Cross-exchange liquidity dynamics: decentralized and centralized crypto platforms during the US banking crisis

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Abstract

Liquidity is a vital indicator of market quality and efficiency, and its role is particularly pronounced in the cryptocurrency space, especially when examining the interaction between centralised and decentralised exchanges. This paper provides empirical evidence of a cointegrated liquidity relationship between Binance, the largest centralised exchange, and Uniswap, the largest decentralised exchange. Our findings reveal that, for certain token pairs, Binance's liquidity exerts a long-run forcing effect on Uniswap. However, during periods of market turmoil, such as the US banking crisis, this relationship breaks down, highlighting the fragility of liquidity linkages in times of crisis.

JEL Classification: D47, D53, G12, G14

Keywords: Liquidity, Cryptocurrencies, Decentralized Exchanges, Uniswap, DEX, DeFi

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1 Introduction

The rise of crypto assets has sparked the emergence of decentralised finance (DeFi), a financial system that operates without intermediaries or centralised authorities. At the core of DeFi are decentralised exchanges (DEXs), which facilitate the peer-to-peer exchange of crypto tokens via smart contracts on the blockchain. These exchanges are governed by rules encoded in mathematical formulae, enabling seamless token swaps and liquidity provision without the need for central oversight. At the start of 2025, DeFi protocols had surpassed $120 billion in Total Value Locked (TVL)[1], with DEXs playing a significant role in the broader cryptocurrency and blockchain ecosystem.

This type of exchange, and more broadly a class of exchanges known as Automated Market Makers (AMMs), are an innovation unique to crypto. Nevertheless, AMMs have sparked interest from other areas of financial markets, for example, central banks experimenting with prototypes for trading wholesale digital currencies (BIS, 2023). While DEXs have proliferated with numerous platforms operating on multiple blockchain networks, they do not operate in a vacuum, and instead rely upon interaction with other DeFi services and centralised exchanges (CEXs). Continuous arbitrage maintains competitive pricing and is an essential characteristic of DEXs (Angeris *et al.*, 2019). In contrast to CEXs, DEXs require self-custody, with customers and traders managing their own wallet and interacting with the blockchain directly. They also do not have direct access to the banking system, a so-called on/off ramp for fiat currencies. Therefore, CEXs commonly act as the gateway in and out of the DeFi ecosystem, providing the ability to exchange crypto tokens directly for euros or dollars.

DEXs have become increasingly sophisticated, incorporating advanced features such as flash swaps and hooks. One characteristic of this system is continuous arbitrage between other DEXs and DeFi services like lending and borrowing protocols, staking platforms, and yield farming strategies. These exchanges both benefit from and face risks associated with Maximal Extractable Value (MEV), which influences the inclusion of transactions in blocks through a network of searchers and validators[2].

As DEXs evolve, they have introduced new variations of the underlying mathematical formulae, expanded onto blockchain networks with faster transaction speeds and alternative transaction ordering mechanisms, and developed interfaces that enable seamless token bridging between different chains. Moreover, DEX protocols are developing their own blockchain networks, creating intent-based markets, where professional market makers can participate in reverse-price auctions, and creating proprietary wallets to facilitate direct interaction with web interfaces, bypassing third-party wallets.

The rise of DEXs forms part of a crypto world defined by significant volatility, as well as increasing adoption. Notable scandals, such as the collapse of the FTX exchange, have raised concerns over the security and

[1] Source: DefiLlama

[2] https://ethereum.org/en/developers/docs/mev/

integrity of centralised platforms, with billions misappropriated in fraud. At the same time, regulatory pressure has played a role, with governments and central banks seeking to implement tighter controls on cryptocurrencies and develop their own digital currencies. This has been marked by the introduction of legislation in the European Union with the Markets in Crypto-Asset Regulation (MiCA), and a number of high-profile enforcement actions in the US brought against CEXs such as Binance and Coinbase, as well as the targeting of Uniswap, one of the original and most popular DEXs. The stance of authorities in the US has somewhat shifted, with the election of a more crypto-friendly administration, plus adoption of Bitcoin, Ether and other crypto Exchange-Traded Funds (ETFs). Although the broader macroeconomic environment has complicated this landscape. High inflation following the Ukraine war and the Covid-19 pandemic, resulting in higher interest rates, contributed to the collapse of several US banks in March 2023, including Silicon Valley Bank (SVB), Silvergate, and Signature Bank, all closely tied to the cryptocurrency industry.

DEXs are constrained by blockchain network protocols that impose gas fees, which shape their economic behaviour, in contrast to CEXs that rely on a central limit order book and traditional infrastructure. Liquidity providers on DEXs must strategically position their price ranges based on expectations of earning fees, while also bearing the risk of impermanent loss. Arbitrageurs, including MEV searchers, exploit inefficiencies by probing various DeFi platforms for profitable opportunities or engaging in strategies like sandwich attacks and transaction reordering. Meanwhile, cross-market arbitrage continuously takes place between CEXs and other actors in the crypto payment space. Under normal conditions, prices on DEXs remain accurate and exhibit characteristics of a healthy market. However, during market shocks, the agility of DEXs may be reduced, impacting their ability to maintain stability.

The recent collapses of FTX and Terra Luna have underscored the crucial role liquidity plays in ensuring the survival of crypto assets and exchanges. These incidents highlight the need for exchanges to effectively protect customers from liquidity crunches and volatility shocks. Some crypto users are attracted to DEX platforms in the search for greater financial decentralisation, and this in part stems from criticism directed at CEXs over mismanagement. The uncertain nature of the cryptocurrency market and elevated counterparty risks expose investors to the real possibility of significant financial loss.

We view past crises and the evolution of these markets as a key opportunity to better understand how crypto exchanges respond to liquidity shocks. Our focus is on the critical role of the interconnection between DEXs and CEXs, which forms a fundamental part of the crypto ecosystem. This relationship must be explicitly quantified and analysed through the dynamics of liquidity flows. Given the symbiotic nature of DEXs and CEXs, we aim to investigate what can be learned about market quality within DeFi. Specifically, we aim to explore whether these connections break down under pressure or prove resilient, and how particular events impact liquidity flows between DEXs and CEXs.

2 Literature review

Academic research on cryptocurrencies has evolved alongside its development and adoption, including DEXs such as Uniswap. The rapid expansion of this field has been accompanied by a growing body of literature that has shaped our understanding of cryptocurrency in general, and more specifically, the liquidity dynamics and economic models underlying them.

Since the launch of Uniswap in 2018, research has expanded to examine the economic design and financial characteristics that underpin DEXs. In particular, Wang *et al.* (2022) focus on the role of cyclic arbitrage in DEXs, revealing how arbitrage opportunities can influence price convergence and liquidity across protocols. Their findings reveal how certain practices within the Uniswap system act as an almost intrinsic check on the price efficiency within the exchange. When discrepancies arise between the assets listed on the exchange, an arbitrageur using a smart contract is ready to step in, correcting the prices. In a related study, Barbon and Ranaldo (2024) compare the market quality between CEXs such as Binance and Kraken, with Uniswap v2 and v3, focusing on liquidity and price efficiency. Their research finds that CEXs are more competitive in terms of transaction costs for small and medium trade sizes, while DEXs are more economical for larger trades, where the cost of gas fees is mitigated. These gas fees are a key factor in determining price efficiency, and are detrimental to DEXs. At the same time, Uniswap v3 made a significant contribution to bringing down transaction costs, as well as improving price efficiency. These contrasts between the two types of exchanges are crucial in understanding the broader market dynamics.

Further research by Zhu *et al.* (2024) has focused on specific factors driving liquidity on DEXs, with a focus on Uniswap v3. Their study examines how gas fees, token pair returns, and volatility affect market depth. The authors find that passive liquidity providers suffer more from liquidity fragmentation than active providers, and this fragmentation is driven by increased competition between DEXs and private sources of liquidity, which in turn acts to reduce TVL.

We contribute to the literature by building on the work of several papers, shifting the focus towards econometric cointegration using liquidity measures, in a similar vein to Lo and Medda (2021), who use cointegration as a framework to view the relationship of prices across exchanges. We specifically explore the liquidity dependence between these two types of exchanges and investigate their reactions to unexpected market shocks. This approach draws upon existing research on price accuracy during periods of market distress, such as that conducted by (Heimbach *et al.*, 2022), which examined the impact of liquidity and volatility on price discovery, uncovering a lack of agility by liquidity providers. Our analysis complements studies that assess market quality over specific time periods, building on Barbon and Ranaldo (2024)'s work on transaction costs and price efficiency across different exchange structures. By analysing liquidity fluctuations and cointegration dynamics, we aim to reveal deeper insights into the resilience of DEXs and CEXs in times of market stress.

Table 1: Top 10 token pairs from Uniswap v3 queried on 23 February 2023, Uniswap data via Messari subgraph

Rank	Base/quote asset	Cumulative volume (in billion $)
1	USDC/WETH	414.9
2	WETH/USDT	83.2
3	WBTC/WETH	64.6
4	USDC/USDT	57.1
5	DAI/WETH	36.9
6	Others < $250m	31.4
7	DAI/USDC	20.3
8	WBTC/USDC	13.0
9	FEI/USDC	8.5
10	APE/WETH	7.2

3 Methodology

This paper takes an econometric approach to studying the liquidity relationship between DEXs and CEXs. We begin our analysis by using a differences-in-differences strategy to examine the impact of the US banking crisis on liquidity between the different types of exchange. This allows us to make causal inferences about the behaviour of liquidity based on the idea of different periods and a treatment, in this case the collapse of US banks. Next, we follow a cointegrated methodology, which has frequently been used to study financial markets (Chou *et al.*, 1994), and provides consistent results for demonstrating interconnectedness. It enables us to analyse the long-run equilibrium and dependence in liquidity between the two types of exchange. In cointegration, we assume that two variables have the same stochastic trend in common, which we judge a reasonable assumption given that DEXs and CEXs facilitate trading for many of the same token.

In choosing the exchanges to study we considered data availability and size. Uniswap, the oldest and largest DEX, was selected, in addition to Binance, one of the world's largest CEXs. For Uniswap, we focused on v3 deployed on Ethereum since it uses concentrated liquidity, has the most volume and has been available for a considerable length of time. Also, we chose Ethereum given the fact that any impact on liquidity from the network itself will be more pronounced compared to other blockchains that have faster transaction times. A choice was made to focus on transaction-based measures of liquidity, which we judged to provide us with a rich dataset.

First, we selected a number of token pairs in common to the two exchanges, using volume to rank them, ensuring they had a reasonable trading history (Table 1). This led to the identification of 8 equivalent token pairs, spanning different characteristics, registering 22.6% of total cumulative volume ($194.7bn) on Uniswap

Table 2: Final selection of 8 token pairs from Uniswap v3 data

Token pair	Base asset	Quote asset
WETH/USDT	Wrapped Ether	Tether (stablecoin)
WBTC/WETH	Wrapped Bitcoin	Wrapped Ether
DAI/WETH	Dai (stablecoin)	Wrapped Ether
LINK/WETH	Chainlink	Wrapped Ether
DAI/USDT	Dai (stablecoin)	Tether (stablecoin)
WBTC/USDT	Wrapped Bitcoin	Tether (stablecoin)
AAVE/WETH	Aave	Wrapped Ether
MANA/WETH	Decentraland	Wrapped Ether

v3. It includes 7 different tokens, with Bitcoin, Ether, two different stablecoins and three tokens with smaller market capitalisations (Table 2). Notably, we do not include the Circle stablecoin, USDC, since Binance paused trading of this token during 2023. For consistency, in this paper we use Binance's nomenclature of base/quote asset to refer to token pairs.

3.1 Data collection

We chose to focus on 2023 given the unique challenges crypto markets faced with regards to the US banking crisis, regulatory pressure and changes to blockchain networks. Data was obtained from historical trades on Binance via their public access platform, processed and saved in parquet files using the Polars dataframe library. We collected 937.3m transactions for 2023 across the 8 token pairs. Uniswap data was collected from Allium[3] and 2.6m swap events were saved from v3 across the targeted token pairs. The Allium platform also enabled us to collect network data on the Ethereum blocks, gas, and transactions. Appendix A contains details on data collection.

We aggregated our dataset across hourly and daily intervals, in the spirit of other work using transaction-based measures of liquidity (Brauneis *et al.*, 2021), deciding not to proceed with a 1-minute frequency due to the relative lack of high-frequency trading on Uniswap. The data was cleaned and we created a number of liquidity features, including returns, variance, number of transactions, volume, trade size, and volume-weighted average price. In addition, we calculated liquidity proxies such as Roll's spread estimator (Roll, 1984), Amihud's illiquidity ratio (Amihud, 2002), and the Kyle and Obizhaeva estimator (Kyle and Obizhaeva, 2016).

[3] DEX Analytics

3.2 Variable selection

After initial exploratory analysis, it was evident that creating liquidity measures from Uniswap data based on returns is problematic because of MEV activity. This creates a number of persistent anomalies throughout the time series, with difficulty in discerning those which may be the result of arbitrage or those originating from other practices. Although these anomalies are problematic for calculating certain liquidity measures, they are in fact an important characteristic of Uniswap trading. We therefore judged it not in our interest to remove them or winsorize them.

Instead, we focused on 3 classic measures of liquidity: volume, number of transactions and trade size. These measures help determine the breadth and depth of a market, 2 of the 5 characteristics of liquidity (Sarr and Lybek, 2002). In traditional markets, they are frequently used to help identify liquid and illiquid securities (Le and Gregoriou, 2020). The number of transactions helps us control for situations that lead to increased or decreased trading volume (Díaz and Escribano, 2019), as well as describe the ability of a market to absorb a large number of orders. It has also been shown to be linked to volatility (Jones *et al.*, 1994). These volume-based measures are not affected by anomalies in our measures derived from price and have quite clear equivalence in our two datasets[4]. Intentionally, we leave our variables denominated in the original token amounts or token value, rather than apply a US dollar conversion. This removes any ambiguity about choice of a source for pricing.

Amongst the network variables, we chose block time, the length of time between blocks, and the base gas fee as the network variables of interest, which are averaged across our intervals. We dismissed the number of transactions in a block, the gas used and the block size. The number of transactions within a block could show correlation with our liquidity measure on Uniswap. The gas used and block size are not completely independent of the base gas fee, so we dropped this to avoid multicollinearity. The gas fee and the block time are key features of the Ethereum network, and are determined by demand for block space and availability of validators, meaning they are different data generating processes (DGP). All of the variables are log-transformed, to both stabilise the variance and aid interpretability, allowing us to describe coefficients as elasticities.

3.3 Testing

There are different methods of testing for cointegration. We decided to use the bounds testing approach (Pesaran *et al.*, 2001) (denoted as PSS), which takes advantage of the Autoregressive Distributed Lag (ARDL) model (Pesaran and Shin, 1997) and the Error Correction Model (ECM) (Engle and Granger, 1987) (Granger and Weiss, 1983). It is advantageous because it can be used with a mixture of $I(0)$ and $I(1)$ variables and uses a single equation based on a dependent variable. After cointegration testing is undertaken, short and long run

[4] Basing equivalence on Binance's configuration of base/quote for a token pair, using v3's $amount0$ and $amount1$ appropriately to calculate the same measure.

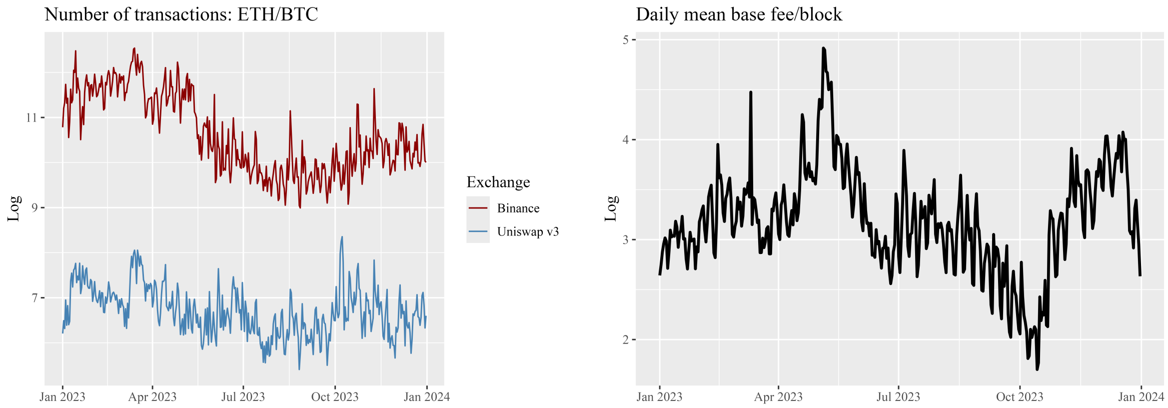
multipliers are constructed, as well as the Error Correction Term (ECT). The number of lags used helps give us insight into the persistence of any memory within the time series DGP. Given the relationship between DEXs and CEXs, we consider Binance's connection to the wider financial world, with fiat on/off ramps, the fact it is world's largest exchange and is not directly affected by the performance of the Ethereum network. This leads us to believe Uniswap liquidity can be explained by Binance, modelling Uniswap as the dependent variable. We use R (R, 2024) for our analysis phase, notably the ARDL package (Natsiopoulos and Tzeremes, 2024) (Natsiopoulos and Tzeremes, 2022), which provides a "gold standard" replication of the original results from PSS.

Testing is undertaken following a rigorous procedure in line with PSS. We create a model specification containing liquidity and Ethereum networks variables for selection based on the long-run cointegrated relationship (Equation 1). The $ARDL(p, q)$ model has p lags of the dependent Uniswap liquidity variable, with q lags of the independent Binance and Ethereum network variables:

$$v3_t = \beta_0 + \beta_p v3_{t-p} + \delta_{q_1} Binance_{t-q_1} + \delta_{q_2} Blocktime_{t-q_2} + \delta_{q_3} Gas_{t-q_3} + e_t \tag{1}$$

$v3_t$ and $Binance_t$ are respective liquidity measures $Volume_t$, $NumTX_t$ and $TradeSize_t$. $Blocktime_t$ and Gas_t are Ethereum network variables, β_p and δ_q are unknown coefficients and e_t is the error term.

We loop through the models and check that no variable is $I(2)$ and the dependent variable is $I(1)$, using the Augmented Dickey Fuller unit root test for each deterministic component (none, trend, drift). We take an agnostic approach to the choice of the 5 deterministic cases outlined in PSS (detailed in Appendix C) and construct the appropriate formulae. Then the best lag orders are calculated using the ARDL package's automatic model selection function, minimising the Akaike Information Criterion (AIC). For the daily interval, a maximum lag of 7 is chosen, representing a week. For the hourly interval, a maximum of 12 is used, representing half a day. We are cautious not to over-parameterise our models per PSS. We test the lag orders proposed by the model selection function and test for serial correlation in the residuals using the Breusch–Godfrey test. If there is evidence for serial correlation we cycle through the next best lag order proposed by the function. And if serial correlation cannot be removed we drop the model from our consideration. We test for heteroscedasticity and note whether robust errors are required. Finally, we carry out the cointegration tests, with the Wald test expressed as an F-statistic, and if relevant, the t-test, both at the 5% significance level. After reviewing the results, determining which show evidence of cointegration, we create the cointegrating equation for each of the deterministic cases that have passed the tests. Next, we calculate the Root Mean Square Error (RMSE) comparing the actual values to the fit of the cointegrating equation, in order to select the best deterministic case.



(a) (b)

Figure 1: ETH/BTC: Num TX & Ethereum Gas fees

4 Results

4.1 Exploratory analysis

Viewing the autocorrelation function (ACF) plots and simple line charts reveals that many of the times series appear nonstationary. For some token pairs and liquidity measures there appears to be some co-movement in the series on Binance and Uniswap. There are discernible peaks and troughs for many of the token pairs, with the impact of the US banking crisis showing an increase in the liquidity measures (Figure 1). Some of the series exhibit possible trends.

Descriptive statistics using our daily interval in 2023 reveal that generally Binance processes more transactions, Uniswap mostly has bigger trade sizes, but volume is a mixed picture (Table 7, Table 8). For 4 token pairs, Binance has both more volume and transactions, such as ETH/BTC, with 60,548 transactions a day on Binance on average compared to 959 for Uniswap. However, some pairs have many more trades on Binance, but considerably higher volume on Uniswap. This is the case with ETH/USDT, with 85.7 million tokens in volume on Uniswap, in contrast to 372,569 on Binance. The only pair that exhibits similar volume on the two exchanges is USDT/DAI. Trade size is considerably larger on Uniswap compared to Binance for most of our token pairs, with only LINK/ETH having bigger trades on Binance. Of the other token pairs, most have trade sizes of much greater magnitude on Uniswap, except for AAVE/ETH and ETH/BTC, which have similar sizes. The token pairs are characterised in 3 groups:

- AAVE/ETH, ETH/BTC, LINK/ETH, MANA/ETH - More transactions/volume on Binance than Uniswap
- BTC/USDT, ETH/DAI, ETH/USDT - More transactions on Binance but bigger trade size/volume on Uniswap

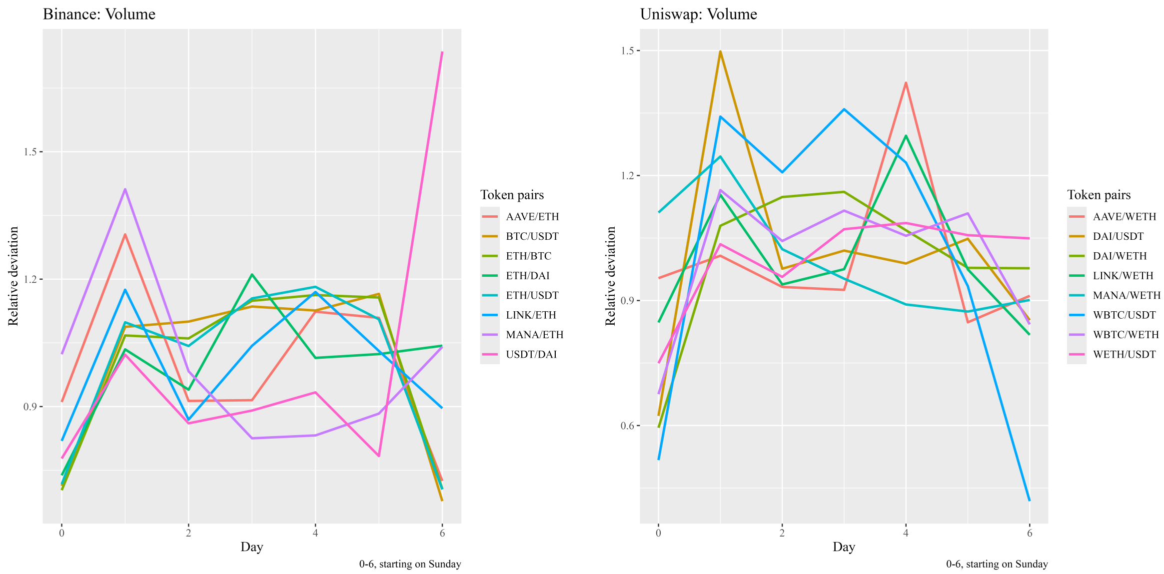


Figure 2: Relative deviation from the mean, daily interval, 2023

- USDT/DAI - More transactions on Binance with the same volume on Uniswap

4.2 Seasonality

Cryptocurrency markets show clear diurnal patterns (Brauneis *et al.*, 2024), with trading activity, volatility and liquidity reaching a high between 16:00 and 17:00 UTC. We see evidence of both hour of the day and day of the week seasonality in ACF plots and in a simple factor regression of our data. Some of this appears common across Binance and Uniswap, for example, most of our token pairs exhibit lower number of transactions at the weekend on both exchanges, although less subtle on Uniswap (Figure 2). This is similar to volume, which spikes on Mondays for both exchanges across token pairs. At other times there appears no pattern and it is harder to discern for some token pairs. For instance, Binance volume appears much higher for Saturdays with the USDT/DAI pair, yet the data reveals this was heavily influenced by one observation on Saturday 11 March 2023 when DAI suffered a depegging event, in itself linked to the depegging of USDC (Polizu *et al.*, 2023).

The network variables also display seasonal patterns (Figure 1). Considerable fluctuations in the base gas fee correspond to market events, with the highest fees recorded in May 2023 associated with demand for the PEPE token, linked to the Pepe the Frog meme[5]. The next highest fees occur during the US banking crisis. The block time remains relatively stable throughout the year, except for April during the upgrade to the Ethereum network when it spiked.

We applied a seasonal adjustment to our data, using Seasonal and Trend decomposition using Loess (STL)

[5]Source: CoinDesk

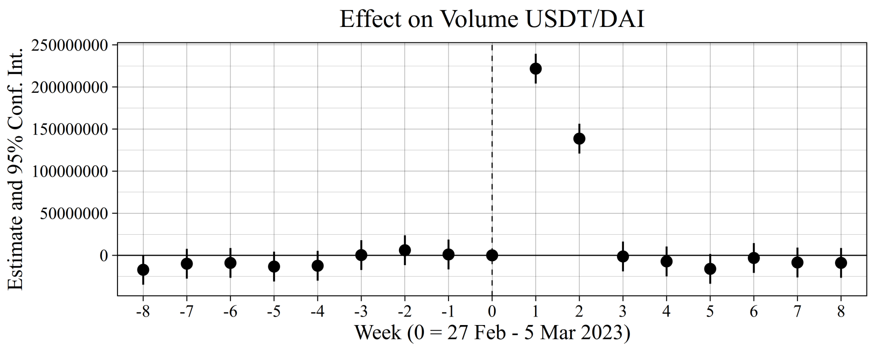


Figure 3: Multi-period differences-in-differences

(Cleveland *et al.*, 1990), with our daily interval adjusted according to day of the week, and our hourly interval by hour of the day, as detailed in Appendix B.

4.3 Differences-in-differences

We initially construct a canonical 2x2 differences-in-differences model. Our event of interest, the US banking crisis, does not have one single fixed date. The voluntary liquidation of Silvergate occurred on 8 March, the authorities stepped in to rescue SVB on 10 March, and Signature Bank was closed on 12 March. Furthermore, there were already signs of trouble at the start of the month, with SEC filings revealing that Silvergate Bank was in difficulty (Silvergate, 2023) and reports from the regulator about the scale of unrealised losses in the banking sector (Gruenberg, 2023). We therefore consider 1 March as the start of our treatment, using a 2 month pre and post period, as per Barbon and Ranaldo (2024) in their examination of the FTX crash. Binance is considered as treated, given its direct connection to the banking system, and we use the fixest R package (Berge, 2018) to run the regressions.

In verification of the parallel trends assumption, we examine our 3 liquidity variables across the 8 token pairs in both levels and log. We notice that the assumption does not hold for MANA/ETH pre-treatment. Furthermore, AAVE/ETH and LINK/ETH do not appear to have any discernible impact from the crisis, with similar post-treatment trends on both DEX and CEX. For the 5 remaining token pairs, the results provide evidence for both an outsized positive and negative impact on Binance liquidity compared to Uniswap, dependent on the token pair. To further discern this, as well as avoid any serial correlation, we proceed to split the model into a multi-period treatment with 17 weeks centred on 1 March. ETH/BTC, ETH/DAI and ETH/USDT do not provide good models, and we find the best evidence for the differences in response to the crisis with BTC/USDT and USDT/DAI (Table 9, Table 10). BTC/USDT Volume is more severely impacted by bank failures on Binance in the aftermath. USDT/DAI Volume sees a more than proportional increase on Binance compared to Uniswap (Figure 3), which is interesting given the depegging event DAI suffered, and the fact that this token

Table 3: Overview of selected models - daily interval. Models denoted by * have been adjusted from Case I to Case II. The ECT is derived from the Restricted ECM.

Token pair	Liquidity variable	Model	ECT
AAVE/ETH	Volume	ARDL(6,4,2,4)*	-0.2683
ETH/BTC	Volume	ARDL(4,4,0,1)	-0.2828
ETH/USDT	Num TX	ARDL(4,4,1,1)*	-0.1482
MANA/ETH	Num TX	ARDL(3,2,0,0)	-0.3822
MANA/ETH	Volume	ARDL(3,0,0,0)	-0.4006
USDT/DAI	Num TX	ARDL(5,1,4,1)*	-0.3702

pair exhibits similar mean volume on the 2 exchanges.

4.4 Cointegration

4.4.1 Daily interval, year-long

In total, we create 24 models (8 token pairs, 3 liquidity measures) and discard those with a lack of evidence for cointegration from the bounds testing, or the inability to get rid of serial correlation during model selection. Of the remaining models, we discard models systematically according to a criteria: degenerate cases, lack of significance in the coefficients for the long-run multipliers, and evidence of functional form misspecification following the application of Ramsey's RESET test (Ramsey, 1969).

In addition to the selection criteria, we carry out a visual inspection of the fit for the long-run relationship, looking for both persistence over the year and the ability to handle the volatility in the particular liquidity measure. We arrive at what we deem as 6 valid cointegrating relationships (summary: Table 3, full results: Table 11, Table 12, Table 13, Table 14, Table 15, Table 16). Case I and Case II are used for half the models, although we adjust all to Case II to aid interpretability (Appendix C). Trade size does not provide any reasonable models.

The models use between 3 and 6 lags of the dependent liquidity variable and between 0 and 4 lags for the independent liquidity variable. MANA/ETH Volume stands out given it uses no lags from the independent variables, although the contemporaneous coefficient of Binance Volume still makes a sizeable contribution. Overall, there is a reduced use of lags for network variables, indicating a less persistent memory is needed for their contribution to Uniswap liquidity. More than half the models demonstrated evidence for heteroscedasticity and were adjusted with robust errors accordingly.

The Error Correction Term (ECT) ranges from 14.82% for ETH/USDT Num TX to 40.06% for MANA/ETH Volume, representing the speed of adjustment to disequilibrium in one interval, in this case one day. These are all highly significant. The Binance liquidity measures in the long-run relationship are all highly significant and demonstrate an inelastic response by Uniswap liquidity. The results illustrate that Binance liquidity indeed has a forcing long-run effect on Uniswap liquidity, but less than proportionally.

None of the models using the network specification show significance at the 10% level for the blocktime or gas base fee coefficients in the long-run relationship, except for MANA/ETH Num TX, which is significant at the 5% level, and has an elasticity of -0.26. ETH/USDT Num TX almost shows significance at the 10% level, with an elasticity of 0.15. In the majority of cases neither the blocktime or base gas fee shows strong evidence for a long-run effect on Uniswap liquidity.

4.4.2 Hourly interval, monthly subsamples

After establishing solid evidence for cointegration with a daily interval for the year, we proceeded with analysis of hourly data to understand how this relationship evolves. We focused our analysis on ETH/USDT Num TX and ETH/BTC Volume since these were both cointegrated and represented the second and third largest cumulative volume on Uniswap. They also distinctly represent two of the key characteristic groups: ETH/BTC with Binance leading in volume and transactions, ETH/USDT with Uniswap leading volume, but Binance leading transactions. We broke down our year of hourly data into monthly subsamples.

Almost all the models used either Case I or Case II, indicating that either no deterministic component is required, or only a restricted intercept. We imposed Case II to aid interpretability, similarly for our daily intervals (Appendix C).

The majority of our final models show evidence for cointegration and pass the testing procedure, except for ETH/BTC Volume in March during the banking crisis. Excluding this month, all the Binance liquidity measures for the two token pairs show very significant evidence for explaining Uniswap liquidity in the long run (Table 5, Table 6). This relationship is inelastic for ETH/USDT Num TX and mostly elastic for ETH/BTC Volume. For ETH/USDT Num TX, the coefficient stays in the range of 0.31 to 0.66, but spikes to 0.86 in March 2023, coinciding with the collapse of US banks. This demonstrates that the liquidity relationship between the two exchanges strengthens under the pressure of this macro liquidity event. The ETH/BTC Volume is elastic throughout the year except during May and October, when it dips just below unity, with coefficients of 0.91 and 0.97. Before the banking crash, the elasticity reached a high of 1.65 in February, showing how Uniswap liquidity responded more than proportionally to Binance liquidity, coinciding with questions being raised over the profitability of some US banks.

The speed of adjustment for ETH/USDT Num TX dropped to its lowest level for the year in March, with 14% of any shock corrected in one hour, compared to an average for the year of 30%. The ECT was largest in October and November, with 44% of Uniswap disequilibrium corrected in one hour. For ETH/BTC Volume, we generally saw a faster speed of adjustment, which increased considerably between January and February

Table 4: Long-run cointegrating relationships

Token pair	Dep. variable	Regressor	Coefficient	Std. Error	HC Std. Error	p-value
AAVE/ETH	Log(Uniswap Volume)	Intercept	18.6123	53.2881	•	0.7271
		Log(Binance Volume)	0.8945	0.1364	•	0.0000
		Log(Blocktime)	-4.8150	21.8203	•	0.8255
		Log(Gas)	-0.3381	0.2357	•	0.1523
ETH/BTC	Log(Uniswap Volume)	Intercept	12.3995	26.7921	HC3	0.6438
		Log(Binance Volume)	0.7178	0.1048	HC3	0.0000
		Log(Blocktime)	-2.4291	11.0388	HC3	0.8260
		Log(Gas)	-0.2756	0.1908	HC3	0.1497
ETH/USDT	Log(Uniswap Num TXs)	Intercept	-3.6666	17.6472	HC3	0.8355
		Log(Binance Num TXs)	0.4860	0.1110	HC3	0.0000
		Log(Blocktime)	0.9422	7.2782	HC3	0.8971
		Log(Gas)	0.1464	0.1034	HC3	0.1576
MANA/ETH	Log(Uniswap Num TXs)	Intercept	22.1081	18.7926	HC3	0.2402
		Log(Binance Num TXs)	0.5793	0.0608	HC3	0.0000
		Log(Blocktime)	-6.0809	7.6097	HC3	0.4248
		Log(Gas)	-0.2615	0.1133	HC3	0.0216
MANA/ETH	Log(Uniswap Volume)	Intercept	21.2361	32.9284	•	0.5194
		Log(Binance Volume)	0.7371	0.0867	•	0.0000
		Log(Blocktime)	-12.1157	13.4803	•	0.3694
		Log(Gas)	0.2060	0.1778	•	0.2473
USDT/DAI	Log(Uniswap Num TXs)	Intercept	-2.0678	39.2091	HC3	0.9580
		Log(Binance Num TXs)	0.6545	0.3705	HC3	0.0782
		Log(Blocktime)	1.6057	16.1017	HC3	0.9206
		Log(Gas)	-0.1177	0.1047	HC3	0.2617

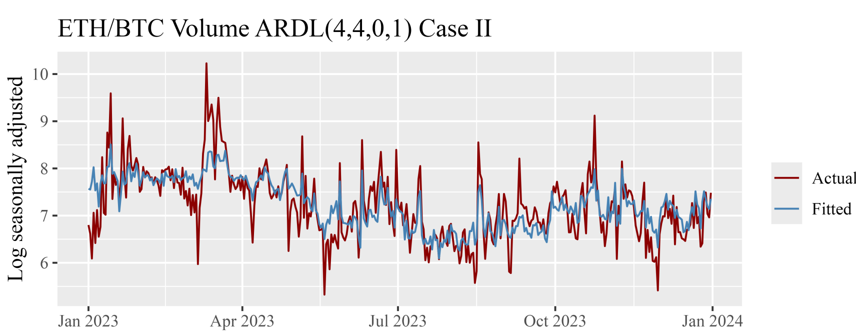


Figure 4: Long-run fitted cointegrated relationship, daily interval

Table 5: ETH/BTC Volume - monthly cointegration. Elasticity is derived from the coefficient of the long-run relationship for the liquidity variable. The network variables are omitted. All demonstrate highly significant evidence, with p-value < 0.01. The ECT is derived from the Restricted ECM. Case II unless otherwise stated.

Month	Model	Elasticity	ECT
Jan	ARDL(7,12,1,0)	1.20	-0.25
Feb	ARDL(1,1,0,7)	1.65	-0.79
Mar	•	•	•
Apr	ARDL(7,12,0,8)	1.29	-0.44
May	ARDL(8,12,2,4)	0.91	-0.47
Jun	ARDL(5,12,3,0)	1.23	-0.63
July	ARDL(4,0,12,0)	1.17	-0.77
Aug	ARDL(8,3,12,0)	1.05	-0.47
Sept	ARDL(5,10,0,0)	1.48	-0.67
Oct	ARDL(10,9,5,2)	0.97	-0.38
Nov	ARDL(10,6,6,10)	1.16	-0.40
Dec	ARDL(2,7,0,2)	1.04	-0.70

from 25% to 79%. During the remainder of the year, the ECT climbed from 44% in April, to 77% in July, with an oscillating pattern until the end of 2023. Although we do not calculate for ETH/BTC in March, owing to the lack of cointegration, we see that the two token pairs reacted differently in the face of the banking crisis. The adjustment to disequilibrium increased in the run-up to the crisis for ETH/BTC Volume, while slowed down for ETH/USDT Num TX, underlining how they responded differently to a shock and tying into the respective elasticity and inelasticity of Uniswap's response to Binance liquidity. Also highlighting the relative scale in the relationship.

The network variables are not consistent and generally do not show significant evidence for explaining Uniswap liquidity. In certain months, the impact on v3 liquidity is nonsensical, suggesting that increased fees can explain both an increase and decrease in volume and the number of transactions. We note that not all our months pass the Ramsey RESET test, suggesting that perhaps some models contain a functional misspecification.

4.5 Conclusion

The banking crisis provides a useful prism through which to view the relationship between DEX and CEX liquidity, particularly in the context of the relative liquidity strength of each exchange for specific token pairs.

Table 6: ETH/USDT Num TX - monthly cointegration. Elasticity is derived from the coefficient of the long-run relationship for the liquidity variable. The network variables are omitted. All demonstrate highly significant evidence, with p-value < 0.01. The ECT is derived from the Restricted ECM. Case II unless otherwise stated.

Month	Model	Elasticity	ECT
Jan	ARDL(2,2,0,1)	0.66	-0.41
Feb	ARDL(5,8,2,5)	0.35	-0.24
Mar	ARDL(3,3,2,2)	0.86	-0.14
Apr	ARDL(3,4,1,1)	0.31	-0.24
May	ARDL(4,4,3,4)	0.51	-0.20
Jun	ARDL(5,3,4,7)	0.64	-0.28
July	ARDL(5,4,4,3)	0.55	-0.30
Aug	ARDL(8,7,4,6)	0.35	-0.42
Sept	ARDL(5,5,1,5)	0.52	-0.27
Oct	ARDL(3,3,3,3)	0.44	-0.45
Nov	ARDL(1,1,0,1) Case IV	0.51	-0.45
Dec	ARDL(5,4,0,3)	0.37	-0.16

In the case of ETH/BTC, where Binance dominates trading volume, the established relationship between the exchanges breaks down completely. The cointegrated dynamics between DEX and CEX liquidity are disrupted as a result of the crisis. In the lead-up to the crisis, Uniswap responds disproportionately to the liquidity on Binance, quickly adjusting to changes in trading volume, which highlights its reliance on Binance for liquidity provision.

For the ETH/USDT pair, Uniswap's dependence on Binance for transaction volume increases. However, as the banking crisis unfolds, the speed of Uniswap's adjustment slows, and while its relationship with Binance strengthens, Uniswap struggles to keep pace with Binance's changes in volume. This lag could reflect underlying technical limitations within the Ethereum network itself. Moreover, it is crucial to explore the inverse relationship between the two exchanges, especially since Uniswap surpasses Binance in volume for some token pairs. This raises the question of whether, despite the cointegrated relationship, CEXs may, in some instances, depend on DEXs for liquidity in specific token pairs.

A key observation is the absence of consistent evidence regarding the influence of Ethereum network variables on Uniswap liquidity. This suggests that our current model may not adequately account for such effects. Furthermore, it may be valuable to investigate the potential cointegration between liquidity on faster blockchains. Since Uniswap operates across multiple chains, examining the impact of technical differences, such as alternative transaction ordering and processing speeds, could provide valuable insights into liquidity dynamics. Such an exploration could help clarify whether these factors contribute to the observed patterns of liquidity dependence between DEXs and CEXs.

Appendices

A Data collection

We initially collected data during 2023 and based our selection of token pairs using curated data from Messari hosted on The Graph protocol, polling statistics on Uniswap v3 USD cumulative volume. Historic data on Binance was available for at least 2020 onwards, aggregated on an order book level and provides relevant checksums for data integrity. We consider wrapped ERC20 format tokens as functionally equivalent, notably for Wrapped Ether (WETH) and Wrapped Bitcoin (WBTC). In reality, if these tokens were to traded on Binance, they would have to be unwrapped, implying an additional gas fee. Classification of tokens was cross-referenced with the CF Digital Asset Classification Structure by CF Benchmarks and a second classification from 21Shares and CoinGecko. Our selected tokens traverse several different categories according to both standards. We verified a sample of v3 transactions, from blockchain data we had directly collected from a blockchain node in a preliminary analysis, against Allium's data and found it to be accurate. The Allium data was gathered using the v3-polars integration. Binance suffered an outage on 24/03/2023 from 12:00 to 13:00 UTC, for which we applied linear interpolation. Our Uniswap data on the hourly basis contained 3 zero values for ETH/BTC Volume, for which we applied a linear interpolation.

B Seasonality

To make a decision on deterministic seasonality we used the Canova and Hansen seasonal unit test (Canova and Hansen, 1995), focusing on the joint test. This did not provide conclusive results for seasonal stability across the liquidity measures and token pairs, suggesting that we could not systematically apply a seasonal difference. Plus, accounting for seasonality with dummy variables in our ARDL model renders the PSS bounds tests invalid. Instead, we opted to make a seasonal adjustment using Seasonal and Trend decomposition using Loess (STL) (Cleveland *et al.*, 1990), which has a number of advantages given the structure of our seasonality. We applied our cointegration testing to both adjusted and non-adjusted data, providing us with very similar results, albeit less lags and slightly better fits for the seasonally adjusted data. Our daily interval was adjusted with day of the week seasonality and hourly interval with hour of the day.

C Deterministic components

The choice of deterministic components in cointegration is often led with a preference for the inclusion of intercepts and trends. We followed an agnostic approach to this choice, with an emphasis on the best fit to the long-run relationship. The selection of Case I models suggests that the cointegrated relationship relies solely on the stochastic components and does not require the formulation of deterministic elements. We take this as a sign of the consistency of the relationship between the two exchanges.

For the sake of interpretability, we reran the models for the daily interval using Case II in place of Case I for three of the concerned models. The results are materially the same, only further adjustment was required for ETH/USDT Num TX, increasing the lags to a ARDL(4,4,1,1) model to eradicate serial correlation in the residuals.

For our models using hourly data, just over half use Case II, so we dropped Case I selections to aid interpretability, and saw a very marginal deterioration in the mean absolute percentage error (MAPE) and little change in the number of lags used. Our model selection leaves us with all Case II and one Case IV, with unrestricted intercepts and restricted trends.

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D Tables

Table 7: Descriptive statistics, daily interval, 2023

	Mean	Std Dev	Q1	Median	Q3
AAVE/ETH					
Binance Num TX	1,134.0521	1,325.8109	347.0000	695.0000	1,368.0000
Uniswap Num TX	59.5808	55.7311	26.0000	44.0000	73.0000
Binance Volume	1,867.1997	2,647.3909	497.3020	1,132.8850	2,125.4530
Uniswap Volume	232.4947	341.4822	54.1024	118.2615	257.5887
Binance Trade Size	1.8296	1.0164	0.9270	1.7150	2.5770
Uniswap Trade Size	3.2256	1.9846	1.8290	2.7872	4.1421
BTC/USDT					
Binance Num TX	2,062,944.5781	2,624,440.6651	590,489.0000	893,647.0000	1,559,618.0000
Uniswap Num TX	88.0548	57.8911	51.0000	77.0000	108.0000
Binance Volume	100,288.5937	129,784.3408	27,503.8769	41,682.3200	88,039.4690
Uniswap Volume	871,007.7464	1,025,698.4981	282,963.7742	551,215.0117	1,029,737.5970
Binance Trade Size	0.0495	0.0138	0.0388	0.0489	0.0601
Uniswap Trade Size	9,338.2175	6,742.0890	4,276.5903	7,321.9474	13,257.6743
ETH/BTC					
Binance Num TX	60,568.6712	54,617.5190	19,629.0000	34,900.0000	95,644.0000
Uniswap Num TX	959.0027	597.3198	550.0000	794.0000	1,191.0000
Binance Volume	46,799.0420	36,575.2451	18,000.5707	35,026.4523	69,683.0998
Uniswap Volume	1,874.5924	1,848.2531	776.6811	1,335.6655	2,276.3571
Binance Trade Size	0.8618	0.2301	0.6783	0.8246	1.0133
Uniswap Trade Size	1.8068	0.7394	1.3178	1.7109	2.1843
ETH/DAI					
Binance Num TX	3,227.1288	4,445.0579	1,099.0000	1,876.0000	3,735.0000
Uniswap Num TX	762.7425	415.7242	539.0000	682.0000	880.0000
Binance Volume	683.1783	1,346.9259	105.3825	216.4014	729.9715
Uniswap Volume	12,800,357.1716	18,787,877.9114	5,856,307.9167	9,915,237.1226	14,479,641.2884
Binance Trade Size	0.1607	0.0957	0.0910	0.1299	0.2369
Uniswap Trade Size	15,076.7701	7,796.2081	9,759.0901	13,670.3391	18,455.1756

Table 8: Descriptive statistics, daily interval, 2023

	Mean	Std Dev	Q1	Median	Q3
ETH/USDT					
Binance Num TX	430,519.3644	201,891.349	264,991.0000	393,522.0000	542,260.0000
Uniswap Num TX	4,763.0849	1,680.345	3,617.0000	4,374.0000	5,488.0000
Binance Volume	372,569.3913	207,837.945	224,092.9059	328,855.6846	472,465.9556
Uniswap Volume	85,746,364.6154	108,748,579.136	38,629,546.3704	58,950,038.9763	101,482,269.8283
Binance Trade Size	0.8542	0.200	0.7003	0.8662	1.0015
Uniswap Trade Size	15,648.8384	8,665.027	9,973.6610	13,658.3862	19,749.8099
LINK/ETH					
Binance Num TX	4,585.6110	3,764.9245	1,764.0000	3,485.0000	6,227.0000
Uniswap Num TX	326.8877	222.4520	174.0000	266.0000	398.0000
Binance Volume	98,197.1687	96,960.5292	34,637.0300	65,770.0300	123,599.5800
Uniswap Volume	4,811.0998	4,666.1691	1,805.9606	3,193.2640	5,718.6926
Binance Trade Size	21.9422	8.4788	15.7239	21.9402	27.5426
Uniswap Trade Size	13.1881	5.2136	9.2477	12.5264	16.5319
MANA/ETH					
Binance Num TX	317.9699	449.6833	89.0000	165.0000	362.0000
Uniswap Num TX	53.8329	53.6336	26.0000	39.0000	63.0000
Binance Volume	80,252.2329	116,645.9877	21,585.0000	42,907.0000	91,439.0000
Uniswap Volume	79.8950	113.4380	24.4539	47.8591	96.7525
Binance Trade Size	276.0461	217.7142	179.3326	234.2179	311.0385
Uniswap Trade Size	1.3221	0.7633	0.8033	1.1561	1.6580
USDT/DAI					
Binance Num TX	4,702.0849	4,240.5509	3,216.0000	4,116.0000	5,228.0000
Uniswap Num TX	105.5370	57.0867	76.0000	96.0000	120.0000
Binance Volume	3,604,761.9975	12,529,666.1412	1,527,444.7000	2,207,320.0000	3,233,184.0000
Uniswap Volume	3,652,481.7991	5,581,139.4780	1,170,232.3383	2,330,038.7133	4,382,058.2339
Binance Trade Size	623.7164	344.5661	399.4844	566.1549	748.9922
Uniswap Trade Size	31,957.0276	27,130.8242	11,981.7406	25,071.3977	43,400.6677

Table 9: Multi-period differences-in-differences - BTC/USDT. Data from daily intervals aggregated by week, with week 0 = 27 Feb – 5 Mar 2023. The pre and post treatment period both represent 2 months.

Dependent Variable:	Volume
Constant	4,282,376.8*** (1,316,556.9)
CEX × week = -8	-3,208,257.7** (1,316,556.9)
CEX × week = -7	-2,180,307.4 (1,316,556.9)
CEX × week = -6	-2,248,522.3* (1,316,556.9)
CEX × week = -5	-2,378,135.1* (1,316,556.9)
CEX × week = -4	-2,245,967.7* (1,316,556.9)
CEX × week = -3	-2,301,182.6* (1,316,556.9)
CEX × week = -2	-1,880,771.7 (1,316,556.9)
CEX × week = -1	-1,946,320.8 (1,316,556.9)
CEX × week = 1	-1,839,856.3 (1,316,556.9)
CEX × week = 2	-447,609.9 (1,316,556.9)
CEX × week = 3	-2,522,152.7* (1,316,556.9)
CEX × week = 4	-3,769,275.1*** (1,316,556.9)
CEX × week = 5	-3,971,009.9*** (1,316,556.9)
CEX × week = 6	-3,898,703.9*** (1,316,556.9)
CEX × week = 7	-3,860,335.1*** (1,316,556.9)
CEX × week = 8	-3,842,703.8*** (1,316,556.9)
Fit statistics	
Observations	34
R^2	0.21076
Adjusted R^2	-0.53204

Clustered (CEX-week) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 10: Multi-period differences-in-differences - USDT/DAI. Data from daily intervals aggregated by week, with week 0 = 27 Feb – 5 Mar 2023. The pre and post treatment period both represent 2 months.

Dependent Variable:	Volume
Constant	28,302,879.0*** (8,707,336.7)
CEX × week = -8	-17,169,248.7* (8,707,336.7)
CEX × week = -7	-9,938,546.1 (8,707,336.7)
CEX × week = -6	-9,008,696.6 (8,707,336.7)
CEX × week = -5	-13,316,894.5 (8,707,336.7)
CEX × week = -4	-12,370,724.1 (8,707,336.7)
CEX × week = -3	307,176.9 (8,707,336.7)
CEX × week = -2	6,086,575.5 (8,707,336.7)
CEX × week = -1	1,057,508.0 (8,707,336.7)
CEX × week = 1	221,728,720.8*** (8,707,336.7)
CEX × week = 2	138,616,763.9*** (8,707,336.7)
CEX × week = 3	-1,315,792.4 (8,707,336.7)
CEX × week = 4	-7,186,007.9 (8,707,336.7)
CEX × week = 5	-16,042,103.0* (8,707,336.7)
CEX × week = 6	-3,128,903.8 (8,707,336.7)
CEX × week = 7	-8,483,351.6 (8,707,336.7)
CEX × week = 8	-8,958,347.0 (8,707,336.7)
Fit statistics	
Observations	34
R^2	0.84642
Adjusted R^2	0.70188

Clustered (CEX-week) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 11: AAVE/ETH Uniswap Volume ARDL(6,4,2,4) Case II. Includes ECT derived from the Restricted ECM. $\bar{R}^2$ is the adjusted coefficient of determination, χ^2_{BG} is the Breusch-Godfrey test for serial correlation (number of lags). χ^2_{BP} is the Breusch-Pagan test for heteroskedasticity and whether HC standard errors applied. F is the upper and lower interval for the bounds test, and result. Relevant p-values reported in square brackets.

Regressor	Coefficient	Std. Error	p-value
$Intercept$	4.9944	14.0380	0.7222
$Log(UniswapVolume)_{t-1}$	0.3250	0.0533	0.0000
$Log(UniswapVolume)_{t-2}$	0.1205	0.0549	0.0287
$Log(UniswapVolume)_{t-3}$	0.0936	0.0544	0.0859
$Log(UniswapVolume)_{t-4}$	0.1329	0.0543	0.0149
$Log(UniswapVolume)_{t-5}$	0.1688	0.0460	0.0003
$Log(UniswapVolume)_{t-6}$	-0.1092	0.0425	0.0106
$Log(BinanceVolume)$	0.6769	0.0471	0.0000
$Log(BinanceVolume)_{t-1}$	-0.1120	0.0599	0.0624
$Log(BinanceVolume)_{t-2}$	-0.1503	0.0597	0.0123
$Log(BinanceVolume)_{t-3}$	-0.0504	0.0597	0.3984
$Log(BinanceVolume)_{t-4}$	-0.1242	0.0585	0.0345
$Log(Blocktime)$	9.7270	5.6128	0.0840
$Log(Blocktime)_{t-1}$	-0.2725	5.8947	0.9632
$Log(Blocktime)_{t-2}$	-10.7466	5.5922	0.0555
$Log(Gas)$	-0.2013	0.1629	0.2175
$Log(Gas)_{t-1}$	0.0362	0.1986	0.8553
$Log(Gas)_{t-2}$	0.1940	0.2006	0.3342
$Log(Gas)_{t-3}$	-0.4947	0.1989	0.0134
$Log(Gas)_{t-4}$	0.3750	0.1646	0.0233
ECT	-0.2683	0.0586	0.0000

$\bar{R}^2$ = 0.7513

$\chi^2_{BG}(6)$ = 10.5174 [0.1045]

χ^2_{BP} = 22.6015 [0.2554]

$F_{I(0),I(1)}$ = 2.775, 3.6595, F = 4.148

Table 12: ETH/BTC Volume ARDL(4,4,0,1) Case II. Includes ECT derived from the Restricted ECM. $\bar{R}^2$ is the adjusted coefficient of determination, χ^2_{BG} is the Breusch-Godfrey test for serial correlation (number of lags). χ^2_{BP} is the Breusch-Pagan test for heteroskedasticity and whether HC standard errors applied. F is the upper and lower interval for the bounds test, and result. Relevant p-values reported in square brackets.

Regressor	Coefficient	Std. Error	p-value
$Intercept$	3.5060	7.6038	0.6450
$Log(UniswapVolume)_{t-1}$	0.3499	0.0722	0.0000
$Log(UniswapVolume)_{t-2}$	0.1326	0.0570	0.0207
$Log(UniswapVolume)_{t-3}$	0.1142	0.0607	0.0608
$Log(UniswapVolume)_{t-4}$	0.1205	0.0686	0.0797
$Log(BinanceVolume)$	1.0682	0.0691	0.0000
$Log(BinanceVolume)_{t-1}$	-0.3539	0.0896	0.0001
$Log(BinanceVolume)_{t-2}$	-0.1808	0.0801	0.0245
$Log(BinanceVolume)_{t-3}$	-0.1665	0.0810	0.0407
$Log(BinanceVolume)_{t-4}$	-0.1641	0.0848	0.0539
$Log(Blocktime)$	-0.6868	3.1081	0.8252
$Log(Gas)$	0.1462	0.2484	0.5565
$Log(Gas)_{t-1}$	-0.2241	0.2210	0.3112
ECT	-0.2828	0.0635	0.0000

$\bar{R}^2$ = 0.7792

$\chi^2_{BG}(4)$ = 1.3498 [0.8529]

χ^2_{BP} = 32.0175 [0.0014] HC3 standard errors

$F_{I(0),I(1)}$ = 2.775, 3.6595, F = 5.0557

Table 13: ETH/USDT Uniswap Num TXs ARDL(4,4,1,1) Case II. Includes ECT derived from the Restricted ECM. $\bar{R}^2$ is the adjusted coefficient of determination, χ^2_{BG} is the Breusch-Godfrey test for serial correlation (number of lags). χ^2_{BP} is the Breusch-Pagan test for heteroskedasticity and whether HC standard errors applied. F is the upper and lower interval for the bounds test, and result. Relevant p-values reported in square brackets.

Regressor	Coefficient	Std. Error	p-value
$Intercept$	-0.5434	2.5944	0.8342
$Log(UniswapNumTXs)_{t-1}$	0.6464	0.0798	0.0000
$Log(UniswapNumTXs)_{t-2}$	0.0389	0.0787	0.6217
$Log(UniswapNumTXs)_{t-3}$	0.0560	0.0777	0.4718
$Log(UniswapNumTXs)_{t-4}$	0.1106	0.0571	0.0538
$Log(BinanceNumTXs)$	0.4515	0.0403	0.0000
$Log(BinanceNumTXs)_{t-1}$	-0.2447	0.0544	0.0000
$Log(BinanceNumTXs)_{t-2}$	-0.0601	0.0535	0.2622
$Log(BinanceNumTXs)_{t-3}$	-0.0216	0.0438	0.6212
$Log(BinanceNumTXs)_{t-4}$	-0.0530	0.0401	0.1868
$Log(Blocktime)$	-0.7835	1.3457	0.5608
$Log(Blocktime)_{t-1}$	0.9232	0.8282	0.2658
$Log(Gas)$	0.1018	0.1152	0.3775
$Log(Gas)_{t-1}$	-0.0801	0.1067	0.4530
ECT	-0.1482	0.0423	0.0005

$\bar{R}^2$ = 0.8489

$\chi^2_{BG}(4)$ = 6.2444 [0.1816]

χ^2_{BP} = 70.517 [0] HC3 standard errors

$F_{I(0),I(1)}$ = 2.775, 3.6595, F = 3.1465

Table 14: MANA/ETH Uniswap Num TXs ARDL(3,2,0,0) Case II. Includes ECT derived from the Restricted ECM. $\bar{R}^2$ is the adjusted coefficient of determination, χ^2_{BG} is the Breusch-Godfrey test for serial correlation (number of lags). χ^2_{BP} is the Breusch-Pagan test for heteroskedasticity and whether HC standard errors applied. F is the upper and lower interval for the bounds test, and result. Relevant p-values reported in square brackets.

Regressor	Coefficient	Std. Error	p-value
$Intercept$	8.4493	7.4080	0.2548
$Log(UniswapNumTXs)_{t-1}$	0.3728	0.0672	0.0000
$Log(UniswapNumTXs)_{t-2}$	0.1740	0.0657	0.0085
$Log(UniswapNumTXs)_{t-3}$	0.0710	0.0570	0.2134
$Log(BinanceNumTXs)$	0.4016	0.0462	0.0000
$Log(BinanceNumTXs)_{t-1}$	-0.0631	0.0641	0.3263
$Log(BinanceNumTXs)_{t-2}$	-0.1172	0.0545	0.0322
$Log(Blocktime)$	-2.3240	2.9596	0.4328
$Log(Gas)$	-0.0999	0.0458	0.0297
ECT	-0.3822	0.0589	0.0000

$\bar{R}^2$ = 0.694

$\chi^2_{BG}(3)$ = 0.3453 [0.9513]

χ^2_{BP} = 20.6175 [0.0082] HC3 standard errors

$F_{I(0),I(1)}$ = 2.775, 3.6595, F = 9.5988

Table 15: MANA/ETH Uniswap Volume ARDL(3,0,0,0) Case II. Includes ECT derived from the Restricted ECM. $\bar{R}^2$ is the adjusted coefficient of determination, χ^2_{BG} is the Breusch-Godfrey test for serial correlation (number of lags). χ^2_{BP} is the Breusch-Pagan test for heteroskedasticity and whether HC standard errors applied. F is the upper and lower interval for the bounds test, and result. Relevant p-values reported in square brackets.

Regressor	Coefficient	Std. Error	p-value
$Intercept$	8.5072	13.2600	0.5216
$Log(UniswapVolume)_{t-1}$	0.3460	0.0521	0.0000
$Log(UniswapVolume)_{t-2}$	0.1280	0.0537	0.0177
$Log(UniswapVolume)_{t-3}$	0.1255	0.0501	0.0127
$Log(BinanceVolume)$	0.2953	0.0440	0.0000
$Log(Blocktime)$	-4.8536	5.4464	0.3735
$Log(Gas)$	0.0825	0.0722	0.2538
ECT	-0.4006	0.0484	0.0000

$\bar{R}^2$ = 0.602

$\chi^2_{BG}(3)$ = 1.0572 [0.7874]

χ^2_{BP} = 10.2119 [0.116]

$F_{I(0),I(1)}$ = 2.775, 3.6595, F = 13.5497

Table 16: USDT/DAI Uniswap Num TXs ARDL(5,1,4,1) Case II. Includes ECT derived from the Restricted ECM. $\bar{R}^2$ is the adjusted coefficient of determination, χ^2_{BG} is the Breusch-Godfrey test for serial correlation (number of lags). χ^2_{BP} is the Breusch-Pagan test for heteroskedasticity and whether HC standard errors applied. F is the upper and lower interval for the bounds test, and result. Relevant p-values reported in square brackets.

Regressor	Coefficient	Std. Error	p-value
$Intercept$	-0.7655	14.4995	0.9579
$Log(UniswapNumTXs)_{t-1}$	0.3697	0.1422	0.0097
$Log(UniswapNumTXs)_{t-2}$	0.0161	0.1511	0.9151
$Log(UniswapNumTXs)_{t-3}$	0.0869	0.1133	0.4437
$Log(UniswapNumTXs)_{t-4}$	0.0447	0.0712	0.5305
$Log(UniswapNumTXs)_{t-5}$	0.1124	0.0539	0.0377
$Log(BinanceNumTXs)$	0.1312	0.1360	0.3355
$Log(BinanceNumTXs)_{t-1}$	0.1111	0.1024	0.2788
$Log(Blocktime)$	1.2670	6.8854	0.8541
$Log(Blocktime)_{t-1}$	2.0500	7.7511	0.7916
$Log(Blocktime)_{t-2}$	-2.5631	6.5677	0.6966
$Log(Blocktime)_{t-3}$	-4.1434	9.6025	0.6664
$Log(Blocktime)_{t-4}$	3.9839	5.0992	0.4352
$Log(Gas)$	-0.1749	0.2213	0.4299
$Log(Gas)_{t-1}$	0.1314	0.2142	0.5400
ECT	-0.3702	0.1220	0.0026

$\bar{R}^2$ = 0.3655

$\chi^2_{BG}(5)$ = 1.6274 [0.8979]

χ^2_{BP} = 67.1287 [0] HC3 standard errors

$F_{I(0),I(1)}$ = 2.775, 3.6595, F = 9.4638