted for their time trend. CEX error bars represent 95% confidence intervals using 10,000 bootstrap samples. This was done due to the missing data when queries were made to CoinAPI

Table 8: Paired Difference t-tests (Hypothesis 3: $\overline{D}_{\Delta x} < 0$)

Δx (ETH)	N	$\overline{D}_{\Delta x}$ [%]	$\sigma_{\overline{D}_{\Delta x}}$	t-stat
0.100	294	0.001178	0.00264684	0.0763
1.000	294	−0.000432	0.000266358	-0.2781
2.000	290	−0.000710	0.000138245	-0.8743
4.000	284	−0.001086**	7.8499×10^{-5}	-2.3317
6.000	283	−0.001218***	6.23918×10^{-5}	-3.2833
8.000	281	−0.001466***	5.94154×10^{-5}	-4.1360
10.000	277	−0.001677***	6.13097×10^{-5}	-4.5519
10.566	276	−0.001737***	6.26158×10^{-5}	-4.6074
15.000	264	−0.002259***	7.69502×10^{-5}	-4.7699
20.000	245	−0.002499***	8.90684×10^{-5}	-4.3919
25.000	205	−0.002964***	1.05611×10^{-4}	-4.0185
30.000	177	−0.003583***	1.22840×10^{-4}	-3.8810
35.000	152	−0.004671***	1.25301×10^{-4}	-4.5962
40.000	129	−0.005168***	1.41732×10^{-4}	-4.1414
45.000	108	−0.005623***	1.59883×10^{-4}	-3.6551
50.000	87	−0.006565***	1.93339×10^{-4}	-3.1673
55.000	79	−0.007209**	2.22476×10^{-4}	-2.8802
60.000	62	−0.005767*	2.19122×10^{-4}	-2.0722
65.000	56	−0.004784	2.39209×10^{-4}	-1.4965
70.000	45	−0.009401***	1.04229×10^{-4}	-6.0505
75.000	36	−0.009549***	1.09709×10^{-4}	-5.2225
80.000	28	−0.010638***	1.04798×10^{-4}	-5.3715
85.000	23	−0.010289***	1.13419×10^{-4}	-4.3506
90.000	19	−0.010311***	1.17310×10^{-4}	-3.8312
95.000	14	−0.010489***	8.4062×10^{-5}	-4.6685
100.000	11	−0.009260***	8.77615×10^{-5}	-3.4996

Note: The table reports one-sided paired t-tests of the hypothesis $\overline{D}_{\Delta x} < 0$. The difference term $\overline{D}_{\Delta x}$ is defined as the mean of the difference in transaction cost change between DEX and CEX, across all events i for a particular trade size:

$$D(\Delta x, i) = \Delta TC_{XY}^{DEX,Adj}(\Delta x, i) - \Delta TC_{XY}^{CEX}(\Delta x, i).$$

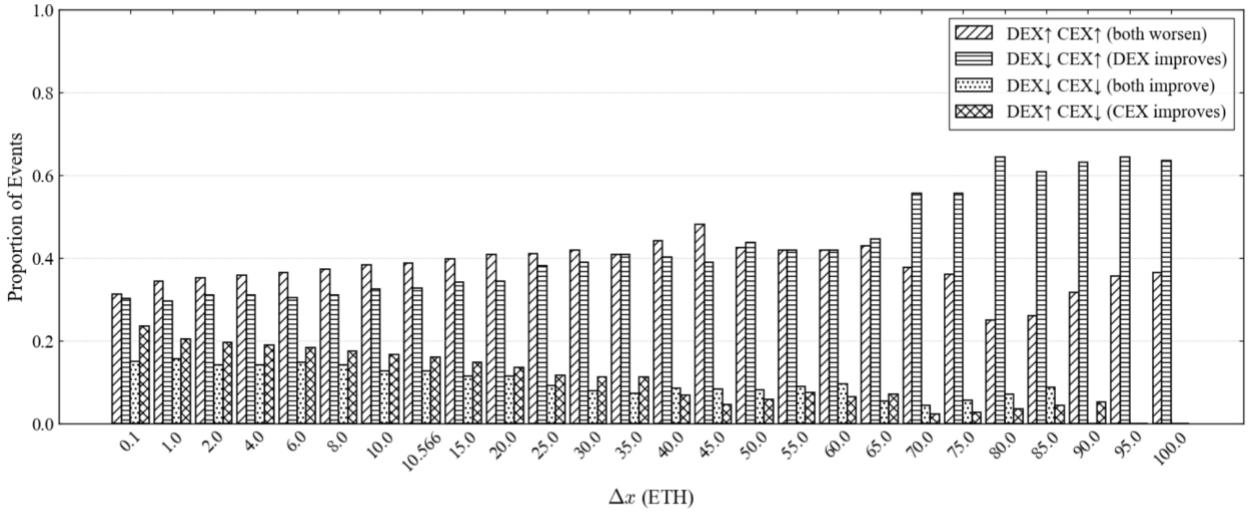
The transaction costs for DEX have their gas component (median priority fee) adjusted for the time effect. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure 9 shows the average liquidity degradation for both the CEX and DEX venues after removing the technological component of the gas fee from the DEX transaction cost. In comparison to figure 5**,** the liquidity degradation for DEX is *smaller*, on average, than that of CEX for larger trade sizes. The adjustment for DEX is also significant in the pattern of the liquidity degradation of DEX across trade sizes. Despite this change, we still observe that for small trades such as 0.1 ETH, the CEX venue experiences superior liquidity resilience, a pattern that reverts around the trade sizes 1

ETH. These observations in Figure 9 backed by our paired difference t-test in Table 8, disproves our hypothesis 3.

A.4 Hypothesis 4: Liquidity improvements post stress

FIGURE 10 — Proportion of Events by Slippage Outcome Across Δx Levels Based on $\Delta S_{XY}^{\text{venue}}$ for DEX and CEX



The figure shows the proportion of events falling into each slippage-outcome quadrant across trade sizes Δx. For each event i, slippage is measured using $\Delta S_{XY,i}^{\text{venue}}(\Delta x)$. Arrows in the legend indicate whether slippage increases (\uparrow) or decreases (\downarrow) following a stress event.

Figure 10 compares the proportion of events in which slippage improves for each venue across trade sizes, grouping events by their quartiles. The figure shows two clear patterns: i) across all trade sizes, the slippage of the CEX venue has a declining proportion of improvement when going from small to large trade sizes and ii) DEX shows that for higher trade sizes, for a large proportion of events, slippage improves. Secondly, we observe that for large trades (> 70 ETH) DEX slippage improves, while CEX worsen, nearly every second of time a stress event occurs.

Table 9: First-Difference interaction Regression Results by Trade Size (Cluster-Robust)

Trade Size (ETH)	β_3 (Market × ΔVolume)	R^2	N
0.100	-1.57×10^{-6}	0.118	294
0.500	-1.57×10^{-6}	0.114	294
1.000	-1.56×10^{-6}	0.113	294
2.000	-1.63×10^{-6}	0.115	290
4.000	$-2.00 \times 10^{-6*}$	0.137	284
6.000	$-1.87 \times 10^{-6*}$	0.124	283
8.000	$-2.08 \times 10^{-6**}$	0.130	281
10.000	$-2.20 \times 10^{-6**}$	0.131	277
10.566	$-2.27 \times 10^{-6**}$	0.131	276
15.000	$-2.71 \times 10^{-6***}$	0.135	264
20.000	$-1.60 \times 10^{-6**}$	0.092	245
25.000	-1.82×10^{-6}	0.078	205
30.000	-9.34×10^{-7}	0.081	177
35.000	4.77×10^{-7}	0.144	152
40.000	3.16×10^{-7}	0.144	129
45.000	-2.53×10^{-7}	0.144	108
50.000	1.76×10^{-7}	0.153	87
55.000	6.43×10^{-7}	0.153	79
60.000	-1.97×10^{-6}	0.151	62
65.000	1.58×10^{-7}	0.093	56
70.000	-2.17×10^{-6}	0.468	45
75.000	-3.42×10^{-6}	0.415	36
80.000	-2.33×10^{-6}	0.439	28
85.000	-3.59×10^{-6}	0.408	23

Notes: This table reports the estimated coefficients from the First-Difference interaction regression run separately for each trade size. $\beta_{interaction}$ (or β_3) corresponds to the interaction term **market** × **ΔVolume**, measuring whether the effect of ΔVolume on slippage differs between the DEX (market = 1) and CEX (market = 0). The dependent variable is the change in XY-price impact (ΔSXY) between normal and stress periods. All regressions include controls for ΔGas, ΔRV, price directionality, and initial price. Reported p-values are based on cluster-robust standard errors at the event level. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. R^2 is computed on stacked observations; N counts matched event clusters.

Table 9 presents the first-difference interaction regression model results for the [%] transaction costs across each trade size in our sample except for the case of x >85 ETH due to very few matched pairs (N) present. Here, we estimate whether increases in pre-stress trade volume on Uniswap V3 actively increase differential improvements of the DEX venue's slippage as compared with the CEX's. The coefficient of interest is β_3, which is the interaction term between the market dummy variable and the change in volume, and it is found to be statistically insignificant, having mostly negative values for differing trade sizes. This, combined with figure 10, indicates that slippage statistically insignificantly improves with pre-stress volume in a DEX exchange. In addition, however, we observe that β_3 is statistically significant for trade size between 4 and 20 ETH. This pattern of negative sign and rising magnitude in the coefficient of the interaction term

for larger trade sizes is consistent with what was observed in Figure 10. However, the discrepancy exists for trade sizes 35, 40, 50, 55, and 65, which are found to be statistically significant at the 5% level.

B. Discussion of findings

We observe that our first hypothesis is proven based on the results found in A.1; across all trade sizes, the mean change in transaction costs for the market of the (W)ETH/USDT pair through Binance and the Uniswap V3 venues are positive and statistically significant, implying that both venues experience higher associated trading costs following an average stress event. The economic intuition behind this comes from the observed price directionality in Figure 4, where it is apparent that stress events are associated with stronger and more unstable price movements when followed by normal periods. This could be because greater price volatility tends to indicate the presence of price information asymmetry in the market and this effectively forces liquidity providers to charge larger premiums to compensate for the adverse selection, consistent with the mechanisms described in the study of Glosten and Milgrom (1985).

Interestingly, the observed behavior of DEX liquidity degradation is disproportionally larger for smaller trade sizes due to gas, as seen in our Table 3 and 4 panel regression, complemented by the decomposition Table 5. A similar conclusion made by Barbon and Ranaldo (2024) outlines that gas affects the transaction cost of smaller trade sizes. However, the economic intuitiveness here differs as, unlike the fixed-cost nature that gas is assumed to be in related literature, gas is found to vary in our data; it is a stochastic variable based on factors such as network congestion derived from, among other factors, the economic urgency to be included in the next block Koutmos (2023). While this paper does not replicate the exact conditions studied by Koutmos (2023), our results echo his findings through our sample selection as stress moments are defined by large price movements. If markets were efficient and there was no arbitrage opportunity, traders would not have the urgency to execute their trade to the point of overpaying by setting higher priority fees than others. Though this relation is not empirically proven in our paper, we can draw a logical connection through the results we have as the disproportionate effect of smaller trade sizes tending to have higher associated liquidity degradation is maintained when moving from a normal to a stress period as users are willing to drive this fixed cost higher based on urgency through priority fee bidding. Therefore, the implication for many smaller traders is to not assume gas costs are fixed, but rather that they tend to change with stress events and to take note of this prior to liquidating assets in the DEX market.

On the contrary, a greater limitation when testing for our second hypothesis and the conclusions drawn from it is that the underlying data may be flawed due to a persistent time effect. Through our additive decomposition leading up to hypothesis 3, we observed a time effect in the base gas fee, both in its trend but also in the variance. This finding aligns with Barbon and Ranaldo (2024) claim that there is a technological aspect to gas prices. While we do not explicitly model for technological advancements, we can draw the connection between the statistically significant downward trend observed in the base gas fee and the economic incentive of Ethereum to lower gas prices; cheaper transactions increase network usage and may ultimately increase the value of the underlying asset (ETH) and, in turn, their competitiveness as a network provider (Ethereum, 2025). Under this perspective, most of the gas price is driven by technological constraints, such as the

base gas fee which is determined mostly by usage of block capacity and processing efficiency. Nevertheless, an anomaly that is observed in Table 6 is the time effect in the median priority fee. This went against our expectations since priority fees, unlike base fees, are not automatically set by the Ethereum protocol, but rather by the users Karaivanov and Zarifian (2024); one reasonable explanation for this could be the correlation between base gas fees and priority gas fees. While this paper does not investigate this, this relationship would examine whether the technological aspect of the base gas fees influence, or is shared by, the priority gas fees and, hence, we offer this as an extension to our work. Economically, simple supply and demand incentive structures could further give light as to why this relationship between base and priority gas fees persists as the block capacity has increased over the past four years, e.g. EIP-1559I. In essence, as users and bot programmers become more aware that there is more room for trading and less competition among other users for block space, the need for out-bidding others competing traders decreases. Despite this, the trend in the median priority fee is particularly economically negligible in comparison to the base fee, making it more difficult to assume that, in the long run, the median priority fee will trend towards zero. As such, for comparative purposes, we adjusted for the time effect in the median priority fee to at least reflect the modern conditions that may persist in the future. Another anomaly observed was the negative trend in variance over time. One technological explanation to this is the presence of bots[12] in DEX venues that can suggest an estimated optimal priority fee based on the current state of the mempool[13]. While modelling gas is outside the scope of this paper, gas-suggestion bots could be an explanatory variable as to why we observe priority fee pricing converges to one point. Regardless of this fact, due to its statistical insignificance, the $\hat{\delta}_{MPr}$ coefficient cannot prove a trend in diminishing noise.

Furthermore, after adjusting for the time effect in the median priority fee and the expected trend in the base gas fee (reaching 0 Gwei in the long-term) to better reflect what might be expected in the future, we observe a complete change from what was found previously in hypothesis 1. For larger trade sizes, the Uniswap V3 venue for the (W)ETH/USDT market tends to experience lower liquidity degradation with only the structural gas components, on average, as opposed to the Binance venue, backed statistically by the findings in Table 8. Despite this change, our third hypothesis was not proven to be correct as, even when assuming long-run base gas fees 0 and the median priority fee adjusted for the time effect, a disproportionate liquidity degradation for smaller trade sizes persists post-stress. This implies that when accounting for technological improvements in the long-term, the effect of gas fees on smaller trade sizes is still present. This, in turn, translates to the fact that degradation in liquidity for the (W)ETH/USDT market for the Uniswap V3 venue for some trade sizes is still greater for the DEX venue than for the CEX venue. Despite this, for larger trade sizes, the long-term liquidity degradation for the DEX venue is shown to be much more competitive than the CEX transaction costs.

To conclude, as shown in Figure 10, the slippage component of the transaction costs in the Uniswap V3 DEX venue *improves* disproportionally through normal-stress events in comparison to CEX for large trade sizes. This phenomenon is attempted to be explained by our first-difference interaction regression model which was grounded in economic incentives for liquidity providers derived by Heimbach et al. (2022). β_3, the coefficient of the interaction term in the regression,

[12] For instance: (Unibot, 2025)

[13] Mempool is the space in which all pending transactions gather. These have an priority fee attached to them and is observable and influences the decisions made by validators.

implies an improved slippage for DEX in comparison to CEX post-stress for most trade sizes. This relationship is observed to be statistically significant for small to mid-trade sizes (4 to 20 ETH) with p-value levels of 10% to 1%. Despite this, we find the discrepancy between the trade sizes, both in terms of significance and sign, to not show enough support for our hypothesis across all trade sizes. Still, the economic intuition is consistent with the literature on liquidity provider behavior; liquidity providers in a market with concentrated liquidity may experience higher fee revenues during increased volatility, incentivizing them to re-enter or reposition liquidity toward the active price (tick) band. We still strongly believe this to be true across all trade sizes rather than only the ones observed in our results (Table 9). An explanation to why we could not observe this phenomenon is because our data only looks at the Uniswap V3 pool with fee tier 0.3%. Through the insights provided by the Heimbach et al. (2022) study, we are confident that liquidity providers will jump to pools with higher fee tier during times of market stress. Despite this essential fact, due to data constraints and query limits, investigating every fee tier pool was not feasible for this paper and, as such, we appreciate that controlling for this or incorporating it into the model in supplement would potentially make this model even more representative. With this, it may be possible to prove that *by shifting the venue fee to liquidity providers (as DEX does in opposition to CEX), slippage will improve in times of stress, which will, ultimately, economically benefit the users and liquidity providers of cryptocurrency exchanges, rather than the exchange itself (e.g. Binance), creating a more efficient market and mitigating the costs associated with stress*.

Another major point of evaluation for insignificant interaction coefficient amongst most trade sizes may be sample heterogeneity, as larger trade sizes may be rarer relative to small trades. A reason for why this may occur, which our simulation for transaction cost does not incorporate, is *MEV* bots. Additionally, data constraints also presented a clear limitation for the analysis of the CEX venue, as observed in all preceding tables featuring trade sizes, the number of observations tended to decrease gradually with increasing trade sizes. For most events, CEX data did not have enough liquidity depth to cover the trade sizes during either normal or stress events. This may have been a significant source for bias in our data considering that when the trade size approaches 75 ETH, there are only 36 valid observations for CEX. These observations may, in addition, share common attributes and thus not truly represent random out of the 417 events we selected. This limitation applies to the rest of the CEX data collected and is regarded in our concluding remarks.

V. Concluding Remarks

The main objective set out in this paper, as per our research question, was to reliably compare the degradation/resilience of liquidity in the (W)ETH/USDT pair market for the centralized Binance exchange crypto venue and the decentralized Uniswap V3 fee tier 0.3% venue, respectively, following volatile stress events, in silo and in relation to one another. One central result of our investigations is that while both venues suffer from liquidity degradation during stress due to the risk aversive tactics employed by liquidity providers against adverse selection, the structure and source of that degradation is fundamentally different. The CEX Binance venue was found to be linear and liquidity depth-dependent, while the DEX Uniswap V3 venue degradation was found to be structurally regressive, implying that smaller traders tended to face larger liquidity degradation for smaller transactions than institutional-sized traders during times.

Furthermore, our second and third hypotheses were focused on exploring the mechanisms as to why smaller trade sizes are affected disproportionately relative to larger trade sizes in the DEX Uniswap V3 venue. This was achieved by i) running a panel regression and panel decomposition to examine whether larger trade sizes for the DEX venue fare better in terms of liquidity resilience relative to stress, and ii) decomposing gas fees into their constituent components: the base gas fee and the priority gas fee. For the former, our results confirm that the DEX liquidity degradation are, indeed, far worse for smaller trade sizes after times of market volatility than for larger trade sizes, and this was mainly in association with the change in gas fees before and after a stress event. For the latter hypothesis, once evaluated, the trend in the base fee of gas and its variance were found to be decreasing significantly with time, akin to what Barbon and Ranaldo (2024) reason for gas being solely technological. However, we observe that in the priority fee the same pattern does not persist. The fundamental contribution that we make, therefore, to this literature is the fact that the *total gas fee of DEXs cannot be assumed to be zero* in the long-term due to the underlying presence a structural aspect of the priority fee which is driven by economic factors. Without this structural component, the validators in the DEX venue lose incentives to provide liquidity for traders who can no longer prioritize their transactions to the validators; thus trading becomes more difficult for traders with urgency Karaivanov and Zarifian (2024). As such, despite the long-run improvement of technologies associated with the blockchain, the necessary persistence of this fundamental economic structure in the DEX venue will not let the (W)ETH/USDT market reach a zero-equivalent value in gas fees. We further contribute by mapping out what liquidity degradation will look like with only the long-term structural component of gas fees, assumed to be only the value long-run priority fees in the (W)ETH/USDT market, which shows, on average, much more favorable and competitive liquidity degradation for most trade sizes relative to the Binance CEX venue. However, retail size trades below 1 ETH are still heavily impacted in the long run.

Finally, our last investigation into this topic came in the form of testing for slippage behavior for the CEX Binance venue and the Uniswap V3 fee tier 0.3% DEX venue. This was achieved through a first-difference interaction regression approach examining whether, during a stress event, the slippage for the DEX venue improves relative to CEX slippage when the change in volume prior to the stress moment increases. Despite a statistically weak and insignificant coefficient for most trade sizes, the interaction terms measuring change in pre-stress/normal event volume to if the event was a stress period or not show improved slippage for DEX relative to CEX. Notably, this only shows a statistically significant relationship for the at least the 5% level for trade sizes between 8 and 20 ETH. *In consequence this shows that in a DEX like Uniswap v3, shifting the*

venue fees into the hands of the liquidity providers favors its users during stress more in comparison to users on Binance, creating a more efficient market to trade in.

With regards to the weaknesses of this study, the limited publicly available data on CEX liquidity depth and volume, unfortunately, meant that we could not simulate the transaction cost for all events; for instance, for trade size 100 ETH, the sample size that could be analyzed with the available liquidity data was only 11. Consequently, this may have biased our results, since some events display greater order-book depth within the nearest 20 bid and ask levels relative to others. In addition, the lack of data on modelling and representing MEV bot trading also made the simulation and analysis of transaction costs for DEX more difficult to accurately analyze. The discovery and incorporation of a variable that can capture the effect of MEV bot trading for stress periods would prove fruitful for the betterment of this area of research. Crucially, this research analyzes only the fee tier 0.3% pool in Uniswap V3, thus not allowing for the full observation of the behavior of liquidity provider across the whole Uniswap V3 venue for (W)ETH/USDT. As such, a comprehensive study focused on accounting for these different fee tier pools could provide a better understanding of liquidity provider behavior in relation to pre-stress volume buildup. Finally, we have only performed a microstructural analysis on one token pair (W)ETH/USDT on two specific venues; a study covering many different venue types for decentralized and centralized exchanges could also be viable towards further examining the effect of stress periods on liquidity degradation and its components.

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Appendix A: Tables and Figures

Table 1: Selecting the k value.

Robustness Summary Statistics		
	k = 10 divergence from k=5 (minutes)	k = 30 divergence from k=5 (minutes)
Num of normal-stress periods	432	432
Average	5.46	18.04
Std	12.24	15.87
min	0	0
25%	2	9
50%	4	17
75%	5	24
Max	192	172

Note: This table details the checking for different k-values (representing minutes before a candle) used to identify the ideal value for the rolling window realized volatility approach to select our normal-to-stress period sample following the ABDL framework. Descriptive statistics for every stress event, i, for two different k values are shown, with a baseline of ($k = 5$). The absolute value of the maximum computed realized volatility timestamp for a given k to the baseline's peak volatility timestamp is compared. The time difference between the two indicates how sensitive stress-detection is to the choice of window size.

FIGURE 1 – Distribution of RS volatility (σ_{RS}) [%]

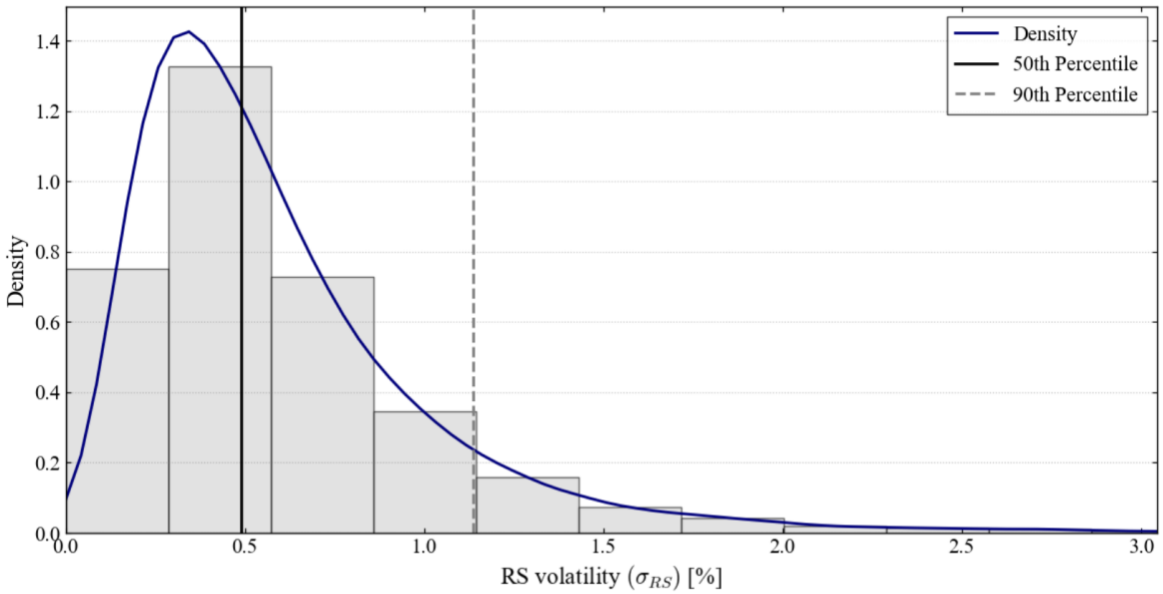


FIGURE 1. This figure shows the density of Roger–Satchell volatility, expressed in percent, computed from hourly ETH/USDT candles on Binance over our four-year period sample, 2021-11-09 to 2025-11-09. The solid black line marks the median (50th percentile), while the grey dashed line marks the 90th percentile. The histogram includes a kernel density estimate for smoothness (blue line).

FIGURE 2 – Realized Volatility $\mathrm{RV}_{10}(t)$ and Timestamp Selection

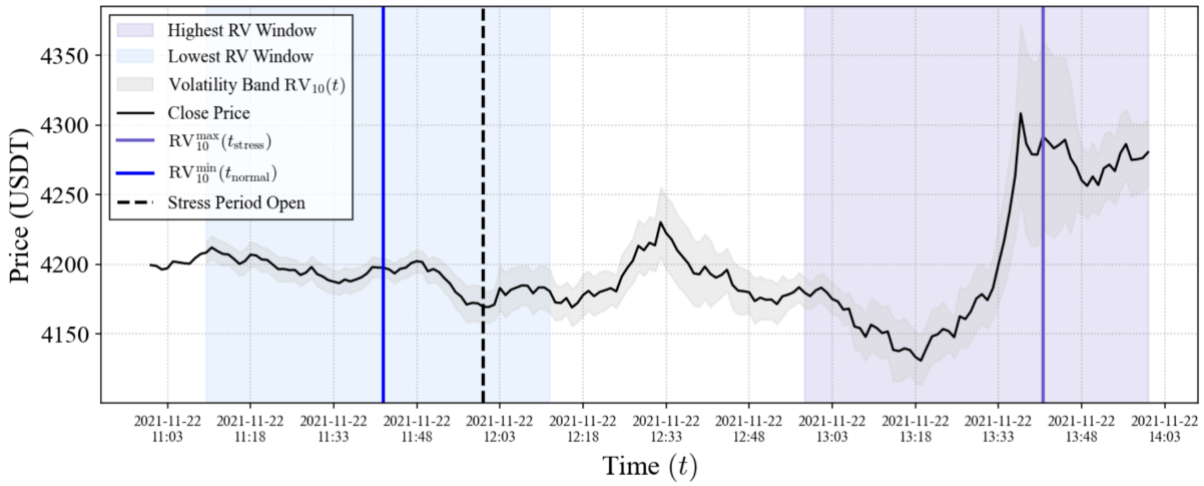


FIGURE 2. This figure displays the ETH/USDT close price and the realized volatility measure $\mathrm{RV}_{10}(t)$ together with the highest- and lowest-volatility 35% windows. The purple line marks the highest $\mathrm{RV}_{10}(t)$ in the purple 35% window, while the blue line marks the minimum $\mathrm{RV}_{10}(t)$ in the blue 35% window. The dashed black line marks the stress-period opening timestamp identified from the hourly RS-based analysis.

FIGURE 3 – Mean Difference in Pre-Event Volume Between Stress and Normal

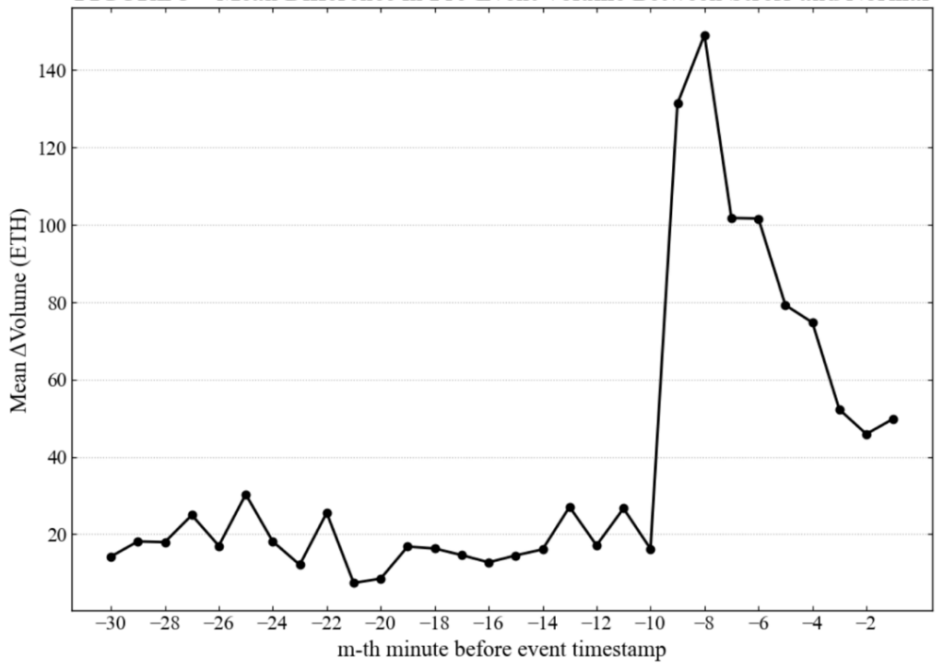


FIGURE 3. This figure shows the mean difference in average minute-by-minute trading volume between stress and normal events on Uniswap v3 (0.3% WETH/USDT) over a 30-minute pre-event window. The x-axis shows the m-th minute before the event timestamp, while the y-axis shows the mean change in trading volume, calculated as the average stress volume minus the average normal volume.

FIGURE 4 – Price Directionality from t − 10 Minutes to Timestamp: Stress vs Normal

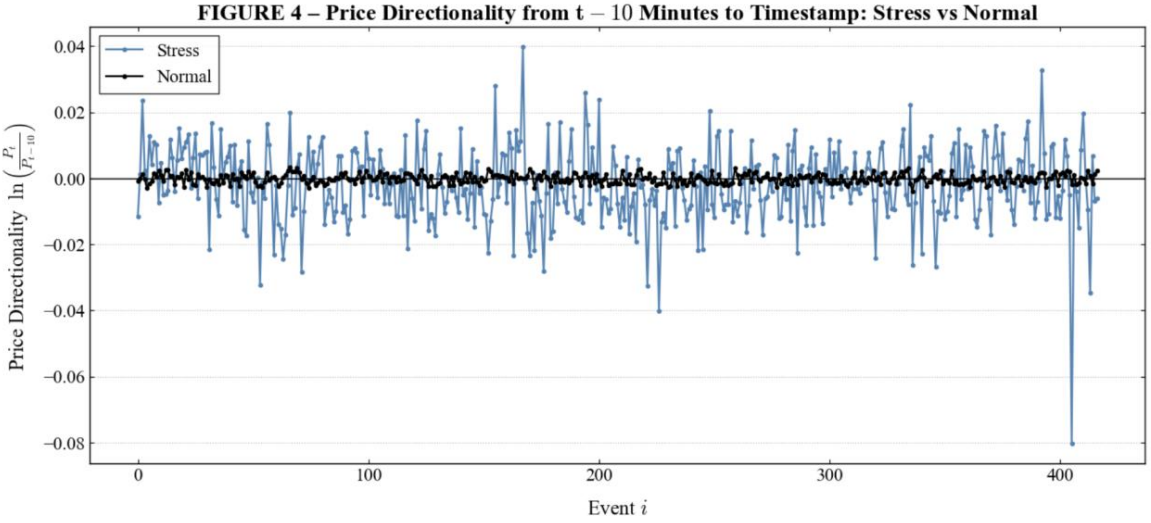


FIGURE 4. This figure shows the log price change $\ln\left(\frac{P_i}{P_{i-10}}\right)$ *ten minutes before the timestamp under stress and normal conditions. The black points represent the log price change for normal events, while the blue points represent stress events. Positive values indicate upward price movement, while negative values reflect downward pressure.*

FIGURE 5 – Average Liquidity Degradation After a Stress Period in Binance (CEX) and Uniswap v3 (DEX)

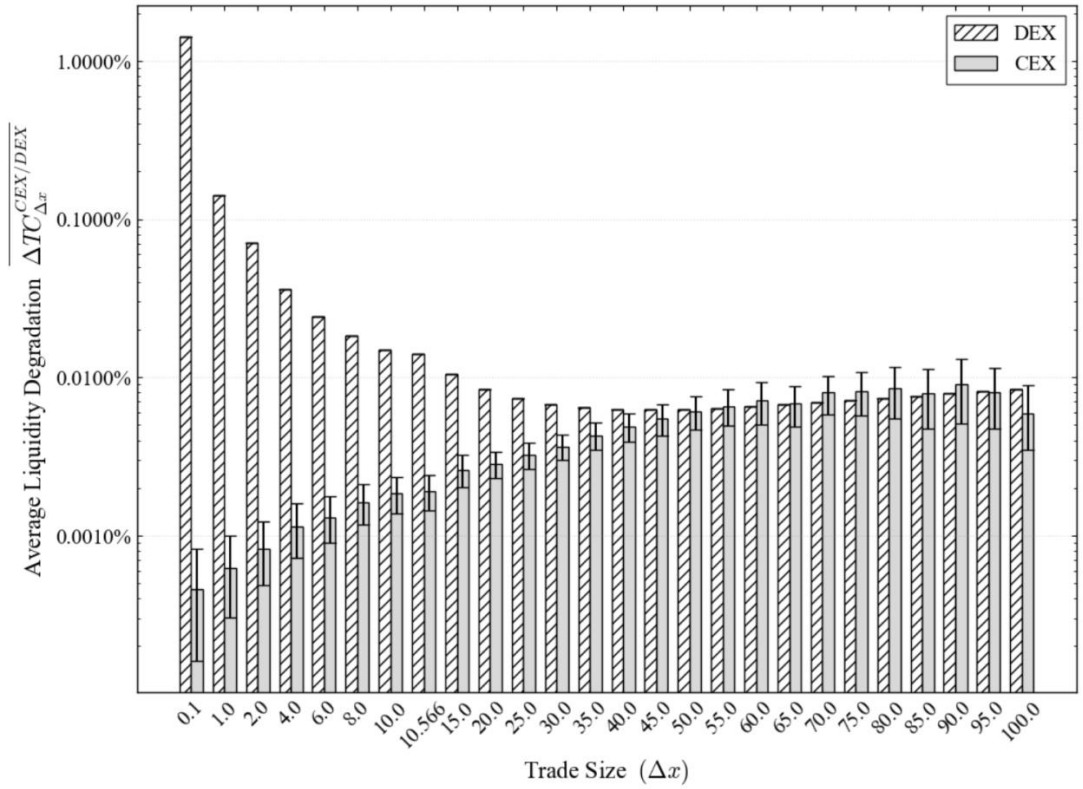


FIGURE 5. This figure displays the average change in Transaction Costs (TC) between stress and normal periods on a [%] log scale, across trade sizes (Δx). The CEX error bars represent 95% confidence intervals, using bootstrapping (n=10,000). This was done due to the missing data when queries were made to CoinAPI

Table 2: T-test results for Hypothesis 1 for the CEX and DEX of fee tier 0.3

Trade Size	N	Mean ΔTC [%]	t-stat
Panel A: CEX			
0.1	294	0.00046***	2.66
0.5	294	0.00053***	2.97
1.0	294	0.00062***	3.44
4.0	284	0.00114***	5.06
10.0	277	0.00184***	7.34
20.0	245	0.00283***	10.17
50.0	87	0.00605***	8.00
100.0	11	0.00592***	4.15
Panel B: DEX			
0.10	417	1.42308***	6.64
0.50	417	0.28465***	6.64
1.00	417	0.14237***	6.64
4.00	417	0.03583***	6.67
10.00	417	0.01488***	6.79
20.00	417	0.00844***	6.83
50.00	417	0.00629***	4.83
100.00	417	0.00846***	3.62

Note: This table presents the t-test results comparing liquidity degradation between the CEX Binance and DEX Uniswap V3 fee tier 0.3 venues at different trade sizes after a stress event in the ETH/USDT and WETH/USDT markets. Panel A reports results for the Binance exchange and Panel B reports results for the Uniswap V3 fee tier 0.3 venue. Δ TC represents the total variable impact (Spread + Gas + Venue fee for Uniswap V3, Spread + venue fee for Binance). Δ Spread represents the Bid-ask spread for the CEX and DEX venues. Δ Gas is the change in median effective gas price, defined by the sum of the median priority and base gas fees from each block number. Statistic significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3: Regression Results for testing Hypothesis 2: Total Transaction Cost [%] for the WETH/USDT Market in the Uniswap V3 Fee Tier 0.3 Venue (Including Gas)

Variable	Coeff. (β)	Std. Err.
Constant	1.1929***	0.057
Stress	0.3959***	0.060
$\ln(\Delta x)$	-0.2320***	0.016
Stress × $\ln(\Delta x)$	-0.1090***	0.017

Model Statistics		***Residual Diagnostics***	
Observations	22,518	Omnibus	42,637.1
R-squared	0.161	Prob(Omnibus)	0.000
Adj. R-squared	0.161	Skew	14.529
F-statistic	89.80	Kurtosis	333.359
Log-Likelihood	-35,368	Durbin-Watson	1.105
AIC	70,740	Jarque-Bera	1.03×10^8
BIC	70,780	Prob(JB)	0.00
		Cond. No.	18.3

Note: This table presents the total simulated transaction cost [in %] for all blocks gathered, both before and after a stress event in our sample. These transaction costs correspond to the WETH/USDT market in the Uniswap V3 fee tier 0.3 pool. Total transaction cost includes slippage, venue fee, and gas fees. Standard errors are clustered by event ID. The variable $\ln(\Delta x)$ represents the natural logarithm of the simulated trade size Δx. The interaction term Stress × $\ln(\Delta x)$ is used to test whether liquidity degradation worsens disproportionately for small trade sizes during stress (Hypothesis 2). Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: Regression Results for Testing Hypothesis 2: Total Transaction Cost for the WETH/USDT Market in the Uniswap V3 Fee Tier 0.3 Venue (Excluding Gas)

Variable	Coeff. (β)	Std. Err.
Constant	0.2946***	0.000
Stress	-0.0004***	0.000
$\ln(\Delta x)$	0.0176***	0.000
Stress $\times \ln(\Delta x)$	0.0011***	0.000

Model Statistics		***Residual Diagnostics***	
Observations	22,518	Omnibus	16,488.0
R-squared	0.365	Prob(Omnibus)	0.000
Adj. R-squared	0.365	Skew	3.288
F-statistic	509.5	Kurtosis	22.541
Log-Likelihood	39,549	Durbin-Watson	0.398
AIC	-79,090	Jarque-Bera	3.99×10^5
BIC	-79,060	Prob(JB)	0.00
		Cond. No.	18.3

Note: This table presents the total simulated transaction cost [in %] for the WETH/USDT pair on Uniswap v3 0.3% fee tier pool during normal and stress conditions. The transaction costs does not include the gas fee component (determined by sum of the base fee of the block and the median priority fee). Standard errors are clustered by event ID. $\ln \Delta x$ denotes the natural logarithm of simulated trade size Δx. The Stress dummy variable indicates whether or not the observation is a transaction cost recorded during stress (1) or normal (0). The interaction term Stress $\times \ln(\Delta x)$ is used to test Hypothesis 2 regarding whether liquidity deterioration during stress is more severe for small trades. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Decomposition of Liquidity Degradation in the ETH/USDT Market for CEX and DEX (bps)

Δx (ETH)	$\overline{\Delta S_{XY}^{\text{venue}}}$	$\overline{\Delta g}$	Δf_{venue}	$\overline{\Delta TC_{XY}^{\text{venue}}}$	N
Panel A: DEX (Uniswap v3)					
0.1	0.0006	142.3072	0	142.3078	417
2.0	0.0129	7.1154	0	7.1283	417
10.0	0.0650	1.4231	0	1.4881	417
25.0	0.1673	0.5692	0	0.7365	417
50.0	0.3446	0.2846	0	0.6292	417
100.0	0.7038	0.1423	0	0.8461	417
Panel B: CEX (Binance)					
0.1	0.0459208	0.0000	0	0.0459208	294
2.0	0.0826946	0.0000	0	0.0826946	290
10.0	0.1836587	0.0000	0	0.1836587	277
25.0	0.3245859	0.0000	0	0.3245859	205
50.0	0.6047814	0.0000	0	0.6047814	87
100.0	0.5921527	0.0000	0	0.5921527	11

Note: This table presents the decomposition of liquidity degradation, measured as the change in total transaction cost between normal and stress periods, for different trade sizes Δx in the ETH/USDT (Binance) and WETH/USDT (Uniswap v3) pair. The notation $\overline{\Delta S_{XY}^{\text{venue}}}$ denotes the mean change in the spread-based measure of slippage, $\overline{\Delta g}$ denotes the mean change in effective gas cost, and Δf_{venue} represents the change in venue fee. The total change in transaction cost is given by $\overline{\Delta TC_{XY}^{\text{venue}}}$, which combines spread, gas, and venue fees for DEX venues and spread plus venue fee for CEX venues. The decreasing number of observations for the CEX at larger Δx reflects book–depth limitations but remains consistent with expected liquidity patterns.

FIGURE 6 - Total Gas Fee Decomposition

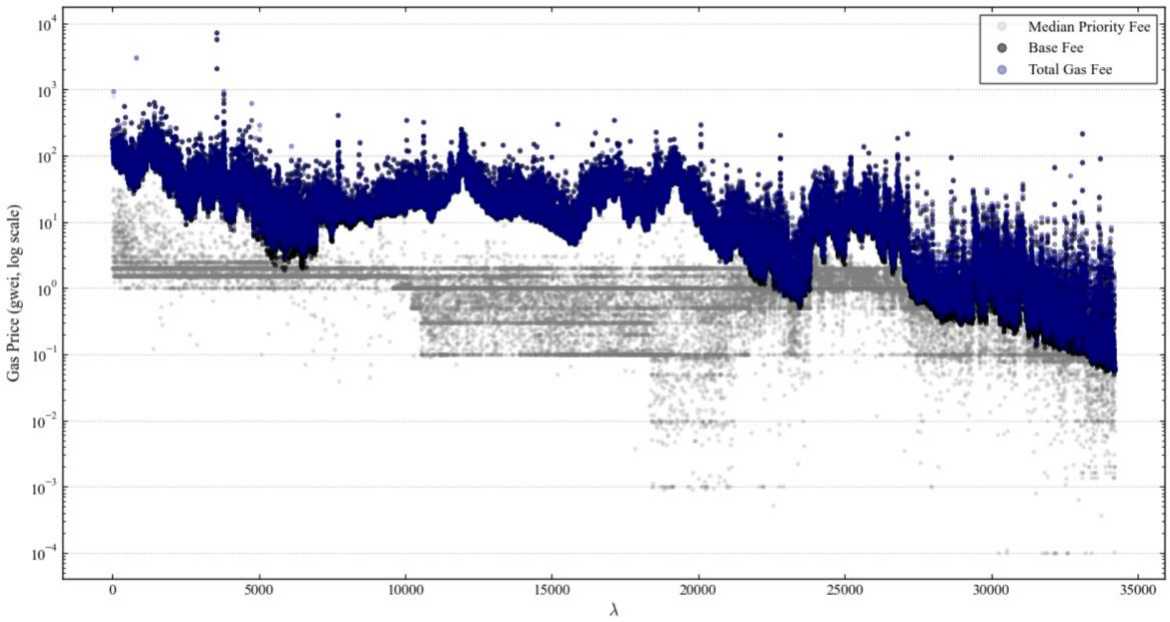


FIGURE 6. This figure reflects, in Gwei, the effective gas prices (blue) together with its components base fee (black) and median priority fee (grey), across observations indexed by λ. All values are plotted on a log scale to illustrate fluctuations across the full range of network conditions. The total gas price appears as the outer series, while the Base Fee and median Priority Fee are shown as separate underlying components.

FIGURE 7 - Median Priority Fee (Sampled Over Time)

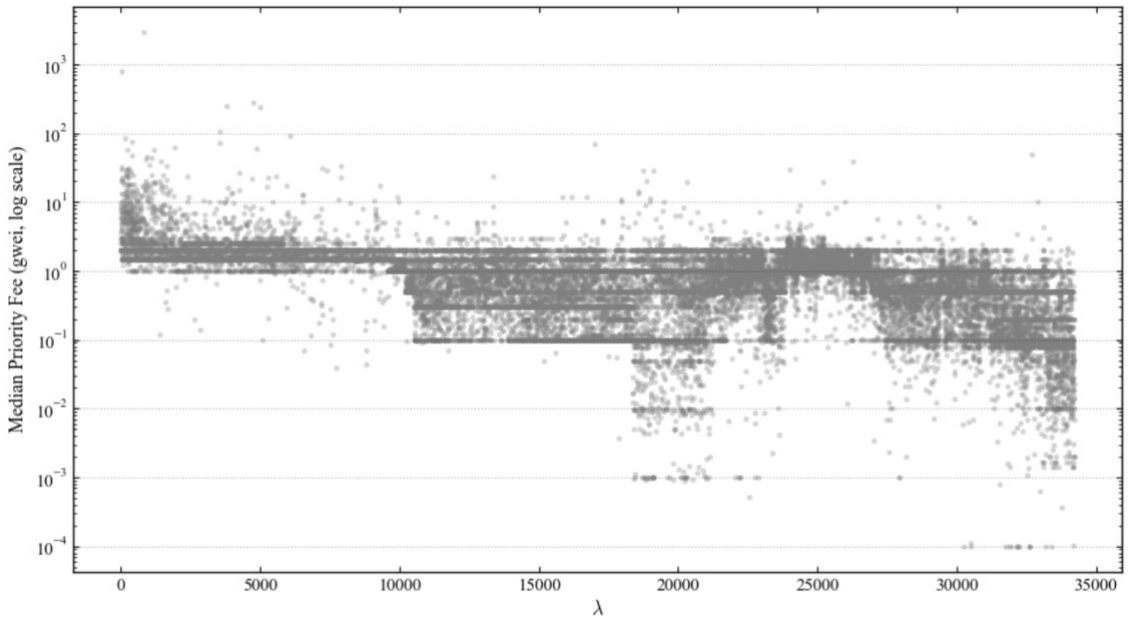


FIGURE 7. This figure displays the median priority fee, in Gwei, across observations indexed by λ which is the 300th block incremental from block number 13,623,124 to 23,886,141. The values are shown on a log scale to capture variation during both calm and congested periods. Each point corresponds to the median Priority Fee, in Gwei, recorded at a sampled block normalized to λ.

FIGURE 8 - Base Fee (Sampled Over Time)

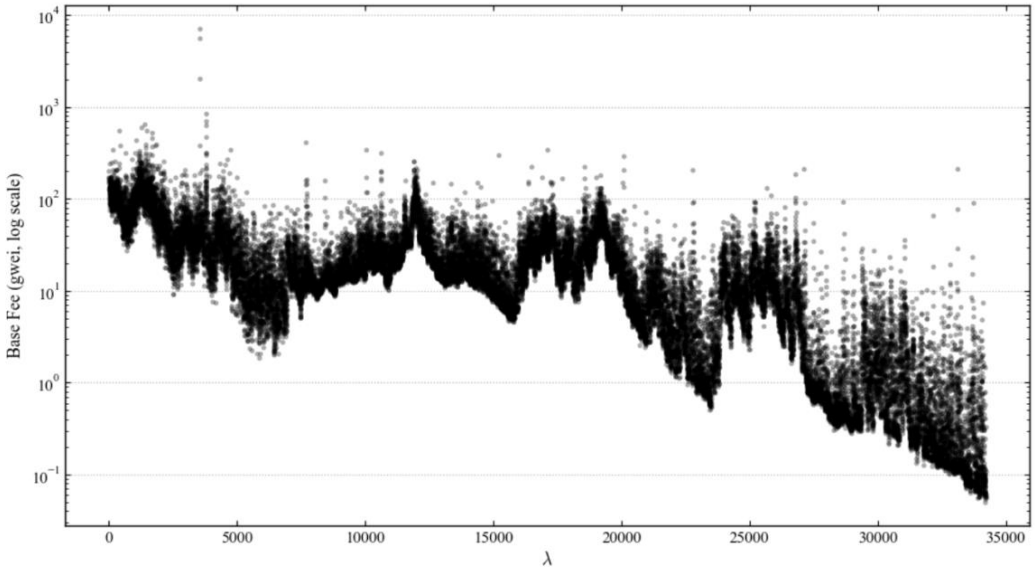


FIGURE 8. This figure shows the evolution of the Base Fee across consecutive observations, indexed by λ which is the 300th block incremental from block number 13,623,124 to 23,886,141. The Base Fee values are plotted on a log scale to display both low and high periods of network activity clearly. Each point represents the Base Fee, in Gwei, recorded at a sampled block normalized to λ.

Table 6: Regression Analysis: Gwei Gas Fee Trends on the Ethereum Blockchain (09-11-2021:09-11-2025)

	Base Fee Trend (B)		**Priority Fee Trend (MPr)**	
Variable	**Coeff. (β)**	**Std. Err.**	**Coeff. (β)**	**Std. Err.**
Constant	55.8606***	0.620	2.6740***	0.180
Lambda (λ)	-0.0019***	3.14e-05	-7.89e-05***	9.10e-06
Model Statistics				
Observations	34,211		34,211	
R-squared	0.094		0.002	
F-Statistic	3,535.0***		75.18***	
Log-Likelihood	-1.871×10^5		-1.447×10^5	
AIC	3.742×10^5		2.894×10^5	
BIC	3.742×10^5		2.894×10^5	
Residual Diagnostics				
Omnibus	128,507.3		157,344.0	
Prob(Omnibus)	0.000		0.000	
Skew	84.007		161.596	
Kurtosis	9,466.3		27,919.7	
Durbin-Watson	0.710		1.995	
Jarque-Bera (JB)	1.28×10^{11}		1.11×10^{12}	
Prob(JB)	0.00		0.00	
Cond. No.	3.95×10^4		3.95×10^4	

Note: This table shows the OLS results for the gas fee (Gwei) trend components over time. λ is the normalized block number defined as $\lambda = \frac{bl - bl_0}{\Delta bl}$, where bl is the block number, $bl_0 = 13,623,124$, and the increment $\Delta bl = 300$. Gas fees, in Gwei, are the additional settlement cost for transactions to be processed and validated on the Ethereum blockchain, in which a decentralized exchange operates. Standard errors are non-robust. Significance levels: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7: Regression Analysis: Gwei Gas Fee Variance Trends on the Ethereum Blockchain (09-11-2021:09-11-2025)

	Base Fee Variance (ϵ_B^2)		Priority Fee Variance ($\epsilon_{\mathbf{MPr}}^2$)	
Variable	**Coeff. (β)**	**Std. Err.**	**Coeff. (β)**	**Std. Err.**
Constant	10,710***	3,462.8	1,061.3**	499.1
Block Number (λ)	-0.4336**	0.175	-0.0459*	0.025
Model Statistics				
Observations	34,211		34,211	
R-squared	0.000		0.000	
F-Statistic	6.116**		3.298*	
Log-Likelihood	-4.822×10^5		-4.160×10^5	
AIC	9.645×10^5		8.319×10^5	
BIC	9.645×10^5		8.320×10^5	
Residual Diagnostics				
Omnibus	150,271.2		163,294.1	
Prob(Omnibus)	0.000		0.000	
Skew	138.642		183.513	
Kurtosis	19,963.3		33,838.1	
Durbin-Watson	1.025		2.000	
Jarque-Bera (JB)	5.68×10^{11}		1.63×10^{12}	
Prob(JB)	0.00		0.00	
Cond. No.	3.95×10^4		3.95×10^4	

Note: OLS regression results for the trend in the squared residuals (variance) of gas fees in Gwei, over time. λ is the normalized block number defined as $\lambda = \frac{bl - bl_0}{\Delta bl}$, where bl is the block number, $bl_0 = 13,623,124$, and the increment $\Delta bl = 300$. Gas fees are the additional cost for transactions and activity to be processed and validated on the Ethereum blockchain, in which decentralized exchanges operate. Standard errors are non-robust. Significance levels: $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

FIGURE 9 – Average Liquidity Degradation ($\Delta TC^{CEX/DEX\text{-}adj}$) Across Trade Sizes ($\Delta x$) in Binance (CEX) and Uniswap v3 (DEX)

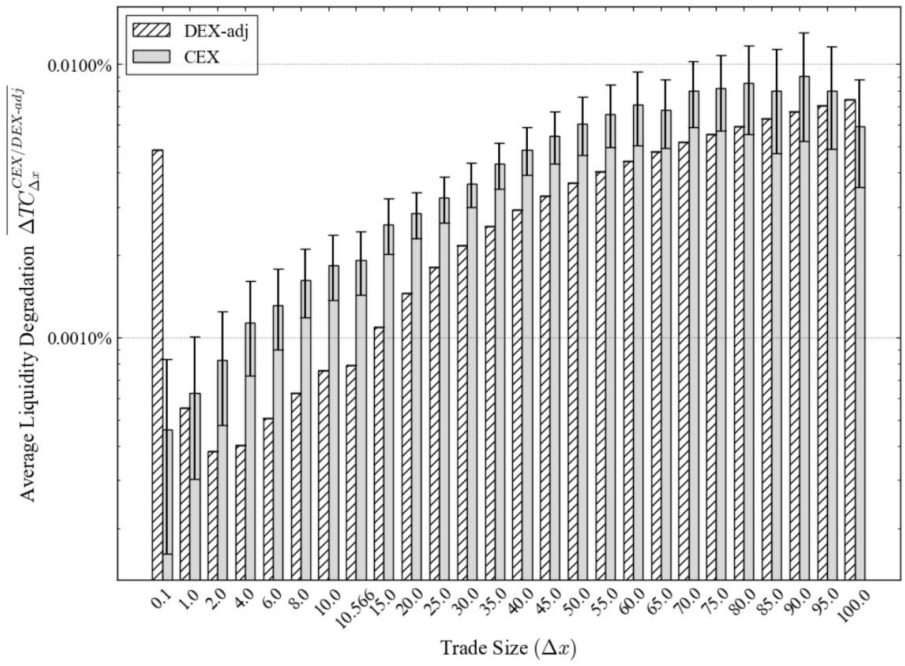


FIGURE 9. This figure displays the change in Transaction Costs (TC) between the stress and normal period for both DEX and CEX. However with DEX median priority fees adjusted for their time trend. CEX error bars represent 95% confidence intervals using 10,000 bootstrap samples. This was done due to the missing data when queries were made to CoinAPI

Table 8: Paired Difference t-tests (Hypothesis 3: $\overline{D}_{\Delta x} < 0$)

Δx (ETH)	N	$\overline{D}_{\Delta x}$ [%]	$\sigma_{\overline{D}_{\Delta x}}$	t-stat
0.100	294	0.001178	0.00264684	0.0763
1.000	294	−0.000432	0.000266358	-0.2781
2.000	290	−0.000710	0.000138245	-0.8743
4.000	284	−0.001086**	7.8499×10^{-5}	-2.3317
6.000	283	−0.001218***	6.23918×10^{-5}	-3.2833
8.000	281	−0.001466***	5.94154×10^{-5}	-4.1360
10.000	277	−0.001677***	6.13097×10^{-5}	-4.5519
10.566	276	−0.001737***	6.26158×10^{-5}	-4.6074
15.000	264	−0.002259***	7.69502×10^{-5}	-4.7699
20.000	245	−0.002499***	8.90684×10^{-5}	-4.3919
25.000	205	−0.002964***	1.05611×10^{-4}	-4.0185
30.000	177	−0.003583***	1.22840×10^{-4}	-3.8810
35.000	152	−0.004671***	1.25301×10^{-4}	-4.5962
40.000	129	−0.005168***	1.41732×10^{-4}	-4.1414
45.000	108	−0.005623***	1.59883×10^{-4}	-3.6551
50.000	87	−0.006565***	1.93339×10^{-4}	-3.1673
55.000	79	−0.007209**	2.22476×10^{-4}	-2.8802
60.000	62	−0.005767*	2.19122×10^{-4}	-2.0722
65.000	56	−0.004784	2.39209×10^{-4}	-1.4965
70.000	45	−0.009401***	1.04229×10^{-4}	-6.0505
75.000	36	−0.009549***	1.09709×10^{-4}	-5.2225
80.000	28	−0.010638***	1.04798×10^{-4}	-5.3715
85.000	23	−0.010289***	1.13419×10^{-4}	-4.3506
90.000	19	−0.010311***	1.17310×10^{-4}	-3.8312
95.000	14	−0.010489***	8.4062×10^{-5}	-4.6685
100.000	11	−0.009260***	8.77615×10^{-5}	-3.4996

Note: The table reports one-sided paired t-tests of the hypothesis $\overline{D}_{\Delta x} < 0$. The difference term $\overline{D}_{\Delta x}$ is defined as the mean of the difference in transaction cost change between DEX and CEX, across all events i for a particular trade size:

$$D(\Delta x, i) = \Delta TC_{XY}^{DEX,Adj}(\Delta x, i) - \Delta TC_{XY}^{CEX}(\Delta x, i).$$

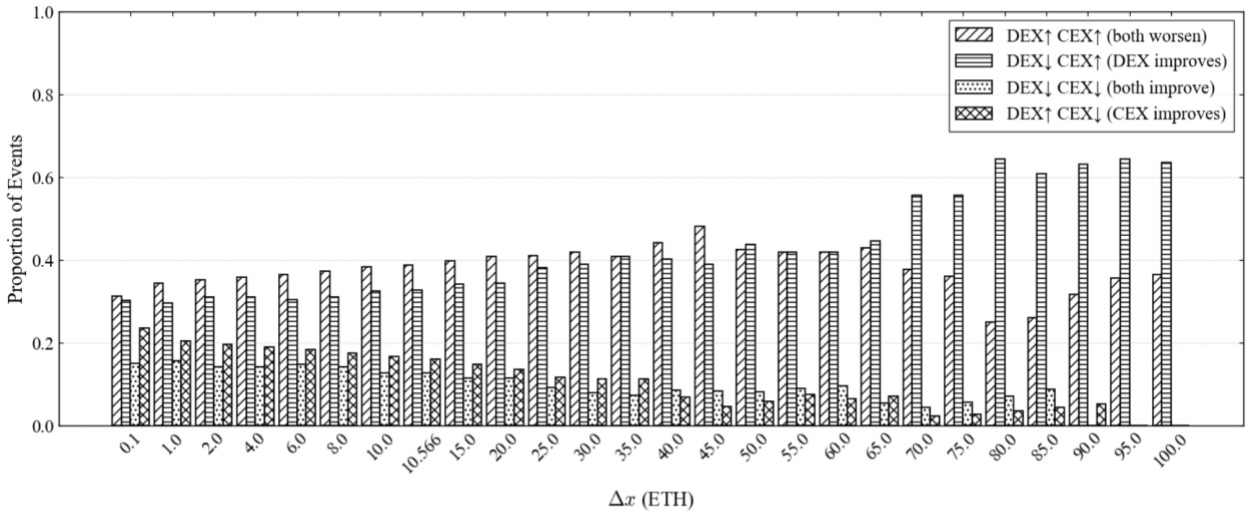
The transaction costs for DEX have their gas component (median priority fee) adjusted for the time effect. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 9: First-Difference interaction Regression Results by Trade Size (Cluster-Robust)

Trade Size (ETH)	β_3 (Market × ΔVolume)	R^2	N
0.100	-1.57×10^{-6}	0.118	294
0.500	-1.57×10^{-6}	0.114	294
1.000	-1.56×10^{-6}	0.113	294
2.000	-1.63×10^{-6}	0.115	290
4.000	$-2.00 \times 10^{-6*}$	0.137	284
6.000	$-1.87 \times 10^{-6*}$	0.124	283
8.000	$-2.08 \times 10^{-6**}$	0.130	281
10.000	$-2.20 \times 10^{-6**}$	0.131	277
10.566	$-2.27 \times 10^{-6**}$	0.131	276
15.000	$-2.71 \times 10^{-6***}$	0.135	264
20.000	$-1.60 \times 10^{-6**}$	0.092	245
25.000	-1.82×10^{-6}	0.078	205
30.000	-9.34×10^{-7}	0.081	177
35.000	4.77×10^{-7}	0.144	152
40.000	3.16×10^{-7}	0.144	129
45.000	-2.53×10^{-7}	0.144	108
50.000	1.76×10^{-7}	0.153	87
55.000	6.43×10^{-7}	0.153	79
60.000	-1.97×10^{-6}	0.151	62
65.000	1.58×10^{-7}	0.093	56
70.000	-2.17×10^{-6}	0.468	45
75.000	-3.42×10^{-6}	0.415	36
80.000	-2.33×10^{-6}	0.439	28
85.000	-3.59×10^{-6}	0.408	23

Notes: This table reports the estimated coefficients from the First-Difference interaction regression run separately for each trade size. $\beta_{interaction}$ (or β_3) corresponds to the interaction term **market** × **ΔVolume**, measuring whether the effect of ΔVolume on slippage differs between the DEX (market = 1) and CEX (market = 0). The dependent variable is the change in XY-price impact (ΔSXY) between normal and stress periods. All regressions include controls for ΔGas, ΔRV, price directionality, and initial price. Reported p-values are based on cluster-robust standard errors at the event level. Significance levels: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. R^2 is computed on stacked observations; N counts matched event clusters.

FIGURE 10 — Proportion of Events by Slippage Outcome Across Δx Levels Based on $\Delta S_{XY}^{\text{venue}}$ for DEX and CEX



The figure shows the proportion of events falling into each slippage-outcome quadrant across trade sizes Δx. For each event i, slippage is measured using $\Delta S_{XY,i}^{\text{venue}}(\Delta x)$. Arrows in the legend indicate whether slippage increases (\uparrow) or decreases (\downarrow) following a stress event.

Appendix B: Technical Appendix

B.1 Finding block numbers

The Ethereum blockchain is indexed by block numbers rather than UTC time. This is such that when a swap is executed, its referenced execution 'time' is the block number in which the transaction was verified by the block validators. Nevertheless, a comparison through the translation of different time units (UTC to block number) can be achieved. In the Ethereum proof-of-stake system, blocks are created for every 12-second slot, meaning effective block time remains approximately 12 seconds. Each block contains a timestamp, set by the validator, indicating the time when the block was proposed to be created and attached to the larger block chain. This makes it possible to identify when a block entered the chain's production process, using UNIX timestamps converted from UTC time. Using the endpoint "getblockbytime" on Etherscan v2 API, a query is made to convert the UTC derived timestamps t_{stress} and t_{normal} from body section III A.1 (Etherscan, 2025). The closest block number, bl, after timestamp t is found using this method. Formally, for a given target timestamp t, the identified block bl satisfies:

$$bl = min\{b \in \mathbb{Z}^+ + |Timestamp\ (b) \geq t|$$

(back to body)

B.2 The stress period sample and deriving the Final sample size

The initial dataset contained some normal-stress cycles that occurred near or adjacent to one another. If this was left unaddressed, these could have contaminated the analysis as shock candles (stress) tend to have a decay effect (Hasbrouck 2007). To resolve this issue, the time gap between all hourly-merged normal-stress event pairs was calculated as the *time difference* between the *close timestamp* of a stress period in one normal-stress pair and the *open timestamp* of the next normal period of the next normal-stress pair. If the gap between these two was ≤ 1 hour and the calm period lasted also only approximately 1 hour, the immediate normal-stress period with the open normal timestamp was removed from the sample and merged with the previous normal-stress period to form a single normal-stress period.

In addition, within normal-stress events, stress timestamps that came before the normal timestamp were also removed. This was done by first selecting our normal and stress periods using hourly candle data and then looking within them using a granularized minute candle approach. This is a tradeoff of having adjacent low volatile periods to stress periods using hourly and narrowing down stress / normal moments using minute candles. This filtering yielded a final sample size of 417 normal-stress periods.

(back to body)

B.3 Deriving Slippage for CEX

The Spread is defined as follows:

$$S_{XY,i}(\Delta x, t) = \frac{A_{XY}(\Delta x, t) - B_{XY}(\Delta x, t)}{A_{XY}(\Delta x, t) + B_{XY}(\Delta x, t)} \quad (A1)$$

Where, $A_{XY}(\Delta x, t)$ $[B_{XY}(\Delta x, t)]$ represent the volume-weighted ask [bid] price for a buy [sell] order of size Δx at time t. $A_{XY}(\Delta x, t)$ and $B_{XY}(\Delta x, t)$ are computed as follows:

$$A_{XY}(\Delta x, t) = \frac{\sum j\, v_j a_j}{\Delta x}, B_{XY}(\Delta x, t) = \frac{\sum I\, v_I b_I}{\Delta x}, where \sum j\, v_j = \Delta x, \sum I\, v_I = \Delta x$$

Where, a_j is the ask price at level j (price of sellers), and v_j is available volume at that ask price a_j. Similarly to the ask structure, b_I is bid price at level I (price of buyers) and v_I is available volume at that bid price b_I.

By running a simulation for a given trade size Δx, we sweep through the liquidity for both buying and and selling:

$$A_{XY} = \{(a_j, v_j): I = 1, \ldots, 20\}, B_{XY} = \{(b_I, v_I): I = 1, \ldots, 20\}$$

This is done until a trade order of Δx ETH is filled or stop if there is no further liquidity to fulfill it in one of the directions, resulting in a computed slippage component for CEX for snapshots.

(back to body)

B.4 Deriving Slippage for DEX

For each normal-stress event i, the slippage cost $[S_{XY,i}^{DEX}(\Delta x, bl)]$ is calculated, using the simulated outcome of test trade sizes that traverse the Uniswap WETH/USDT V3 0.3% pool liquidity distribution. In Uniswap V3, the function allowing liquidity providers (LPs) to set a range for their reserves has the consequence of changing the active liquidity L_{active} as price moves across the venue's internal price measurement called ticks, where $P = 1.0001^{tick}$. While price can move to any tick number, the range set by LPs must have its upper and lower tick divisible by 60, which is the *tick spacing* for a 0.3% fee tier on Uniswap. This creates multiple 60 incremental intervals $[P_{tick}, P_{tick+60}]$, also referred to as tick (price) band, that contain a constant active liquidity. This constant is determined by the virtual reserves provided by LPs, and is defined as:

$$L_{active} = \sqrt{xy} \quad (A2)$$

The virtual reserves at in a tick band and at the tick boundaries (*) are given by

$$x = \frac{L_{active}}{\sqrt{P}} \qquad y = L_{active} \cdot \sqrt{P} \qquad x^* = \frac{L_{active}}{\sqrt{P^*}} \qquad y^* = L_{active} \cdot \sqrt{P^*}$$

Thus, the relationship for a change in the virtual reserves within a 60-tick boundary is identified as:

$$\Delta x = L_{active}\left(\frac{1}{\sqrt{P^*}} - \frac{1}{\sqrt{P}}\right), \quad \Delta y = L_{active}\left(\sqrt{P^*} - \sqrt{P}\right)$$

By knowing the net liquidity, L_{net}, at each tick boundary, the liquidity curve can be constructed, thus allowing for an updated, L_{active}, and reuse this relationship across all prices and trade sizes. Simulating a trade entails trading until the lower (higher) tick bound is reached, and then subtracting (adding) the net liquidity at that tick, and updating all initial parameters, such as price, active liquidity, and the remaining ETH (x) to be traded. The effective price ($P_{eff,bl}$) of doing a swap (Δx), at block number bl is represented as:

$$P_{eff\ buy/sell,bl} = \frac{\Delta y}{\Delta x}$$

From which the slippage for buying and selling was computed as:

$$S_{buy}(\Delta x, bl) = \frac{P_{eff\ buy} - P_0}{P_0}, S_{sell}(\Delta x, bl) = \frac{P_0 - P_{eff\ buy}}{P_0},$$

(back to body)

B.5 DEX gas component of transaction cost

The gas cost, $(g_{bl}(tx))$, for a user in a given block (bl) executing a transaction (tx) is calculated with two components, the effective gas price, $G(tx)$, which reflects the cost per unit of computation, and the gas used, $(U_c(tx))$, which reflects the amount of computation required for the transaction.

$$g_{bl}(tx) = U_c(tx) \cdot G(tx) \qquad (A3)$$

Gas used, $U_c(tx)$, is determined by the underlying contract that the DEX trader calls upon. In Uniswap V3 swap, this varies depending on the ticks crossed to complete the transaction and the complexity of the underlying swap, for instance doing multiple coin swaps in one call. The effective gas price $G(tx)$ is further constructed with two components following the introduction of the EIP-1559 design; the base fee of the block B_{bl} (a fixed cost for all users in the block) and the priority fee $Pr(tx)$ set by the users.

$$G(tx) = B_{bl} + Pr(tx) \qquad (A4)$$

Thus, the effective gas cost for a user, for transaction number, tx, in block number, bl, can be expressed as,

$$G_{bl}(tx) = U_c(tx)(B_{bl} + Pr(tx))$$

For our paper we assume, similar to Barbon and Ranaldo (2024), a constant U_c gas used of 130 881, which is approximately how much a Uniswap V3 smart contract required, and similarly once again we use the median priority fee in the block, defining the effective ETH gas cost component of $TC_{XY,i}^{DEX}(\Delta x, bl)$ as:

$$G_{bl}(tx) = U_c(tx)(B_{bl} + Pr(tx))$$

(back to body)

Appendix C: AI Disclosure

This section of the appendices outlines what AI tools were used to aid our investigation, the purpose of their use for this paper and our statement of integrity. These tools were used in compliance with the course guidelines for the bachelor's thesis in Finance at Stockholm School of Economics and were strictly used to improve the efficiency and structure of the investigation's workflow, meaning all ideas, arguments, and the final writing were our original work.

Tools Used: Gemini AI and VSC copilot (Via Github Copilot)

Purpose of their Use

Gemini was used for: helping with understanding the ideal structural organization and style for the sections/subsections of this paper; accurately interpreting and comprehending some of the more complicated literature reviewed due to the high-level understandings required for some of the more nuanced and extensive PhD level papers studied; for aid in how to use word styles to match that of a bachelor level thesis.

VSC copilot (via Github copilot) was utilized in the Virtual Studio Code (VSC) software to help with debugging code produced for errors and to ensure that the codes ran as efficiently as possible once written, due to API query limits and for the sake of time saving during data extraction. This is following the standard practice when programming through VSC.