Review of Quantitative Finance and Accounting
https://doi.org/10.1007/s11156-024-01304-1

ORIGINAL RESEARCH

# The crypto world trades at tea time: intraday evidence from centralized exchanges across the globe

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Accepted: 23 May 2024


## Abstract

It is a stylized fact that trading activity, volatility and liquidity in equity and other financial markets follow specific intraday patterns. These patterns are to a large extent determined by institutional features such as exchange trading hours or batch settlement procedures. We analyze the intraday patterns that emerge when these institutional constraints are absent. We compile a large sample of 1940 currency pairs traded on 38 cryptocurrency exchanges located on five continents. These exchanges operate 24 h a day, seven days a week, and settle trades instantly. We find that there are pronounced time-of-day patterns in trading activity, volatility and liquidity. These patterns are remarkably similar across exchanges, time zones and cryptocurrency pairs. Specifically, trading activity, volatility and illiquidity all peak between 16:00 and 17:00 Coordinated Universal Time (UTC), i.e. during U.K. tea time. We find that characteristics of the exchanges (such as their locations) and of the traded currency pairs (e.g. whether two pairs share a common currency) explain some, but not all of the commonality in intraday patterns.

We thank Christoph Bertsch (discussant), Chase P. Ross (discussant), Stefan Scharnowski and participants of the 6th Cryptocurrency Research Conference in Monaco, the 2023 annual meeting of the German Finance Association and the Economics of Financial Technology Conference 2023 for valuable comments. We gratefully acknowledge financial support from the University of Graz, Austria. Erik Theissen gratefully acknowledges financial support from Deutsche Forschungsgemeinschaft under grant TH 724/7-1.

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Published online: 10 June 2024

**Keywords** Cryptocurrencies · Seasonalities · Time-of-the-day patterns · Liquidity

**JEL Classification** G12 · G14

# 1 Introduction

## 1.1 Motivation

It is a well documented stylized fact that asset returns, trading activity, volatility, and liquidity on traditional financial markets follow specific intraday patterns (e.g. Harris 1986; McInish and Wood 1992; Chang et al. 2008; Heston and Sadka 2008). There are at least three reasons for these patterns to emerge. First, there are institutional features such as overnight trading halts that lead to specific intraday patterns. Private and public information accumulated overnight feeds into prices after market opening, resulting in higher trading activity, higher volatility, and lower liquidity. Similarly, traders' desire to close positions before the overnight trading halt leads to higher trading volume before and at the market close. Second, trader behavior may affect intraday patterns, possibly leading to regularities such as lower trading activity during lunchtime. Note that institutional features and trader behavior are locally determined and may thus vary across trading venues. Third, the flow of public and private information relevant to the value of an asset will affect intraday patterns. For example, trading activity and volatility will be higher at times of the day with more news events. The release of new information is independent of the specific trading venue and the traders operating there. The flow of new information can therefore be understood as a global determinant of possible intraday trading patterns.

For several reasons, cryptocurrency markets provide an ideal test bed for an in-depth analysis of intraday trading patterns and their possible unique (local) or common (global) determinants. These markets are open 24 h, seven days a week. Thus, there are no scheduled trading halts that affect intraday patterns. Second, transactions are not settled on a daily basis (as is the case in equity markets) but are rather settled immediately. Consequently, there is no pressure to trade at a specific time-of-the-day to avoid holding positions for an extended period of time (e.g., overnight). We conclude that if such institutional features were the main reason for intraday trading patterns, such regularities are unlikely to be observed in cryptocurrency markets.

Moreover, the same currency pairs (either cryptocurrency against cryptocurrency or cryptocurrency against fiat currency) are traded on a large number of exchanges on different continents and in different time zones. While the flow of information is the same across all trading venues, trader population and trader behavior are venue-specific. This allows us to decouple the effects on intraday patterns of trader behavior from those of the information flow. We conclude that if intraday trading patterns were predominantly caused by trader behavior, these regularities should be specific to the corresponding venue and we would find no pronounced commonality in intraday trading patterns. On the other hand, if the patterns were mainly due to (non site-specific) information flow, we would expect to find similar intraday patterns on different trading venues.

### 1.2 Research questions

Building on the preceding discussion we formulate the research questions of our paper as follows:

1. What are the time-of-day patterns observed in returns, volatility, liquidity, trading volume, transaction count, and average trade size across numerous cryptocurrency trading pairs listed on several global exchanges, and how do these patterns compare to previous findings, which primarily focused on return patterns in a limited set of cryptocurrencies?
2. To what extent can similarities in time-of-day patterns be attributed to specific features of trading pairs and venues, and what portion of these patterns is explained by broader market characteristics of the global cryptocurrency market?
3. How do additional features of trading pairs, such as the presence of dominant coins like bitcoin and ether, the inclusion of stablecoins or fiat currencies, and the reputation of the exchange, contribute to the (dis)similarity of time-of-day patterns across trading pairs?

### 1.3 Outline of the empirical approach and results

Our analysis proceeds as follows. We compile a large intraday data set covering 1940 trading pairs traded on 38 cryptocurrency exchanges around the globe. Note that these trading pairs are very diverse in that they include cryptocurrencies and stablecoins, both traded against each other and traded against fiat currencies. We thoroughly analyze the intraday patterns of returns, volatility, illiquidity, and trading activity. As a first step, we regress, separately for each trading pair, the variable of interest on a set of 24-h-of-day dummies. The de-meaned coefficients of these dummy variables are the basis for our analysis.

To describe the intraday patterns, we show figures for the overall average and the continent-specific averages of these coefficients. This allows us to gain a comprehensive overview of intraday trading patterns on cryptocurrency markets. In the second step we calculate the correlations between the coefficients for all combinations of trading pairs in our sample. We use this pairwise setting to analyze the extent to which the characteristics of the trading pairs, as well as the characteristics of the trading venue where the pairs are traded, affect the intraday patterns. Specifically, we use hierarchical cluster analysis to identify groups of trading pairs with similar intraday patterns. We further estimate regressions where pairwise correlations are regressed on variables that capture characteristics of the currency pair under consideration (e.g., does it contain a fiat currency?) and the venues where they are traded (e.g., are the venues located on the same continent?). The analysis enables us to identify variables that affect the similarity of the intraday patterns across trading venues and currency pairs. In particular, we focus on the relative importance of global and local factors determining intraday patterns.

Our results reveal that there are pronounced intraday patterns. Returns are lowest in the early morning hours (in Coordinated Universal Time, UTC) and highest in the early afternoon and evening. Trading volume, volatility and illiquidity are lowest in the early morning hours and in the evening and highest in the afternoon and around midnight. When we sort the trading pairs in our sample by venue location (Americas, Asia, Europe) we find that these patterns (again in UTC, not in local time) are strikingly similar, implying that the patterns are not primarily caused by local factors such as trader population or trader behavior. The correlations are higher for trading activity, volatility and liquidity than for returns.

Our regression analysis reveals that the intraday patterns are more highly correlated when the trading venues are on the same continent, when the time difference between the venue locations is lower, and when the currencies in the trading pair are similar (e.g. because they share a common currency, such as BTCETH and BTCXRP). Thus, and notwithstanding the high degree of commonality, local factors do play a role in shaping the intraday patterns.

### 1.4 Related literature, contributions and implications

There is not much theory to inform our empirical analysis. In their seminal paper on intraday patterns, Admati and Pfleiderer (1988) develop a theoretical model in which uninformed liquidity traders and informed insiders trade a risky asset. They show that liquidity traders have an incentive to pool their trades, i.e., to trade at the same time. This pooling of trades leads to a concentration of trading in particular periods during the day. The model further implies that volatility is higher during periods of concentrated trading. These patterns yield the predictions that there are periods of increased trading activities, and that volatility also peaks at these periods of concentrated trading. The logic of the Admati and Pfleiderer (1988) model extends to a multi-market setting. If the same asset is traded on different venues, liquidity traders will have an incentive to concentrate their trading on all venues at the same time. This, in turn, implies that the intraday patterns will be correlated across venues. To the extent that information arrival is correlated across currency pairs, we also expect correlated intraday patterns across currency pairs.

Our research is related to several strands of empirical literature. First, it is related to previous papers documenting intraday patterns in cryptocurrency markets, mainly for bitcoin only (e.g. Baur et al. 2019; Ben Omrane et al. 2023; Dyhrberg et al. 2018; Eross et al. 2019; Hansen et al. 2024; Petukhina et al. 2021; Su et al. 2022).[1] Our paper adds to this literature by considering a much larger sample in terms of the number of currency pairs and trading venues we analyze, and by including a broader set of explanatory variables in our analysis. Second, our research is related to studies of intraday patterns in financial markets more generally. Most of that literature relates to equity markets (e.g. the classical studies by Wood et al. (1985) and McInish and Wood (1992) or more recently Heston et al. (2010)). As mentioned earlier, the cryptocurrency markets we analyze differ from equity markets in that they operate 24 h a day, and because the same currency pairs are traded on various trading venues located in different time zones and continents. In this respect, foreign exchange (FX) markets are more similar to cryptocurrency markets than equity markets because they also operate 24 h a day. Of the papers that analyze intraday patterns in FX markets (e.g. Andersen and Bollerslev 1998; Baillie and Bollerslev 1991; Breedon and

[1] There is also a growing literature on calendar and day-of-the-week effects in cryptocurrencies (e.g. Aharon and Qadan 2019; Caporale and Plastun 2019; Dorfleitner and Lung 2018; Kaiser 2019; Kinateder and Papavassiliou 2021; Long et al. 2020; Ma and Tanizaki 2019; Qadan et al. 2021. Moreover, several papers deal with dynamic market linkages across cryptocurrencies. For example, Aslanidis et al. (2021), Bouri et al. (2021), Hu et al. (2019) and Shams (2022) examine the correlation of return and / or volatility correlations between several cryptocurrencies and find that there are strong and increasing market linkages for both variables over time. Hasan et al. (2022) and Tripathi et al. (2021) focus on commonality in liquidity and document a significant presence of linkages in cryptocurrency markets. However, none of these papers uses intraday observations to examine cryptocurrency linkages or identifies potential determinants over the course of a day.

Ranaldo 2013; Ito and Hashimoto 2006; Ranaldo 2009), two are of particular relevance. Ranaldo (2009) analyzes six fiat currency pairs and identifies return patterns related to local business hours. In contrast, Baillie and Bollerslev (1991) report that intraday patterns in FX volatility are similar across currencies and are related to the opening hours of major financial markets. Our results are more similar to those of Baillie and Bollerslev (1991), as we document that intraday patterns are remarkably similar across trading venues in different continents and time zones. However, we note that our setting is different because our sample contains data for the same currency pairs from different trading venues. By contrast, all previous papers on intraday patterns in FX markets analyze only one time series per currency pair.

Our paper improves our understanding of intraday patterns that are ubiquitous in financial markets. It provides the most comprehensive analysis of intraday patterns in cryptocurrencies to date. Since there are no trading halts in cryptocurrency markets, the existence of pronounced intraday patterns in these markets implies that intraday patterns in returns, trading activity, volatility, and liquidity are not driven solely by trading frictions such as the overnight and weekend trading halts. The similarity of intraday patterns across geographic regions and time zones that we document suggests that asset-specific determinants such as information flow are more important than local factors such as trader population or trader behavior.

Our findings may be relevant for both market participants and operators of trading venues. First, the findings on intraday patterns in different market data categories have significant implications for traders. For example, day traders need to select optimal trading windows, with their strategies depending on market conditions characterized by varying volatility and liquidity. Similarly, institutional investors, such as bitcoin spot ETF providers, need to consider current trading volume and liquidity to effectively manage fund rebalancing requirements. Second, a comprehensive examination of daily patterns across different trading venues can reveal the information value of trading activity emanating from specific exchanges and provide insights into information shares and price discovery mechanisms. Consequently, prioritizing the monitoring of specific exchanges over arbitrary data feeds can provide a strategic advantage in trading decisions. Thirdly, trading venues themselves must be able to cope with increased demand at exceptional times during the trading day. In addition, temporal patterns observed in cryptocurrency markets may correlate with exogenous, synchronously recurring events in traditional financial markets, such as the settlement conventions for derivatives on cryptocurrencies like bitcoin and ether. Deciphering and establishing the relationship between these phenomena is crucial for navigating the cryptocurrency markets.

The remainder of the paper is organized as follows. In Sect. 2 we describe the data used in the empirical analyses, Sect. 3 outlines the methodology. The results are presented in Sects. 4, and 5 concludes.

## 2 Data

We source our data from www.cryptotick.com, a commercial vendor of high quality cryptocurrency data. We add to existing literature on cryptocurrency time-of-day patterns by studying a comprehensive data set on an hourly resolution. Our data includes observations for opening (O), high (H), low (L), and closing (C) prices as well as the trading volume (V) and the total number of transactions (Tx). The sample period extends from July 1 00:00, 2018 to January 1 24:00, 2022 and covers 1281 trading days (30,744 h). At the beginning of the sample period, the raw data set includes 8598 trading pairs traded on 74 exchanges. Due to the issuance of new cryptocurrencies and the emergence of new trading venues the sample increases over time. At the end of the sample period on January 1, 2022, it includes 25,408 trading pairs traded on 120 exchanges. A "trading pair" is defined at the currency pair—exchange level. If the same currency pair is traded on multiple venues (which is often the case), it will be included several times in our data set.

We apply several filters to our data set. First, for a trading pair to be included in the sample we require that at least 75% (23,058 out of 30,744) hourly observations of O/H/L/C/V/Tx are available. Second, we use the rating information available from coinmarketcap.com and coingecko.com which can be retrieved at https://coinmarketcap.com/rankings/exchanges/ and https://www.coingecko.com/en/exchanges, respectively. We discard data from unrated trading venues and data from venues with a poor rating (below 2/10 from both rating providers). We do so in order to remove from our sample exchanges that report inflated trading volume figures (see Hougan et al. 2019).

The final data set comprises 1940 trading pairs traded on 38 exchanges around the globe. Table 1 lists the 38 venues and includes information about their ratings, the number of trading pairs included in our sample, the number of trading pairs that include bitcoin (BTC), ether (ETH), or a fiat currency as one currency, the country where the trading venue is located, and the difference between local time and UTC.

Of the 38 trading venues, 10 are located in North and South America, 19 in Asia and Oceania, and 9 in Europe. The majority of trading pairs in our sample are traded in Asian trading venues (1518 out of 1940), while 254 (168) are traded in venues in the Americas (Europe). We also note that the sample includes 386 different cryptocurrency coins or tokens, including 23 fiat currencies and stablecoins. Note that we 'un-wrap' wrapped versions of a coin, e.g. the pair WETHUSDT will enter the data set as ETHUSDT.

Over the course of the sample period of 3 years and a half, the crypto market has evolved substantially.[2] We address the representativity of the sample by referring to coinmarketcap's historical snapshots of the state of the cryptomarket.[3] Based on historical snapshots of the 200 largest coins in terms of market capitalization as of July 2018, July 2019, July 2020, July 2021 and January 2022 our data set covers 153/142/109/98/84 of the largest 200 coins accounting for 97/97/94/90/83 percent of the total market capitalization and 99/99/97/91/86 percent of the total trading volume.

## 3 Methodology

We use our data on open, high, low and closing prices as well as trading volume and the number of transactions to calculate hourly measures of return, volatility, illiquidity, and trading activity. Specifically, we calculate the following variables.

[2] For instance, top coins of the past have completely disappeared while during the crypto bull market of mid 2021 (the end of the sample period) some new projects such as Solana, Polkadot, Terra, and Avalanche have quickly made it to the top100 coins.

[3] Available at https://coinmarketcap.com/historical/.

**Table 1** Properties of exchanges in the sample

| | Exchange | CMC | CG | Pairs | BTC | ETH | Fiat | Country | UTC |
|---|---|---|---|---|---|---|---|---|---|
| 1 | BIBOX | 3.8 | 7 | 49 | 17 | 18 | 17 | Hong Kong | 8 |
| 2 | BINANCE | 9.9 | 10 | 284 | 120 | 75 | 60 | China | 8 |
| 3 | BITBANK | 5.1 | 9 | 5 | 2 | 1 | 4 | Japan | 9 |
| 4 | BITFINEX | 7.3 | 10 | 52 | 22 | 8 | 33 | Hong Kong | 8 |
| 5 | BITFOREX | 4.2 | 7 | 42 | 10 | 11 | 24 | Hong Kong | 8 |
| 6 | BITHUMB | 6.5 | 8 | 49 | 1 | 1 | 49 | South Korea | 9 |
| 7 | BITSO | 4.7 | 10 | 10 | 3 | 2 | 8 | Mexico | − 7 |
| 8 | BITSTAMP | 7.0 | 9 | 15 | 6 | 3 | 11 | Luxembourg | 1 |
| 9 | BITTREX | 6.0 | 10 | 93 | 65 | 11 | 23 | U.S. Seattle | − 8 |
| 10 | BTCBOX | 3.5 | 6 | 1 | 1 | 0 | 1 | Japan | 9 |
| 11 | BTCMARKETS | N/A | 6 | 4 | 1 | 1 | 4 | Australia | 11 |
| 12 | BW | 2.4 | 5 | 8 | 1 | 1 | 8 | Australia | 11 |
| 13 | CEXIO | 4.5 | 7 | 13 | 6 | 3 | 11 | U.K. | 0 |
| 14 | COINBASE | 8.4 | 10 | 40 | 12 | 5 | 32 | U.S. San Fran | − 7 |
| 15 | COINFLOOR | 2.9 | N/A | 1 | 1 | 0 | 1 | U.K. | 0 |
| 16 | COINMATE | 3.8 | N/A | 2 | 2 | 0 | 2 | U.K. | 0 |
| 17 | COINONE | 6.4 | 7 | 8 | 1 | 1 | 8 | South Korea | 9 |
| 18 | CREX24 | 2.6 | 4 | 3 | 3 | 1 | 0 | Cyprus | 2 |
| 19 | EXMO | 4.4 | 9 | 96 | 29 | 12 | 62 | U.K. | 0 |
| 20 | GATEIO | 7.5 | 10 | 82 | 8 | 8 | 69 | China | 8 |
| 21 | GEMINI | 7.1 | 10 | 6 | 2 | 2 | 5 | U.S. New York | − 5 |
| 22 | HITBTC | 4.2 | 6 | 140 | 64 | 36 | 47 | Hong Kong | 8 |
| 23 | HUOBIPRO | 7.4 | 10 | 400 | 184 | 137 | 74 | Hong Kong | 8 |
| 24 | INDEPENDENTRESERVE | 4.1 | 7 | 2 | 1 | 1 | 2 | Australia | 11 |
| 25 | ITBIT | 0.1 | 4 | 2 | 1 | 1 | 2 | U.S. | − 7 |
| 26 | KRAKEN | 7.9 | 10 | 54 | 20 | 6 | 35 | U.S. San Fran | − 7 |
| 27 | KUCOIN | 7.7 | 10 | 142 | 92 | 32 | 22 | Singapore | 8 |
| 28 | LUNO | 4.5 | 7 | 4 | 4 | 0 | 4 | Singapore | 8 |
| 29 | MERCADOBITCOIN | 4.3 | 7 | 2 | 1 | 0 | 2 | Brazil | − 3 |
| 30 | OKEX | 6.6 | 10 | 192 | 70 | 34 | 89 | Hong Kong | 8 |
| 31 | POLONIEX | 6.3 | 8 | 43 | 24 | 5 | 19 | U.S. San Fran | − 7 |
| 32 | SOUTHXCHANGE | 2.3 | 4 | 2 | 2 | 0 | 0 | Argentina | − 3 |
| 33 | THEROCKTRADING | 3.8 | 6 | 5 | 2 | 1 | 4 | Italy | 1 |
| 34 | TIDEX | 4.0 | 6 | 2 | 2 | 1 | 0 | U.S. San Fran | − 7 |
| 35 | UPBIT | 6.1 | 8 | 51 | 4 | 1 | 49 | South Korea | 9 |
| 36 | YOBIT | 2.4 | 4 | 29 | 12 | 4 | 18 | Russia | 3 |
| 37 | YUNEX | 1.7 | 3 | 2 | 1 | 0 | 2 | China | 8 |
| 38 | ZAIF | 5.8 | 7 | 5 | 1 | 1 | 5 | Japan | 9 |
| | | | | 1940 | 798 | 424 | 806 | | |

This table presents details on the exchanges used in the empirical analyses. The table presents each exchange's coinmarketcap.com's spot exchange rating (CMC, max 10) and coingecko.com's exchange trust score (CG, max 10) as of April 13, 2022. Furthermore, it shows the number of total trading pairs in the data set coming from each exchange (Pairs), the number of pairs including bitcoin (BTC), ether (ETH) and fiat or tokenized fiat (Fiat) as one of the currencies in each pair. The last two columns report the country of the respective exchange (according to cryptocompare.com) and the time zone relative to Coordinated Universal Time (UTC)

1. Hourly log returns $R_t = \log(C_t/C_{t-1})$, where $C_t$ denotes the closing price in interval $t$.
2. The Garman and Klass (1980) volatility estimator[4] $\hat{\sigma}_t = \sqrt{0.5 \cdot (\ln(H_t/L_t))^2 - (2 \cdot \ln(2) - 1) \cdot (\ln(C_t/O_t))^2}$, where $O_t$, $H_t$, $L_t$ and $C_t$ denote the respective hourly opening, high, low and closing prices in interval $t$.
3. The Corwin and Schultz (2012) estimator (CS) of the percentage bid-ask spread.[5] The CS estimator is calculated from the high and low prices of two adjacent hourly intervals $t, t+1$ as $CS_{t,t+1} = \frac{2(\exp(\alpha)-1)}{1+\exp(\alpha)}$, where $\alpha = (1+\sqrt{2}) \cdot (\sqrt{\beta} - \sqrt{\gamma})$, $\beta = \left[\ln\left(\frac{H_t}{L_t}\right)\right]^2 + \left[\ln\left(\frac{H_{t+1}}{L_{t+1}}\right)\right]^2$, $\gamma = \left[\ln\left(\frac{H_{t,t+1}}{L_{t,t+1}}\right)\right]^2$. $H_t$ and $L_t$ denote the high and low prices in interval $t$, while $H_{t,t+1}$ and $L_{t,t+1}$ refer to the high and low price of two adjacent intervals $t$ and $t+1$. We follow Corwin and Schultz (2012) and set negative values of the proxy to zero. The $CS_t$ estimator for period $t$ is then calculated as $(CS_{t-1,t} + CS_{t,t+1})/2$
4. The total hourly log-trading volume in interval $t$, $\log(V_t)$
5. The number of transactions in interval $t$, $Tx_t$.
6. The average trade size, defined as $V_t/Tx_t$, in interval $t$.

The resulting time series are denoted by $X_{t,i}^{(m)}$, where $t = \{1, 2, \dots, 30744\}$ denotes the hourly interval, $i = \{1, 2, ..., 1940\}$ denotes the trading pair and $(m)$ denotes the respective variable. To facilitate comparison across the markedly heterogeneous time series we de-trend them (by removing a linear trend[6]), de-mean them and divide them by their respective standard deviation. We denote the resulting normalized time series as $x_{t,i}^{(m)}$. Note that the resulting time series will uniformly feature a zero mean and unit variance while preserving the respective intraday structure. Hence, even highly heterogeneous trading pairs will be forwarded to further analyses on a level data basis. In the next step we regress, in the tradition of French (1980) and Gibbons and Hess (1981), the normalized time series of hourly observations on a set of dummy variables representing the 24 h of the trading day, i.e.

$$x_t = \sum_{j=1}^{24} \beta_j \cdot D_j + \epsilon_t. \tag{1}$$

The dummy variable $D_j$, with $j = \{1, 2, ..., 24\}$, takes the value 1 if $t \equiv j - 24(\mod -24)$ (in other words, if $t$ is an observation from hour $j$) and zero otherwise, and $\epsilon_t$ is the error term. This regression delivers, for each of the 1,940 trading pairs and six variables, a time series of 24 coefficients which capture the intraday pattern for the trading pair and variable under consideration. These sets of 24 coefficients are the basis for our analysis.

[4] We opt for this OHLC based volatility estimator as it is more efficient than e.g. the Parkinson (1980) measure. Furthermore, as there are no overnight trading halts and related jumps, we do not resort to the Garman-Klass Yang-Zhang extension or Yang and Zhang (2000) estimators either.

[5] We opt for the Corwin and Schultz (2012) spread estimator because Brauneis et al. (2021) show that it performs best in capturing time series variations in cryptocurrency liquidity.

[6] We get virtually identical results when not detrending the data.

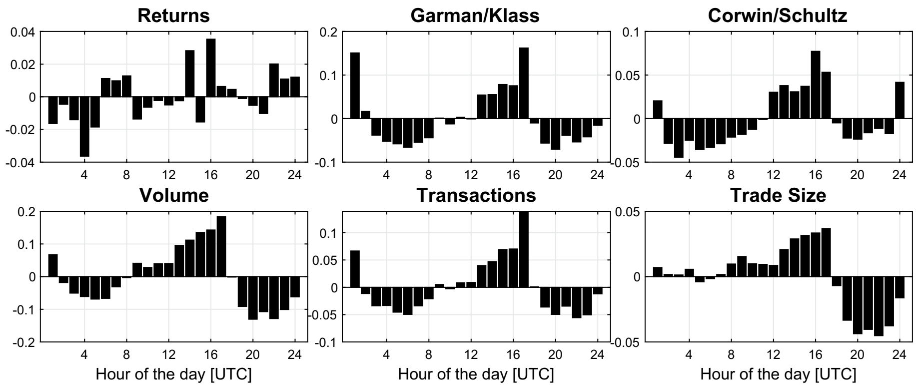


**Fig. 1** Time-of-the-day patterns. This figure reports simple averages of the coefficients of the dummy variable regressions defined in Eq. (1) for the six measures returns, volatility (Garman/Klass), liquidity (Corwin/Schultz), log-trading volume, the number of transactions and the average trade size. Hours refer to Coordinated Universal Time (UTC). E.g., hour 4 covers the period 03:00 to 04:00 UTC

## 4 Results

### 4.1 Hour of the day patterns

We start by plotting simple averages of the coefficients derived from Eq. (1) for the entire sample. We deliberately abstain from weighting the sets coefficients—e.g. by trading volume of the respective pair—in order to derive an overall time-of-the-day pattern rather than one that is mainly driven by a few heavily traded pairs. Figure 1 shows the results for each of the six measures.

We find that returns tend to be below average over the course of the day from 1:00 to 5:00 UTC and reach their peak between 15:00 and 16:00 UTC. This corresponds to the time window during which the major stock exchanges in the U.S. and Europe are simultaneously open. Returns are also positive in the last 3 h of the day.

For the remaining five measures, we find very clear and broadly similar intraday patterns. Volatility, illiquidity, trading volume, and the number of transactions are uniformly below average in the first third of the day in UTC (except for the first hour). This corresponds to the period when European and U.S. stock markets are closed. Trading volume and the number of transactions develop very similarly in this interval, an observation which is mirrored in the fact that the average trade size is close to the daily average. Between 08:00 and 12:00 UTC all five variables are close to zero. Thereafter, however, the values for all variables increase steadily, peaking between 16:00 and 17:00 UTC (the only exception being the Corwin/Schultz spread estimator that peaks between 15:00 and 16:00 UTC). Obviously, most trading activity in cryptocurrency markets occurs around London tea time (late morning in New York) and is accompanied by high volatility and low market liquidity.[7] The finding that liquidity

[7] Note that in this time interval, the most important daily cryptocurrency reference rates like the CME CF Reference Rates are calculated and published. See: https://www.cmegroup.com/markets/cryptocurrencies/cme-cf-cryptocurrency-benchmarks.html.

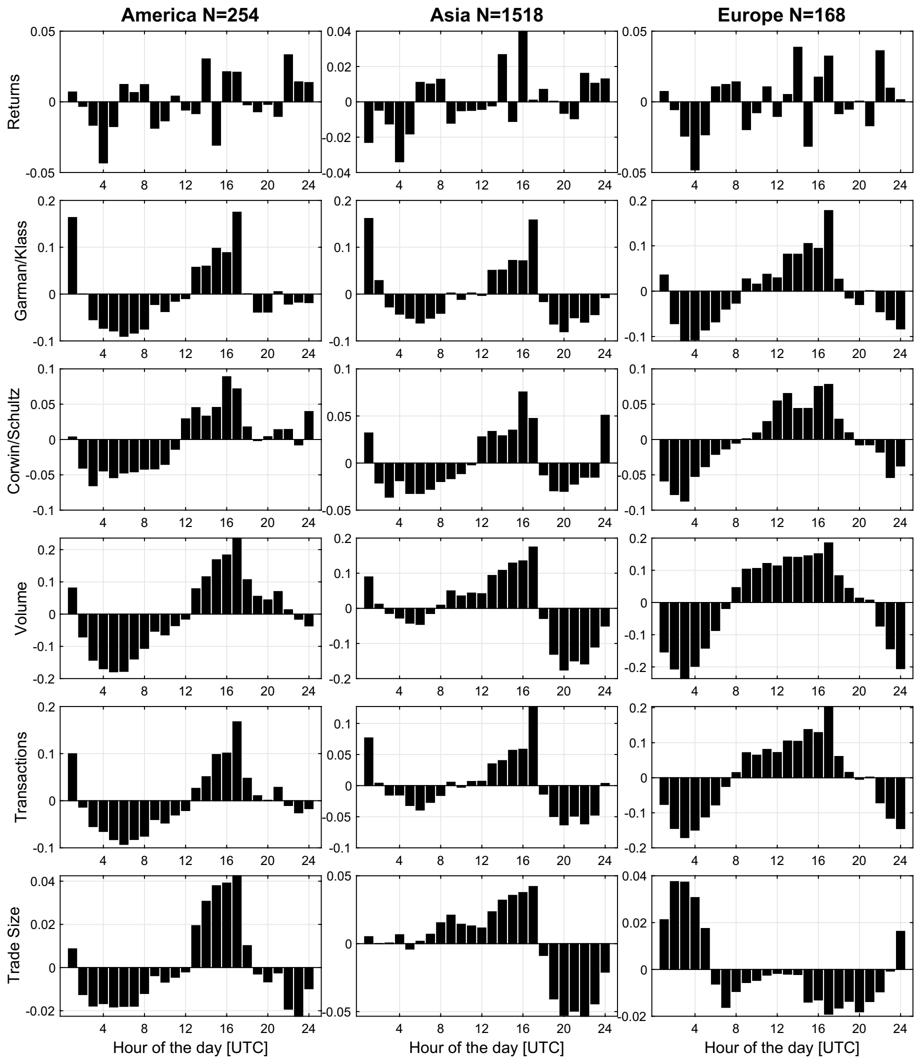


**Fig. 2** Time-of-the-day patterns per continent. This figure reports simple averages of the coefficients of the dummy variable regressions defined in Eq. (1) for the six measures returns, volatility (Garman/Klass), liquidity (Corwin/Schultz), log-trading volume, the number of transactions and the average trade size. Results are grouped by location, i.e. the continent in which the headquarters of the respective stock exchange is located. Hours refer to Coordinated Universal Time (UTC). E.g., hour 4 covers the period 03:00 to 04:00 UTC

is low when volume is high confirms the results reported in Brauneis et al. (2022) and Dyhrberg et al. (2018), among others. The observation that trading activity and volatility peak simultaneously is consistent with the Admati and Pfleiderer (1988) model. The remaining hours of the day are characterized by below-average values of volatility and trading activity, as well as increased liquidity.

**Table 2** Average correlations of dummy variable sets

| | Returns | | | Garman/Klass | | |
|---|---|---|---|---|---|---|
| | America | Asia | Europe | America | Asia | Europe |
| America | 0.2056 | 0.1385 | 0.2229 | 0.6227 | 0.5404 | 0.4979 |
| Asia | | 0.1393 | 0.1413 | | 0.5489 | 0.4167 |
| Europe | | | 0.2521 | | | 0.6178 |
| | Corwin/Schultz | | | Volume | | |
| America | 0.4550 | 0.3723 | 0.3230 | 0.5707 | 0.3535 | 0.3716 |
| Asia | | 0.3949 | 0.2517 | | 0.5321 | 0.3531 |
| Europe | | | 0.3865 | | | 0.6593 |
| | Transactions | | | Trade Size | | |
| America | 0.5139 | 0.3898 | 0.3822 | 0.1336 | 0.1200 | -0.0130 |
| Asia | | 0.4277 | 0.3513 | | 0.2241 | 0.0385 |
| Europe | | | 0.7333 | | | 0.0349 |

This table reports average correlations of dummy coefficient sets for tradings pairs in American, Asian and European exchanges and for each of the six figures—returns, volatility, liquidity, volume, transactions and trade size, respectively. The value 0.2056 in column 1/line 1 denotes the average correlation of dummy coefficient sets for returns for all pairs traded in American venues, while 0.2229 in column 3/line 1 denotes the average correlation of dummy coefficient sets for returns of American vs. European trading pairs

We next calculate, for each of our six measures of returns, volatility, liquidity and trading activity, simple averages of the time-of-day dummies at the continent level. Figure 2 shows the results.

The intraday patterns bear striking similarities across continents. The lowest returns are always observed in the early morning hours (UTC), the highest returns in the early afternoon and late evening. Volatility, trading volume, the number of transactions and illiquidity have, with few exceptions, similar intraday patterns. They have a peak in the first hour of the day (Europe is an exception here), then are below their respective means until lunchtime, peak in the afternoon and are again below their means in the evening. Despite these similarities, there are also patterns which relate to local time, in particular for trading volume and the number of transactions. These variables tend to take on their lowest values at night time in the respective continent, that is, evening UTC time for Asia, night time UTC for Europe and early morning UTC for the Americas. In spite of these regional differences, though, trading activity as well as volatility and illiquidity peak in afternoon UTC, at U.K. tea time.

Figure 2 provides initial evidence that the intraday patterns in trading activity, volatility and illiquidity that emerge at trading venues around the globe share many similarities. There is thus pronounced commonality in the intraday trading patterns of cryptocurrency markets. We note, though, that the intraday patterns are also affected by local factors such as the time zone the venue is located in. We will provide a more detailed analysis of our observed intraday patterns in the subsequent sections.

## 4.2 Correlations

To analyze the extent and the determinants of the commonality in intraday patterns more formally we need a quantitative measure of the similarities of the intraday patterns. An intuitive measure is the correlation between the 24 h-of-day dummies for two trading pairs. All subsequent analyses are therefore based on the $1940 \times 1940$ correlation matrix of dummy coefficient sets. This matrix holds a total of $1940 \cdot (1940 - 1)/2 = 1{,}880{,}830$ unique correlation coefficients for each of the six measures.

In a first step, we arrange the correlation matrix into a 3-by-3 grid of all trading pairs from American, Asian and European trading venues and then report the average correlation for each of the nine cells. The results are shown in Table 2. The figures on the diagonal are the mean correlations for trading pairs from the same continent while the off-diagonal elements show cross-continent averages.

The correlations are generally lowest for returns and average trade size, both within and across continents. The correlations for volatility, trading volume and the number of transactions are much larger. Unsurprisingly, the within-continent correlations are always higher than the across-continent correlations. These findings fully confirm our earlier results that there is strong commonality in the intraday patterns of trading activity, volatility and illiquidity, and that local (continent-specific) factors also play a role in shaping the intraday patterns. European trading venues have the highest within-continent correlations for returns, trading volume, and transactions, while trading venues in the Americas have the highest commonality for volatility and liquidity. Across continents, correlations are highest between exchanges in Asia and the Americas (Europe and the Americas) for volatility, liquidity, the number of transactions and trade size (returns and trading volume).

In the next step, we examine average correlations at a lower level of aggregation. Specifically, we report exchange-level mean correlations. Figure 3 shows the results for returns, similar figures for the other measures can be found in the appendix (Figs. 5, 6, 7, 8, 9).

Green (red) color indicates positive (negative) correlations. More intense colors and larger circles mean higher numerical values of the correlations. The overall color is light

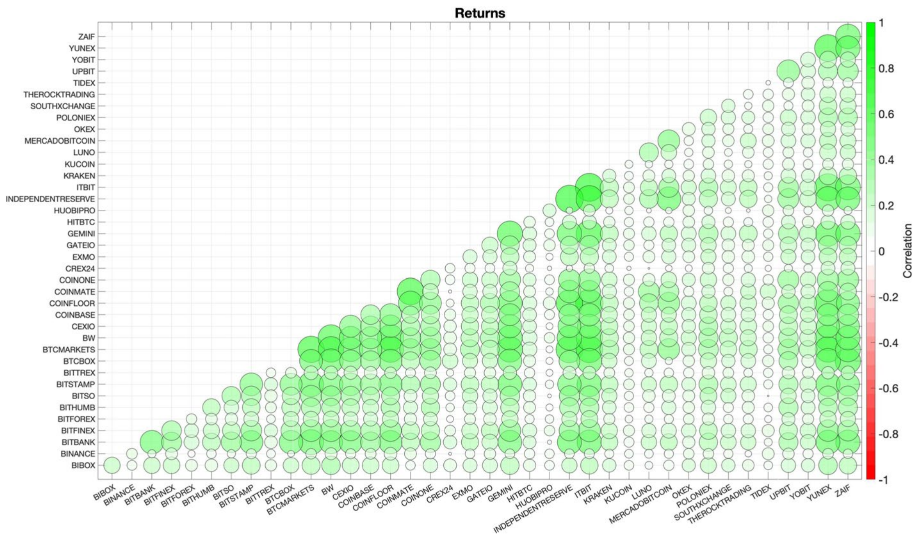


**Fig. 3** Average returns correlations across exchanges. This figure shows average correlations of dummy variable sets for each exchange (diagonal bubbles in the plot) and average correlations of dummy variable sets across individual exchanges (off-diagonal bubbles in the plot)

green, confirming our earlier evidence of moderately positive correlation between the intraday patterns of returns. However, there are individual exchanges (such as BTCMARKETS, INDEPENDENTRESERVE, ITBIT, YUNEX, or ZAIF) that have much higher positive correlations with most other trading venues.

Considering the figures for volatility, illiquidity and trading activity in the appendix, we find much higher average correlations. While this holds for almost all exchange pairs for volatility, there are some notable exceptions for the intraday patterns in liquidity and trading activity. For these measures there are some exchanges that have intraday patterns which are negatively correlated with those of other trading venues. An important question that arises in this context is whether we can identify determinants of the degree of commonality in intraday patterns between trading pairs. We address this question in the following sections.

### 4.3 Correlation clustering

So far, we have only considered bivariate correlations between intraday patterns of two trading pairs. We now go one step further and analyze, separately for each of our six variables, how similar the correlations are between two trading pairs and the 1938 other trading pairs. For this purpose, we use (agglomerative) hierarchical cluster analysis. In doing so, we proceed as follows. We start from the 1940 by 1940 matrix **C**, which contains the correlations between the intraday patterns of our trading pairs, and consider two trading pairs labelled $j$ and $k$. Let $c_j$ and $c_k$ be the $j^{th}$ and $k^{th}$ rows of **C**, respectively. $c_j$ ($c_k$) contains the correlations between the intraday patterns for the $j$ ($k$) trading pair and all 1940 trading pairs in our sample. We then calculate the Euclidean distance[8] between $c_j$ and $c_k$ as

$$d^2_{j,k} = (c_j - c_k) \cdot (c_j - c_k)'.$$

This procedure is repeated for all $1940 \cdot 1939/2$ distinct trading pairs. The hierarchical clustering algorithm then selects the two pairs with the lowest distance metric into a group A. It then considers the second-lowest distance. If this distance is between a trading pair that is not included in group A and one of the two pairs in group A, this third pair is added to group A. If the second-lowest distance is between two pairs which are both not included in group A, then these two pairs form a second group B. In each further step, the algorithm can either add an element to an existing group, form a new group, or merge two existing groups. The latter operation requires a measure of the distance between groups.[9] If the algorithm is not stopped, it continues until all trading pairs form a single large group. Two procedures allow the algorithm to be stopped. Either one defines a threshold for the distance metric and the algorithm stops when all remaining distances are above that threshold. Alternatively, one can pre-define the number of clusters to be created. We opt for the second approach and choose a number of five clusters.[10]

[8] Hierarchical cluster analysis can also be performed with other distance metrics. We choose Euclidean distance because of its intuitive appeal.

[9] There are several alternatives. We opt for the complete linkage procedure (Macnaughton-Smith 1965), which assigns to two groups a distance equal to the maximum of the distances of the elements within the groups. We have also implemented alternative procedures (e.g. the minimum distance as well as the average distance of the elements within the groups) and found that they yield qualitatively similar results.

[10] We repeated the analysis with values from three to eight and found five to be the most reasonable choice. Allowing more than five groups results in some very small groups, allowing less than five results in one dominating group.

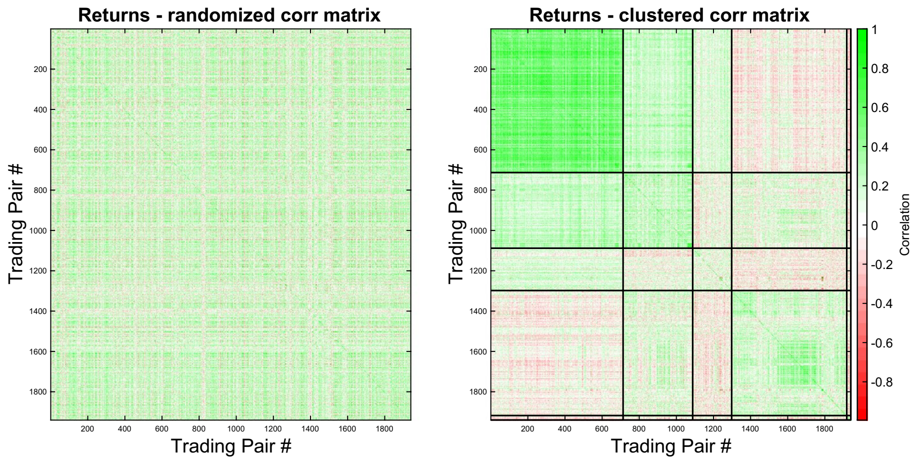


**Fig. 4** Hierarchical clustering correlation matrix—Returns. This Figure plots the randomized correlation matrix for returns (left subplot) and the corresponding clustered correlation matrix (right subplot) with five distinct clusters

To illustrate the procedure we consider intraday patterns in returns. We first randomize the correlation matrix **C**, i.e. we randomly assign the 1,940 trading pairs to the rows and columns of the matrix.[11] The randomized correlation matrix is shown in the left Panel of Fig. 4.[12] The color coding is such that positive (negative) correlations are represented by green (red) dots, and a more intense color indicates a higher numerical value of the correlation coefficient. The observation that the matrix is light green confirms our previous finding that the intraday patterns in returns are generally positively correlated. Next, we deploy the hierarchical cluster analysis. It identifies two large clusters, two medium-sized clusters and one very small cluster. The right-hand Panel of Fig. 4 shows the correlation matrix when we order the trading pairs by their group membership. The five blocks along the diagonal represent the correlations within a cluster, while the remaining blocks represent the correlations between clusters. Visual inspection of the right-hand Panel of Fig. 4 reveals the structure identified by cluster analysis. For example, the trading pairs in cluster 1 have a high correlation within the cluster, but a low or even negative correlation with the trading pairs in clusters 4 and 5.

It is interesting to see *which* trading pairs are grouped together. We take into account the location of the trading venue (America, Asia, Europe) as well as whether a trading pair contains bitcoin, ether, a fiat currency, or a stablecoin as one currency. For each cluster, the first five rows of Table 3 show the number of trading pairs traded on a trading venue in the Americas, Asia, and Europe, as well as the number of pairs that contain bitcoin, ether, a fiat currency or a stablecoin as one currency. In addition to the actual numbers, the table also indicates (in parentheses) the numbers that would be expected if the trading pairs were randomly assigned to clusters of the respective size.

[11] Note that the randomization is not necessary. It is used to better illustrate how hierarchical cluster analysis reveals structure in what is initially a completely unstructured matrix.

[12] Figures similar to Fig. 4 for the other five variables are shown in the appendix, Figs. 10, , 11, 12, 13, 14.

**Table 3** Results from hierarchical clustering

| Cluster | Size | America | Asia | Europe | BTC | ETH | Fiat |
|---|---|---|---|---|---|---|---|
| Returns 1 | 713 | 122 (93) | 489 (558) | 102 (62) | 193 (282) | 92 (156) | 539 (290) |
| 2 | 620 | 41 (81) | 563 (485) | 16 (54) | 311 (245) | 237 (136) | 59 (252) |
| 3 | 375 | 39 (49) | 314 (293) | 22 (32) | 180 (148) | 57 (82) | 136 (153) |
| 4 | 210 | 49 (27) | 139 (164) | 22 (18) | 104 (83) | 34 (46) | 47 (86) |
| 5 | 22 | 3 (3) | 13 (17) | 6 (2) | 10 (9) | 4 (5) | 9 (9) |
| Garman/Klass 1 | 1420 | 184 (186) | 1145 (1111) | 91 (123) | 524 (562) | 316 (310) | 629 (578) |
| 2 | 262 | 35 (34) | 166 (205) | 61 (23) | 159 (104) | 44 (57) | 75 (107) |
| 3 | 195 | 15 (26) | 174 (153) | 6 (17) | 88 (77) | 49 (43) | 65 (79) |
| 4 | 33 | 2 (4) | 21 (26) | 10 (3) | 9 (13) | 9 (7) | 14 (13) |
| 5 | 30 | 18 (4) | 12 (23) | 0 (3) | 18 (12) | 6 (7) | 7 (12) |
| Corwin/Schultz 1 | 1316 | 154 (172) | 1129 (1030) | 33 (114) | 471 (521) | 293 (288) | 590 (536) |
| 2 | 412 | 69 (54) | 243 (322) | 100 (36) | 234 (163) | 74 (90) | 133 (168) |
| 3 | 88 | 15 (12) | 68 (69) | 5 (8) | 42 (35) | 30 (19) | 16 (36) |
| 4 | 79 | 8 (10) | 57 (62) | 14 (7) | 30 (31) | 21 (17) | 29 (32) |
| 5 | 45 | 8 (6) | 21 (35) | 16 (4) | 21 (18) | 6 (10) | 22 (18) |
| Volume 1 | 1297 | 79 (170) | 1124 (1015) | 94 (112) | 502 (513) | 305 (283) | 503 (528) |
| 2 | 485 | 149 (64) | 273 (380) | 63 (42) | 263 (192) | 101 (106) | 173 (198) |
| 3 | 104 | 1 (14) | 97 (81) | 6 (9) | 12 (41) | 7 (23) | 92 (42) |
| 4 | 50 | 25 (7) | 21 (39) | 4 (4) | 21 (20) | 9 (11) | 21 (20) |
| 5 | 4 | 0 (1) | 3 (3) | 1 (0) | 0 (2) | 2 (1) | 1 (2) |
| Transactions 1 | 1483 | 197 (194) | 1130 (1160) | 156 (128) | 632 (587) | 300 (324) | 601 (604) |
| 2 | 328 | 22 (43) | 297 (257) | 9 (28) | 107 (130) | 92 (72) | 142 (134) |
| 3 | 85 | 33 (11) | 52 (67) | 0 (7) | 42 (34) | 19 (19) | 28 (35) |
| 4 | 26 | 0 (3) | 26 (20) | 0 (2) | 11 (10) | 9 (6) | 7 (11) |
| 5 | 18 | 2 (2) | 13 (14) | 3 (2) | 6 (7) | 4 (4) | 12 (7) |
| Trade Size 1 | 812 | 60 (106) | 737 (635) | 15 (70) | 298 (321) | 183 (177) | 348 (331) |
| 2 | 523 | 69 (68) | 398 (409) | 56 (45) | 237 (207) | 118 (114) | 192 (213) |
| 3 | 278 | 97 (36) | 168 (218) | 13 (24) | 157 (110) | 57 (61) | 82 (113) |
| 4 | 244 | 18 (32) | 151 (191) | 75 (21) | 71 (97) | 52 (53) | 132 (99) |
| 5 | 83 | 10 (11) | 64 (65) | 9 (7) | 35 (33) | 14 (18) | 36 (34) |
| Total values | 1940 | 254 | 1518 | 168 | 768 | 424 | 790 |

This table reports properties of the clusters derived from the correlation matrices of the dummy variable sets for each of the six measures returns, Garman/Klass, Corwin/Schultz, volume, number of transactions, and average trade size, respectively. Column 2 (size) refers to the number of trading pairs in each cluster, columns 3 to 8 report the number of trading pairs in the respective cluster with respect to the location of the trading venue (America, Asia, Europe) and whether the trading pairs feature bitcoin (BTC), ether (ETH) and a fiat currency / stablecoin (Fiat) as the base / quote currency, respectively. Numbers in parentheses report expected values if trading pairs were assigned randomly to the clusters

The table shows clear patterns. Cluster one (with 713 trading pairs) consists mainly of pairs containing a fiat currency or a stablecoin. 539 pairs exhibit this characteristic. If the pairs were randomly assigned to a cluster of size 713, we would expect only 290 pairs with this property. Cluster 1 also contains a disproportionately large number of pairs from exchanges in the Americas and Europe, while pairs from Asian exchanges are underrepresented. In addition, a disproportionately small number of pairs in cluster 1 contain bitcoin or ether while the opposite is true for trading pairs in cluster 2. Thus, we conclude that the similarity of intraday return patterns is determined by the location of the trading venue and the presence of bitcoin, ether or a fiat currency or stablecoin in the trading pair.

Table 3 also shows results of the hierarchical cluster analysis for the other variables (volatility, spreads, trading volume, number of trades and average trade size). They are consistent with the results for returns in that they also suggest that the location of the exchange is a determinant of the intraday patterns. However, unlike the results for returns, the numbers of pairs containing bitcoin, ether, or a fiat currency or a stablecoin do not deviate significantly from their expected values.

## 4.4 Drivers of intraday patterns

The hierarchical cluster analysis presented in the previous section allows us to draw conclusions about the determinants of intraday patterns by considering the properties of trading pairs in the resulting clusters. A regression analysis can deliver additional insights. We use the $1940 \cdot 1939/2$ correlations between the intraday patterns for the trading pairs as the dependent variable. The independent variables are dummy variables that identify (1) trading pairs traded on venues on the same continent (variable *Cont*), (2) trading pairs that trade on the same trading venue (*Venue*), (3) identical currency pairs traded on different venues (*Pair*), (4) trading pairs that share one currency (*Share*), (5) pairs that both contain bitcoin (*BBTC*), (6) pairs that both contain ether (*BETH*), (7) pairs that both contain a fiat currency or a stablecoin (*BFiat*). It is well known that some cryptocurrency exchanges report inflated trading volume figures (e.g. Cong et al. 2023). The fake volume that is reported may, in turn, affect the intraday patterns. We therefore include two additional dummy variables to capture the reliability of exchange reporting. For this purpose we rely on the exchange rating provided by coinmarketcap.com and categorize trading venues with a score above 6 as reliable.[13] We then define the dummy variables *BTrust* and $1$*Trust* which are set to one when both venues and one venue, respectively, in a pair are traded on a reliable venue. Finally, we add as an independent variable the absolute time difference, measured in hours, between the two trading venues (*Time*), resulting in the following specification (the subscripts have been omitted for ease of notation).

$$\begin{aligned}\hat{\rho} =& c + \beta_1 Cont + \beta_2 Venue + \beta_3 Pair + \beta_4 Share + \beta_5 BBTC + \\ &+ \beta_6 BETH + \beta_7 BFiat + \beta_8 Time + \beta_9 BTrust + \beta_{10} 1Trust + \epsilon\end{aligned} \tag{2}$$

We estimate one such regression for each of our six dependent variables. The results are shown in Table 4. The constants (representing estimates of the correlation of intraday patterns for a hypothetical trading pair for which all independent variables are zero) are positive and reflect our earlier results—the correlation of intraday patterns is highest for volatility, intermediate for spreads, trading volume, and the number of transactions, and lowest for returns and average trade size. The coefficient estimates of the dummy variables have an intuitive interpretation. They provide an estimate of the change in the correlation of the intraday patterns when the value of the respective dummy variable is increased from 0 to 1. Due to the large number of observations, all coefficient estimates are statistically

[13] An alternative to this ranking is the "trust score" provided by coingecko.com. All venues which have a score above 6 in the coinmarketcap.com rating also have a coingecko trust score above 6. However, coingecko assigns scores above 6 to a much larger number of venues.

**Table 4** Results correlation regression

| Variable | Returns | Garman/Klass | Corwin/Schultz | Volume | Transactions | Trade Size |
|---|---|---|---|---|---|---|
| Constant | 0.0908 | 0.4832 | 0.2280 | 0.3755 | 0.3941 | 0.0527 |
| | (0.0010) | (0.0011) | (0.0011) | (0.0013) | (0.0013) | (0.0015) |
| Cont | 0.0098 | 0.0324 | 0.0271 | 0.1198 | – 0.0083 | 0.0970 |
| | (0.0005) | (0.0005) | (0.0006) | (0.0007) | (0.0006) | (0.0007) |
| Venue | 0.0527 | 0.1804 | 0.1807 | 0.2582 | 0.1959 | 0.2220 |
| | (0.0007) | (0.0008) | (0.0008) | (0.0009) | (0.0009) | (0.0010) |
| Pair | 0.5843 | 0.2801 | 0.3570 | 0.2470 | 0.3152 | 0.0630 |
| | (0.0038) | (0.0041) | (0.0044) | (0.0051) | (0.0048) | (0.0056) |
| Share | 0.0071 | 0.0316 | 0.0418 | 0.0590 | 0.0598 | 0.0128 |
| | (0.0007) | (0.0007) | (0.0008) | (0.0009) | (0.0008) | (0.0010) |
| BBTC | 0.0120 | – 0.0614 | – 0.0552 | – 0.0431 | – 0.0556 | – 0.0019 |
| | (0.0008) | (0.0008) | (0.0009) | (0.0010) | (0.0009) | (0.0011) |
| BETH | – 0.0194 | 0.0045 | – 0.0383 | – 0.0538 | – 0.0898 | – 0.0220 |
| | (0.0010) | (0.0011) | (0.0011) | (0.0013) | (0.0012) | (0.0015) |
| BFiat | 0.3027 | 0.0561 | 0.0997 | – 0.0272 | 0.0491 | 0.0278 |
| | (0.0006) | (0.0006) | (0.0007) | (0.0008) | (0.0007) | (0.0009) |
| Time | – 0.0002 | 0.0003 | – 0.0007 | – 0.0037 | – 0.0043 | – 0.0018 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| BTrust | – 0.0133 | 0.0042 | 0.1474 | 0.0397 | 0.0472 | 0.0454 |
| | (0.0009) | (0.0010) | (0.0010) | (0.0012) | (0.0011) | (0.0013) |
| 1Trust | – 0.0179 | 0.0020 | 0.0685 | 0.0395 | 0.0240 | 0.0521 |
| | (0.0010) | (0.0010) | (0.0011) | (0.0013) | (0.0012) | (0.0014) |
| Adj. R2 | 0.1690 | 0.0679 | 0.0873 | 0.1140 | 0.0587 | 0.0578 |
| Observations | 1,880,830 | | | | | |

This table reports results from the regression defined in Eq. (2). Dependent variables are correlation coefficients of the dummy variable sets (columns 2 to 7). Independent variables are dummy variables indicating if two pairs: (1) are traded in venues on the same continent (Cont), (2) are traded in the same exchange (Venue), (3) are exactly the same trading pair (Pair), (4) share one common currency (Share), (5) both feature bitcoin (BBTC), (6) both feature ether (BETH), (7) both feature a stablecoin or fiat (BFiat). (8) Time refers to the time gap in hours between the trading venues, (9) BTrust denotes if both pairs are traded in trusted exchanges, and (10) 1Trust indicates that exactly one pair is traded in a trusted exchange. Standard errors in parentheses, all coefficients are significant at the 1% level

significant. When interpreting our results we therefore emphasize the economic significance of the estimates.

The coefficient of the dummy variable *Cont* is positive for five out of six measures (the exception being the number of transactions), suggesting that the intraday patterns of two pairs are generally more highly correlated when the pairs are traded on venues on the same continent. The effects are particularly strong for trading volume and trade size, and are negligible for returns and the number of transactions. The coefficient for *Venue* is always positive, implying that pairs traded on the same trading venues have more similar intraday patterns. The effects are strong for all dependent variables, with coefficient estimates ranging from 0.05 (returns) to 0.26 (volume). Similarly, the intraday patterns of the same currency pair traded on different venues are more highly correlated than those of different currency pairs. The effects are again very strong, with coefficient estimates between 0.06 (trade size) and 0.58 (returns). The large coefficient estimate for returns is no surprise. If the same currency pair is traded on two different venues, returns should move in lockstep in efficient financial markets. The correlation between the intraday patterns is also higher for pairs that share a common currency. However, the coefficients are markedly lower than the coefficients for identical currency pairs, with values ranging between 0.007 (returns) and 0.06 (number of transactions). Interestingly, the coefficients for *BBTC* and *BETH* are mostly negative while those for *BFiat* are mostly positive.[14] Thus, if two pairs both include bitcoin or ether as one currency, then the intraday patterns tend to be less similar. On the other hand, if both pairs contain a fiat currency or a stablecoin, the intraday patterns tend to be more similar. The coefficients for the dummy variables that capture trading venue reliability are positive for five of our six measures (the exception being returns) and are of an economically significant magnitude for the Corwin and Schultz (2012) spread estimator and the measures of trading activity (volume, number of trades and trade size). The coefficient estimate in the return regression is numerically small and negative, implying that intraday patterns in returns generated on reliable exchanges are, if anything, less similar than those from unreliable exchanges. A potential explanation may be that venues reporting fake transactions (or wash trades) report prices "borrowed" from other venues, thereby artificially creating intraday patterns of returns that resemble the patterns generated on other venues. Finally, the coefficients for the time difference variable are predominantly negative, suggesting that the intraday patterns of two trading pairs are more highly correlated when the time difference between the locations of the trading venues is lower. The only exception is the intraday pattern in volatility. Here, the coefficient of the time difference variable is positive, but, because of its small size, economically negligible.

It is worth noting that the intraday patterns in volatility are indeed strongly positively correlated. Given that all coefficients except BBTC are positive in the volatility regression, the lowest predicted value (0.453) obtains when Share and BBTC are set to one[15] and all other independent variables are set to zero. This estimate implies that the (predicted) correlation between the intraday patterns in volatility never drops below 45.3%, even when the two trading pairs have nothing in common and are traded on different venues located on different continents. This finding suggests a high degree of commonality in cryptocurrency volatility.

Overall, the regression results confirm our earlier findings that intraday patterns are generally positively correlated, that the correlation is highest for volatility, followed by our measures of the spread and trading activity, and that it is lowest for returns and average trade size. We also find that correlations increase when the venues where trading pairs are traded are located on the same continent or in closer time zones, and when trading pairs share a common currency, or are traded on the same venue.

[14] Note that, when two trading pairs contain bitcoin or ether, the variable *Share* is also set to 1. Thus, the total effect when bitcoin or ether are contained in two pairs is obtained by adding the coefficients for the *Share* variable and *BBTC* or *BETH*. The same is true for the variable *BFiat* when the two trading pairs under consideration contain the same fiat currency.

[15] Note that Share must have the value 1 when BBTC is set to 1.

### 4.5 Robustness of results

In this section we address the robustness of our results. For this purpose, various subsets of the full data set are being considered. We look at time-of-the-day patterns arising from those as well as at the drivers of the patterns.

We start by dividing the dataset with a total of 1,281 days or 30,744 h into three series of equal length (i.e., 10,248 observations each). This roughly corresponds to the time periods of (1) July 2018 to August 2019, (2) September 2019 to October 2020, and (3) November 2020 to December 2021. Put differently, the first time frame covers the period after the bitcoin's peak by the end of 2017 (reaching a previous all-time-high of USD 20,000). The second time frame witnessed a sideways trading market, while the third time frame covers the bull run of 2021 with bitcoin's price rising from roughly USD 15,000 (by the end of October 2020) to it's 2021 all-time-high of almost USD 70,000. Even though these time periods substantially differ in terms of market conditions and market sentiment, we do not find results deviating from our baseline analysis. The patterns found there still prevail, all measures under consideration peak in afternoon UTC (see Fig. 15 in the appendix).[16]

Furthermore, we test if results are driven by the first and, in terms of market capitalization, dominating coin, i.e. bitcoin. To that end, we separately analyze pairs that (1) involve bitcoin and (2) those which do not. Again, we find the same intraday patterns as with the full sample (see Fig. 16 in the appendix).

Additionally, we run the analyses outlined in the previous sections separately for trading pairs (1) with and (2) without a fiat currency or a stablecoin as one of the currencies. The results from the baseline analysis are reflected in both sub-samples (see Fig. 17 in the appendix).

Finally, we address temporal effects and varying macroeconomic conditions in more detail by forming 3 (6) subsets of 10,248 (5124) hours each. We still find the same time-of-the-day patterns, however, here we elaborate further on the drivers of intraday patterns as outlined in Sect. 4.4. I.e., for each of the three (six) subsets we derive the correlation coefficients of the time-of-the-day dummy coefficients. We then perform a (1) pooled regression with all correlation coefficients from the three (six) subsets, as well as (2) a time-fixed-effects regression.[17] Results for all measures under consideration (Returns, Garman/Klass, Corwin/Schultz, Volume, Transactions, Trade Size) are virtually identical to those obtained for the full sample. We note, though, that the similarity of time-of-the-day appears to be somewhat lower in the first subset, i.e., the beginning of our data sample.

In summary, our results do not appear to be driven by a specific model, time frame, or parameter specification.

[16] It is worth noting that we still impose the data availability restriction of at least 75% of observations in each subinterval. I.e., a coin that enters the full sample might not be in subsample 1 or 3 due to being listed only after the beginning of the dataset or being delisted during the third sub-period. Hence, the coins in each subsample may and will be different from the set of coins in the full sample.

[17] We thank an anonymous referee for proposing this specification, results available upon request.

## 5 Conclusion

In this paper we identify pronounced intraday patterns in trading activity, volatility and illiquidity for a large sample of cryptocurrencies traded on 38 trading venues around the world. These patterns are remarkably similar across trading pairs and venues. A detailed analysis of the correlation of intraday patterns between a large number of trading pairs shows that the intraday patterns are more highly correlated when the pairs are more similar (e.g. share a common currency) or when the pairs are traded on the same trading venue or on venues on the same continent and/or in the same time zone. Our results suggest that distinct intraday patterns emerge endogenously, i.e. without institutional frictions. They further imply that these patterns cannot be fully explained by local factors, but that there rather exists a pronounced commonality in intraday patterns.

Based on our results, several avenues for future research emerge. Firstly, the underlying determinants of intraday patterns remain puzzling, especially given their striking similarity across different exchanges and trading pairs. The influence of exogenous factors on cryptocurrency markets warrants thorough investigation. For example, the introduction of bitcoin futures towards the end of 2017, whose settlement conventions are tied to specific times within the trading day, could cause unique market behaviors observed in our dataset (cf., Pati 2022). Likewise, the recent approval of bitcoin spot exchange-traded funds (ETFs) by the Securities and Exchange Commission (SEC) in January 2024, especially given the trading conventions of major ETF providers, could contribute to intraday patterns. It is worth noting that conventions in traditional markets could also play a role in shaping the observed patterns. Therefore, future research efforts should aim to shed light on these factors and deepen our understanding of the dynamics inherent in 24/7 cryptocurrency markets.

Secondly, consistent patterns observed over prolonged periods of time prompt inquiries into the possible development of profitable trading strategies based on such findings. Although there is ample evidence of trading strategies that utilize price data (e.g., time series models, machine learning algorithms, or technical analysis tools), the understanding of the feasibility of developing effective trading algorithms to exploit intraday seasonalities in volatility, liquidity, trading volume, and trade size is still limited. Future research efforts could aim to investigate the profitability of trading strategies contingent upon the time-of-day, as well as liquidity and trading volume at that time.

Finally, with regard to the different patterns in average trade size that emerge from our findings, it is crucial to understand which types of traders are active at certain times of the day and what their motivations are. One plausible explanation for the observed variations in the average dollar value of transactions throughout the day is the assumption that different cohorts, e.g. retail and institutional investors, prefer to trade in different time windows. However, it remains unclear whether the characterization of trader types by time-of-day is conclusive, underscoring the need for further research. Essentially, our comprehensive intraday results lay the groundwork for a deeper investigation into the temporal structures that drive cryptocurrency markets.

## Figures for Appendix

See Figs. 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17

**Funding** Open access funding provided by University of Graz.

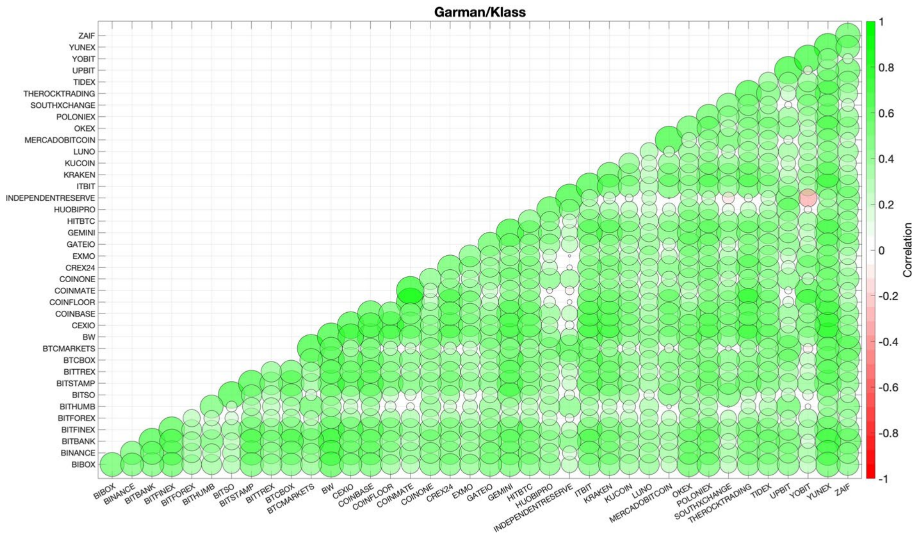


**Fig. 5** Average volatility correlations across exchanges. This figure shows average correlations of dummy variable sets for each exchange (diagonal bubbles in the plot) and average correlations of dummy variable sets across individual exchanges (off-diagonal bubbles in the plot)

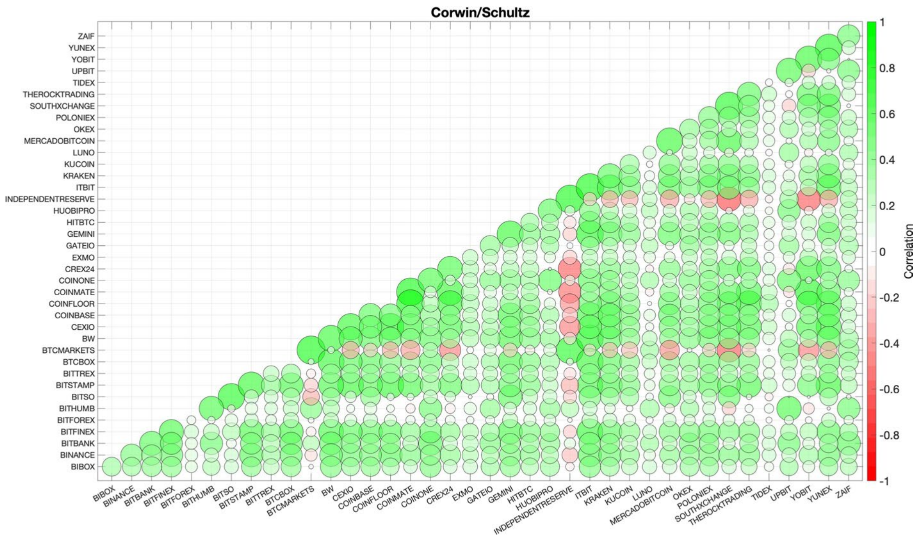


**Fig. 6** Average liquidity correlations across exchanges. This figure shows average correlations of dummy variable sets for each exchange (diagonal bubbles in the plot) and average correlations of dummy variable sets across individual exchanges (off-diagonal bubbles in the plot)


**Fig. 7** Average volume correlations across exchanges. This figure shows average correlations of dummy variable sets for each exchange (diagonal bubbles in the plot) and average correlations of dummy variable sets across individual exchanges (off-diagonal bubbles in the plot)

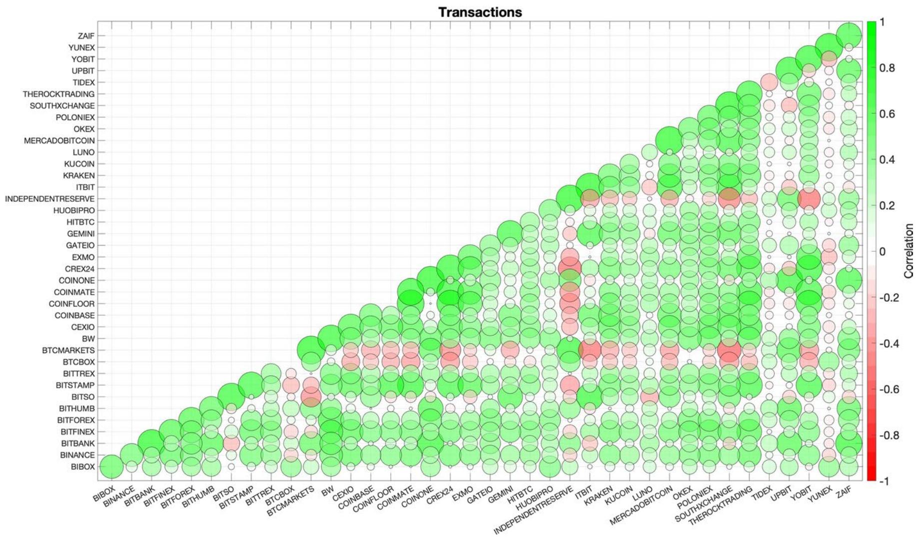


**Fig. 8** Average transactions correlations across exchanges. This figure shows average correlations of dummy variable sets for each exchange (diagonal bubbles in the plot) and average correlations of dummy variable sets across individual exchanges (off-diagonal bubbles in the plot)

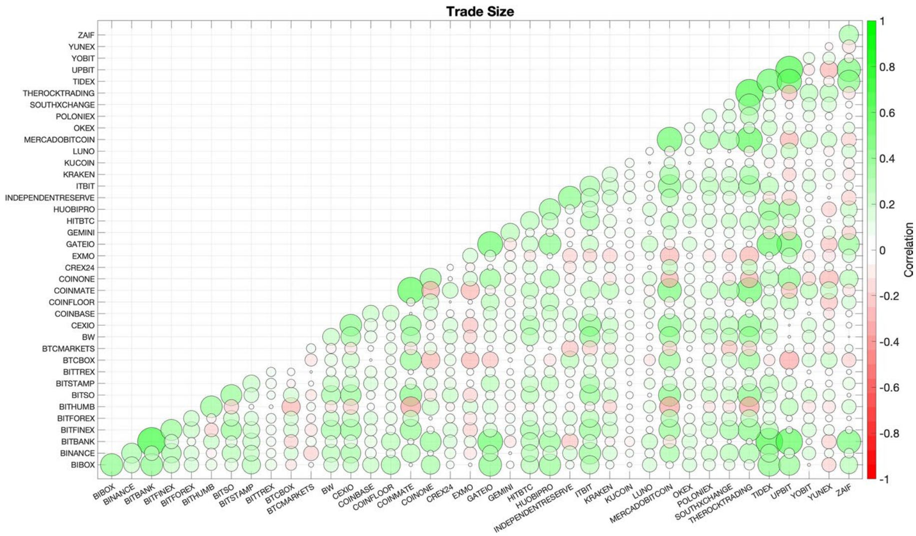


**Fig. 9** Average trade size correlations across exchanges. This figure shows average correlations of dummy variable sets for each exchange (diagonal bubbles in the plot) and average correlations of dummy variable sets across individual exchanges (off-diagonal bubbles in the plot)

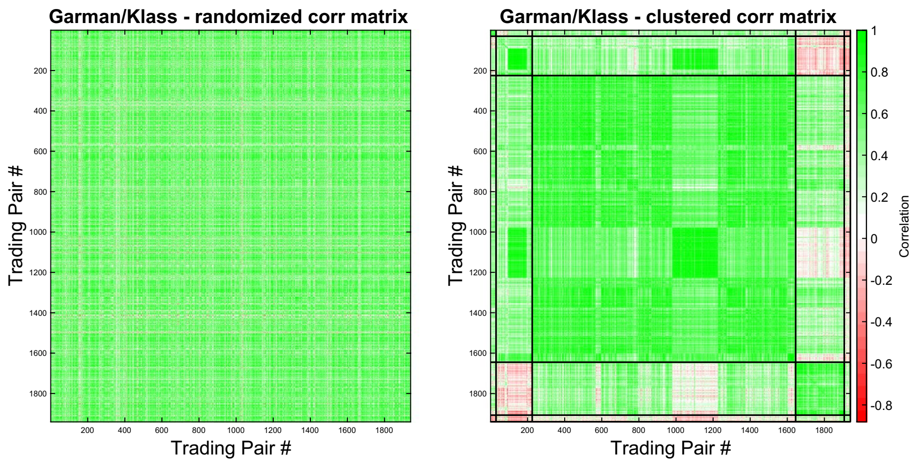


**Fig. 10** Hierarchical clustering correlation matrix—Garman/Klass. This Figure plots the randomized correlation matrix for the Garman/Klass volatility estimator (left subplot) and the corresponding clustered correlation matrix (right subplot) with five distinct clusters

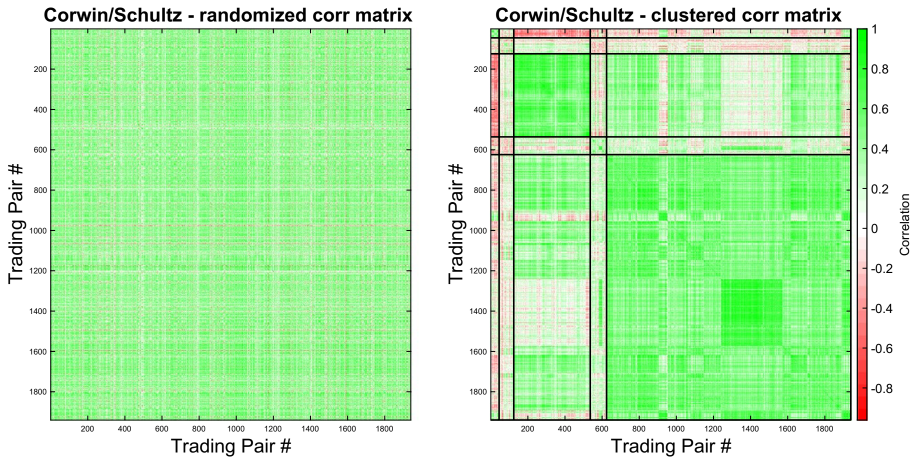


**Fig. 11** Hierarchical clustering correlation matrix—Corwin/Schultz. This Figure plots the randomized correlation matrix for the Corwin/Schultz spread estimator (left subplot) and the corresponding clustered correlation matrix (right subplot) with five distinct clusters

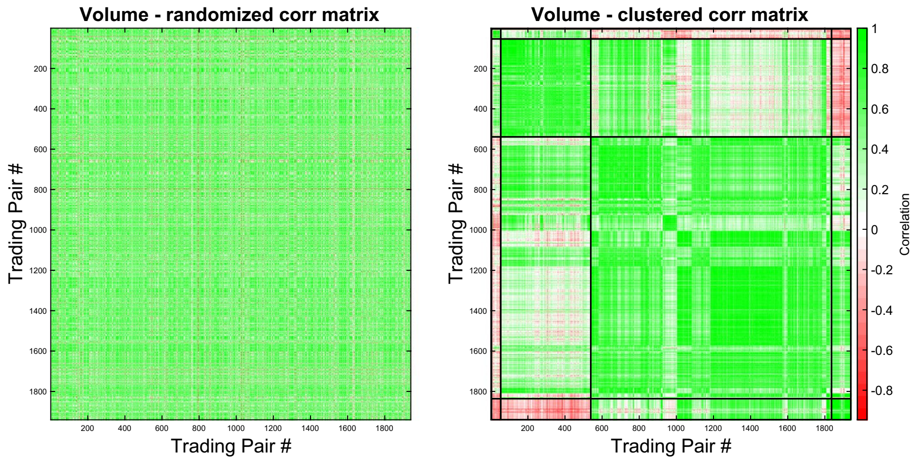


**Fig. 12** Hierarchical clustering correlation matrix—Volume. This Figure plots the randomized correlation matrix for the log trading volume (left subplot) and the corresponding clustered correlation matrix (right subplot) with five distinct clusters

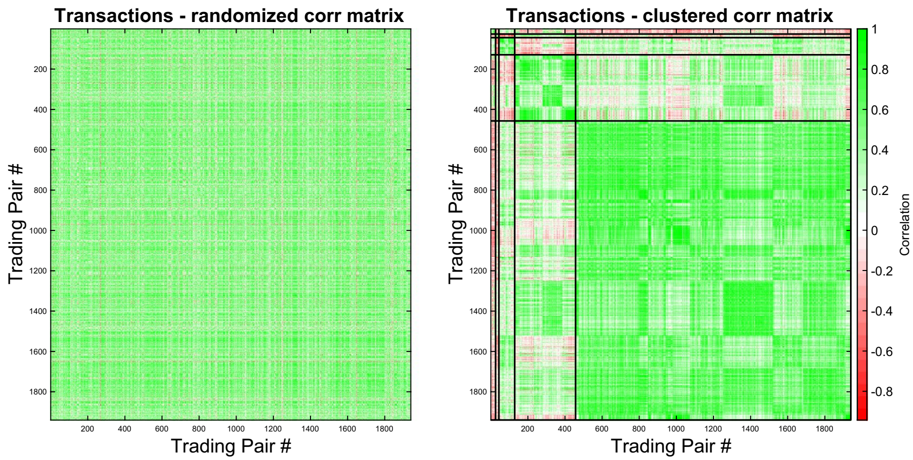


**Fig. 13** Hierarchical clustering correlation matrix—Transactions. This Figure plots the randomized correlation matrix for the number of transactions (left subplot) and the corresponding clustered correlation matrix (right subplot) with five distinct clusters

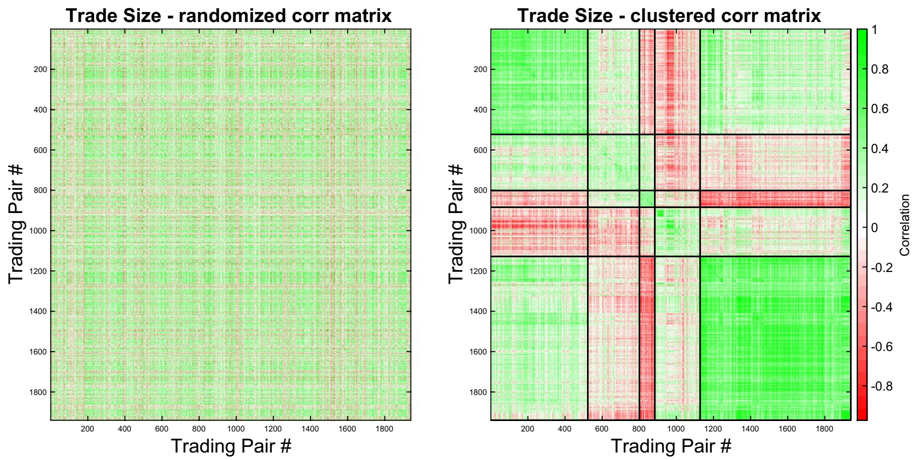


**Fig. 14** Hierarchical clustering correlation matrix—Trade Size. This Figure plots the randomized correlation matrix for the average trade size (left subplot) and the corresponding clustered correlation matrix (right subplot) with five distinct clusters

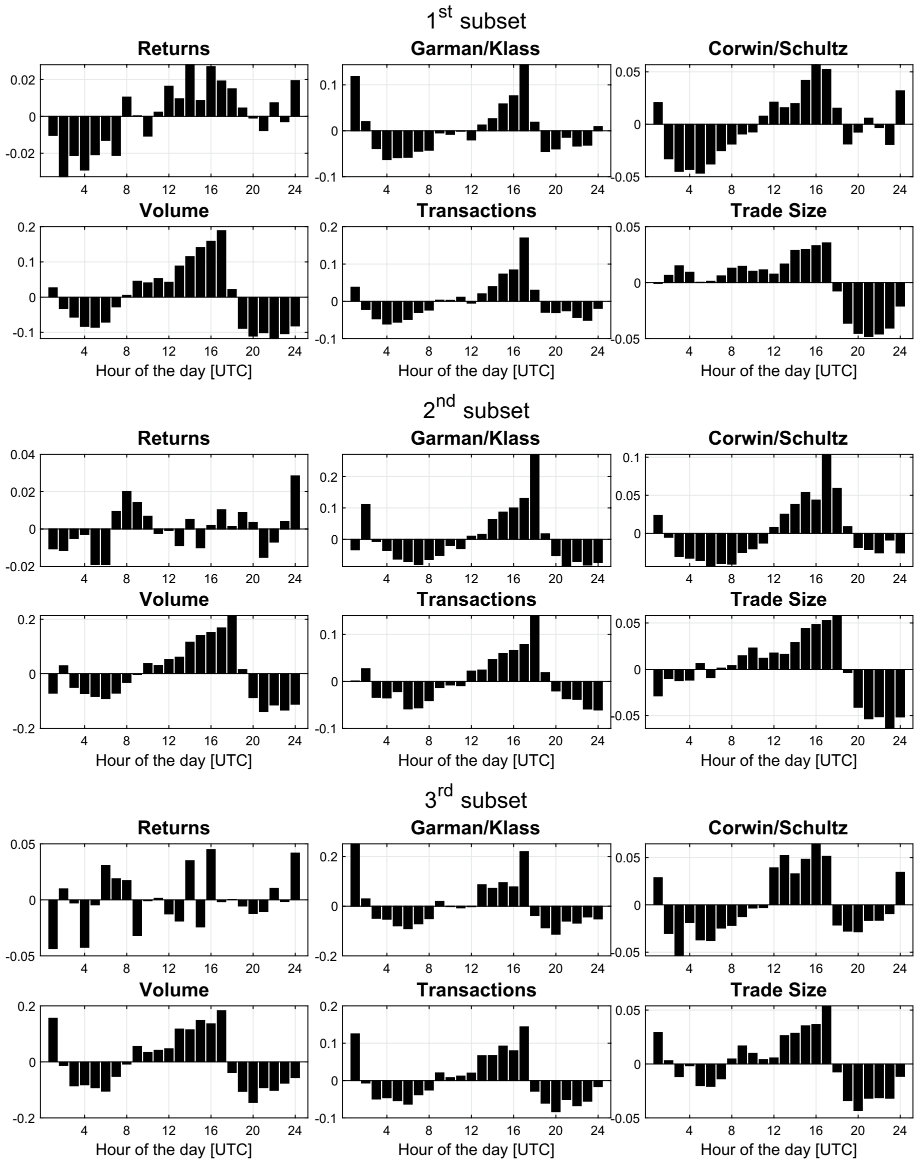


**Fig. 15** Time-of-the-day patterns for split datasets. This figure reports simple averages of the coefficients of the dummy variable regressions defined in Eq. (1) for the six measures returns, volatility (Garman/Klass), liquidity (Corwin/Schultz), log-trading volume, the number of transactions and the average trade size. Hours refer to Coordinated Universal Time (UTC). E.g., hour 4 covers the period 03:00 to 04:00 UTC. The first (second, [third]) subplot depicts results for the first (second, [third]) datatset, respectively

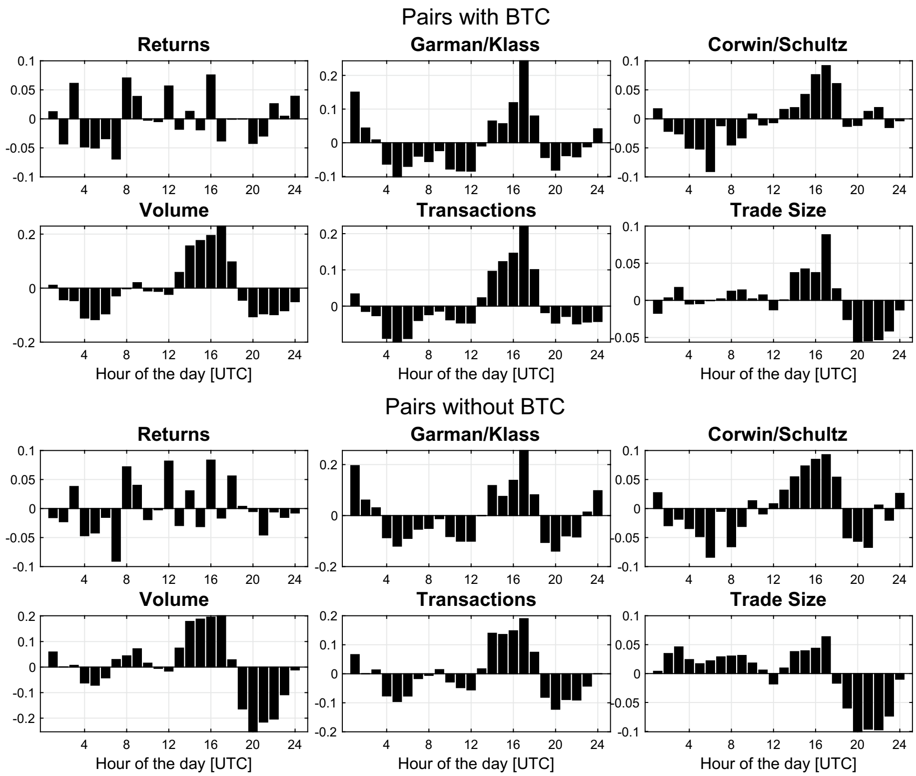


**Fig. 16** Time-of-the-day patterns for trading pairs with and without bitcoin. This figure reports simple averages of the coefficients of the dummy variable regressions defined in Eq. (1) for the six measures returns, volatility (Garman/Klass), liquidity (Corwin/Schultz), log-trading volume, the number of transactions and the average trade size. Hours refer to Coordinated Universal Time (UTC). E.g., hour 4 covers the period 03:00 to 04:00 UTC. The upper (lower) subplot reports results for trading pairs with (without) bitcoin as one of the currencies

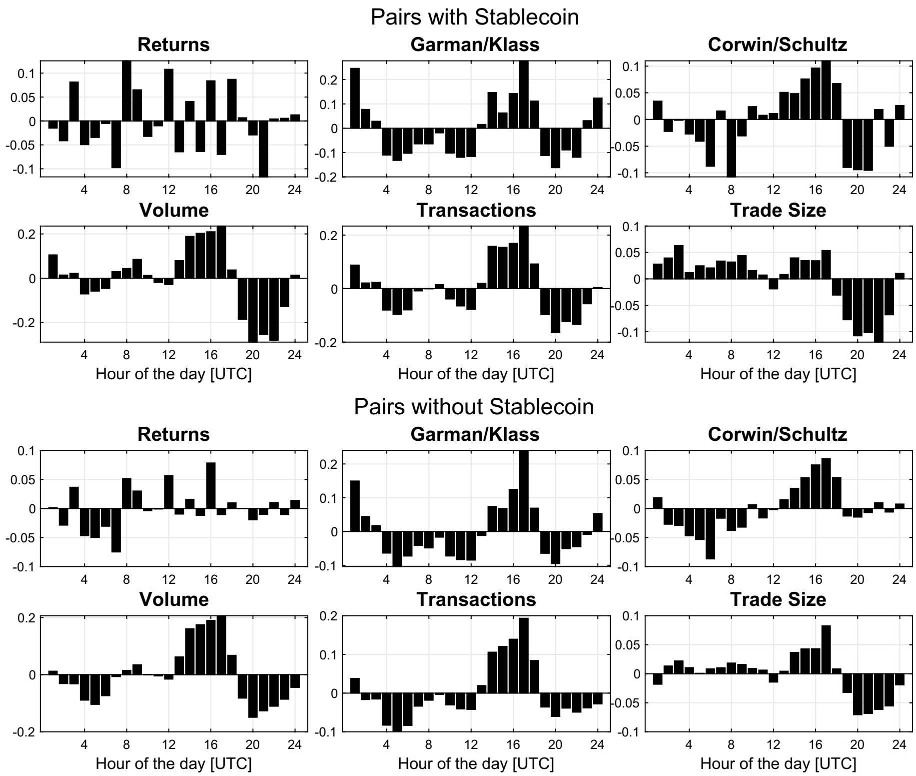


**Fig. 17** Time-of-the-day patterns for trading pairs with and without stablecoins. This figure reports simple averages of the coefficients of the dummy variable regressions defined in Eq. (1) for the six measures returns, volatility (Garman/Klass), liquidity (Corwin/Schultz), log-trading volume, the number of transactions and the average trade size. Hours refer to Coordinated Universal Time (UTC). E.g., hour 4 covers the period 03:00 to 04:00 UTC. The upper (lower) subplot reports results for trading pairs with (without) a fiat currency or stablecoin as one of the currencies

## Declarations

**Conflict of interest** The authors have no conflicts of interest (financial or non-financial).

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