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# Co-movement between Decentralized and Centralized Exchanges: Evidence from Cryptocurrencies


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# Co-movement between Decentralized and Centralized Exchanges: Evidence from Cryptocurrencies

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**Abstract**

Using data from Centralized Exchanges (CEXs) and Decentralized Exchanges (DEXs), we examine the interaction of cryptocurrencies trading between CEXs and DEXs. Specifically, we apply a Gaussian Process (GP) model to describe the CEX time series of prices and volumes. For every time point within the DEX dataset, we ascertain the discrepancy between the expected posterior of the DEX time point—considering CEX data as the prior—and the actual DEX price at that specific time point. By systematically advancing the DEX dataset and continuously calculating the average error for each day, we determine the Optimal Time Lag between DEX and CEX asset prices daily. This approach yields a quantitative assessment of the most likely delay between DEX and CEX asset prices. Based on the Optimal Time Lag measure, we observe that the asset prices and volumes of all DEXs follow the CEXs, yet they exhibit distinct evolutionary trends on BTC.USDT trading price over the last two years. For some DEXs, the evolution of time lag demonstrates a pattern similar to that of the time lag in trading volume (e.g. the intensity of trading activity).

**Keywords**: Decentralized exchange; Centralized exchange; Liquidity; Arbitrage; Decentralized Market Makers

**JEL Classification:** D4, D53, G14

# 1 Introduction

The financial market, since its inception, has had two fundamental functions: price discovery and liquidity provision. Price discovery is a dynamic process in which market price adjusts to the arrivals of new information and converges to the fundamental value of the assets (Schreiber and Schwartz (1986), Baillie et al. (2002), and Lehmann (2002)), whereas liquidity provision aims at facilitating a better allocation of financial resources. To organize cryptocurrency trading, almost all of the world's major exchanges have adopted either a centralized Limit Order Book, which is widely used for traditional financial assets trading (e.g., equity), or a decentralized Blockchain-based automated market maker (AMM). It should be noted that each type of market has its advantages and challenges, and the choice between them often depends on user preferences, trading strategies, and regulatory considerations.

Compared to a traditional quote-driven market where the designated market makers provide liquidity to the whole market at the same quoted price, the order-driven market has dramatically changed how liquidity is provided and how the price is formed. One essential feature of an order-driven market is that there are no designated market makers and traders trade between themselves (Jain (2005)). Apart from market orders, any market participant could play a market maker role by submitting limit orders (i.e. orders standing in the LOB with quoted buying and selling prices that are different from the best available price on the market). Accordingly, in a purely automatic order-driven market, market activity becomes very transparent and it is divided into limit-order-related quoting activity and market-order-related trading activity. Liquidity is visible and fully offered by the open LOB, and price formation process is the outcome of a complex trading process between market orders and limit orders.

Alternatively, with blockchain technology, traders can also trade under decentralized protocols without relying on a central authority. Specifically, in markets organized by a decentralized Blockchain-based automated market maker, liquidity providers deposit funds into liquidity pools, traders interact with these pools by swapping assets at prices determined by the smart contract and the prices are determined algorithmically based on the ratio of assets in the pool. Smart contracts execute trades autonomously in DeFi and liquidity in DeFi is provided by users who deposit funds into liquidity pools. Today, more than 700 million USD transactions have been settled through the leading AMM-based decentralized exchanges (DEXs) and the traded instruments in overall DEXs have ranged from fungible crypto tokens to tokenized equity shares (Lehar and Parlour (2024)). Despite of DEXs' growing importance, there is few formal analysis of the DEXs' role in overall cryptocurrency price discovery and liquidity provision. To bridge this gap, our study attempts to enhance the understanding of DEXs for market participants by comparing the price formation mechanism in DEXs with that in centralized exchanges (CEXs). Further, we seek to identify the presence of arbitrage opportunities between CEXs and DEXs and their implications on liquidity. Finally, our study investigates the lead-lag relationship of price and trading volume between DEXs and CEXs.

Our research project provides a detailed comparison between CEXs and DEXs, which raise the awareness of market participants and enable them to make rational choices. We show that the DeFi market trading volume increases over time and represents less than 10% CeFi market trading volume. Given that DeFi systems inherently operate as closed systems,[1] trading activities in DeFi follow those in CeFi where public information can be instantaneously incorporated into price. Our results suggest that the delay in DeFi price relative to CeFi price becomes smaller over time. This finding implies that the connectedness between CeFi and DeFi increases over time.

Our findings help policymakers to reflect on the regulatory rules and policies to make the most appropriate decisions. Finally, our research project provides insights into the possibility of including the design of DEXs in traditional financial instrument trading.

[1]The DeFi rules that govern the smart contracts are predefined and written into the code, creating a closed and deterministic system. Even though DeFi relies on Oracles to interact with the external, non-blockchain world, enabling DeFi applications to respond to changing conditions and events beyond the blockchain environment, it still remains a relatively closed system compared to CeFi.

The rest of the paper proceeds as follows. In Section 2, we describe the data, and in Section 3.1, we discuss the construction of model. In Section 4, we present and discuss results of empirical tests. Section 5 concludes.

# 2 Data and Market Structure

## 2.1 Data

To conduct our DeFi and CeFi observations based on various time intervals, we use the intraday-level data. The intraday transaction data used in this paper are from the leading cryptocurrency market data provider Kaiko. Its raw cryptocurrency data covers 20,000+ pairs across worldwide exchanges. Our dataset is at the tick-by-tick level, including unique trade id, exchange codes, currency pairs, prices, volumes, trade directions, and timestamps, for all exchanges where BTC.USDT is traded. We remove the tick-by-tick level extreme trading volume and price for all exchanges before computing the variables. For the total Bitcoin trading volume at the daily level for the sample period, we retrieve the data from Coinbase.

Table 1 displays the trading volume of BTC.USDT for both DeFi and CeFi exchanges during the sample period. It is important to note that during this period, certain exchanges ceased operations while new ones were established. The final two columns of Table 1 indicate the commencement and conclusion dates of the respective exchanges.

[Insert Table 1 here]

Figure 1 presents the Bitcoin price and trading volume during the sample period. The price reach the maximum of around 70,000 $ in the June 2021 and decreases to the minimum of 20,000 $ in the January 2023. The trading volume follows a declining trend over time.

[Insert Figure 1 here]

Figure 2 and 3 compare the trading volume of BTCUSDT in CeFi with that in DeFi. The trading volume in DeFi increases gradually over time but is dominated by trading volume in CeFi. In general, the DeFi trading volume represents less than 10% trading volume in CeFi.

[Insert Figure 2 and 3 here]

## 2.2 Automatic Market Maker in DeFi

Automated Market Makers (AMMs) play a crucial role in decentralized finance (DeFi) ecosystems. The AMM mechanism is a decentralized trading protocol that facilitates the automatic exchange of assets without the need for traditional intermediaries. AMMs rely on liquidity pools provided by liquidity provider[2] for trading. Each pool consists of pairs of tokens. liquidity provider can contribute to these pools by depositing an equivalent value of both tokens. The most common AMM model is based on a mathematical formula known as the constant product formula. Uniswap, one of the pioneering AMMs, utilizes this formula. It ensures that the product of the quantities of two tokens in a liquidity pool remains constant. The formula is typically expressed as $x \times y = k$, where $x$ and $y$ represent the quantities of the two tokens, and $k$ is a constant. One issue about the constant product is that the formula implies that as one token is bought from the pool, the quantity of the other token in the pool adjusts automatically to maintain the product constant. This results in an automated and algorithmic determination of the price of the tokens based on the ratio of their quantities in the pool, which could lead to a slippage.[3] In addition, liquidity provider are also exposed to the risk of impermanent loss, which occurs when the price of the tokens in the liquidity pool diverges from the external market prices. This risk is inherent in AMMs due to the automated nature of price adjustments.

[2] AMMs often introduce a fee mechanism to reward liquidity providers. When users trade within the liquidity pool, a small fee is charged, and a portion of this fee is distributed among liquidity providers, incentivizing them to contribute assets to the pool.

[3] Traders can execute trades by swapping one token for another directly through the AMM. The smart contract calculates the slippage, which is the difference between the expected price and the execution price, based on the changing pool ratios.

Overall, the AMM mechanism (e.g., Uniswap, SushiSwap, and Balancer) in DeFi provides a decentralized and automated way for users to trade digital assets while offering liquidity providers an opportunity to earn fees by contributing to liquidity pools. However, due to the nature of closed systems, DeFi exchanges are led by CeFi exchanges.

# 3 Methodology

## 3.1 A Quantitative Analysis of the Time Lag in Bitcoin Price Response

To effectively model the dynamics of the BTC-USDT exchange, we employed a Gaussian Process (GP) model. This choice was motivated by the GP's versatility and robustness in time series modelling. As a non-parametric approach, the GP does not assume a specific functional form for the underlying data generation process. This flexibility allows them to adapt to a wide range of patterns in the data, from linear trends to complex and non-linear behaviors. They also allow probabilistic forecasts, in environments like financial markets, where risk management is important, the ability to estimate not just future values but also their associated uncertainties is invaluable. This makes GP particularly suited for understanding and predicting the behaviour of cryptocurrency markets.

A GP is fully specified by its mean function $m(\cdot)$ and covariance function $k(\cdot,\cdot)$. The mean function represents the average trend of the time series, and the covariance function, also known as the kernel, defines how the values of the time series are correlated with each other over time. In our experiment, we adopt a Rational Quadratic Kernel function, defined as follows:

$$k(x_i,x_j) = (1 + \frac{d(x_i,x_j)^2}{2al^2}), \tag{1}$$

in which $a$ and $l$ represent the scale mixture and scale length parameters, respectively, $d(\cdot,\cdot)$ represents an Euclidean distance function. Given a set of time series data indexed by an index $i$: $\mathbb{D} = \{x_i\}, i \in \mathbb{T}$, a GP assumes the data are generated from an underlying multi-dimenional Gaussian distribution:

$$\begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix} \sim N(0, \begin{bmatrix} K(1{,}1),...,K(1{,}n) \\ \vdots \\ K(n{,}1),...,K(n{,}n)) \end{bmatrix}) = N(0, \mathbf{K}(\mathbb{T}{,}\mathbb{T})). \tag{2}$$

In analyzing the time series datase $X \in pow(\mathbb{D})$, each element $x_i \in X$ is indexed by $i \in \mathbb{T}$, The posterior distribution of any random variable $x_t$ can be deduced as follows:

$$P(x_t|X) \sim N(\mathbf{K}(t{,}\mathbb{T})^T\mathbf{K}(\mathbb{T}{,}\mathbb{T})^{-1}X, K(t{,}t) + \mathbf{K}(t{,}\mathbb{T})^T\mathbf{K}(\mathbb{T}{,}\mathbb{T})^{-1}\mathbf{K}(t{,}\mathbb{T})), \tag{3}$$

using posterior inference from Gaussian Processes, for two sets of time series data $D_A, D_B$ from two different exchanges A and B. The GP reconstruction loss $L(D_A, D_B)$ between these two different exchanges can be calculated as follows:

$$L(D_A, D_B) = \frac{\sum_{x_i \in D_B} |E(P(x_i|D_A)) - x_i|}{|D_B|}. \tag{4}$$

Considering the inter-data set loss $L$, when the price of exchange B follows exchange A, to quantitatively assess the time lag between exchanges A and B, we define the optimal time lag $t_o$ by minimizing the inter-dataset loss $L$:

$$t_o = arg\, min_t L(D_A, D_B^{+t}), \tag{5}$$

where $D_B^{+t}$ represents a modified version of dataset $D_B$ with the index of each time series data point $x_i$ have been shifted forwardly $t$ time steps, leading to $x_{i+t}$. An example of the GP reconstruction loss evolution with different time lags is given in Figure 4, where the global minimum $t_o = 7$.

[Insert Figure 4 here]

The proposed Optimal time lag can be seen as a measure indicating the most probable delay between two sets of time series data. In this report, we studied the optimal time lag on BTC-USDT price between different pairs of DEXs and CEXs, results demonstrate that, generally, DEX prices follow CEX prices, but the amount of time lag varies among different DEXs.

## 4 Empirical Results

As shown in Figure 5, DEX exchange *Curve V2* maintains the low price time leg compared to Binance price among all the five DEXs. Notably, *Uniswap V3* has achieved a similar level of price immediacy, particularly after 2022.

As can be seen from the mean values over fixed-length intervals shown as red lines in Figure 5. The trend in the evolution of the price time lag across various DEXs exhibits three distinct patterns. Specifically, the price time leg between Binance and both *Curve V2* and *Uniswap V2* remains constant throughout the valid period. Conversely, *Sushiswap* and *Uniswap V3* exhibit a decreasing trend in time lag. Meanwhile, *OneInch* stands out from the other DEXs by showing an increasing time lag in the BTC-USDT price.

[Insert Figure 5 here]

The varying patterns in the price time lag could be attributed to several factors, including the design of the smart contract, trading volume, and the payoff mechanism for liquidity providers. We will investigate the detailed impact of these factors on the price time leg in the next step of our work.

Further analysis on the optimal time lag trading volume, as shown in Figure 6, indicates that for the DEXs demonstrating a significant evolutionary trend in BTC.USDT price time lag, their trading volumes exhibit similar behaviour. Specifically, *OneInch* shows an increasing time lag in both price and trading volume, while *Sushiswap* displays a decreasing trend in both price and volume. From this, we can conclude that the intensity of trading volume is an important factor in determining the price time lag between DEXs and Centralized Exchanges (CEX). Due to the limitations in data availability, we did not present an analysis on *Uniswap* DEX trading volume. This aspect will be included in our further work.

## 5 Conclusion

Using data from Centralized Exchanges (CEXs) and Decentralized Exchanges (DEXs), this study examines the interaction of cryptocurrencies trading between CEXs and DEXs. To do so, we developed a new methodology for the quantitative analysis of time delay phenomena in BTC.USDT trading price and volume. Utilizing CEX time series data on asset prices and volumes, we employ a GP model to characterize the data. For each time point in the DEX dataset, we determine the discrepancy between the expected posterior of the DEX time point (based on CEX data as the prior), and the actual DEX price at that time. By incrementally advancing the DEX dataset and calculating the average error daily, we establish the Optimal Time Lag between DEX and CEX asset prices.

Our findings reveal that while asset prices and volumes of all DEXs tend to follow those of the CEXs, they demonstrate unique evolutionary trends in BTC.USDT trading price over the previous two years. Notably, exchanges such as *OneInch* and *Sushiswap* show that the evolution of time lag mimics the pattern observed in trading volume. This suggests that the intensity of trading activity on DEXs is a crucial factor affecting the price time lag following CEX prices. Further research is necessary to elucidate the intricate mechanisms driving these distinct evolutionary trends.

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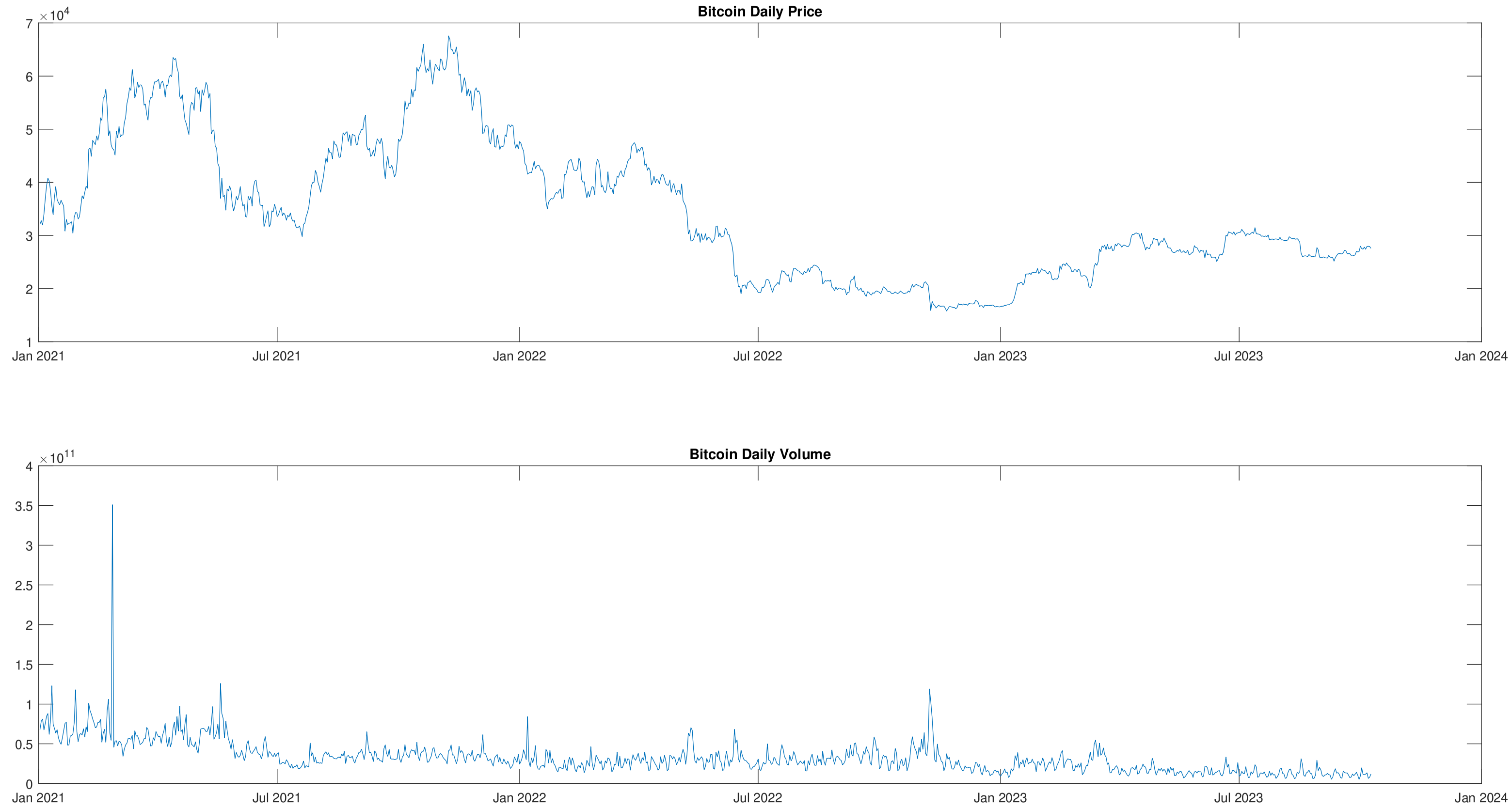
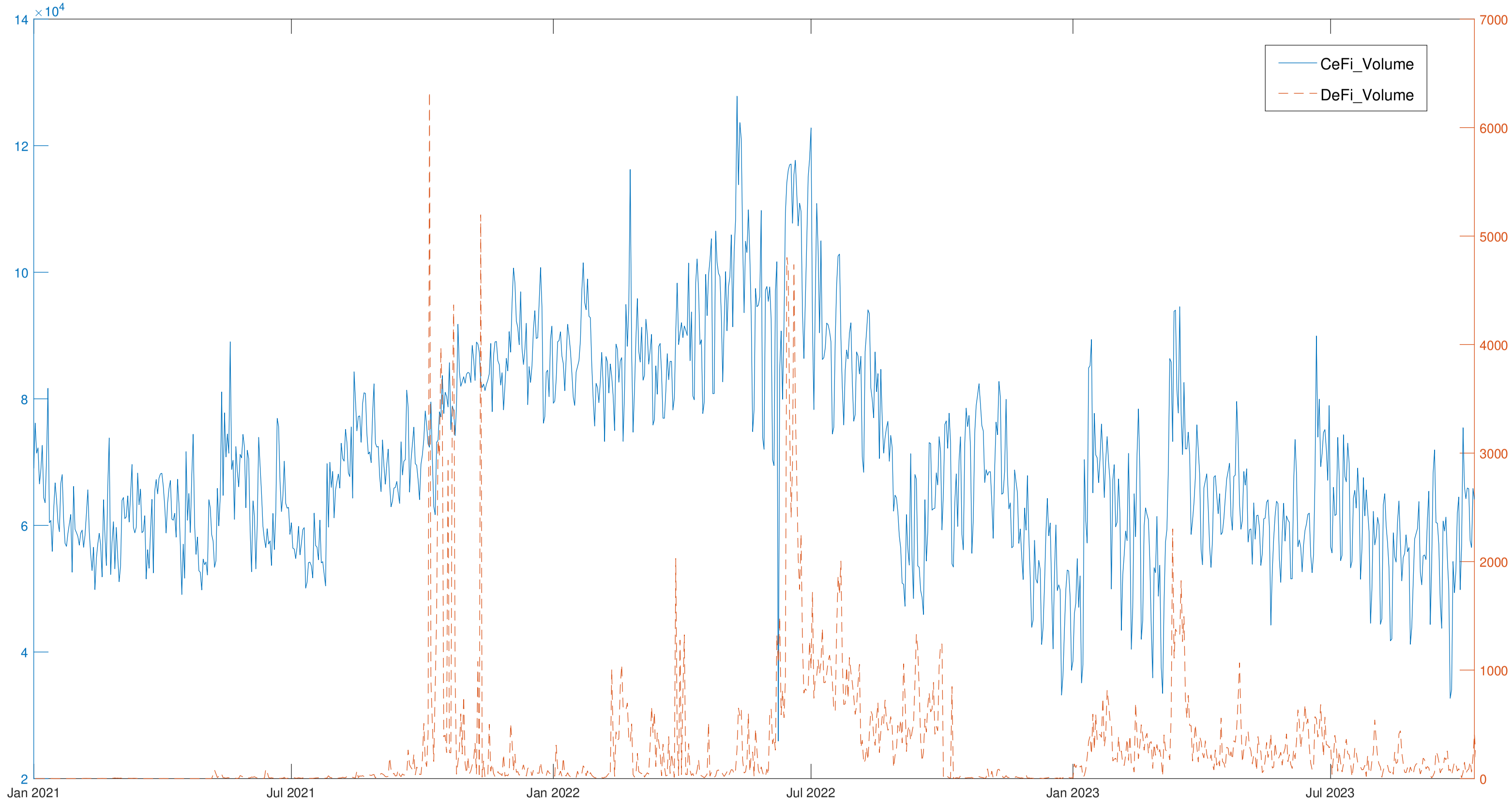
Figure 1: Bitcoin Price and Volume



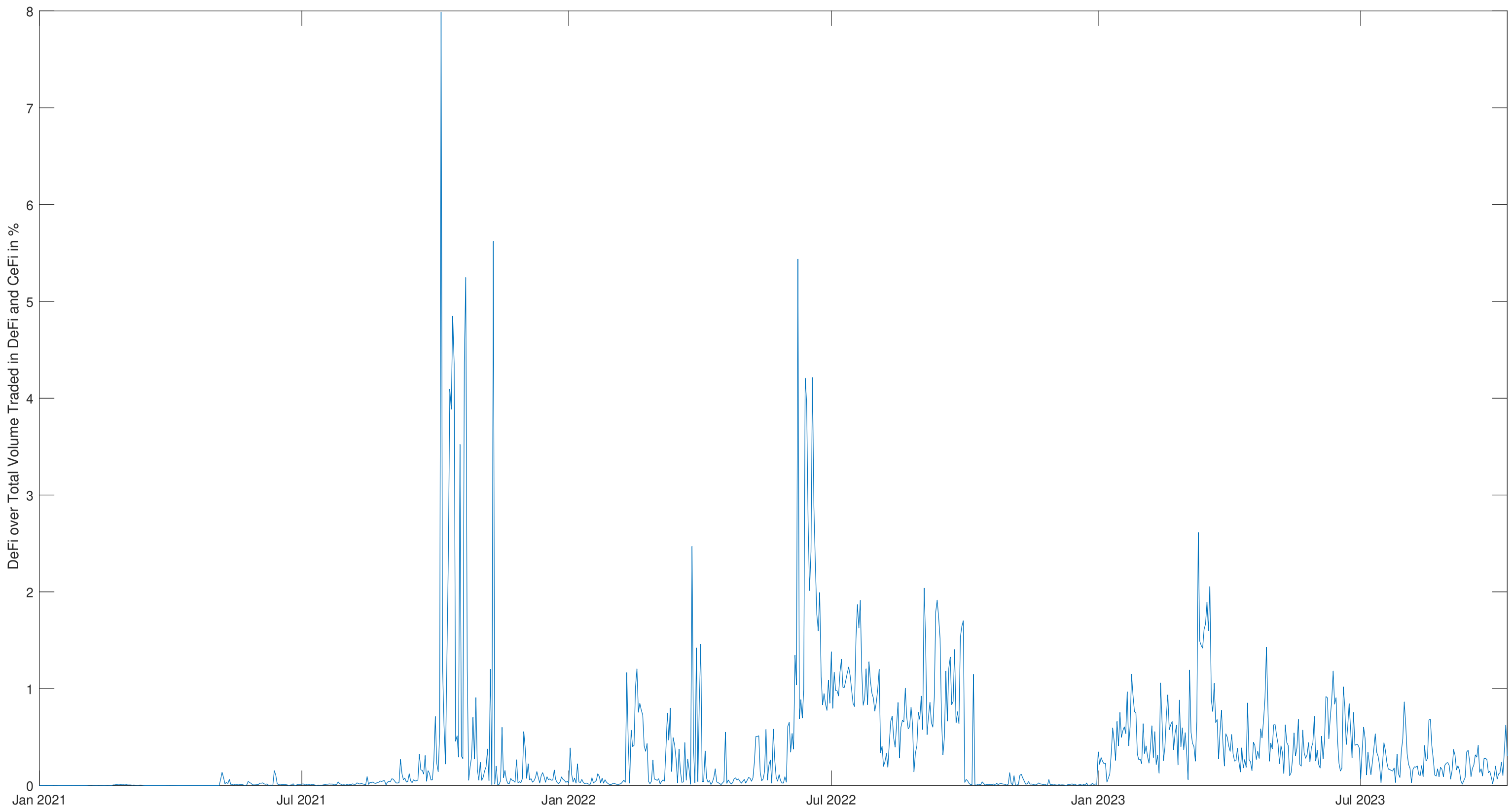

The figure presents the evolution of bitcoin price during the period between 1st January 2020 and 10 October 2023.

Figure 2: CeFi v.s. DeFi Volume



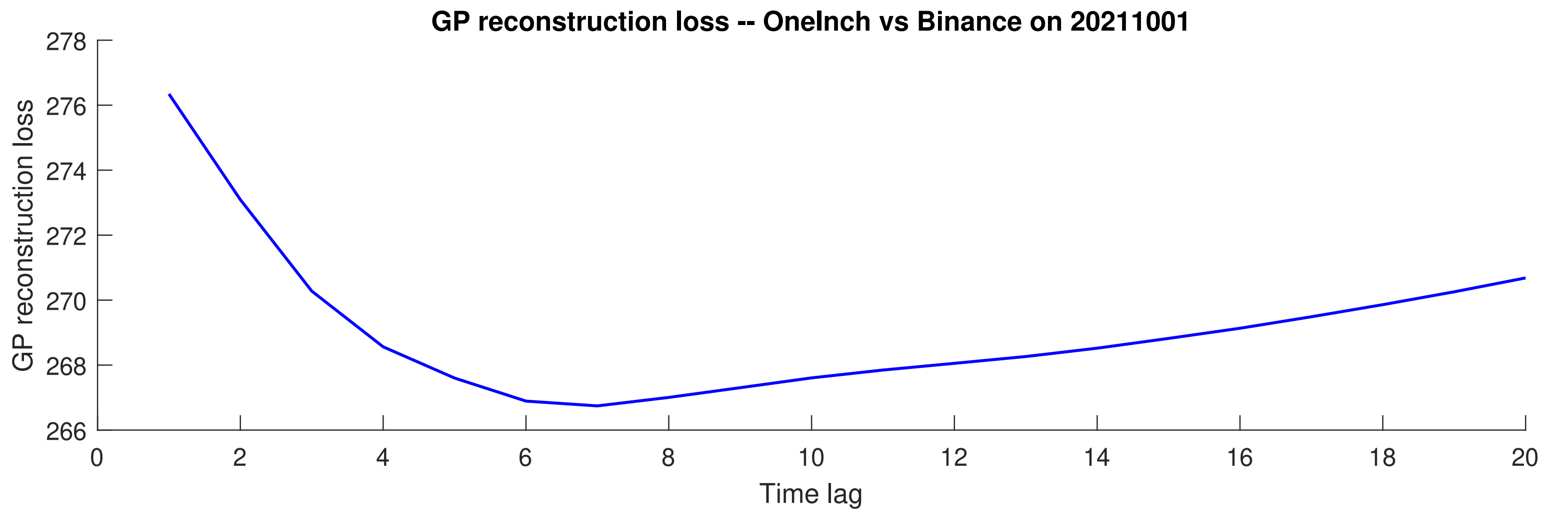

The figure presents the evolution of CeFi volume and DeFi volume of BTC.USDT during the period between 1st January 2020 and 10 October 2023.

Figure 3: Volume traded in DeFi over total volume traded



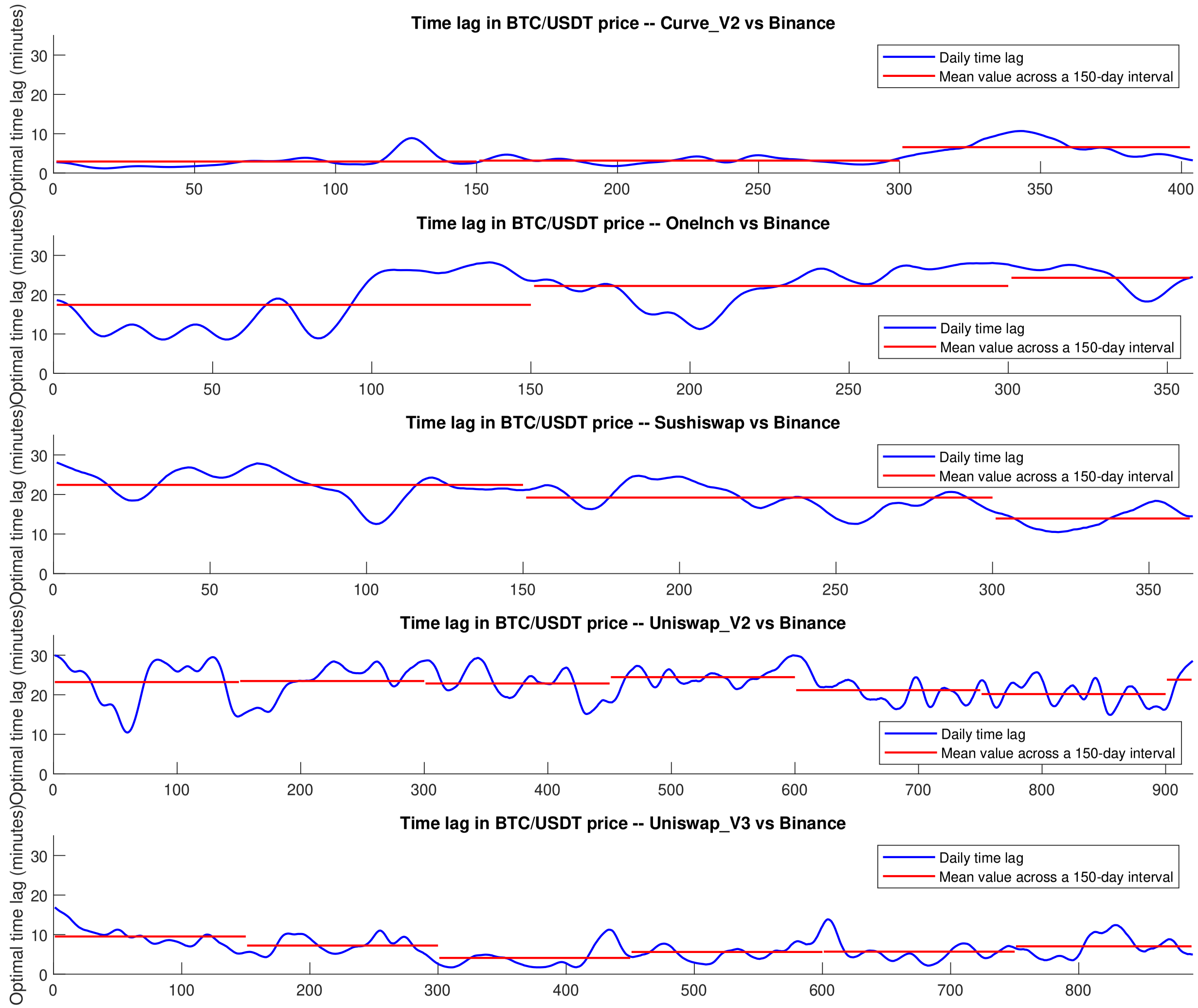

The figure presents the evolution of BTC.USDT traded volume in DeFi over total BTC.USDT traded volume in DeFi and CeFi during the period between 1st January 2020 and 10 October 2023.

Figure 4: Bitcoin-USTD price GP reconstruction loss example



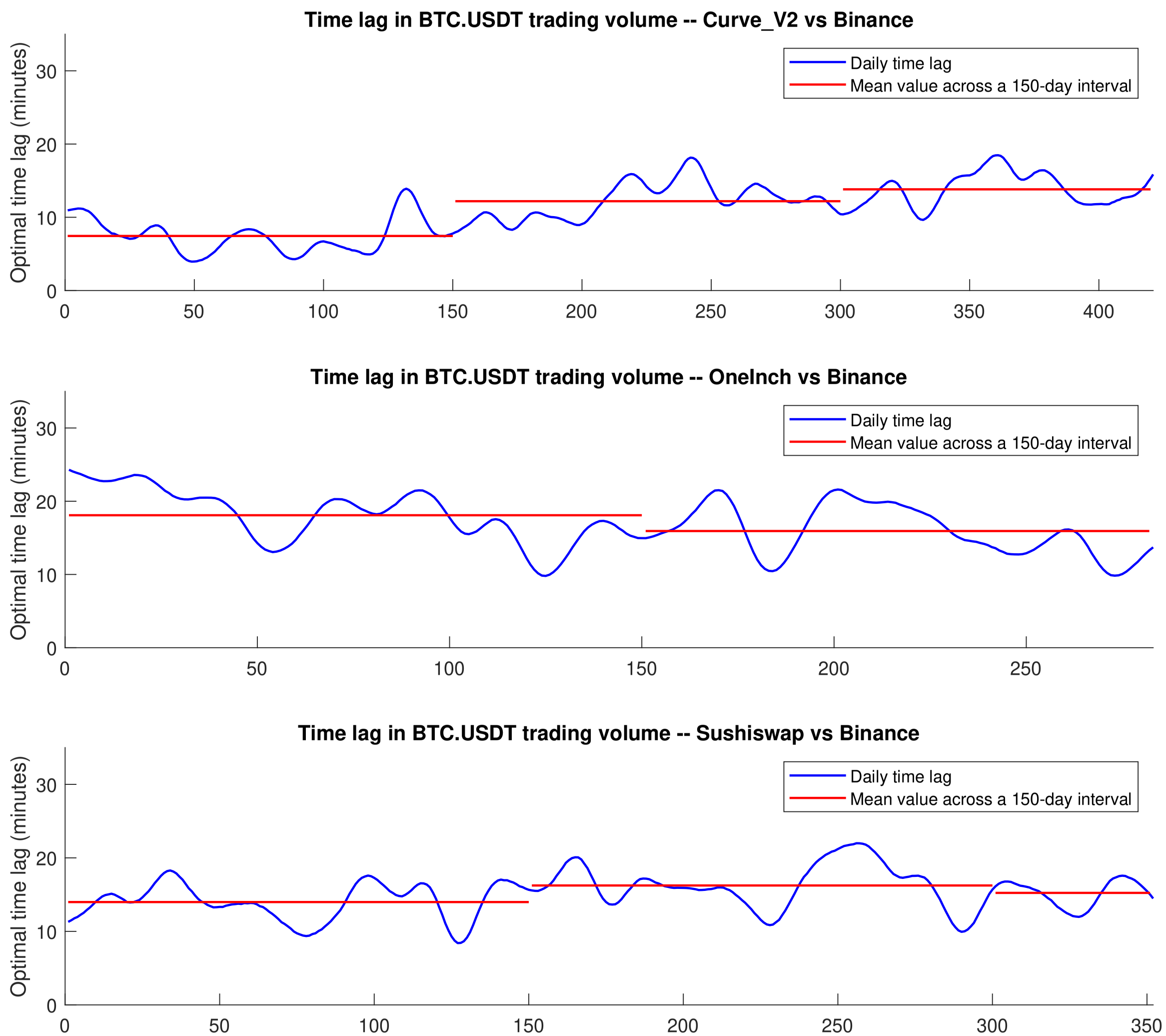

This figure illustrates the GP reconstruction loss for different time lags between CEX Binance and DEX OneInch on Oct. 1st, 2021

Figure 5: Bitcoin-USTD price time lag




This figure illustrates the time lag in Bitcoin's price, measured in minutes, relative to USDT across five distinct DEXs in comparison with a CEX (Binance). Daily optimal time lag plot (blue line) has been smoothed by Gaussian-weighted average method with a window size of 25.

Figure 6: Bitcoin-USTD volume time lag




This figure illustrates the time lag in Bitcoin's trading volume, measured in minutes, relative to USDT across three distinct DEXs in comparison with a CEX (Binance).

Daily optimal time lag plot (blue line) has been smoothed by Gaussian-weighted average method with a window size of 25.

Table 1: Distribution of BTC.USDT Traded Volume Among CeFi and DeFi Exchanges

| Panel A | | | |
|---|---|---|---|
| CeFi Exchange | Volume | Start Date | End Date |
| Allcoin | 6.72 | 20210101 | 20210411 |
| BTC-Alpha | 607,463.01 | 20210101 | 20220801 |
| BeQuant | 4,486,013.37 | 20210101 | 20231010 |
| Bibox | 1,840,451.60 | 20210101 | 20221224 |
| BigONE | 5,270,384.78 | 20210101 | 20231010 |
| BinanceUS | 971,195.69 | 20210101 | 20231010 |
| Binance_V2 | 5,026,768.75 | 20210101 | 20231010 |
| Bit-Z | 942,591.47 | 20210101 | 20211021 |
| BitBay | 18,561.96 | 20210101 | 20220214 |
| BitForex | 4,800,777.39 | 20210101 | 20231010 |
| BitMEX | 24,236.53 | 20220517 | 20231010 |
| Bitfinex | 957,076.64 | 20210101 | 20231010 |
| Bitpanda | 2,789.20 | 20230120 | 20231010 |
| Bitstamp | 28,952.46 | 20210615 | 20231010 |
| Bittrex | 176,061.47 | 20210101 | 20231010 |
| Bybit_V2 | 3,993,704.95 | 20210617 | 20231010 |
| Bybit_spot | 1,936,958.76 | 20220922 | 20231010 |
| Bybit_staging | 98,719.96 | 20221017 | 20221121 |
| CEX.IO | 10,879.23 | 20210101 | 20231010 |
| CRCO | 4,226,746.34 | 20210101 | 20231010 |
| CoinEgg | 32,379.85 | 20210101 | 20210417 |
| CoinEx | 487,626.09 | 20210101 | 20231010 |
| Coinbase | 806,499.22 | 20210504 | 20231010 |
| Currency.com | 956.99 | 20210101 | 20231010 |
| Delta_Exchange | 41,255.55 | 20230625 | 20230731 |
| EXX | 427,680.04 | 20210101 | 20211022 |
| FTX | 1,794,413.15 | 20210101 | 20221112 |

**Table 1 continued from previous page**

| | | | |
|---|---|---|---|
| Panel A | | | |
| FTX_US | 135,439.35 | 20211117 | 20221111 |
| Gemini | 308.83 | 20230110 | 20231010 |
| HitBTC | 919,531.19 | 20230101 | 20231010 |
| Huobi | 6,831,197.80 | 20210101 | 20231010 |
| Kraken | 407,007.76 | 20210101 | 20231010 |
| KuCoin | 5,993,830.76 | 20210101 | 20231010 |
| OSL | 13,562.07 | 20210921 | 20231010 |
| OkCoin | 8,964.53 | 20210101 | 20221208 |
| OkEX | 6,378,922.73 | 20210101 | 20231010 |
| Poloniex | 881,896.80 | 20210101 | 20231010 |
| Quoine | 18,053.29 | 20210101 | 20221120 |
| TheRockTrading | 417.64 | 20210603 | 20230217 |
| Tidex | 14,382.14 | 20210101 | 20220310 |
| UPbit | 11,310.65 | 20210101 | 20231010 |
| ZB | 4,379,022.15 | 20210101 | 20220904 |
| Mexc | 229,487.39 | 20230616 | 20231010 |
| Panel B | | | |
| CeFi Exchange | Volume | Start Date | End Date |
| Balancer_V2 | 0.01 | 20221110 | 20230409 |
| Curve_V2 | 176,750.50 | 20220601 | 20231010 |
| OneInch | 74,711.70 | 20211001 | 20230623 |
| Sushiswap | 1.60 | 20210612 | 20231010 |
| Uniswap_V2 | 131.48 | 20210101 | 20231010 |
| Uniswap_V3 | 31,126.99 | 20210505 | 20231010 |