# When Markets Never Sleep: Intraday Liquidity Patterns and Volatility Effects in Cryptocurrency Trading

Aleksander Mercik[1] and Barbara Będowska-Sójka[2]

[2]Department of Econometrics, Institute of Informatics and Quantitative Economics, Poznan University of Economics and Business, al. Niepodległości 10, 61-875 Poznań, Poland; email: barbara.bedowska-sojka@ue.poznan.pl

[1]Wroclaw University of Economics and Business, Department of Financial Investments and Risk Management, ul. Komandorska 118/120, 53-345 Wrocław, Poland; email: aleksander.mercik@ue.wroc.pl

July 2, 2025



**Abstract**

This paper examines the microstructure of cryptocurrency markets through the lens of liquidity dynamics, using high-frequency (15-minute) spread data from Binance and Coinbase for bitcoin and ethereum, paired with both fiat currencies and stablecoins. Using spectral analysis techniques, we identify significant cyclical patterns in intraday liquidity. Our analysis reveals distinct differences between weekday and weekend liquidity patterns, with weekend trading exhibiting significantly flatter intraday fluctuations and generally tighter spreads. This contrast highlights the influence of institutional trading activity that follows traditional market hours, even in markets theoretically designed for continuous operation. Out-of-sample tests confirm that models incorporating periodic components significantly improve predictive accuracy for most cryptocurrency pairs.

**Keywords**: cryptocurrency, liquidity, spread, forecasting.

# 1 Introduction

Assessing liquidity is critical to developing robust investment strategies, as liquidity directly affects transaction costs and the ability to enter or exit positions without significant price impact. From a market efficiency perspective, understanding liquidity dynamics helps assess the extent to which cryptocurrency markets are efficient and where inefficiencies may lie (Al-Yahyaee et al., 2020).

The cryptocurrency market presents unique challenges in measuring liquidity due to the lack of standardized metrics and the fragmented nature of trading across multiple exchanges. Cryptocurrencies are traded on hundreds of platforms, each with its order book and liquidity profile. Furthermore, cryptocurrencies can be traded 24 hours a day, seven days a week against fiat currencies and other cryptocurrencies (Brauneis et al., 2021). This fragmentation requires empirical verification of models originally proposed for equity and traditional currencies markets to assess their applicability and accuracy in the cryptocurrency context.

Many studies highlight the potential for higher returns from illiquid cryptocurrencies. Zhang and Li (2023) show a negative relationship between liquidity and expected returns in the cryptocurrency market. Specifically, cryptocurrencies with higher liquidity in a given week tend to have lower returns in the following week. Han (2023) argues that cryptocurrencies with high liquidity risk (beta) earned a risk-adjusted return that was 4.4% higher per week than those with low liquidity risk, after controlling for market, size, and reversal factors. Zaremba et al. (2021) show a daily reversal effect, but the pattern is cross-sectional by liquidity, and the handful of the largest and most tradable coins show daily momentum rather than reversal.

If alphas are concentrated in hard-to-trade assets and critically dependent on harvesting extreme returns on small, illiquid, and volatile coins (see also Cakici et al. (2024), an important consideration is whether these returns remain attractive after accounting for the higher transaction costs prevalent in this market. As liquidity itself is unobservable, we apply one of the most popular proxies, which is the difference between ask and bid prices named the spread (Będowska-Sójka, 2018; Fong et al., 2017).

This study aims to analyze spreads calculated at 15-minute intervals for 12 cryptocurrency trading pairs across two major exchanges (Binance and Coinbase). We focus on Bitcoin and Ethereum—the two largest cryptocurrencies by market capitalization—paired with various quote currencies including fiat (USD, EUR) and stablecoins (USDT, USDC, FDUSD). This comprehensive approach allows us to investigate liquidity dynamics across different trading venues and quote currencies within the cryptocurrency ecosystem.

Our analysis proceeds in multiple stages. First, we examine basic statistical properties of cryptocurrency spreads, testing for autocorrelation and stationarity. Second, we apply spectral analysis techniques including Fast Fourier Transform (FFT) and harmonic regression to identify and characterize cyclical patterns in intraday liquidity. Third, we investigate differences between weekday and weekend trading patterns to understand how trading behavior varies across the continuous 24/7 market cycle. Fourth, we develop an integrated model of spread determinants that incorporates market returns, volatility measures, and the periodic components identified through our spectral analysis. Finally, we conduct out-of-sample forecasting experiments to assess whether incorporating these periodic patterns improves predictive accuracy.

In the literature, there are papers devoted to the application of machine learning methods in cryptocurrency price forecasting (Bouteska et al., 2024; Cheng et al., 2024; Maciel et al., 2022; Nasirtafreshi, 2022). Although there are some works applying traditional financial econometrics models in forecasting liquidity (Fiszeder et al., 2024; Tzeng and Su, 2024), there is a lack of such studies devoted to intraday liquidity forecasting based on a machine learning approach.

Our paper makes several important contributions to the literature on cryptocurrency market microstructure. While various studies have examined price dynamics and return patterns in cryptocurrency markets, far less attention has been paid to the temporal patterns of liquidity provision in these markets. Studies examining intraday patterns have been conducted on stock markets (Boudt and Petitjean, 2014; Będowska-Sójka, 2021) and traditional currency markets, but systematic analysis of cryptocurrency liquidity at high frequency remains limited. Contrary to the U-shaped patterns commonly observed in equity markets (Będowska-Sójka, 2020; Cenesizoglu and Grass, 2018), we uncover distinct cyclical patterns in cryptocurrency spreads that follow global trading hours despite the market's 24/7 operation.

Furthermore, we extend the emerging literature on cryptocurrency liquidity forecasting by evaluating whether the incorporation of these cyclical patterns enhances predictive accuracy. While several studies have applied machine learning approaches to cryptocurrency price prediction (Bouteska et al., 2024; Cheng et al., 2024; Maciel et al., 2022; Nasirtafreshi, 2022), there remains a gap in research on modeling and forecasting intraday liquidity dynamics in these markets. Our findings demonstrate that traditional econometric models incorporating periodic components can effectively capture the systematic variations in cryptocurrency spreads, providing valuable insights for market participants seeking to optimize trading strategies in these rapidly evolving markets.



# 2 Data and Preliminary Results

## 2.1 Data Sources

The dataset used in this study consists of high-frequency order book data collected from two major cryptocurrency exchanges: Binance and Coinbase. Following Hansen et al. (2024), we focused on two major cryptocurrencies: Bitcoin (BTC) and Ethereum (ETH), selected for their dominant market positions and fundamental importance to the broader crypto ecosystem. Bitcoin remains the benchmark cryptocurrency with the largest market capitalization, while Ethereum is the primary platform for decentralized applications and smart contracts.

On Binance, these cryptocurrencies have been paired with three stablecoins that provide significant liquidity in the ecosystem: Tether (USDT), USD Coin (USDC), and First Digital

USD (FDUSD), resulting in six cryptocurrency-stablecoin trading pairs. In parallel, on Coinbase, we collected data for the same cryptocurrencies paired with USD, EUR, and USDT, providing an additional six trading pairs and enabling cross-exchange comparisons. For each trading pair, we collected the best bid and ask prices as well as order book depth information at 15-minute intervals, allowing us to calculate the mid-price and spread metrics. The data collection period spanned until March 31, 2025.

A key aspect of our research design is the deliberate inclusion of different types of trading pairs across multiple exchanges. By examining both centralized exchange environments (Binance and Coinbase) and different quote currencies (USDT, USDC, FDUSD, USD, EUR), we can identify similarities and differences in market microstructure across these distinct liquidity environments. This comprehensive approach enables us to analyze liquidity patterns specifically within the cryptocurrency ecosystem, comparing how the same assets perform across different trading venues and against different stablecoins or fiat currencies.



## 2.2 Spreads Calculation

To ensure a robust measurement of liquidity in cryptocurrency markets, we employ a volume-weighted approach for calculating bid-ask spreads. For our liquidity proxy, we use the Percent Quoted Spread (PQS) (**?**), defined as:

$$\mathrm{PQS}_t = \frac{P^t_{\mathrm{ask,VW}} - P^t_{\mathrm{bid,VW}}}{P^t_{\mathrm{mid,VW}}} \tag{1}$$

where $P^t_{\mathrm{ask,VW}}$ and $P^t_{\mathrm{bid,VW}}$ represent the volume-weighted ask and bid prices at time $t$, and $P^t_{\mathrm{mid,VW}}$ is the mid-price calculated as the average of volume-weighted bid and ask prices.

Unlike traditional spread calculations that rely solely on the best bid and ask prices, our methodology incorporates volume-weighted prices calculated based on all orders where the cumulative transaction volume exceeds **USD 100,000**. Specifically:

$$P^t_{\text{bid,VW}} = \frac{\sum_{i=1}^{N} P^t_{\text{bid},i} \times V^t_{\text{bid},i}}{\sum_{i=1}^{N} V^t_{\text{bid},i}} \tag{2}$$

$$P^t_{\text{ask,VW}} = \frac{\sum_{i=1}^{N} P^t_{\text{ask},i} \times V^t_{\text{ask},i}}{\sum_{i=1}^{N} V^t_{\text{ask},i}} \tag{3}$$

where:

- $P^t_{\text{bid},i}$ and $P^t_{\text{ask},i}$ are the bid and ask prices at level $i$ of the order book at time $t$.
- $V^t_{\text{bid},i}$ and $V^t_{\text{ask},i}$ are the corresponding bid and ask volumes at level $i$.

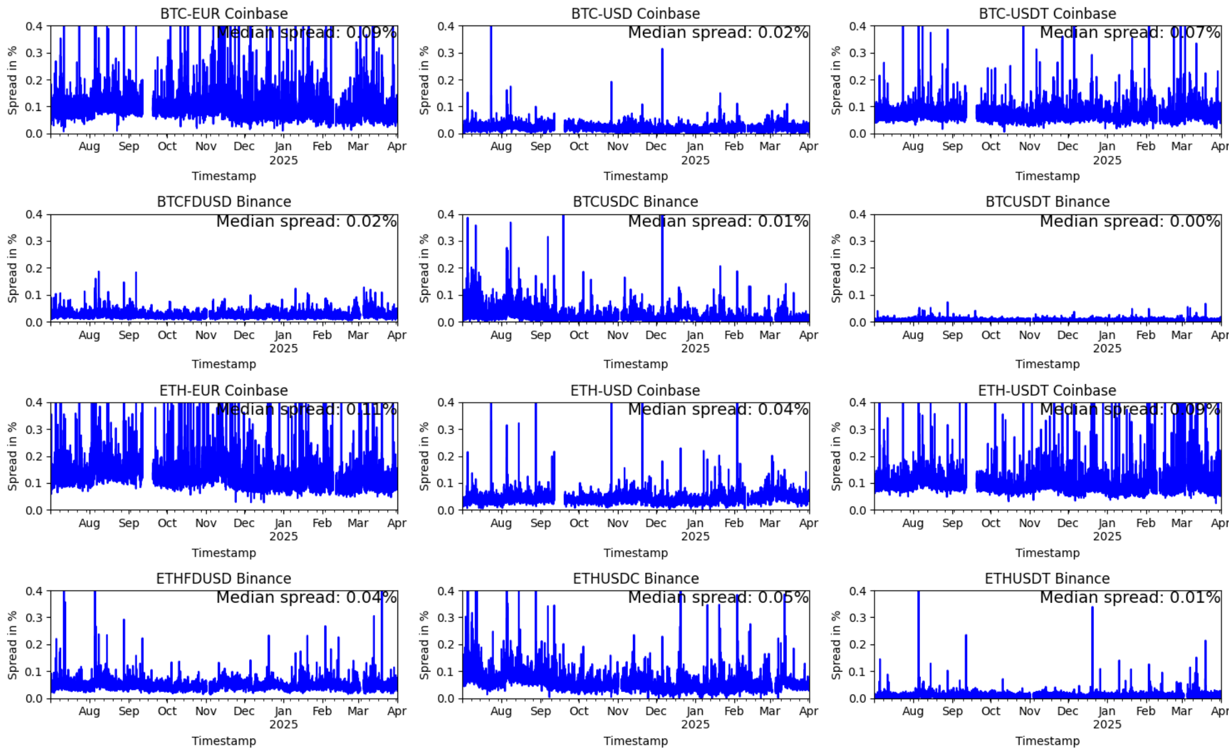
This volume-weighted approach offers several advantages for studying cryptocurrency markets. It provides a more accurate estimate of liquidity by filtering out small nominal trades and reducing bias from small trades that may not reflect true market conditions. It also facilitates comparability across cryptocurrency pairs and exchanges, ensuring consistency regardless of the specific asset being traded. We applied this methodology consistently across all cryptocurrency trading pairs from both Binance and Coinbase, collecting data at 15-minute intervals to capture intraday liquidity dynamics.

Figure 1 shows the time series of spreads for all 12 cryptocurrency markets in our study. Each chart displays the spread dynamics over time for a particular market, with the average spread level shown in the upper right-hand corner. The figure highlights significant differences in both spread behavior and liquidity levels across cryptocurrency markets and exchanges.

## 2.3 Descriptive Statistics

Table 1 presents the descriptive statistics for the spread series across all 18 market pairs analyzed: twelve cryptocurrency pairs (from both Binance and Coinbase) and six traditional currency pairs. The statistics include the count (number of observations), mean, standard deviation, percentiles (1%, 25%, median, 75%, 99%), skewness, and kurtosis, with all values

Figure 1: Time Series of Spreads for Cryptocurrency Pairs




Note: The figure shows the time series of spreads for cryptocurrency pairs from both Binance (BTC and ETH paired with USDT, USDC, and FDUSD) and Coinbase (BTC and ETH paired with USD, EUR, and USDT). Data was collected at 15-minute intervals through March 31, 2025. Each chart shows the spread dynamics over time for a particular market, with the average spread level shown in the upper right-hand corner. The figure highlights significant differences in both spread behavior and liquidity levels across different trading pairs and exchanges.

expressed as percentages (i.e., a value of 0.01 corresponds to 0.01%).

Panel A shows that cryptocurrency markets on Binance generally exhibit extremely tight spreads, with means ranging from nearly 0.00% (BTCUSDT, BTCUSDC) to 0.01% (BTCFDUSD, ETHUSDC, ETHFDUSD). The data shows significant differences between trading pairs denominated in different stablecoins, with FDUSD pairs consistently showing wider spreads than their USDT counterparts. All Binance cryptocurrency pairs exhibit extremely high positive skewness (ranging from 4.95 to 35.98) and excess kurtosis (95.85 to 1881.17), indicating that their distributions are highly skewed to the right with frequent extreme values. Panel B reveals that cryptocurrency pairs on Coinbase generally have wider spreads than their Binance counterparts, with means ranging from 0.01% (BTC-USD, ETH-USD) to

Table 1: Descriptive Statistics of Market Spreads for Cryptocurrency and Traditional Currency Pairs

| Symbol | Count | Mean | Std | 1% | 25% | Median | 75% | 99% | Skew | Kurtosis |
|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Binance** | | | | | | | | | | |
| BTCFDUSD | 25665 | 0.02 | 0.01 | 0.01 | 0.02 | 0.02 | 0.03 | 0.05 | 2.44 | 19.09 |
| BTCUSDC | 25665 | 0.02 | 0.02 | 0.00 | 0.01 | 0.01 | 0.02 | 0.09 | 5.05 | 60.98 |
| BTCUSDT | 25665 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.02 | 2.56 | 16.45 |
| ETHFDUSD | 25665 | 0.05 | 0.01 | 0.02 | 0.04 | 0.04 | 0.05 | 0.09 | 6.91 | 144.51 |
| ETHUSDC | 25665 | 0.05 | 0.03 | 0.02 | 0.04 | 0.05 | 0.06 | 0.14 | 4.99 | 75.83 |
| ETHUSDT | 25665 | 0.01 | 0.01 | 0.00 | 0.00 | 0.01 | 0.01 | 0.03 | 12.84 | 502.90 |
| **Panel A: Coinbase** | | | | | | | | | | |
| BTC-EUR | 24835 | 0.09 | 0.06 | 0.04 | 0.07 | 0.09 | 0.10 | 0.23 | 21.54 | 755.67 |
| BTC-USD | 24835 | 0.02 | 0.01 | 0.00 | 0.02 | 0.02 | 0.03 | 0.05 | 10.46 | 459.05 |
| BTC-USDT | 24835 | 0.07 | 0.04 | 0.04 | 0.06 | 0.07 | 0.08 | 0.15 | 31.35 | 1414.19 |
| ETH-EUR | 24835 | 0.12 | 0.11 | 0.07 | 0.09 | 0.11 | 0.13 | 0.30 | 37.81 | 1876.99 |
| ETH-USD | 24835 | 0.04 | 0.02 | 0.02 | 0.03 | 0.04 | 0.05 | 0.08 | 29.50 | 1403.03 |
| ETH-USDT | 24835 | 0.09 | 0.07 | 0.05 | 0.08 | 0.09 | 0.10 | 0.21 | 55.68 | 5019.49 |

Note: This table presents descriptive statistics for percent quoted spreads (PQS) for cryptocurrency and traditional currency markets. The data spans through March 31, 2025, collected at 15-minute intervals. Panel A shows statistics for Bitcoin (BTC) and Ethereum (ETH) pairs on Binance with three stablecoins: Tether (USDT), USD Coin (USDC), and First Digital USD (FDUSD). Panel B shows the same cryptocurrencies on Coinbase paired with USD, EUR, and USDT.



0.04% (ETH-EUR, ETH-USDT). Notably, EUR-denominated pairs show consistently wider spreads than USD-denominated pairs on the same exchange. Similar to Binance, Coinbase pairs also exhibit extremely high skewness (2.63 to 48.12) and kurtosis (25.82 to 3191.46), with ETH-EUR showing the most extreme distributional characteristics. The observed data includes approximately 25,665 observations for Binance cryptocurrency pairs, 24,835 for Coinbase cryptocurrency pairs, and between 20,526 and 23,139 observations for traditional currency pairs.

We perform several stationarity tests on our spread series, as reported in Table A.3 in Appendix A. The Augmented Dickey-Fuller (ADF), DF-GLS, Phillips-Perron and Zivot-Andrews tests consistently reject the null hypothesis of a unit root for all currency pairs, indicating the absence of stochastic trends (The Zivot-Andrews test, which allows for a possible structural break, also rejects the null hypothesis of a unit root in all cases). However, the KPSS test, which uses stationarity as the null hypothesis, shows mixed results, with some series potentially showing non-stationarity. As shown in Table A.4, both the Box-Pierce and Ljung-Box tests strongly reject the null hypothesis of no autocorrelation for all series, with particularly high test statistics for traditional currency pairs. These results confirm the presence of significant temporal dependencies in spread dynamics in both cryptocurrency and traditional currency markets, justifying our focus on periodicity patterns.

## 2.4 How Liquidity is Distributed over Time

### 2.4.1 Intraday Patterns of Liquidity and Volatility

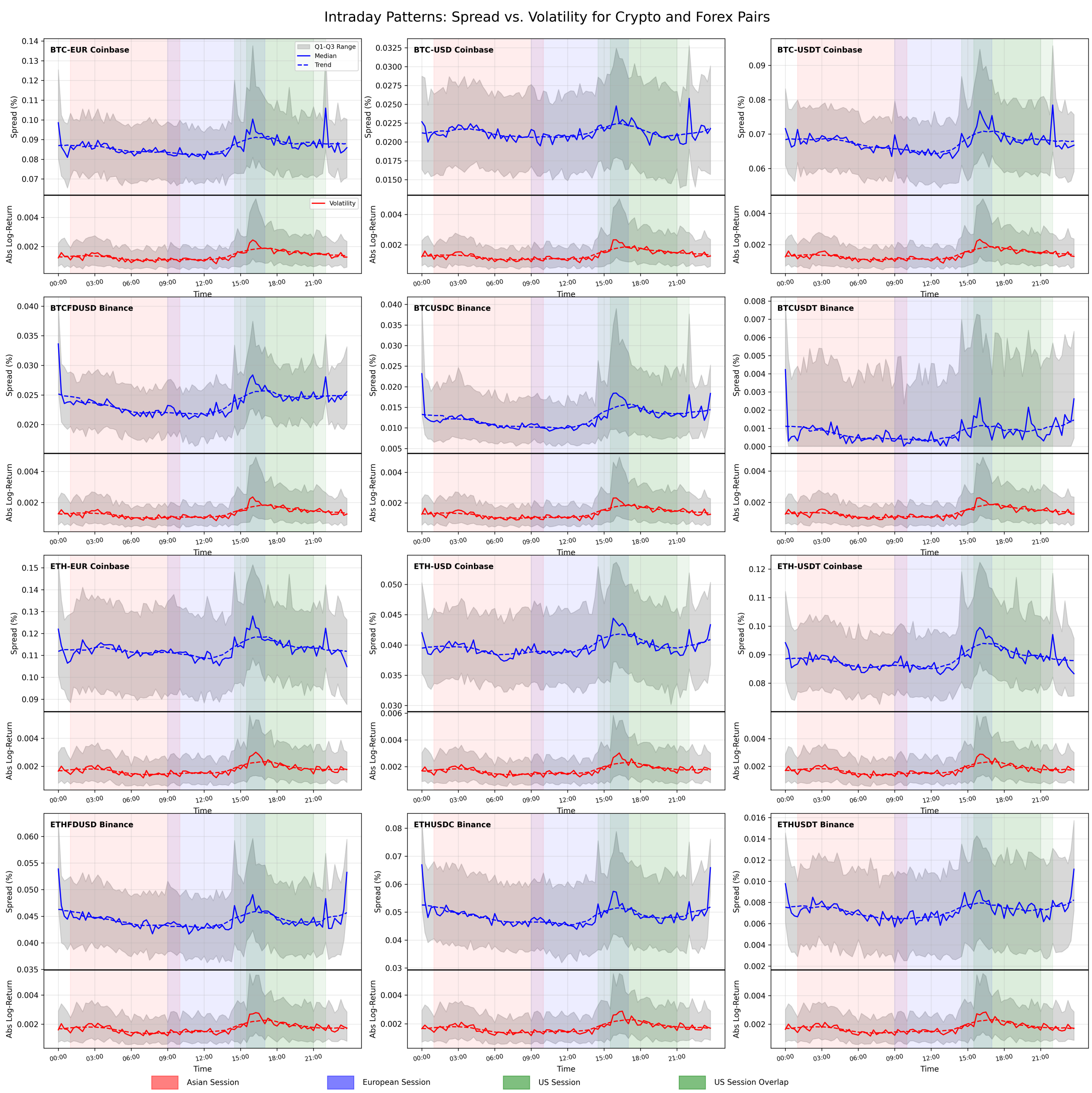
As the first step, we explore the relationship between market liquidity and volatility throughout the trading day. For each cryptocurrency pair, we organize observations into 15-minute time intervals across the trading day. For each time interval and trading pair, we compute three key statistical measures: the 25th percentile (Q1), median, and 75th percentile (Q3) of both spread and absolute log return values. This approach captures both the typical liquidity and volatility levels (median) and their dispersion (interquartile range) at different times of day, while minimizing the impact of outliers that frequently occur in high-frequency cryptocurrency data.

To extract the general trend that may be obscured by time-specific noise, we apply a centered moving average to the median values. For each time of day, we calculate a 15-period window (corresponding to a 3.75-hour interval) that smooths out short-term fluctuations while preserving the underlying periodic patterns.

Figure 2 presents a paired visualization where each cryptocurrency pair's spread (top panel) and volatility (bottom panel) are displayed directly above one another. The gray shaded areas indicate the interquartile range (25th to 75th percentile) for both metrics, capturing the typical variation around the median. To facilitate interpretation, we overlay time zone bands corresponding to primary global market hours: Asian markets (01:00-10:00 CET, light red), European markets (09:00-17:00 CET, light blue), and US markets (14:30-22:00 CET, light green).

Our analysis of intraday liquidity and volatility patterns reveals important insights into cryptocurrency market microstructure. For cryptocurrency pairs on both Coinbase and

Figure 2: Joint Intraday Analysis of Spreads and Volatility for Cryptocurrency Pairs




Note: For each cryptocurrency pair, the top panel shows the median spread (blue) and the bottom panel shows the median volatility (red). Both panels include the interquartile range (gray shaded area) and a 15-period moving average (dashed lines). Background colors indicate primary market hours in CET: Asian markets (01:00-10:00, light red), European markets (09:00-17:00, light blue), and US markets (14:30-22:00, light green). The analysis covers all 12 cryptocurrency pairs across Binance and Coinbase exchanges.

Binance, we observe a distinct inverted sinusoidal pattern in spreads, characterized by the lowest spreads during Asian and early European market hours, followed by a rapid transition that peaks at the beginning of the US trading session. Volatility follows a remarkably similar pattern, with price fluctuations rising exactly as spreads increase.

This strong temporal correspondence suggests that liquidity in cryptocurrency markets responds directly to changes in market volatility, regardless of whether the quoted currency is a fiat currency (USD, EUR) or a stablecoin (USDT, USDC, FDUSD). The synchronized movement between spreads and volatility across nearly all cryptocurrency markets supports the hypothesis of market-making risk models, where liquidity providers require wider spreads as compensation for taking positions during periods of higher price uncertainty.

This relationship appears to be particularly strong in cryptocurrency markets, suggesting that despite their 24/7 operation, these markets experience significant intraday fluctuations in liquidity that are closely tied to global trading patterns and volatility regimes. Interestingly, we observe consistent patterns across both major cryptocurrencies (BTC and ETH) and across different exchanges (Binance and Coinbase), indicating that these liquidity dynamics may be fundamental characteristics of cryptocurrency markets rather than exchange-specific phenomena.

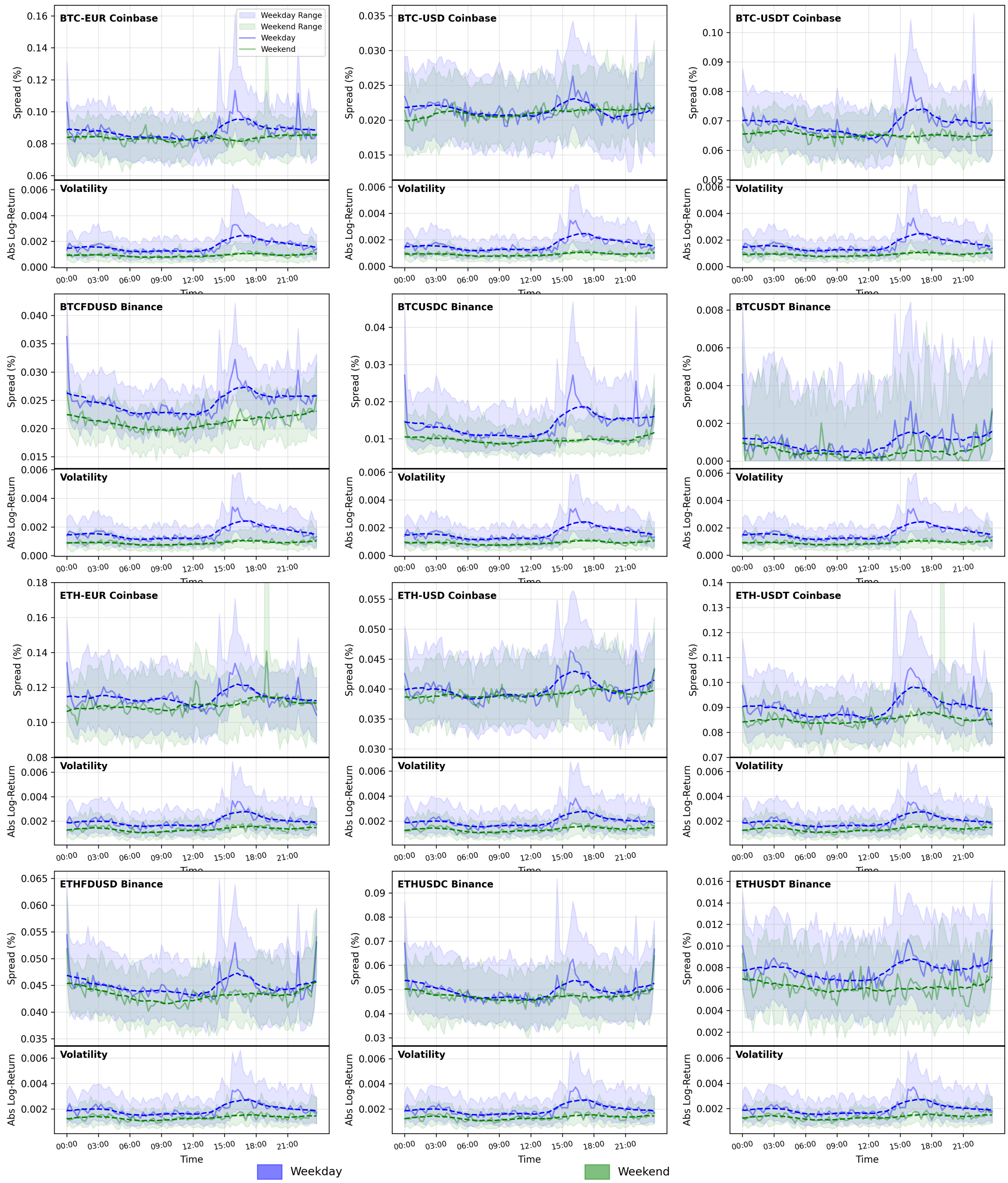
#### 2.4.2 Weekend vs. Weekday Patterns in Cryptocurrency Markets

One of the distinct features of cryptocurrency markets is their continuous 24/7 operation, which allows us to examine the contrast between weekend and weekday trading conditions. Figure 3 presents a detailed comparison of intraday spread and volatility patterns between weekdays (blue) and weekends (green) for twelve cryptocurrency pairs across Binance and Coinbase exchanges.

Our analysis reveals a notable contrast between weekday and weekend trading dynamics in cryptocurrency markets.

First, spreads are consistently lower on weekends for nearly all cryptocurrency pairs,

Figure 3: Comparison of Weekday and Weekend Liquidity and Volatility Patterns for Cryp-




Note: For each cryptocurrency pair, the top panel shows spread patterns and the bottom panel shows volatility (absolute log returns). Blue lines and shading represent weekday patterns (Monday-Friday), while green represents weekend patterns (Saturday-Sunday). Solid lines show median values, dashed lines show 15-period moving averages, and shaded areas represent the interquartile range. The analysis covers six pairs each from Binance and Coinbase exchanges.

with the gap being most pronounced during periods that coincide with typical global trading hours (15:00-18:00 CET). This pattern is particularly evident for the BTC-EUR, BTC-USD and BTCFDUSD pairs, where median spreads can be 20-50% higher on weekdays than on weekends during peak hours. Importantly, the weekend spread narrowing is accompanied by a corresponding decrease in volatility. For all cryptocurrency pairs, weekend median volatility is lower than weekday volatility, especially during these hours. This parallel movement reinforces our earlier finding that liquidity provision in cryptocurrency markets is closely linked to volatility.

Second, weekend spreads display a substantially flattened pattern with minimal intraday variation. The characteristic peaks observed during weekday trading hours are almost entirely absent on weekends, resulting in a relatively stable spread throughout the day. Weekend volatility is remarkably flat across all hours, appearing as an almost horizontal line for most pairs. To further explore intraday patterns in market liquidity and volatility, we conducted a granular day-of-week analysis for each trading day (Monday through Sunday) in Figure A.3 in the Appendix. The results confirm that weekends show flattened patterns as demonstrated earlier.

These findings indicate that despite the 24/7 nature of cryptocurrency markets, their microstructure dynamics remain heavily influenced by global trading patterns. The near-complete flattening of intraday patterns during weekends strongly suggests that the characteristic volatility and spread fluctuations observed during weekdays are largely driven by institutional trading activity that follows traditional hours. When this institutional pressure is reduced during weekends, cryptocurrency markets exhibit fundamentally different and more stable liquidity characteristics.

This weekend-weekday dichotomy provides valuable insights into the evolving market structure of cryptocurrencies, suggesting that despite their technological innovations and continuous operation, these markets still reflect important aspects of traditional trading behavior and institutional participation.

# 3 Relative analysis

## 3.1 Relative volatility and spread for Hour-of-the-Day

To examine the intraday behavior of market liquidity and volatility, we use a relative analysis technique that examines how these measures vary over different time periods. Unlike absolute measures, this approach normalizes values against recent history, allowing direct comparisons between different market pairs despite their different starting levels. Our first step was to examine how volatility and spread behave at different hours of the day relative to other hours within the same day. Following Hansen et al. (2024), we compute hour-specific relative measures for both volatility and spread:

$$\lambda_{\sigma}^{\text{hour}}(h) = \frac{1}{n_h} \sum_{w,d} \frac{|y_{\tau(w,d,h)}|}{\sum_{j=0}^{23} |y_{\tau(w,d,h-j)}|} \tag{4}$$

$$\lambda_{s}^{\text{hour}}(h) = \frac{1}{n_h} \sum_{w,d} \frac{s_{\tau(w,d,h)}}{\sum_{j=0}^{23} s_{\tau(w,d,h-j)}} \tag{5}$$

where:

- $h$ – hour of the day, $h = 0, \ldots, 23$
- $w$ – week number in our sample
- $d$ – day of the week
- $y_{\tau(w,d,h)}$ – absolute return at time point $(w, d, h)$
- $s_{\tau(w,d,h)}$ – spread at time point $(w, d, h)$
- $n_h \approx 7 \times W$ – number of observations per hour, where $W$ is the total number of weeks in our sample

The interpretation of these measures is straightforward - if $\lambda_{\sigma}^{\text{hour}}(h) > 1$, volatility is higher at hour $h$ compared to the daily average. If $\lambda_{s}^{\text{hour}}(h) > 1$, the spread is higher at hour $h$, indicating lower liquidity. This hourly analysis allows us to identify specific times of day when liquidity conditions systematically deviate from the daily average, which is particularly important for understanding market microstructure in 24/7 cryptocurrency markets compared to traditional currency markets with more defined trading sessions.

Figure 4 shows the results of this analysis across all market pairs in polar coordinates, where the angle represents the hour of the day and the distance from the center represents the relative measure. Cryptocurrency pairs show remarkably similar patterns across exchanges and pairs, with volatility and spreads forming clear directional patterns around US trading hours (15:00-18:00 CET). In contrast, traditional currency pairs show more varied patterns, with volatility and spread measures sometimes moving in opposite directions during certain hours. In particular, all traditional currency pairs show a sharp decrease in both volatility and spreads during the market lull between the US close and the Asian open (22:00-01:00 CET).

## 3.2 Relative Volatility and Spread for Day-of-the-Week

Building on our hour-of-the-day analysis, we apply a similar normalization approach to examine day-of-the-week patterns of volatility and spreads, and see if both characteristics are lower during the weekend. For each day of the week, we compute a ratio measure that compares the sum of the spread (or volatility) on that day to the sum over the previous seven days. Formally, for each market pair, we calculate:

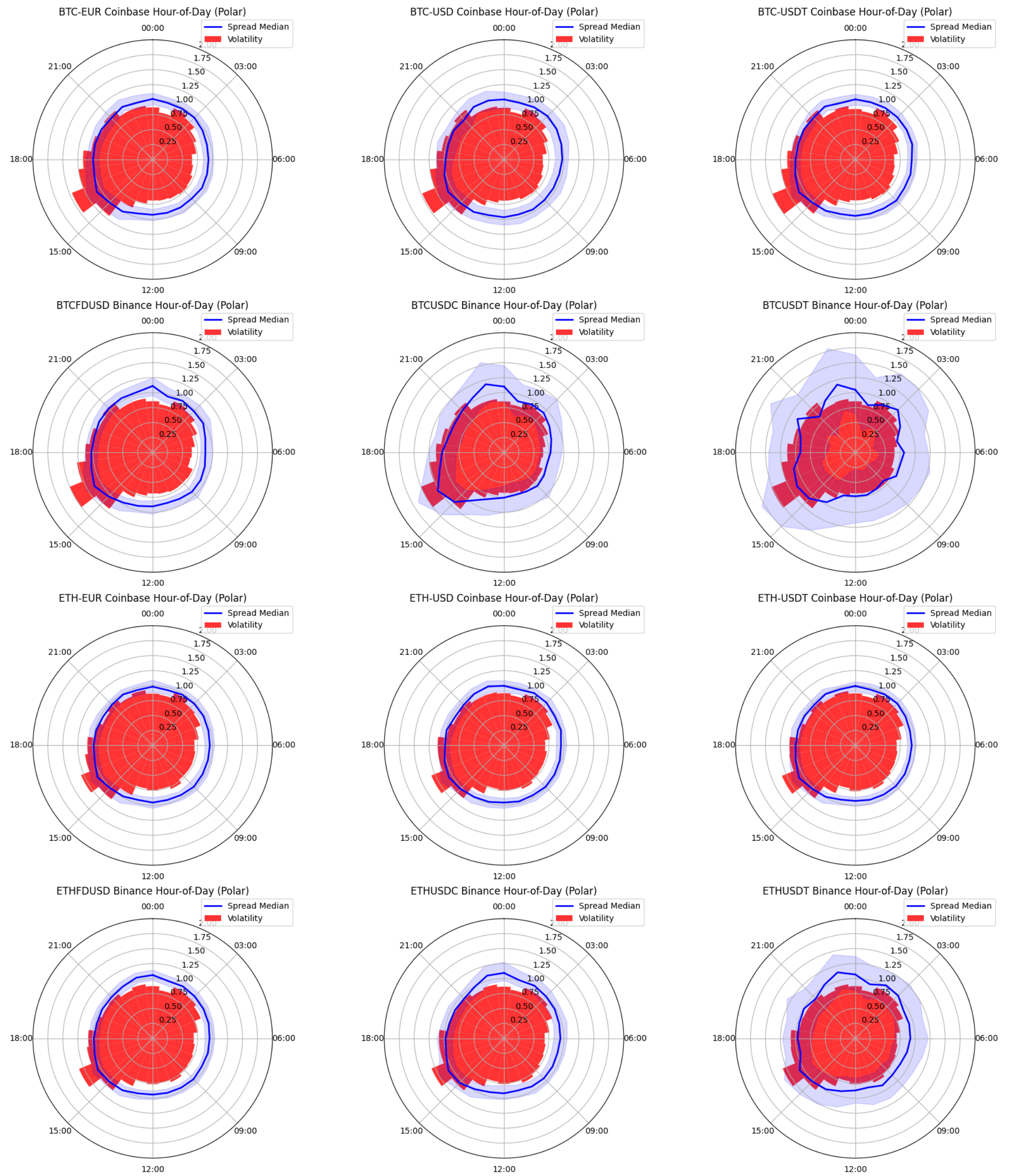
$$\lambda_\sigma^{\text{day}}(d) = \frac{1}{n_d} \sum_w \frac{|y_{\tau(w,d,h)}|}{\sum_{i=0}^{6} |y_{\tau(w,d-i,h)}|} \tag{6}$$

$$\lambda_s^{\text{day}}(d) = \frac{1}{n_d} \sum_w \frac{s_{\tau(w,d,h)}}{\sum_{i=0}^{6} s_{\tau(w,d-i,h)}} \tag{7}$$

where:

- $d$ – day of the week, $d = 1, \ldots, 7$
- $w$ – week number

Figure 4: Polar Representation of Hour-of-Day Relative Measures




Note: Each chart shows the relative volatility measure (red bars) and spread measure (blue line) in polar coordinates. The radial axis represents the ratio value, with the circle at 1.0 indicating the average level. The angular coordinate represents the hour of the day, with midnight at the top and proceeding clockwise.

- $h$ – hour of the day
- $y_{\tau(w,d,h)}$ – absolute return at time point $(w, d, h)$
- $s_{\tau(w,d,h)}$ – spread at time point $(w, d, h)$

- $n_d \approx W$ – number of observations per day of the week

If $\lambda_\sigma^{\text{day}}(d) > 1$, volatility is higher on day $d$ compared to the weekly average. If $\lambda_s^{\text{day}}(d) > 1$, the spread is higher on day $d$, indicating lower liquidity. Figure 5 presents the results of this analysis for selected cryptocurrency pairs. For cryptocurrency pairs, weekdays (Monday through Friday) show relatively stable volatility and spread measures near the neutral threshold, while weekends show low volatility (often 30-40% below average) and narrower spreads.

# 4 Fast Fourier Transform Analysis and Harmonic Modeling

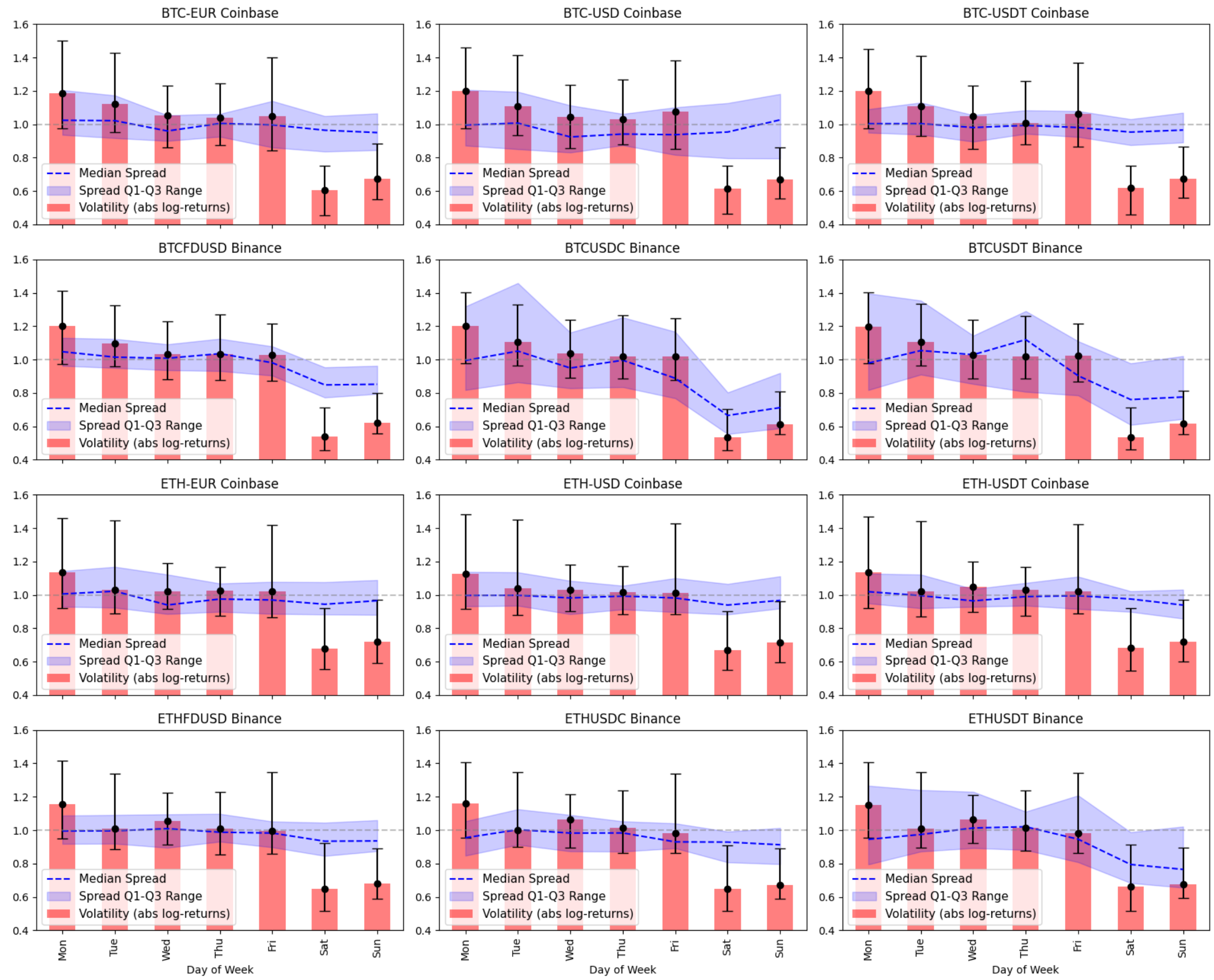
To rigorously characterize the underlying periodicities in the spread time series, apply spectral analysis techniques to logarithmic bid-ask spreads. We employ a three-stage approach: (1) objectively identify the dominant frequencies in liquidity patterns, (2) estimate the phase relationships that determine cycle timing, and (3) statistically validate the significance of these cyclical components using the complete time series data.

We begin by computing the median log-spread values for each time point across the day, resulting in a 96-element vector (representing 15-minute intervals). Fast Fourier Transform (FFT) is then applied to this median pattern to decompose it into its frequency components. FFT efficiently transforms time-domain data into the frequency domain by expressing the signal as a sum of sinusoidal components of varying frequencies and amplitudes:

$$X(k) = \sum_{n=0}^{N-1} x(n) e^{-i2\pi kn/N} \tag{8}$$

where $X(k)$ represents the spectral components, $x(n)$ is our time-series data, and $N$ is the number of time points. By analyzing the magnitude of these spectral components, we identify the dominant frequencies $f_1, f_2, ..., f_n$ ranked by their power in the spectrum. These

Figure 5: Day-of-Week Relative Volatility and Spread Measures




Note: The bars (red) represent the relative volatility measure for each day of the week, with error bars showing the statistical uncertainty (Q1 to Q3 range). The blue dashed line shows the corresponding relative spread measure. The horizontal line at 1.0 indicates the average level. Values above 1.0 indicate higher-than-average volatility or spreads for that day.

frequencies represent the most important cyclical patterns in the intraday spread data.

Using the dominant frequencies identified in Step 1, we fit two harmonic regression models to the median log-spread pattern:

1. Single-frequency model:

$$\log(S_t) = a_0 + A_1 \sin(2\pi f_1 t + \phi_1) + \varepsilon_t \tag{9}$$

2. Two-frequency model:

$$\log(S_t) = a_0 + A_1 \sin(2\pi f_1 t + \phi_1) + A_2 \sin(2\pi f_2 t + \phi_2) + \varepsilon_t \tag{10}$$

where $a_0$ is the intercept, $A_1$ and $A_2$ are amplitude parameters, and $\phi_1$ and $\phi_2$ are phase shift parameters that determine the timing of peaks and troughs in the cyclical pattern[1]. The phase parameters $\phi_1$ and $\phi_2$ are particularly important as they capture the timing of liquidity cycles throughout the day. These phase shifts allow us to determine when spreads tend to widen or narrow within the identified periodic cycles.

Finally, to validate the periodicity patterns identified in the previous step and ensure they represent genuine cyclical behavior rather than random fluctuations, we extend our analysis beyond the median pattern to the full log-spread time series. We implement a formal statistical testing framework using harmonic regression. We first convert timestamps into normalized time to standardize the analysis across different market pairs:

$$t_{\text{norm}} = \frac{\text{hours} + \text{minutes}/60}{24} \tag{11}$$

Next, using the frequencies and estimated phase parameters from Steps 1 and 2, we construct explanatory variables of the form:

$$X_1(t) = \sin(2\pi f_1 t + \hat{\phi}_1) \tag{12}$$

$$X_2(t) = \sin(2\pi f_2 t + \hat{\phi}_2) \tag{13}$$

where $\hat{\phi}_1$ and $\hat{\phi}_2$ are the phase parameters estimated in Step 2. We then perform linear regression on the complete time series of log-spreads:

$$\log(S_t) = \beta_0 + \beta_1 X_1(t) + \beta_2 X_2(t) + \epsilon_t \tag{14}$$

[1] We estimate these parameters using non-linear least squares optimization with the the function, which minimizes the sum of squared residuals between the observed median pattern and the harmonic model

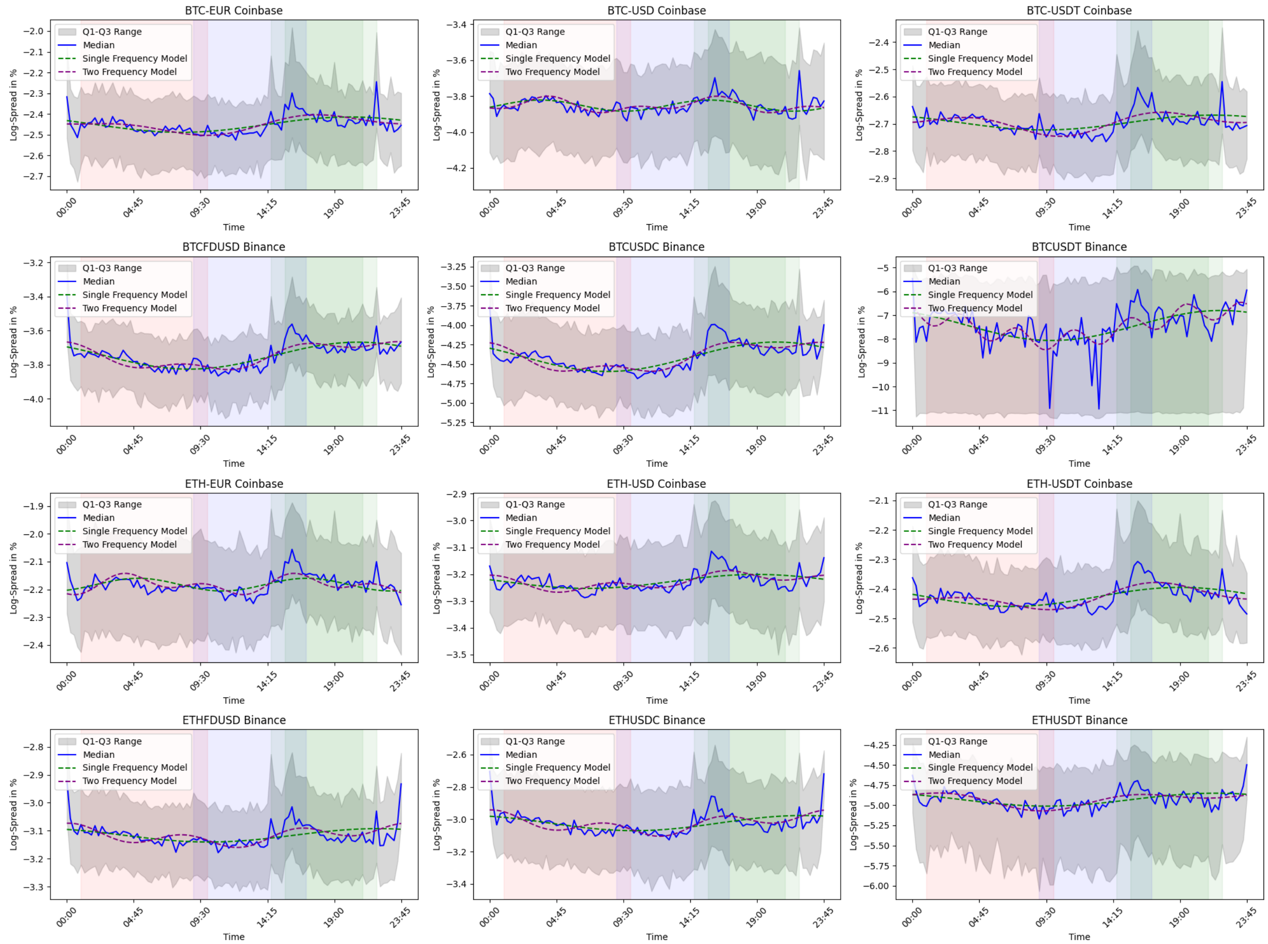
This allows us to apply standard statistical inference techniques to assess the significance of the periodic components. This regression uses heteroskedasticity and autocorrelation consistent (HAC) standard errors to account for potential serial correlation in the residuals. The t-statistics and p-values from this regression provide formal statistical tests of the significance of the identified cyclical components across the entire sample period, not just in the median pattern. Additionally, we evaluate the overall explanatory power of the periodic components using the coefficient of determination ($R^2$).

To visualize the fit of our harmonic models, Figure 6 presents the results of both single-frequency and two-frequency harmonic regressions for each market pair in our sample. The figure displays the median log-spread across the trading day (blue line) along with the interquartile range (gray shaded area), and overlays the fitted values from the single-frequency model (green dashed line) and the two-frequency model (purple dashed line).

Table 2 presents the results of our harmonic regression analysis. The table reports the dominant frequencies, phase shifts, parameter estimates, and corresponding t-statistics for both single-frequency and two-frequency models across all cryptocurrency assets in our sample. A notable pattern emerges: almost all cryptocurrency assets exhibit a primary cyclical component with frequency of approximately 0.01, corresponding to a daily (24-hour) cycle. This consistency suggests a strong global trading pattern affects cryptocurrency liquidity regardless of trading venue or specific asset. The t-statistics reported in Table **??** reveal that the cyclical components are highly significant for all cryptocurrency assets.

Our analysis reveals several key insights about cryptocurrency market microstructure. First, the majority of cryptocurrency pairs exhibit a consistent primary cycle with frequency around 0.01 (corresponding to one cycle per day), suggesting that despite their 24/7 operation, these markets are heavily influenced by global daily trading patterns. The phase shifts ($\phi$) are also relatively consistent across most pairs, indicating synchronized timing of liquidity provision across different cryptocurrency markets. Second, the t-statistics for both the primary and secondary frequencies are highly significant (many exceeding $|15|$), confirm-

Figure 6: Harmonic Model Fit to Intraday Log-Spreads.




Note: This figure shows the median log-spread pattern across the trading day (blue solid line) with the interquartile range (gray shaded area). The green dashed line represents the fitted values from the single-frequency harmonic model, while the purple dashed line shows the fitted values from the two-frequency model. Colored bands highlight major trading sessions: Asian (red), European (blue), and US (green).

ing that these cyclical patterns represent genuine market phenomena rather than random variations. This provides strong statistical evidence for the presence of predictable intraday liquidity cycles in cryptocurrency markets. Third, while secondary frequencies vary somewhat between different cryptocurrency pairs, they commonly fall in the range of 0.02-0.03, corresponding to approximately 8-12 hour cycles. These secondary cycles may reflect the influence of major global trading sessions (Asian, European, and US) on cryptocurrency liquidity provision. It is important to note that despite the strong statistical significance of these cyclical components, the overall explanatory power of the harmonic models remains

Table 2: Harmonic Regression Results for Intraday Spread Periodicity

| | **Single-frequency harmonic model** | | | | | **Two-frequency harmonic model** | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Symbol | $f_1$ | $\phi$ | $\beta_1$ | $T_{\beta_1}$ | $R^2$ | $f_1$ | $\beta_1$ | $T_{\beta_1}$ | $f_2$ | $\beta_2$ | $T_{\beta_2}$ | $R^2$ | $N_{\text{obs}}$ |
| **Panel A: Binance** | | | | | | | | | | | | | |
| BTCFDUSD | 0.01 | -0.71 | -0.08 | **-28.49** | 0.03 | 0.01 | -0.08 | **-23.84** | 0.03 | 0.03 | **7.68** | 0.03 | 25665 |
| BTCUSDC | 0.01 | -0.62 | -0.18 | **-21.35** | 0.02 | 0.01 | -0.18 | **-16.87** | 0.03 | 0.08 | **6.85** | 0.02 | 25665 |
| BTCUSDT | 0.01 | 2.12 | 0.26 | **10.73** | 0.00 | 0.01 | 0.26 | **10.16** | 0.06 | -0.17 | **-6.53** | 0.01 | 25665 |
| ETHFDUSD | 0.01 | -1.07 | -0.03 | **-12.76** | 0.01 | 0.01 | -0.03 | **-10.37** | 0.03 | 0.03 | **9.05** | 0.01 | 25665 |
| ETHUSDC | 0.01 | -1.12 | -0.05 | **-13.31** | 0.01 | 0.01 | -0.05 | **-10.31** | 0.03 | 0.04 | **8.24** | 0.01 | 25665 |
| ETHUSDT | 0.01 | -0.92 | -0.09 | **-8.98** | 0.00 | 0.01 | -0.09 | **-7.95** | 0.02 | 0.06 | **5.27** | 0.00 | 25665 |
| **Panel B: Coinbase** | | | | | | | | | | | | | |
| BTC-EUR | 0.01 | -0.55 | -0.05 | **-17.31** | 0.01 | 0.01 | -0.05 | **-13.91** | 0.02 | 0.02 | **6.69** | 0.01 | 24835 |
| BTC-USD | 0.02 | -0.31 | 0.04 | **8.80** | 0.00 | 0.02 | 0.04 | **7.51** | 0.04 | -0.03 | **-4.31** | 0.00 | 24835 |
| BTC-USDT | 0.01 | -0.88 | -0.04 | **-16.53** | 0.01 | 0.01 | -0.04 | **-13.35** | 0.02 | 0.03 | **9.64** | 0.02 | 24835 |
| ETH-EUR | 0.02 | -1.07 | 0.02 | **8.83** | 0.00 | 0.02 | 0.02 | **6.83** | 0.04 | -0.02 | **-4.29** | 0.00 | 24835 |
| ETH-USD | 0.01 | -0.25 | -0.02 | **-7.05** | 0.00 | 0.01 | -0.02 | **-5.54** | 0.03 | 0.02 | **5.75** | 0.00 | 24835 |
| ETH-USDT | 0.01 | -0.27 | -0.05 | **-20.03** | 0.02 | 0.01 | -0.05 | **-15.77** | 0.02 | 0.03 | **9.90** | 0.02 | 24835 |

Note: The table presents harmonic regression results for log-transformed spreads using two model specifications. The first model includes a single-frequency component, while the second incorporates two frequency components. Bold and underlined values indicate t-statistics with absolute values greater than 3, representing statistical significance at approximately the 0.1% level. T values represent t-statistics for the amplitude parameters. Freq represents the identified dominant frequencies from Fourier analysis, measured in cycles per day. $R^2$ represents the coefficient of determination for each model. $\phi$ represents the estimated phase shift in radians.

modest, with $R^2$ values between 0.00 and 0.03 in all cases. This suggests that while cyclical patterns are significant contributors to spread variation in cryptocurrency markets, they are only one component of the complex factors driving market liquidity. The consistent presence of significant cyclical patterns across different exchanges (Binance and Coinbase) and different cryptocurrency pairs (BTC and ETH with various quote currencies) indicates that these periodic liquidity fluctuations may be fundamental features of cryptocurrency market microstructure rather than exchange-specific phenomena.



## 4.1 Integrated Model

Having shown the existence of significant cyclical patterns in liquidity through our FFT analysis, we now incorporate these periodic components into a comprehensive model of spread determinants. We construct a regression framework that captures multiple dimensions of market conditions that may affect liquidity:

$$\log(S_t) = \alpha + \sum_{j=0}^{3} \beta_j r_{t-j} + \gamma_1 r_t^2 + \gamma_2 \sigma_t + \delta \cdot FFT_t + \varepsilon_t \tag{15}$$

where $\log(S_t)$ is the logarithm of the bid-ask spread at time $t$, $r_{t-j}$ represents returns at various lags (with $j = 0$ being contemporaneous returns), $r_t^2$ is the squared return as a measure of instantaneous volatility, $\sigma_t$ is the exponentially weighted moving average (EWMA) volatility with a decay factor of 0.1, and $FFT_t$ is the periodic component identified through our Fourier analysis, defined as $\sin(2\pi f_1 t + \hat{\phi}_1)$. This specification allows us to disentangle the effects of market returns, volatility dynamics, and cyclical patterns on market liquidity.

The model incorporates three key categories of explanatory variables:

1. **Return dynamics**: Current and lagged returns $(r_t, r_{t-1}, r_{t-2}, r_{t-3})$ capture the relationship between price movements and liquidity, including potential asymmetric responses to positive versus negative returns.

2. **Volatility measures**: Two complementary measures of volatility are included: squared returns $(r_t^2)$ as a high-frequency indicator of instantaneous volatility, and EWMA volatility $(\sigma_t)$ as a smoothed measure of sustained volatility.

3. **Periodicity component**: The $FFT_t$ variable incorporates the dominant cyclical pattern identified through our Fourier analysis, enabling us to capture the systematic intraday variations in liquidity that follow regular temporal patterns.

To facilitate direct comparison of coefficient magnitudes across variables and market pairs, all explanatory variables are standardized to have a mean of zero and a standard deviation of one. This standardization ensures that the reported coefficients represent the effect of a one standard deviation change in the explanatory variable on the log spread.

To ensure robust statistical inference, we estimate this model using heteroskedasticity and autocorrelation consistent (HAC) standard errors with Newey-West correction. This approach accounts for potential serial correlation and time-varying volatility in the residuals. Additionally, we apply a Bonferroni correction to our significance threshold to address the multiple testing problem arising from analyzing 18 different market pairs simultaneously. Specifically, we divide the standard 2.5% significance level by 12, resulting in an adjusted significance level of approximately 0.00139. This corresponds to a t-statistic threshold of approximately 3. Consequently, in Table 3, we highlight coefficients with t-statistics exceeding 3 in absolute value as statistically significant.

Table 3 presents the regression results for all market pairs in our sample. Several key patterns emerge across different cryptocurrency pairs and exchanges. First, volatility emerges as the strongest determinant of spreads for all cryptocurrency pairs. The EWMA volatility measure ($\sigma_t$) shows particularly large and highly significant positive coefficients, ranging from 0.18 for BTCUSDT on Binance to 0.47 for ETH-USDT on Coinbase. This strong positive relationship indicates that sustained periods of high volatility significantly increase spreads, consistent with increased risk for market makers during volatile conditions. The instantaneous volatility measure ($r_t^2$) shows more mixed effects, with significant positive coefficients for several bitcoin pairs (particularly on Coinbase), but weaker effects for other pairs. This suggests that the persistent component of volatility (captured by the EWMA) is a more consistent determinant of liquidity than instantaneous volatility spikes.

Second, we observe consistently negative and statistically significant coefficients on both contemporaneous and lagged returns across most cryptocurrency pairs. This inverse relationship between returns and spreads suggests that liquidity tends to decrease (spreads widen) during periods of price declines. The effect is particularly pronounced for ETH pairs, where the contemporaneous return coefficient reaches -0.06 for ETH-USD on Coinbase (t-statistic: -6.38). Lagged returns also show significant negative relationships with spreads, especially in the first lag ($r_{t-1}$), indicating persistent effects of price movements on liquidity. This finding suggests that cryptocurrency market makers may adjust their liquidity provision asymmetrically in response to price movements, potentially reflecting risk management considerations during market downturns.

Third, the periodicity component (FFT) shows statistical significance for several cryptocurrency pairs, but with varying directions and magnitudes. For Binance, BTCFDUSD, BTCUSDC, and ETHUSDC show significant negative coefficients, while BTCUSDT shows a significant positive coefficient. On Coinbase, BTC-EUR shows a significant negative coefficient, while BTC-USD and ETH-EUR show significant positive coefficients. These mixed effects suggest that while cyclical patterns are present in cryptocurrency liquidity, their influence varies across different trading pairs and exchanges. The fact that some pairs show negative coefficients (indicating tighter spreads during peak cycle times) while others show positive coefficients highlights the complexity of intraday liquidity patterns in cryptocurrency markets

Fourth, the weekend dummy variable reveals interesting patterns in weekend trading behavior. Six out of the twelve cryptocurrency pairs show statistically significant weekend effects, but with differing signs. BTC-USD, BTC-USDT, and ETH-USD on Coinbase, along with ETHFDUSD on Binance, show significant positive coefficients, indicating wider spreads during weekends. In contrast, BTCFDUSD and ETHUSDT on Binance show significant negative coefficients, suggesting tighter spreads during weekends. These divergent patterns may reflect different types of market participants and trading behaviors across exchanges and cryptocurrency pairs during non-business days. Finally, the explanatory power of our model varies across cryptocurrency pairs. The highest $R^2$ values are observed for ETH-USDT on Coinbase (0.28), BTCFDUSD on Binance (0.25), and ETHFDUSD on Binance (0.23), indicating that our model captures a substantial portion of the variation in spreads for these pairs. The lowest $R^2$ is for BTCUSDT on Binance (0.04), suggesting that additional factors may be driving liquidity for this pair. Overall, the model performs well for most cryptocurrency pairs, with a median $R^2$ of approximately 0.17 across all pairs.

In addition, to quantify the relative importance of each explanatory variable, we use a standardized approach that takes into account the different scales and distributions of the predictors. We standardize all explanatory variables and the dependent variable to have a mean of zero and a standard deviation of one, and fit an OLS regression model with the

Table 3: Regression Results for Log-Spread

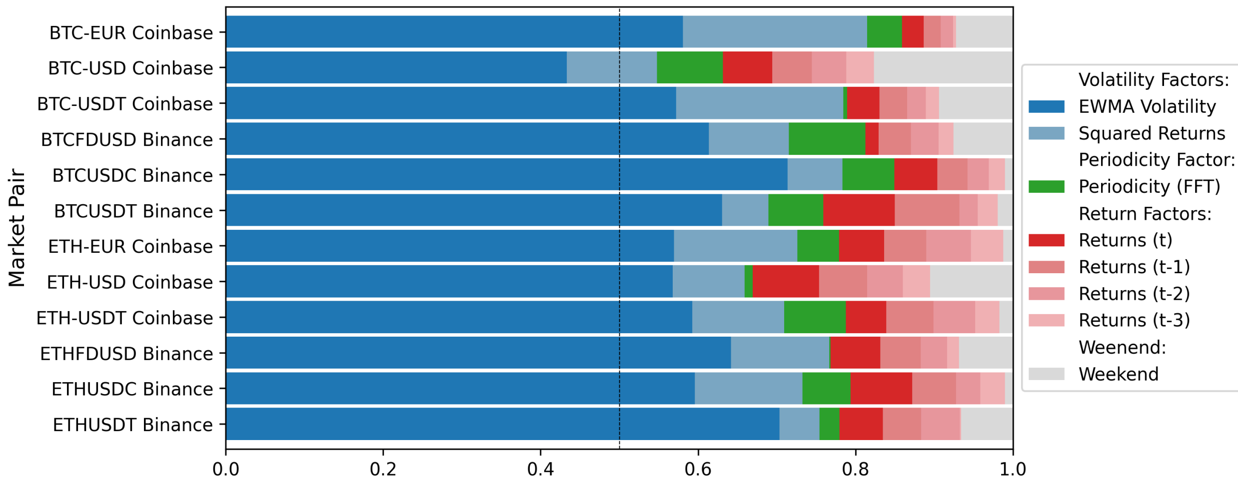
| | | **Returns** | | | | **Volatility** | | **Periodicity** | **Calendar** | |
|---|---|---|---|---|---|---|---|---|---|---|
| Symbol | $\alpha$ | $r_t$ | $r_{t-1}$ | $r_{t-2}$ | $r_{t-3}$ | $r_t^2$ | $\sigma_t$ | FFT | Weekend | $R^2$ |
| **Panel A: Binance** | | | | | | | | | | |
| BTCFDUSD | 0.03 | -0.01 | **-0.03** | **-0.02** | -0.01 | **0.07** | **0.43** | **-0.07** | **-0.12** | 0.25 |
| | (4.48) | (-1.85) | **(-4.70)** | **(-4.40)** | (-2.28) | **(5.24)** | **(45.04)** | **(-10.53)** | **(-7.42)** | |
| BTCUSDC | 0.00 | **-0.03** | **-0.02** | -0.01 | -0.01 | **0.04** | **0.39** | **-0.04** | -0.01 | 0.18 |
| | (0.40) | **(-5.00)** | **(-3.79)** | (-2.68) | (-2.07) | **(3.46)** | **(40.49)** | **(-4.87)** | (-0.72) | |
| BTCUSDT | -0.00 | **-0.03** | **-0.02** | -0.01 | -0.01 | 0.02 | **0.18** | **0.02** | 0.01 | 0.04 |
| | (-0.45) | **(-4.56)** | **(-4.03)** | (-1.15) | (-1.29) | (2.64) | **(24.86)** | **(3.06)** | (0.81) | |
| ETHFDUSD | -0.03 | **-0.04** | **-0.04** | -0.02 | -0.01 | 0.09 | **0.44** | 0.00 | **0.10** | 0.23 |
| | (-3.69) | **(-5.79)** | **(-5.11)** | **(-3.70)** | (-1.56) | (2.23) | **(34.51)** | (0.17) | **(6.98)** | |
| ETHUSDC | 0.00 | **-0.04** | **-0.03** | -0.01 | -0.01 | 0.06 | **0.28** | **-0.03** | -0.01 | 0.11 |
| | (0.33) | **(-5.44)** | **(-4.34)** | (-2.50) | (-2.57) | (1.92) | **(25.56)** | **(-3.70)** | (-0.59) | |
| ETHUSDT | 0.02 | -0.02 | **-0.02** | **-0.02** | 0.00 | 0.02 | **0.26** | -0.01 | **-0.05** | 0.08 |
| | (1.91) | **(-3.61)** | **(-3.28)** | **(-3.10)** | (0.12) | (1.32) | **(31.51)** | (-1.39) | **(-3.48)** | |
| **Panel B: Coinbase** | | | | | | | | | | |
| BTC-EUR | -0.03 | -0.02 | -0.01 | -0.01 | -0.00 | **0.13** | **0.33** | **-0.02** | **0.09** | 0.16 |
| | (-2.96) | (-1.99) | (-1.54) | (-1.19) | (-0.35) | **(8.57)** | **(28.65)** | **(-3.34)** | **(5.38)** | |
| BTC-USD | -0.06 | **-0.03** | **-0.03** | **-0.02** | **-0.02** | **0.06** | **0.22** | **0.04** | **0.20** | 0.06 |
| | (-6.45) | **(-5.42)** | **(-4.63)** | **(-4.16)** | **(-3.34)** | **(7.46)** | **(28.97)** | **(6.03)** | **(12.28)** | |
| BTC-USDT | -0.04 | **-0.03** | **-0.02** | -0.02 | -0.01 | **0.15** | **0.40** | 0.00 | **0.14** | 0.22 |
| | (-4.97) | **(-3.67)** | **(-3.60)** | (-2.53) | (-1.92) | **(9.91)** | **(40.65)** | (0.48) | **(8.99)** | |
| ETH-EUR | -0.00 | -0.03 | **-0.03** | **-0.03** | -0.02 | **0.09** | **0.31** | **0.03** | 0.01 | 0.13 |
| | (-0.49) | (-2.77) | **(-3.79)** | **(-3.32)** | (-2.70) | **(3.33)** | **(22.75)** | **(3.79)** | (0.80) | |
| ETH-USD | -0.05 | **-0.06** | **-0.04** | **-0.03** | -0.02 | 0.06 | **0.39** | 0.01 | **0.16** | 0.17 |
| | (-5.63) | **(-6.38)** | **(-6.20)** | **(-4.72)** | **(-3.46)** | (2.47) | **(35.41)** | (0.94) | **(9.21)** | |
| ETH-USDT | -0.01 | **-0.04** | **-0.05** | **-0.04** | -0.02 | **0.09** | **0.47** | **-0.06** | 0.03 | 0.28 |
| | (-1.17) | **(-3.83)** | **(-6.53)** | **(-4.07)** | **(-4.15)** | **(3.06)** | **(37.99)** | **(-9.14)** | (1.92) | |

Note: This table presents regression results for spread predictability, with variables grouped into three categories: (1) Returns, (2) Volatility, and (3) Intraday Periodicity. For each currency pair, the first row shows coefficient estimates and the second row (in parentheses) shows corresponding t-statistics. We apply a Bonferroni correction to our significance threshold to address the multiple testing problem arising from analyzing 12 different market pairs simultaneously. Bold and underlined values indicate coefficients with t-statistics having absolute values above 3 (we divide the standard 2.5% significance level by 18, resulting in an adjusted significance level of approximately 0.00139). Returns variables include contemporaneous returns ($r_t$) and three lags of returns ($r_{t-1}$ through $r_{t-3}$). Volatility measures include squared returns ($r_t^2$) and exponentially weighted moving average volatility ($\sigma_t$). The periodicity component (FFT) captures cyclical intraday patterns identified through Fourier analysis. The $R^2$ column shows the model's explanatory power.

standardized variables. We then calculate the absolute value of each standardized coefficient and normalize these absolute values by dividing by their sum, expressing the contribution of each variable as a proportion of the total explained effect.

Figure 7 shows the relative importance of each explanatory variable across all cryptocurrency pairs. For all pairs, volatility ($\sigma_t$) emerges as the overwhelmingly dominant factor, accounting for 40-70% of the explained variation in spreads. Returns (both contemporaneous and lagged) collectively make a substantial contribution, particularly for pairs on Coinbase. The cyclical component and weekend effect show varying levels of importance across different pairs, with the weekend effect being particularly important for BTC-USD and BTC-USDT on Coinbase.

Figure 7: Relative Importance of Factors in Log-Spread Determination




Note: This table presents the normalized variable importance for each explanatory factor across all market pairs. Values represent the proportion of total explained effect attributable to each variable, calculated from the absolute standardized regression coefficients and normalized to sum to 1. Higher values indicate greater relative importance in explaining log-spread variation.



# 5 Out-of-Sample Forecasting Performance

## 5.1 Forecasting Methodology

To assess the practical value of incorporating periodic patterns into liquidity modeling, we evaluate the out-of-sample predictive performance of our models. For our forecasting exercise, we implement a more focused set of explanatory variables than in our full regression analysis, selecting variables with the strongest predictive power. We prepare a set of predictive features including:

- Lagged spread values (three lags of the spread variable: $\log(S_{t-1})$, $\log(S_{t-2})$, $\log(S_{t-3})$);
- Return measures (three lags: $r_{t-1}$, $r_{t-2}$, $r_{t-3}$);
- Volatility measures (lagged volatility values: $\sigma_{t-1}$, $\sigma_{t-2}$, $\sigma_{t-3}$);

- Mean reversion term (difference between the previous spread and its medium-term moving average - 96 previous observations);
- Intraday periodical component (sine wave with the dominant frequency and phase identified in our spectral analysis).

For each market pair, we split the data into training (60%) and testing (40%) sets. We estimate two model specifications on the training data: full model (including all variables with intraday periodical component) and restricted model (excluding intraday periodical component but retains all other variables). We generate out-of-sample forecasts for logarithmic spreads using both models on the test data. We evaluate forecasting performance using multiple complementary metrics like Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) nad Directional Accuracy (DA). We formally test for statistically significant differences in forecast accuracy using the Diebold-Mariano test, which evaluates whether one forecasting method consistently outperforms another.



Table 4: Out-of-Sample Forecast Performance Comparison

| | **DM Test** | | **Forecast-accuracy metrics** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | MSE | | RMSE | | MAE | | MAPE (%) | | DA (%) | |
| Symbol | Stat | $p$-value | Full | No FFT | Full | No FFT | Full | No FFT | Full | No FFT | Full | No FFT |
| **Panel A: Binance** | | | | | | | | | | | | |
| BTCFDUSD | -1.605 | 0.108 | **0.081** | 0.081 | **0.285** | 0.285 | **0.222** | 0.223 | **6.00** | 6.00 | **33.10** | 33.00 |
| BTCUSDC | **-5.539** | **0.000** | **0.541** | 0.545 | **0.736** | 0.738 | **0.489** | 0.490 | **9.80** | 9.80 | **34.80** | 34.70 |
| BTCUSDT | -0.375 | 0.708 | **7.729** | 7.731 | **2.780** | 2.781 | **2.563** | 2.564 | **36.00** | 36.00 | **40.60** | 40.00 |
| ETHFDUSD | 0.985 | 0.324 | **0.037** | 0.037 | **0.193** | 0.193 | **0.139** | 0.139 | **4.60** | 4.60 | **33.30** | 33.10 |
| ETHUSDC | **3.721** | **0.000** | 0.083 | **0.082** | **0.287** | 0.287 | 0.189 | **0.188** | **6.10** | 6.10 | **33.70** | 33.70 |
| ETHUSDT | -0.401 | 0.689 | **1.028** | 1.028 | **1.014** | 1.014 | 0.789 | **0.788** | **14.90** | 14.90 | **34.80** | 34.80 |
| **Panel B: Coinbase** | | | | | | | | | | | | |
| BTC-EUR | **-3.674** | **0.000** | **0.068** | 0.068 | **0.261** | 0.261 | **0.187** | 0.187 | **7.90** | 7.90 | 33.90 | **34.00** |
| BTC-USD | **-2.136** | **0.033** | **0.281** | 0.281 | **0.530** | 0.530 | **0.304** | 0.305 | **7.10** | 7.10 | **34.00** | 33.80 |
| BTC-USDT | **-2.473** | **0.013** | **0.039** | 0.039 | **0.198** | 0.198 | **0.140** | 0.141 | **5.60** | 5.60 | **33.60** | 33.60 |
| ETH-EUR | **-2.776** | **0.006** | **0.048** | 0.048 | **0.219** | 0.219 | **0.153** | 0.153 | **7.60** | 7.60 | **32.60** | 32.50 |
| ETH-USD | 0.939 | 0.348 | **0.049** | 0.049 | **0.222** | 0.222 | **0.151** | 0.151 | **4.80** | 4.80 | **33.50** | 33.50 |
| ETH-USDT | **-2.060** | **0.039** | **0.057** | 0.057 | **0.239** | 0.240 | **0.171** | 0.171 | **10.20** | 10.20 | **32.90** | 32.90 |

Note: This table presents forecast evaluation metrics comparing models with and without the periodicity (FFT) component. The Diebold-Mariano test evaluates whether forecast improvements are statistically significant, with negative values favoring the FFT model and bold underlined values indicating statistical significance at the 5% level or better. For each metric, the better performing model is highlighted in bold. For error metrics (RMSE, MAE, MAPE), lower values are better, while for directional accuracy (DA), higher values are better.

Table 4 presents the results of our forecasting analysis for cryptocurrency pairs across Binance and Coinbase exchanges. The Diebold-Mariano test results reveal that the inclusion of the FFT component significantly improves forecasting accuracy for several cryptocurrency pairs, though the pattern is not uniform across all pairs.

For Binance cryptocurrencies, BTCUSDC shows a highly significant improvement (DM = -5.539, p-value $< 0.001$) when incorporating the FFT component, suggesting that cyclical patterns substantially enhance predictive power for this pair. Interestingly, ETHUSDC shows a significant positive DM statistic (3.721, p-value $< 0.001$), indicating that for this particular pair, the model without the FFT component performs better. The remaining four Binance pairs (BTCFDUSD, BTCUSDT, ETHFDUSD, and ETHUSDT) show DM statistics that are not statistically significant, suggesting that the inclusion of the FFT component neither significantly improves nor harms forecast accuracy for these pairs.

For Coinbase cryptocurrencies, four out of six pairs show statistically significant improvements with the inclusion of the FFT component: BTC-EUR (DM = -3.674, p-value $< 0.001$), BTC-USD (DM = -2.136, p-value = 0.033), BTC-USDT (DM = -2.473, p-value = 0.013), and ETH-EUR (DM = -2.776, p-value = 0.006). ETH-USDT also shows a significant improvement (DM = -2.060, p-value = 0.039). ETH-USD is the only Coinbase pair that does not show a significant difference between the models, with a positive but non-significant DM statistic (0.939, p-value = 0.348).

Examining the error metrics in detail, both MSE and RMSE generally favor the full model for most cryptocurrency pairs, though the improvements are often quite modest. For instance, BTCUSDC on Binance shows an MSE improvement from 0.545 to 0.541, while BTC-USDT on Coinbase shows an RMSE improvement from 0.198 to 0.198 (difference visible only at more decimal places). While these gains appear small numerically, their statistical significance in several cases (as confirmed by the Diebold-Mariano test) suggests consistent improvements that could yield economically meaningful benefits over numerous transactions.

Mean Absolute Error (MAE) follows a similar pattern to RMSE, with the full model generally outperforming the restricted model, albeit with small margins. In two cases (ETHUSDT on Binance and ETHUSDC on Binance), the restricted model actually performs marginally better in terms of MAE. Percentage errors (MAPE) show the full model consistently performing better across all cryptocurrency pairs, though the improvements are very small, typically around 0.1 percentage points or less.

In terms of directional accuracy (DA), which measures the ability to correctly predict the direction of spread changes, the full model generally performs better than the restricted model. BTC-USDT on Binance shows the largest improvement, with the full model correctly predicting 40.6% of direction changes compared to 40.0% for the restricted model. For most other pairs, the improvements in directional accuracy are minimal (0.1-0.2 percentage points), and in one case (BTC-EUR on Coinbase), the restricted model actually achieves slightly higher directional accuracy (34.0% versus 33.9%).

The relatively modest improvements in forecast metrics despite statistically significant DM test results for several pairs suggest that while periodic patterns do contribute to forecast accuracy, their impact varies considerably across different cryptocurrency pairs and exchanges. This heterogeneity in forecasting performance may reflect differences in market microstructure, trading activity, or liquidity provision mechanisms across different cryptocurrency markets.

# 6 Concluding Remarks

This study provides an examination of market liquidity dynamics in the cryptocurrency markets, focusing on Bitcoin and Ethereum traded on two major exchanges: Binance and Coinbase. By analyzing high-frequency order book data through the lens of spectral analysis and statistical techniques, we have uncovered several key insights into the nature of liquidity provision in these relatively new but increasingly important markets.

Our results show that despite their 24/7 operation, cryptocurrency markets exhibit strong and statistically significant cyclical patterns in liquidity. These patterns are characterized by an inverted sinusoidal structure, with the lowest spreads typically observed during Asian and early European trading hours, followed by wider spreads during the North American trading session. The remarkable consistency of these patterns across cryptocurrencies and exchanges suggests the presence of global factors affecting the provision of liquidity in cryptocurrency markets, regardless of the specific trading venue or cryptocurrency.

The harmonic regression analysis shows that most cryptocurrency pairs share a dominant frequency of approximately 0.01 cycles per observation (corresponding to a daily cycle), with additional secondary frequencies that likely reflect the influence of major global trading sessions. These periodic components are highly statistically significant, as evidenced by the robust t-statistics obtained in our regression analysis. This finding suggests that cryptocurrency liquidity is significantly influenced by traditional business hours and global trading patterns, despite the theoretical capacity of markets to operate around the clock.

Our analysis of weekend versus weekday trading patterns further supports this conclusion. We document a striking flattening of intraday spread patterns during weekends, with significantly lower volatility and generally tighter spreads compared to weekdays. This marked difference between weekend and weekday liquidity patterns strongly suggests that institutional trading activity, which follows traditional market hours, plays a key role in shaping the microstructure of the cryptocurrency market.

The integrated regression model shows that volatility is the dominant determinant of spread variation, accounting for 40-70% of the explained variation across all cryptocurrency pairs. This finding is consistent with risk-based theories of liquidity provision, where market makers demand wider spreads as compensation for taking positions during periods of higher price uncertainty. Returns also exhibit a significant and consistent negative relationship with spreads, suggesting that market liquidity tends to deteriorate during price declines. This asymmetric liquidity response to price movements may reflect risk management considerations by liquidity providers during market downturns.

The forecasting analysis shows that the inclusion of periodic components can improve the accuracy of spread predictions for many cryptocurrency pairs, particularly those traded on Coinbase. While the numerical improvements in predictive metrics are modest, the statistical significance of these improvements for several pairs suggests potential economic value for market participants engaged in high-frequency or high-volume trading.

Several avenues for future research emerge from our analysis. First, examining how these liquidity patterns have evolved over time, particularly as institutional participation in cryptocurrency markets has increased, could provide insights into the evolution of the market. Second, exploring the relationship between liquidity patterns and the specific characteristics of different cryptocurrencies (such as market capitalization, use case, or technological features) could help identify factors that contribute to more robust liquidity. Third, examining how liquidity dynamics differ between centralized exchanges, decentralized exchanges, and over-the-counter markets would enhance our understanding of the cryptocurrency market ecosystem more broadly.

# References


Al-Yahyaee, K. H., Mensi, W., Ko, H.-U., Yoon, S.-M., and Kang, S. H. (2020). Why cryptocurrency markets are inefficient: The impact of liquidity and volatility. The North American Journal of Economics and Finance, 52:101168.

Boudt, K. and Petitjean, M. (2014). Intraday liquidity dynamics and news releases around price jumps: Evidence from the DJIA stocks. Journal of Financial Markets, 17:121–149.

Bouteska, A., Abedin, M. Z., Hajek, P., and Yuan, K. (2024). Cryptocurrency price forecasting – a comparative analysis of ensemble learning and deep learning methods. International Review of Financial Analysis, 92:103055.

Brauneis, A., Mestel, R., Riordan, R., and Theissen, E. (2021). How to measure the liquidity of cryptocurrency markets? Journal of Banking Finance, 124:106041.

Będowska-Sójka, B. (2018). The coherence of liquidity measures. the evidence from the emerging market. Finance Research Letters, 27:118–123.

Będowska-Sójka, B. (2020). Do aggressive orders affect liquidity? an evidence from an emerging market. Research in International Business and Finance, 54:101307.

Będowska-Sójka, B. (2021). Is liquidity wasted? the zero-returns on the warsaw stock exchange. Annals of Operations Research, 297(1-2):37 – 51.

Cakici, N., Shahzad, S. J. H., Będowska-Sójka, B., and Zaremba, A. (2024). Machine learning and the cross-section of cryptocurrency returns. International Review of Financial Analysis, 94:103244.

Cenesizoglu, T. and Grass, G. (2018). Bid- and ask-side liquidity in the nyse limit order book. Journal of Financial Markets, 38:14–38.

Cheng, J., Tiwari, S., Khaled, D., Mahendru, M., and Shahzad, U. (2024). Forecasting bitcoin prices using artificial intelligence: Combination of ml, sarima, and facebook prophet models. Technological Forecasting and Social Change, 198:122938.

Fiszeder, P., Małecka, M., and Molnár, P. (2024). Robust estimation of the range-based garch model: Forecasting volatility, value at risk and expected shortfall of cryptocurrencies. Economic Modelling, 141:106887.

Fong, K. Y. L., Holden, C. W., and Trzcinka, C. A. (2017). What Are the Best Liquidity Proxies for Global Research?*. Review of Finance, 21(4):1355–1401.

Han, S. (2023). Is liquidity risk priced in cryptocurrency markets? Applied Economics Letters, 30(17):2481–2487.

Hansen, P. R., Kim, C., and Kimbrough, W. (2024). Periodicity in Cryptocurrency Volatility and Liquidity. Journal of Financial Econometrics, 22(1):224–251.

Maciel, L., Ballini, R., Gomide, F., and Yager, R. (2022). Forecasting cryptocurrencies prices using data driven level set fuzzy models. Expert Systems with Applications, 210:118387.

Nasirtafreshi, I. (2022). Forecasting cryptocurrency prices using recurrent neural network and long short-term memory. Data Knowledge Engineering, 139:102009.

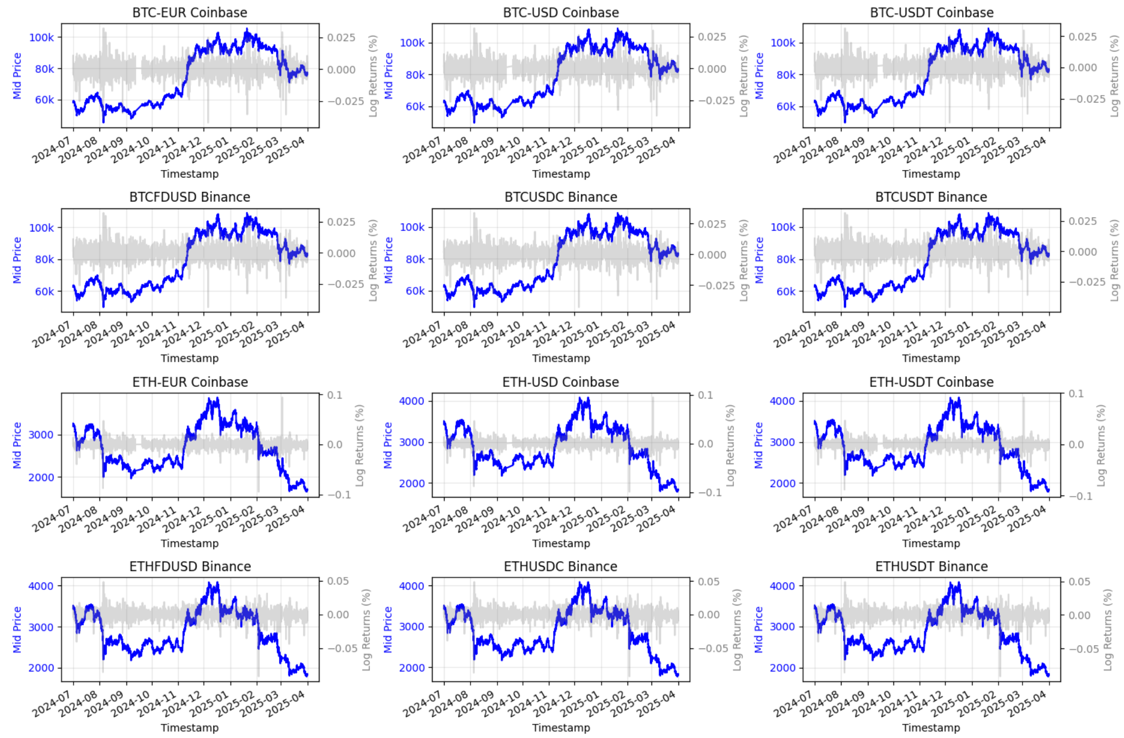
Tzeng, K.-Y. and Su, Y.-K. (2024). Can u.s. macroeconomic indicators forecast cryptocurrency volatility? The North American Journal of Economics and Finance, 74:102224.

Zaremba, A., Bilgin, M. H., Long, H., Mercik, A., and Szczygielski, J. J. (2021). Up or down? short-term reversal, momentum, and liquidity effects in cryptocurrency markets. International Review of Financial Analysis, 78:101908.

Zhang, W. and Li, Y. (2023). Liquidity risk and expected cryptocurrency returns. International Journal of Finance & Economics, 28(1):472–492.

# A Appendix

Figure A.1: Time series of mid prices for cryptocurrency and traditional currency pairs from July 1, 2024 to February 16, 2025.




Note: The chart shows the evolution of mid prices calculated as $(P^t_{\text{ask}} + P^t_{\text{bid}})/2$ for the analyzed market pairs. Cryptocurrency prices display higher volatility compared to the traditional currency pairs. All series are normalized to their initial values for comparison purposes.

Table A.1: Stationarity Test Results for Cryptocurrency Market Spreads

| Symbol | ADF | | DFGLS | | PP | | ZA | | KPSS | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Stat | p-val | Stat | p-val | Stat | p-val | Stat | p-val | Stat | p-val |
| Symbol | | | | | | | | | | |
| BTC-EUR Coinbase | -12.47 | 0.0 | -11.09 | 0.0 | -140.63 | 0.0 | -13.96 | 0.0 | 1.20 | 0.01 |
| BTC-USD Coinbase | -8.78 | 0.0 | -6.45 | 0.0 | -155.73 | 0.0 | -11.24 | 0.0 | 1.31 | 0.01 |
| BTC-USDT Coinbase | -16.93 | 0.0 | -10.71 | 0.0 | -80.78 | 0.0 | -17.47 | 0.0 | 0.55 | 0.01 |
| BTCFDUSD Binance | -11.71 | 0.0 | -11.59 | 0.0 | -182.80 | 0.0 | -12.29 | 0.0 | 0.52 | 0.01 |
| BTCUSDC Binance | -8.16 | 0.0 | -8.00 | 0.0 | -154.23 | 0.0 | -12.17 | 0.0 | 1.30 | 0.01 |
| BTCUSDT Binance | -14.61 | 0.0 | -6.92 | 0.0 | -196.81 | 0.0 | -15.43 | 0.0 | 0.83 | 0.01 |
| ETH-EUR Coinbase | -16.09 | 0.0 | -13.06 | 0.0 | -83.99 | 0.0 | -17.81 | 0.0 | 0.56 | 0.01 |
| ETH-USD Coinbase | -13.68 | 0.0 | -6.69 | 0.0 | -100.87 | 0.0 | -14.71 | 0.0 | 0.93 | 0.01 |
| ETH-USDT Coinbase | -15.74 | 0.0 | -12.87 | 0.0 | -132.75 | 0.0 | -16.55 | 0.0 | 0.53 | 0.01 |
| ETHFDUSD Binance | -11.32 | 0.0 | -5.17 | 0.0 | -169.32 | 0.0 | -11.88 | 0.0 | 0.34 | 0.01 |
| ETHUSDC Binance | -7.50 | 0.0 | -4.98 | 0.0 | -140.26 | 0.0 | -10.56 | 0.0 | 2.32 | 0.01 |
| ETHUSDT Binance | -11.03 | 0.0 | -4.20 | 0.0 | -199.37 | 0.0 | -11.34 | 0.0 | 0.41 | 0.01 |

Note: The table presents the results of stationarity tests for the spread series of 12 cryptocurrency markets. Both the Augmented Dickey-Fuller (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests were run. The ADF test consistently rejects the null hypothesis of a unit root for all series, while the KPSS test gives mixed results, with some markets showing signs of non-stationarity. These tests were performed on spreads calculated at 15-minute intervals, collected from 1 July 2024 to 31 March 2025.

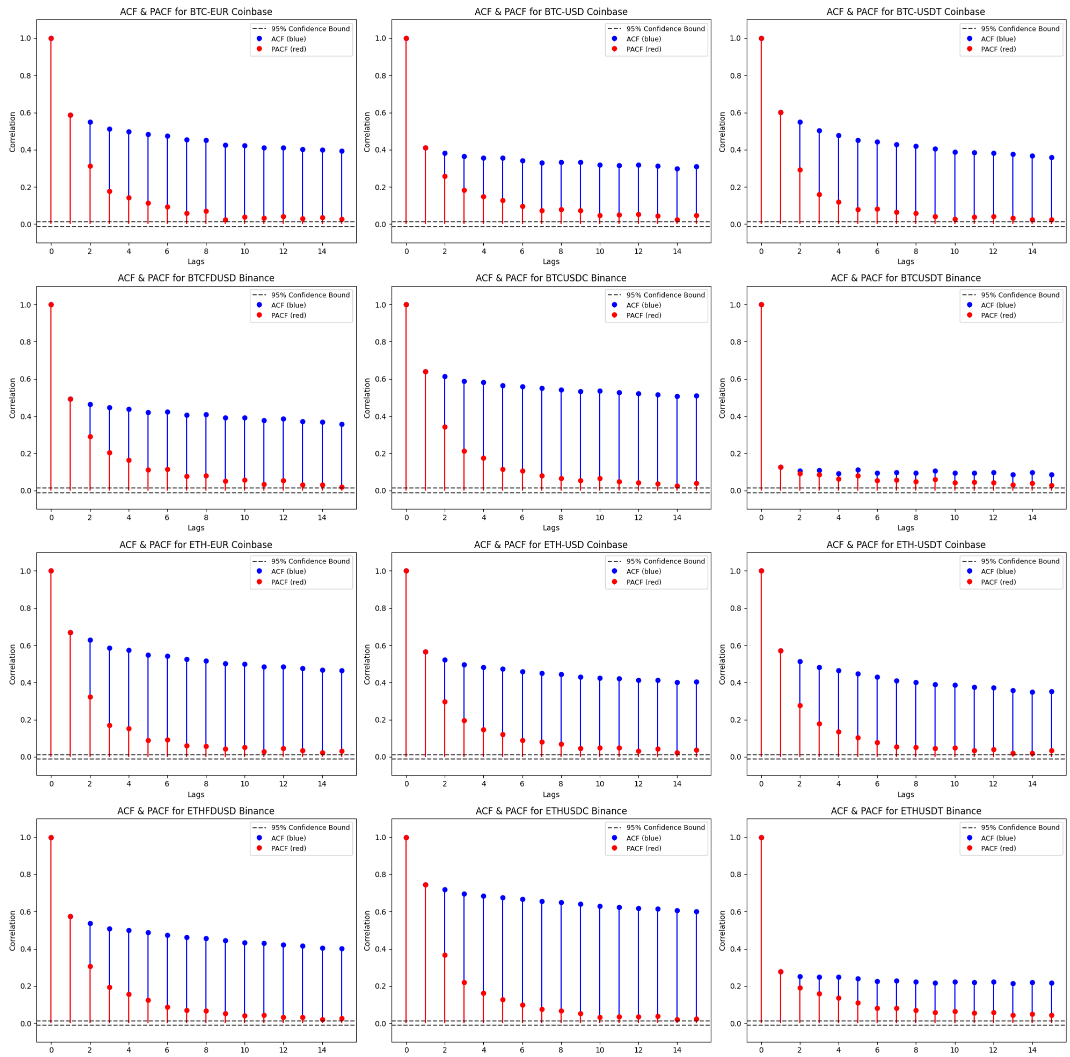


Table A.2: Results of the Box-Pierce and Ljung-Box Tests for Autocorrelation in Spread Series

| | Box-Pierce Stat | Box-Pierce p-value | Ljung-Box Stat | Ljung-Box p-value |
|---|---|---|---|---|
| Symbol | | | | |
| BTC-EUR Coinbase | 20427.45 | 0.0 | 20431.93 | 0.0 |
| BTC-USD Coinbase | 40414.08 | 0.0 | 40424.82 | 0.0 |
| BTC-USDT Coinbase | 22796.32 | 0.0 | 22800.14 | 0.0 |
| BTCFDUSD Binance | 45298.06 | 0.0 | 45310.39 | 0.0 |
| BTCUSDC Binance | 71069.75 | 0.0 | 71089.14 | 0.0 |
| BTCUSDT Binance | 4889.24 | 0.0 | 4890.56 | 0.0 |
| ETH-EUR Coinbase | 23845.75 | 0.0 | 23849.67 | 0.0 |
| ETH-USD Coinbase | 26605.78 | 0.0 | 26610.90 | 0.0 |
| ETH-USDT Coinbase | 8759.59 | 0.0 | 8761.13 | 0.0 |
| ETHFDUSD Binance | 47721.17 | 0.0 | 47733.93 | 0.0 |
| ETHUSDC Binance | 88257.49 | 0.0 | 88281.88 | 0.0 |
| ETHUSDT Binance | 10472.65 | 0.0 | 10475.42 | 0.0 |

Note: This table presents the test statistics and p-values from the Box-Pierce and Ljung-Box tests applied to the spread series of various cryptocurrency pairs (symbols). Both tests assess the presence of autocorrelation in the spread data up to a specified number of lags. These tests were performed on spreads calculated at 15-minute intervals, collected from 1 July 2024 to 31 March 2025.

Figure A.2: Partial Autocorrelation (PACF) Plots for Cryptocurrency Market Spreads




Note: The table shows the results of autocorrelation analysis for the spread series of 12 cryptocurrency markets using the Box-Pierce and Ljung-Box tests. Both tests indicate significant autocorrelation in the spread series, with p-values of 0.00 across all markets. This highlights the persistence of spread values over time and suggests predictive patterns within liquidity dynamics. These tests were performed on spreads calculated at 15-minute intervals, collected from from 1 July 2024 to 31 March 2025.

Figure A.3: Day-of-Week Analysis of Spread Patterns for Cryptocurrency Pairs

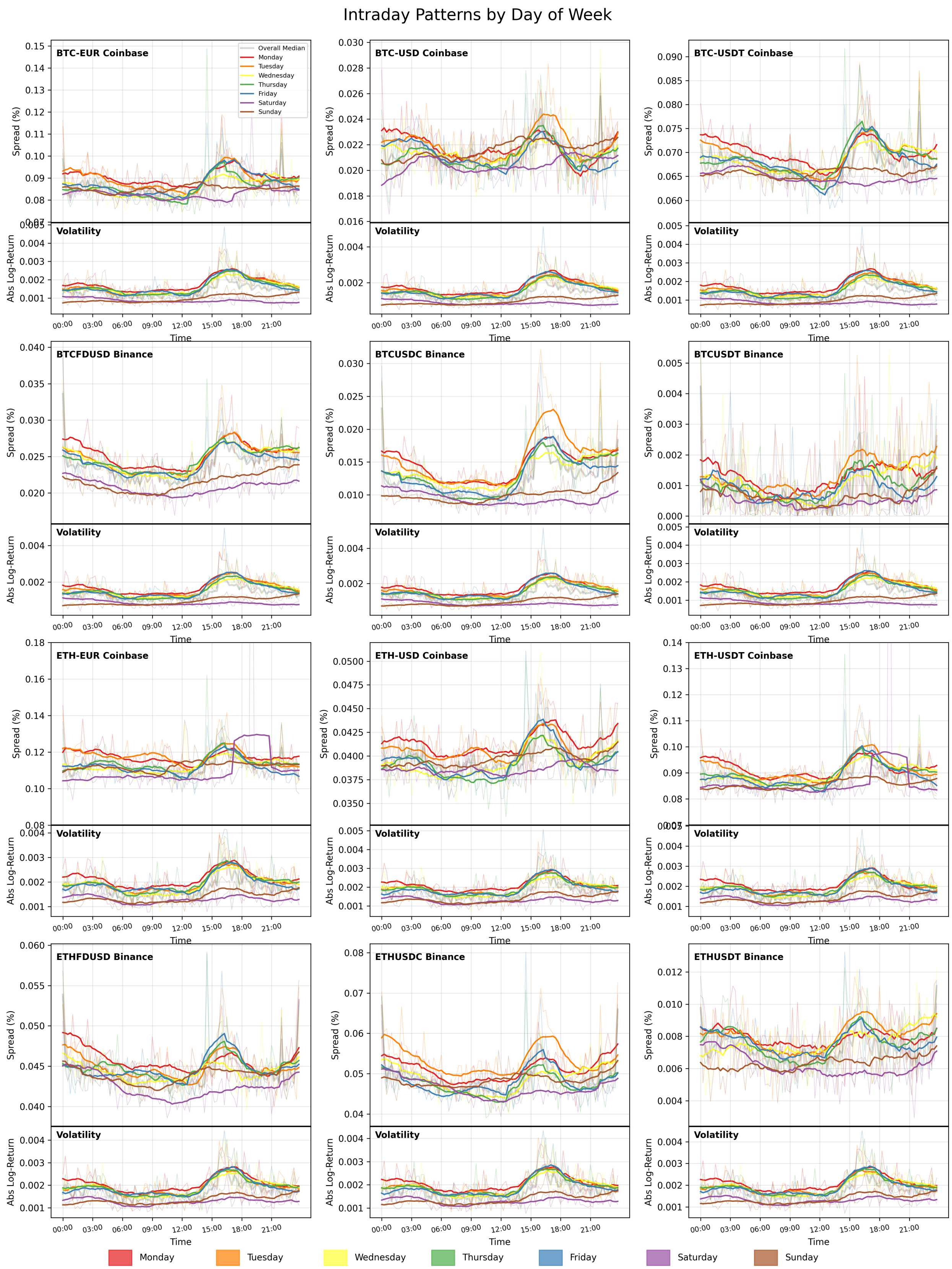


Table A.3: Stationarity Test Results for Cryptocurrency Market Log-Spreads

| Symbol | ADF | | DFGLS | | PP | | ZA | | KPSS | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Stat | p-val | Stat | p-val | Stat | p-val | Stat | p-val | Stat | p-val |
| BTC-EUR Coinbase | -7.66 | 0.00 | -6.24 | 0.00 | -164.22 | 0.0 | -12.16 | 0.00 | 0.94 | 0.01 |
| BTC-USD Coinbase | -12.15 | 0.00 | -9.46 | 0.00 | -194.13 | 0.0 | -13.30 | 0.00 | 0.12 | 0.09 |
| BTC-USDT Coinbase | -9.51 | 0.00 | -7.36 | 0.00 | -181.48 | 0.0 | -11.25 | 0.00 | 1.06 | 0.01 |
| BTCFDUSD Binance | -12.10 | 0.00 | -10.78 | 0.00 | -198.12 | 0.0 | -12.72 | 0.00 | 0.24 | 0.01 |
| BTCUSDC Binance | -9.84 | 0.00 | -9.84 | 0.00 | -210.24 | 0.0 | -12.12 | 0.00 | 1.00 | 0.01 |
| BTCUSDT Binance | -8.46 | 0.00 | -4.68 | 0.00 | -212.85 | 0.0 | -15.85 | 0.00 | 0.56 | 0.01 |
| ETH-EUR Coinbase | -8.49 | 0.00 | -8.49 | 0.00 | -164.50 | 0.0 | -11.90 | 0.00 | 0.75 | 0.01 |
| ETH-USD Coinbase | -9.64 | 0.00 | -3.02 | 0.00 | -195.71 | 0.0 | -11.06 | 0.00 | 1.12 | 0.01 |
| ETH-USDT Coinbase | -10.44 | 0.00 | -10.43 | 0.00 | -176.39 | 0.0 | -11.33 | 0.00 | 0.46 | 0.01 |
| ETHFDUSD Binance | -9.55 | 0.00 | -7.93 | 0.00 | -200.07 | 0.0 | -12.17 | 0.00 | 0.87 | 0.01 |
| ETHUSDC Binance | -5.94 | 0.00 | -4.57 | 0.00 | -200.36 | 0.0 | -8.07 | 0.00 | 3.45 | 0.01 |
| ETHUSDT Binance | -8.09 | 0.00 | -7.87 | 0.00 | -224.38 | 0.0 | -10.91 | 0.00 | 1.59 | 0.01 |

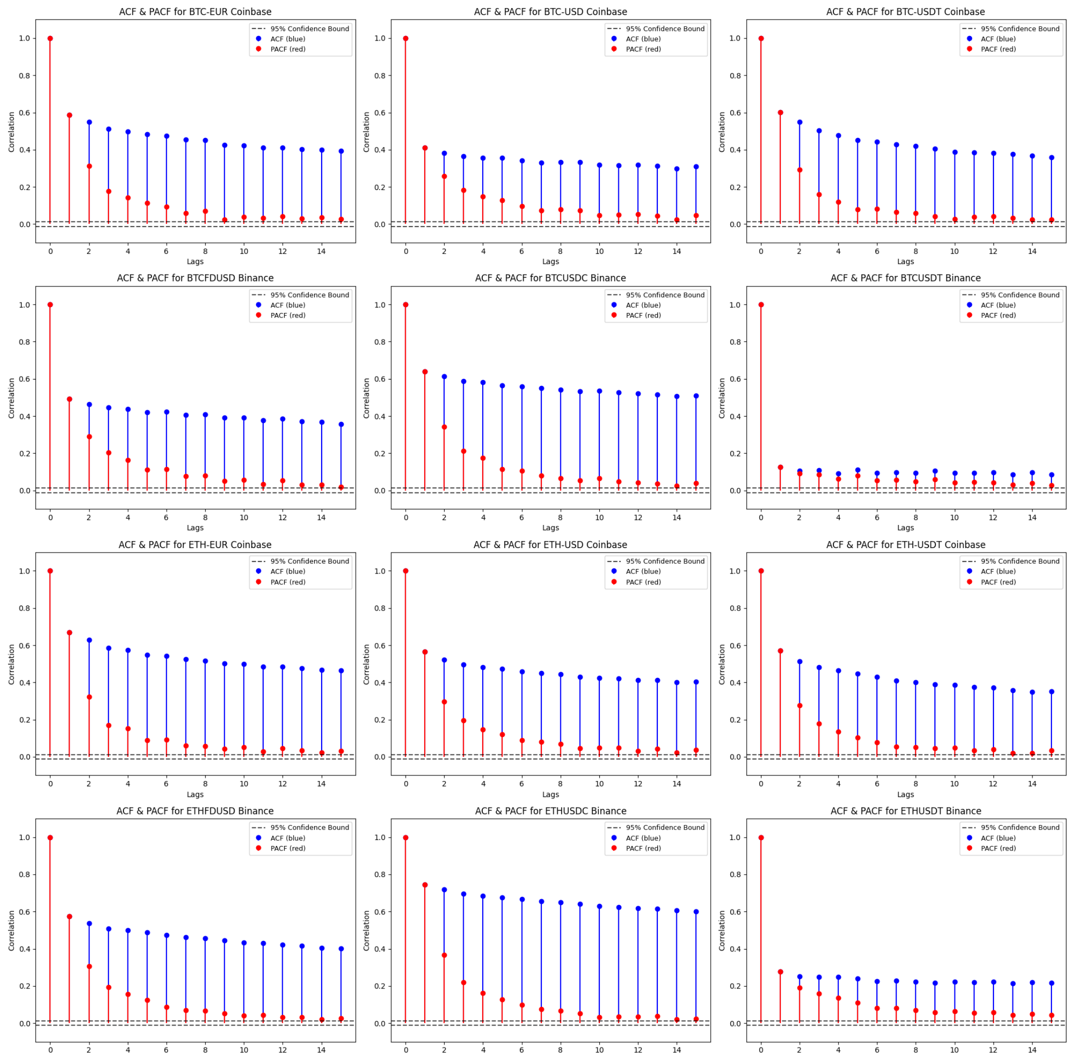
Note:

Table A.4: Results of the Box-Pierce and Ljung-Box Tests for Autocorrelation in Spread Series

| Symbol | Box-Pierce Stat | Box-Pierce p-value | Ljung-Box Stat | Ljung-Box p-value |
|---|---|---|---|---|
| BTC-EUR Coinbase | 70065.93 | 0.0 | 70086.17 | 0.0 |
| BTC-USD Coinbase | 9773.53 | 0.0 | 9776.21 | 0.0 |
| BTC-USDT Coinbase | 36909.35 | 0.0 | 36919.56 | 0.0 |
| BTCFDUSD Binance | 33251.93 | 0.0 | 33261.11 | 0.0 |
| BTCUSDC Binance | 30663.87 | 0.0 | 30672.48 | 0.0 |
| BTCUSDT Binance | 36945.82 | 0.0 | 36956.38 | 0.0 |
| ETH-EUR Coinbase | 56426.98 | 0.0 | 56442.87 | 0.0 |
| ETH-USD Coinbase | 27926.11 | 0.0 | 27933.98 | 0.0 |
| ETH-USDT Coinbase | 37809.88 | 0.0 | 37820.30 | 0.0 |
| ETHFDUSD Binance | 32144.03 | 0.0 | 32152.84 | 0.0 |
| ETHUSDC Binance | 55566.84 | 0.0 | 55582.72 | 0.0 |
| ETHUSDT Binance | 22205.16 | 0.0 | 22211.49 | 0.0 |

Note: This table presents the test statistics and p-values from the Box-Pierce and Ljung-Box tests applied to the spread series of various cryptocurrency pairs (symbols). Both tests assess the presence of autocorrelation in the spread data up to a specified number of lags. These tests were performed on spreads calculated at 15-minute intervals, collected from 1 July 2024 to 31 March 2025.

Figure A.4: Partial Autocorrelation (PACF) Plots for Cryptocurrency Market Spreads




Note: The table shows the results of autocorrelation analysis for the spread series of 12 cryptocurrency markets using the Box-Pierce and Ljung-Box tests. Both tests indicate significant autocorrelation in the spread series, with p-values of 0.00 across all markets. This highlights the persistence of spread values over time and suggests predictive patterns within liquidity dynamics. These tests were performed on spreads calculated at 15-minute intervals, collected from from 1 July 2024 to 31 March 2025.