Intraday and Daily Dynamics of Cryptocurrency

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Keywords: cryptocurrency, periodicity, stablecoin, token, Bitcoin, PCA, market portfolio, functional regression

JEL codes: F30, G10, G15

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1 Introduction

We document intraday and intraweek patterns in hourly and daily cryptocurrency data. The analysis is focused on cryptocurrencies traded on Bitstamp (https://www.bitstamp.net), which include the native cryptocurrencies (natives, henceforth), stablecoins and tokens. We find the evidence of common intraday and intraweek patterns in the series of prices, returns, volumes and volatility of the native cryptocurrency and tokens. These patterns are compared to determine a "typical" behavior in each cryptocurrency class. Our findings corroborate and extend the results reported in Eross et al. (2019) who documented periodic patterns in Bitcoin returns and volumes, and in Ma and Tanizaki (2019) who described day-of-the-week effects in returns and volatility.

The periodic patterns also characterize the portfolios of cryptocurency because of the correlation and connectedness of returns on native cryptocurrencies, tokens and stablecoins. The principal component analysis (PCA) of the cross-sectional return variance matrix reveals common cryptocurrency market factors at each frequency. We find the evidence in favor of one factor on the cryptocurrency market in hourly and daily returns. The high explanatory power of the factor indicates that the native cryptocurrencies and tokens are connected in a systemic way, confirming the findings of e.g. Nyakurukwa, Seetharam (2023). However, we find that the stablecoin returns, either daily or hourly, appear uncorrelated with other cryptocurrencies and with one another.

We follow the approach of Avellaneda et al. (2022) and build a cryptocurrency market portfolio with allocations determined by the first principal component of cryptocurrency return variance. The intraweek patterns in the cryptocurrency market portfolio are then compared to those in the S&PCBDM index, lunched in July 2021 and recorded daily Monday through Friday. The S&P Cryptocurrency Broad Digital Market (BDM) Index is designed to track the performance of digital assets listed on recognized open digital exchanges that meet minimum liquidity and market capitalization criteria [1]. The composition of S&PCBDM is determined by the software Lukka that verifies those criteria and computes the allocations of individual cryptocurrency.

As the common cryptocurrency factor reflects the systemic risk on cryptocurrency market, we use functional regression to investigate the relationship between the individual cryptocurrency returns and the market factor returns. The functional regression of individual cryptocurrency (excess) returns on the market portfolio (excess) return is performed on the

[1] https://www.spglobal.com/spdji/en/indices/digital-assets/sp-cryptocurrency-broad- digital-market-index/#overview

hourly and daily data. We observe that the functional relation is affine and the functional coefficients ("betas") vary across the day and week.

The main findings of the paper can be summarized as follows:

1. Common periodic intraday and intraweek patterns are observed in prices, volumes and volatility of native cryptocurrency and tokens. The intraday patterns are strongly influenced by the opening and closing times of major stock exchange markets. This is in line with the literature suggesting the comovements and spillovers between the stock market and cryptocurrency.

2. In general, the investors can benefit from lower prices between 4 pm and 10 pm Eastern Standard Time, i.e. between the closing time of NYSE and the opening time of Hang Seng. The return volatility tends to be low on Thursdays and Fridays.

3. Stablecoins have distinct intraday and intraweek dynamics. Moreover, while the correlation between the returns on native cryptocurrencies and tokens is strong, the returns on stablecoins appear uncorrelated with other cryptocurrencies and with one another.

4. The PCA applied to the hourly and daily returns suggests the presence of one factor in the cryptocurrency market, to which the stablecoins do not contribute. Therefore, they are immune to the systemic risk associated with the cryptocurrency market. Among the cryptocurrencies considered, Bitcoin has the lowest exposure to the systemic risk, according to the PCA-based connectedness measure.

5. The S&PCBDM index is collinear with the daily cryptocurrency market factor and their intraweek patterns are similar.

6. The functional regression shows an affine relationship between the (excess) cryptocurrency returns and the (excess) returns on the market portfolio with coefficients (betas) that vary across the day and week.

Literature Review

In addition to the papers by Eross et al. (2019) and Ma and Tanizaki (2019) mentioned earlier in the Introduction, several other studies on seasonal effects in cryptocurrency markets can be found in the recent literature. Long et al. (2020) explore seasonality patterns in cryptocurrency returns and provide evidence of a significant seasonal effect. This paper suggests that past same-weekday returns can predict future performance in the cross-section of cryptocurrencies. This phenomenon is not explained by other established return predictors and reveals the cross-sectional seasonality in cryptocurrency markets. Fraz et al. (2019) explore seasonality in the Bitcoin market, analyzing day-of-the-week and month-of-the-year effects. This study identifies the existence of seasonality in Bitcoin returns, with Mondays showing higher returns. These findings suggest a violation of the weak-form market efficiency hypothesis, indicating potential profit opportunities for investors. Caporale and Plastun (2019) investigate the day-of-the-week effect in the cryptocurrency market, with a particular focus on Bitcoin. They find that Bitcoin returns on Mondays are significantly higher than on other days, which implies evidence against market efficiency. Their study also highlights exploitable profit opportunities. Kinateder and Papavassiliou (2021) study calendar effects, including Halloween, day-of-the-week, and month-of-the-year effects, in Bitcoin returns and volatility. They identify lower risk over the weekend and higher volatility at the beginning of the week. Their study also mentions a reverse January effect.

Several studies have investigated the connectedness and relationships in cryptocurrency markets. Katsiampa et al. (2022) focus on the connectedness and correlations between Bitcoin and other top-traded cryptocurrencies during the COVID-19 crisis. They find that protocols and decentralized applications (dApps) have become more attractive to investors than pure cryptocurrencies. Their study provides insights into the evolving dynamics of cryptocurrency markets during a crisis. Le (2023) explores the connectedness between cryptocurrency volatility and renewable energy volatility during significant events like the COVID-19 pandemic and Ukraine-Russia conflicts. Le identifies dynamic changes in connectedness and highlights the influence of these events on both markets. Yousaf et al. (2023) investigate the connectedness between energy cryptocurrencies and common asset classes, particularly oil. Their paper emphasizes that energy cryptocurrencies, typically seen as diversifiers, can be highly sensitive to shocks and changes in uncertainty. This study sheds light on the role of energy cryptocurrencies in broader financial markets. The paper by Umar et al. (2021) examines the connectedness between the technology sector and cryptocurrency markets across different countries. It finds that contributions to and from the cryptocurrency market are negligible, suggesting that the cryptocurrency market is structurally less exposed to systemic risk.

The relationship between the cryptocurrencies was also studied recently in the framework of Capital Asset Pricing Model (CAPM). Dunbar and Owusu-Amoako (2022) investigate the predictability of cryptocurrency returns based on investors' risk premia. Their paper identifies a significant return predictability of cryptocurrencies based on the cryptocurrency market risk premium. The findings align with CAPM theory and suggest that investors require higher positive returns before taking on additional risks, particularly in riskier assets like cryptocurrencies. Shen et al. (2020) propose a three-factor pricing model for cryptocurrencies, considering market, size, and reversal factors. The authors analyze over 1700 cryptocurrencies and find that smaller cryptocurrencies tend to yield higher returns. They claim that their model outperforms the cryptocurrency CAPM model, indicating its effectiveness in explaining cryptocurrency returns. Tavares et al. (2021) examine the formation of prices in the cryptocurrency market using the CAPM model with regime-switching. They consider ten cryptocurrencies and use the CRIX index as the market factor. The study finds that this market risk factor partially explains cryptocurrency returns. Additionally, incorporating regime change estimation enhances the explanatory power of the market risk factor model. Shahzad et al. (2021) propose a four-factor pricing model for cryptocurrencies incorporating the contagion risk. They estimate contagion measures for large left-tail events in idiosyncratic disturbances of cryptocurrencies. Their research empirically tests the four-factor pricing model and demonstrates that it outperforms both the cryptocurrency-CAPM and three-factor models.

Our contribution to the literature is in considering both the intraday and intraweek patterns of a relatively large number of cryptocurrencies, including the natives, tokens and stables, and in revealing their common and distinct behaviors. In addition, our study fills the gap in the literature by revealing periodic patterns in the systemic risk through the dependence of cryptocurrency returns on the cryptocurrency market factor. These findings have implications for understanding cryptocurrency anomalies and quantitative strategies in the cryptocurrency market.

The paper is organized as follows: Section 2 describes the hourly and daily data used in the analysis. Section 3 discusses the methodology. The intraday and intraweek patterns are presented in Section 4. The market factor is computed in Section 5 and compared with the S&PCBDM index. Section 6 presents the functional regression results. Section 7 contains the summary and conclusion. Appendix A and the Online Appendix contain additional results and figures.

2 Data Description

The data source is Bitstamp, the biggest European cryptocurrency exchange platform, which has been operating since 2011. It is recommended as a reliable data provider in Vidal-Tomás (2022). Our intraday data are sampled hourly over the period of 6 months, starting from 2022-01-01 until 2022-06-28 with a total number of 179 days. Our daily data are observed over one year: 2022-01-01 to 2022-12-30 with a total number of 52 weeks of data. The extracted time series of daily prices are the adjusted closing prices in US Dollars at 0:00 hour of the Coordinated Universal Time (UTC). The volumes of trades are defined as the numbers of coins traded.

The UTC is the time scale of reference. For comparison, we provide below the local

operating times of the major stock markets, which are as follows:
The US markets (NYSE, NASDAQ): 9:30 to 16:00 of Eastern Standard Time (EST). The UTC equivalent of EST time is obtained by adding 4;
London Stock Exchange (LSE): 8:00 to 16:30 of Greenwich Mean Time (GMT). The GMT is equivalent to the UTC time;
Hong Kong market time (Hang Seng): 9:30 to 16:00 with a break from 12:00 to 13:00 of Hong Kong Time (HKT). The UTC equivalent of HKT time is obtained by substracting 8;

There exist small differences due to the daylight saving times. Table 1 compares the 24-hour scale of UTC time with Eastern Standard Time (ETS), Hong Kong Time (HKT) and Greenwich Mean Time with daylight saving (panel A) and without it (panel B). We observe that the opening hours of NYSE and LSE overlap by 3 hours. The LSE overlaps with Hang Seng by one hour and only when Eastern Daylight Saving Time is implemented.

Table 1: Intraday timeline: UTC clock and local time of major markets

UTC	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Panel A																								
NYSE	-20	-21	- 22	-23	0	1	2	3	4	5	6	7	8	***9***	***10***	***11***	***12***	***13***	***14***	***15***	16	17	18	19
LSE	1	2	3	4	5	6	7	***8***	***9***	***10***	***11***	***12***	***13***	***14***	***15***	***16***	17	18	19	20	21	22	23	+0
Hang Seng	8	***9***	***10***	***11***	12	***13***	***14***	***15***	16	17	18	19	20	21	22	23	+0	+1	+2	+3	+4	+5	+6	+7
Panel B																								
NYSE	-19	-20	-21	- 22	-23	0	1	2	3	4	5	6	7	8	***9***	***10***	***11***	***12***	***13***	***14***	***15***	16	17	18
LSE	0	1	2	3	4	5	6	7	***8***	***9***	***10***	***11***	***12***	***13***	***14***	***15***	***16***	17	18	19	20	21	22	23
Hang Seng	8	***9***	***10***	***11***	12	***13***	***14***	***15***	16	17	18	19	20	21	22	23	+0	+1	+2	+3	+4	+5	+6	+7

2.1 The Variables of Interest

The Bitstamp records of prices and volumes are used to compute the intraday and intraweek averages, as well as the series of returns and realized volatilities following the approach of Eross et al. (2019).

2.1.1 Hourly Data

The hourly data are indexed by t, t = 0,1,..., 23, with t=0 at UTC hour 00:00 on day d, d = 1, ..., 179, which is the number of days in the sample. The variables of interest are defined as follows:

1. The average intraday price over 179 days at time t: $\bar{P}_t = \frac{1}{179}\sum_{d=1}^{179} P_{t,d},\ t = 0, 1, ..., 23$
2. The intraday log-return: $r_{t,d} = (lnP_{t,d} - lnP_{t-1,d}) \times 100$, with the average over 179 days at hour t: $\bar{r}_t = \frac{1}{179}\sum_{d=1}^{179} r_{t,d},\ t = 0, 1, ..., 23$

3. The intraday realized volatility (RV) at hour t: Realized variance$_{t,d} = \frac{1}{179}\sum_{d=1}^{179}\left(ln\frac{P_{t,d}}{P_{t-1,d}}\right)^2 \times$ 10000. The square root of the realized variance at hour t is: $RV_t = \sqrt{\text{Realized variance}_{t,d}},\ t = 0, 1, ..., 23$

4. The average intraday volume at hour t: $\bar{v}_{t,d} = \frac{1}{179}\sum_{d=1}^{179} volume_{t,d}$

2.1.2 Daily Data

The daily variables are indexed by the days of the week denoted by n (n = 1,2,..,7 for Monday, Tuesday, ..., Sunday). The weekly averages are computed over 52 weeks of year 2022. For days $n = 1, 2, ..., 7$ of the week, we define:

5. The average daily price over 52 weeks, $\bar{P}_n = \frac{1}{52}\sum_{j=1}^{52} P_{n,j},\ n = 1, .., 7$

6. The average daily return over 52 weeks, $\bar{r}_n = \frac{1}{52}\sum_{j=1}^{52} r_{n,j},\ n = 1, .., 7$ where $r_{n,j} = (lnP_{n,j} - lnP_{n,j-1}) \times 100$

7. The square root of RV over 52 weeks, $RV_n = \sqrt{\text{Realized variance}_{n,j}},\ n = 1, .., 7$ where Realized variance$_n = \frac{1}{52}\sum_{j=2}^{52}\left(ln\frac{P_{n,j}}{P_{n,j-1}}\right)^2 \times 10000$

8. The average daily volume over 52 weeks, $\bar{v}_n = \frac{1}{52}\sum_{j=1}^{52} volume_{n,j}$

Our data contains records on 45 cryptocurrencies including 10 natives coins, 6 stablecoins and 29 tokens (Sehra et al., 2018) (Grobys et al., 2021). The stablecoins considered in our study are pegged 1:1 to the US Dollar, except for EURT, which is pegged 1:1 to the Euro. For the empirical analysis, we consider an additional important characteristic of coins, which is their trading frequency and volume. Tables 10 and 11, Appendix A provides the information on coins' frequency and volumes of trades at hourly and daily frequencies, respectively. Based on these results, we distinguish the frequently traded coins at the hourly frequency (with more than 50% of non-zero volumes in the sample) and frequently traded coins at the daily frequency (with more than 90% of non-zero volumes in the sample) [2]. All natives are frequently traded at both the hourly and daily frequencies. These are the big-cap natives BTC, ETH and XRP with the market capitalization of over 10 billion Dollars and small-cap natives XLM, LTC, BCH, ADA, ALGO, SGB and HBAR.

At the hourly frequency, only the two big-cap stablecoins Tether and USD Coin with the largest capitalizations in the market are frequently traded. At the daily frequency, we have three stablecoins: Tether, USD Coin and DAI.

At the hourly frequency 18 tokens satisfy the frequent trade requirement, while at the daily frequency, 23 tokens are frequently traded. All of those tokens are considered to be

[2] In the case of zero volumes, the prices are considered constant.

small-cap coins. Among them we distinguish the Decentralized Finance (DeFi) Platforms and Tokens: Aave (AAVE), Compound (COMP), Curve Finance (CRV), Synthetix (SNX), Maker (MKR), Uniswap (UNI), Yearn.finance (YFI), UMA (UMA), Alpha Finance (ALPHA) and Perpetual Protocol (PERP); the Decentralized Oracle Network Chainlink (LINK); and the Blockchain-Based Gaming and NFTs: The Sandbox (SAND), Axie Infinity (AXS), Enjin Coin (ENJ), Smooth Love Potion (SLP) and Gala (GALA).

3 Methodology

3.1 Principal Component Analysis (PCA)

The PCA is a decomposition of the variance-covariance matrix (variance matrix, henceforth) of a multivariate random variable. For matrix X of dimension $n \times m$ with columns containing the random variables denoted by $x_i, i = 1, ..., m$ of length n, the theoretical variance matrix is $E[(X - E(X))(X - E(X))']$, where $E(X)$ is the vector of expected values. In practice, the expected values are estimated from the sample averages and the variance matrix is estimated from the sample of n demeaned observations as $\tilde{X}'\tilde{X}/n$.

Alternatively, the PCA can be applied to the variance matrix of standardized random variables, containing the columns $\tilde{x}_i/\sigma(\tilde{x}_i)$, where $\sigma(\tilde{x}_i)^2$ is the variance of component $\tilde{x}_i$.

The PCA is a system of linear combinations of the variables (James et al., 2013). The first principal component is the linear combination of all variables that explains the highest percentage of the total variance. The remaining linear combinations are orthogonal to the first principal component and explain lower percentages of the variance. The PCA applied to the symmetric matrix $\tilde{X}'\tilde{X}$ is:

$$\tilde{X}'\tilde{X} = Q\Lambda Q' = \sum_{i=1}^{m} \lambda_i q_i q_i'.$$

where Q is an orthogonal $m \times m$ matrix whose columns $q_i, i = 1, ..., m$ are the eigenvectors of $\tilde{X}'\tilde{X}$ and Λ is a diagonal matrix whose elements are the eigenvalues of $\tilde{X}'\tilde{X}$.

From the financial point of view, we can interpret those outcomes as follows: λ_1 points to the maximum risk portfolio with the allocation vector q_1. The CAPM theory implies that $\lambda_2, ..., = 0$ and the first principal component $\tilde{X}q_1$ is the market portfolio with positive allocations.

In our application to cryptocurrency data, the PCA decomposes the variance-covariance matrix of daily and hourly returns into orthogonal common factors (principal components) with respect to their decreasing explanatory power. The higher the fraction of total variance explained by the first few common factors for a group of cryptos, the more interconnected the cryptos in that group. Therefore, a larger return connectedness implies a greater systemic risk among the cryptos.

3.2 Connectedness Measure

The inter-connectedness of cryptocurrencies can be assessed by using the connectedness measure of Billio et al. (2012) based on the PCA applied to the variance-covariance matrix of $\mathcal{N}$ demeaned and standardized asset returns [3]. This measure provides us with the exposure and contribution of each cryptocurrency to the cryptocurrency market risk, which can be interpreted as the systemic risk. Billio et al. (2012) compare the total risk of the system defined by $\Omega = \sum_{k=1}^{\mathcal{N}} \lambda_k$ with the risk associated with the first n principal components, defined by $\omega_n = \sum_{k=1}^{n} \lambda_k$. This ratio is called the cumulative variance percentage and defined as:

$$h_n = \frac{\omega_n}{\Omega}$$

where h_n denotes the cumulative variance percentage explained by the first n principal components and Ω is the sum of all eigenvalues. The system is highly interconnected if a small number of n principal components can explain most of the total variance.

Billio et al. (2012) measure the connectedness in terms of individual exposure and contribution to the system, denoted by $PCAS_{i,n}$. It is the contribution of asset i to the risk of the system, conditional on a strong common component across the returns $h_n \geq H$ where H is a pre-specified threshold level, and defined as:

$$PCAS_{i,n} = \frac{1}{2} \frac{\sigma_i^2}{\sigma_S^2} Q^2 \Lambda |_{h_n \geq H}$$

where σ_i^2 is the variance of returns on asset i, Q is the matrix of eigenvectors, Λ is the diagonal matrix of eigenvalues, $\sigma_S^2 = \sigma' Q \Lambda Q' \sigma$ is the total variance of the system and σ is a vector containing the standard deviations of all asset returns.

3.3 Portfolios of Cryptocurrencies

We build a principal eigenportfolio by using the first eigenvector of the variance-covariance matrix of demeaned and standardized returns. It is widely recognized that the principal eigenportfolio is a good market portfolio proxy for the stocks (Avellaneda et al., 2022). We

[3] We apply the PCA to demeaned and rescaled returns in Section 5.

extend this concept to the cryptocurrency market with $\mathcal{N}$ assets, and denote the principal eigenportfolio by E^1, where $E^1 = \frac{1}{c}v^{-1}q^1$ and $v = diag(v_1, ..., v_N)$ is given below

$$v = \begin{pmatrix} v_1 & & & \\ & v_2 & & \\ & & \ddots & \\ & & & v_N \end{pmatrix}$$

where $v_i = \sqrt{\frac{1}{T-1}\sum_{t=1}^{T}(r_i(t) - \bar{r}_i)^2}$, $r_i(t)$ is the return on asset i at time t, q^1 is the first eigenvector and $c = \sum_{i=1}^{\mathcal{N}} q_i^1/v_i$. Note that the eigenportfolio is normalized to sum to one by using c. The return of the principal eigenportfolio at time t is denoted by

$$f(t) = \sum_{i=1}^{\mathcal{N}} r_i(t)E_i^1$$

The principal eigenportfolio accounts for the highest proportion of the variance of returns (Avellaneda et al., 2022).

3.4 Functional Regression

We estimate the functional regression (Ramsay and Silverman, 2005) with the functions of 24 hourly returns on a given cryptocurrency as the dependent variable and the functions of 24 hourly returns on the cryptocurrency market portfolio (eigenportfolio) as the regressor. More specifically, we consider the excess returns and estimate a functional equivalent of the CAPM model:

$$y_d(s) = \int_{-24}^{72} \Pi(s,t)x_i(t)dt + u_d(s)$$

where $y_d(s)$ is the excesss return of time $s \in S$ of day d on a cryptocurrency, $x_d(t)$ is the excess market return on day d at time t, $u_d(s)$ is a zero-mean error term and $\Pi(s,t)$ is the integral operator. The integral operator Π depicts the dynamic relation between the returns on a specific cryptocurrency and the cryptocurrency market factor. By integrating over the range -24 to 72, we examine the functional relationship over the previous, current and next days.

The daily functional regression of the return function on the market factor portfolio function is:

$$y_i(s) = \int_{-7}^{14} \Pi(s,t)x_i(t)dt + u_i(s)$$

where $y_i(s)$ is the return of day $s \in S$ of the week i on a cryptocurrency. $x_i(t)$ is the excess market return on week i (the week starts on Monday, i.e. 1 to 7 represents Monday to Sunday respectively) at day t, and $u_i(s)$ is a zero-mean error term. By integrating over the range -7 to 14, we examine the functional relationship over the previous and current week.

Benatia et al. (2017) shows that the estimator of $\Pi(s,t)$ calculated from discrete data can be written as

$$\hat{\pi}_\alpha(s,t) = \frac{1}{N}\underline{y}(s)'(\alpha I + M)^{-1}\underline{x}(t)$$

where N is the number of days in the sample, $\underline{y}$ and $\underline{x}$ are the $N \times 1$ vectors with ith element $y_i(t)$ and $x_i(t)$ respectively. The matrix M is of dimension $N \times N$ with (l,i) element $\langle x_l, x_i \rangle / N$. The regularization parameter α is chosen by leave-one-out cross-validation (LOOCV).
The variance of the integral operator $\hat{\Pi}(.)$ for discrete data can be calculated as follows:

$$V\hat{\pi}_u(s) \simeq \left(\sum x_i x_i' + \alpha_u I\right)^{-1} \sum x_i x_i' \hat{u}_i^2(s) \left(\sum x_i x_i' + \alpha_u I\right)^{-1}$$

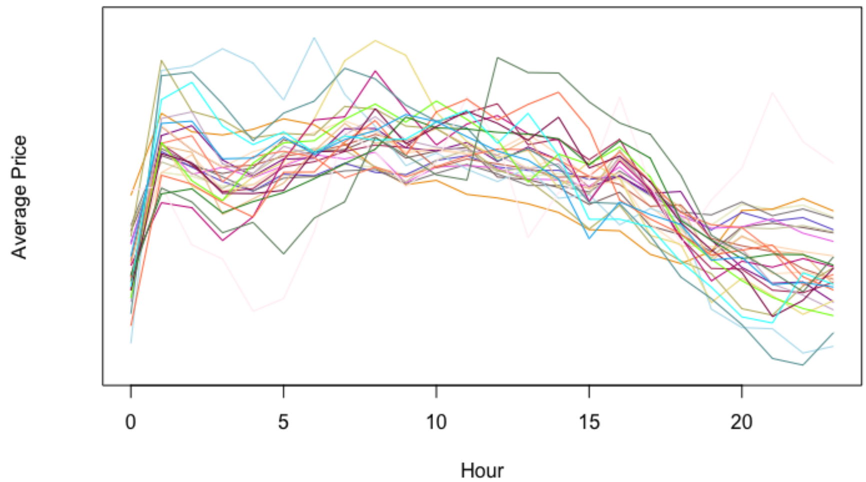
This expression is used to assess the statistical significance of coefficients in the daily functional regressions. In intraday regressions, we use the cut-off points of estimated coefficients to determine the statistical significance because of sparsity and singularity issues in high dimensional data.

4 Intraday and Intraweek Patterns

4.1 Intraday Patterns

This section describes the common intraday patterns observed in the natives, stablecoins and tokens. The intraday dynamic of hourly prices of cryptocurrency motivating this research is illustrated in Figure 1. The curves represent the prices of all frequently traded natives and tokens rescaled by their own daily price averages over 24 hours of UTC day.

Figure 1: Hourly Average Price of Frequently Traded Coins (No Stablecoins)



All hourly average prices of coins are rescaled (but not demeaned) by their own average prices, e.g., BTC's hourly average prices are rescaled (but not demeaned) by the average price of BTC between UTC hours 0 to 23.

We observe that the (rescaled) prices of those frequently traded cryptocurrencies are relatively steady across the first part of UTC day and decrease after UTC hour 14:00 corresponding to the opening of NYSE [4].

4.1.1 Native cryptocurrency

The hourly averages computed over the sampling period are used to describe the common intraday behaviour of the natives. Figure 2 shows the patterns of BTC as an example [5].

The hourly average price of native cryptocurrencies tend to decrease between UTC hour 14:00 of NYSE opening until the end of UTC day. This price decrease is associated with high volatility of returns at UTC hour 14:00, as indicated by large intra-quartile range of returns, and peaks in both daily RV volatility and volume. The price rebounds slightly in some natives at UTC hour 20:00, which coincides with the NYSE closing time, except for ALGO, SGB and HBAR. An increase in volatility and volume is reported at UTC hour 20:00 as well. Afterwards, the prices, volumes and volatilities tend to remain low until the

[4]We use panel B as the time of reference for intraday pattern description.

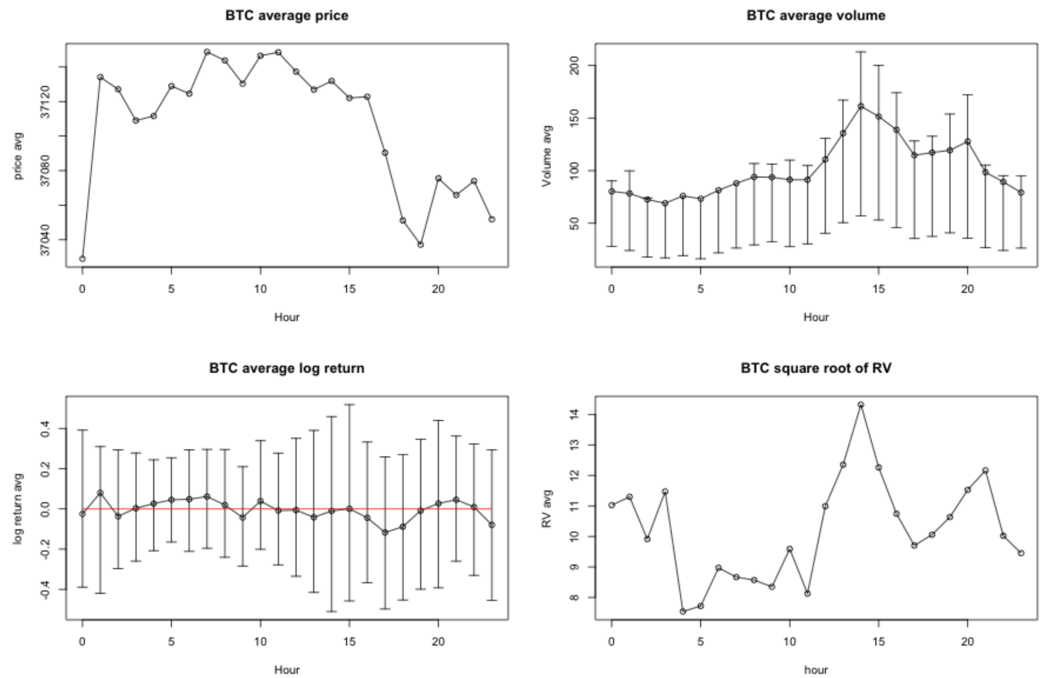
[5]For comparison, the intraday patterns of other natives are given in Figures 34 to 42, Online Appendix.

price increases sharply at the opening of Hang Seng at UTC hour 1:00. Another, although smaller price increase is observed at UTC hour 5:00 (except for SGB), which coincides with the re-opening of the second part of Hang Seng trading day.

Positive average returns tend to be associated with the price increases at UTC hours 1:00, 5:00 (BTC, XLM, XRP, ETH, LTC, ADA, ALGO, HBAR) and 20:00 (BTC, XLM, XRP, ETH, LTC, ADA). During the NYSE trading hours (UTC hours 14:00 to 20:00), the hourly average returns of native cryptocurrencies are close to 0 or negative.

We find that most of the natives display their highest hourly average volumes during the overlap of the operating times of LSE and NYSE (UTC hours 14:00 to 16:00). The exceptions are XRP, SGB and HBAR. The hourly average volume of XRP peaks at UTC hour 10:00 and decreases after the LSE closing time. According to Bitstamp (https://www.bitstamp.net), XRP is unavailable in the US, which may explain this pattern. The hourly average volumes of SGB and HBAR peak at UTC hour 19:00, i.e. one hour before NYSE closes. The RV of most of the natives (except for SGB) is high during UTC hours 12:00 to 16:00, i.e. the second part of LSE trading day. For most of the natives, this period of high volatilities is associated with high volumes and close to 0 returns.

Figure 2: BTC



The top left graph displays the average prices of Bitcoin at each hour of the day. The top right graph displays the average volumes of Bitcoin at each hour of the day. The bottom left displays the average return of Bitcoin at each hour of the day. The bottom right graph displays the volatility of Bitcoin at each hour of the day. The vertical lines in the average volumes and log returns plots indicate the 25th and 75th percentiles of sample density. The red line in average log returns is at zero.

The intraday patterns of other frequently traded natives are displayed in Figures 34 to 42 in Online Appendix.

4.1.2 Tokens

A common periodic pattern of the tokens (except for KNC) is a price decrease following the opening of NYSE at UTC hour 14:00, which also characterizes the prices of natives. For illustration, Figure 3 displays the hourly averages of Chainlink (LINK). The prices tend to be low after NYSE closes at UTC hour 20:00 until the opening of Hang Seng at UTC hour 1:00 when they increase sharply. The prices of most of the tokens, like the natives, increase again at the re-opening of the second part of Hang Seng trading day at UTC hour 5:00, which leads to positive average returns in most of the tokens [6]. There is another slight rebound observed in the prices of several tokens (e.g. LINK, UNI, SAND, AAVE, CRV, SNX, YFI,

[6] LINK, UNI, ENJ, AAVE, CRV, SNX, UMA, AXS, CHZ, MKR, GRT, GALA, BAT

GRT, MKR) at UTC hour 16:00, which corresponds to the closing of LSE. Similarly to the natives, some of the Decentralized Finance (DeFi) and Financial Services tokens, such as AAVE, AUDIO, BAT and FTM, show a slight price increase at UTC hour 20:00, i.e. the closing of NYSE. These two effects are not found in GALA, CHZ, and AXS.

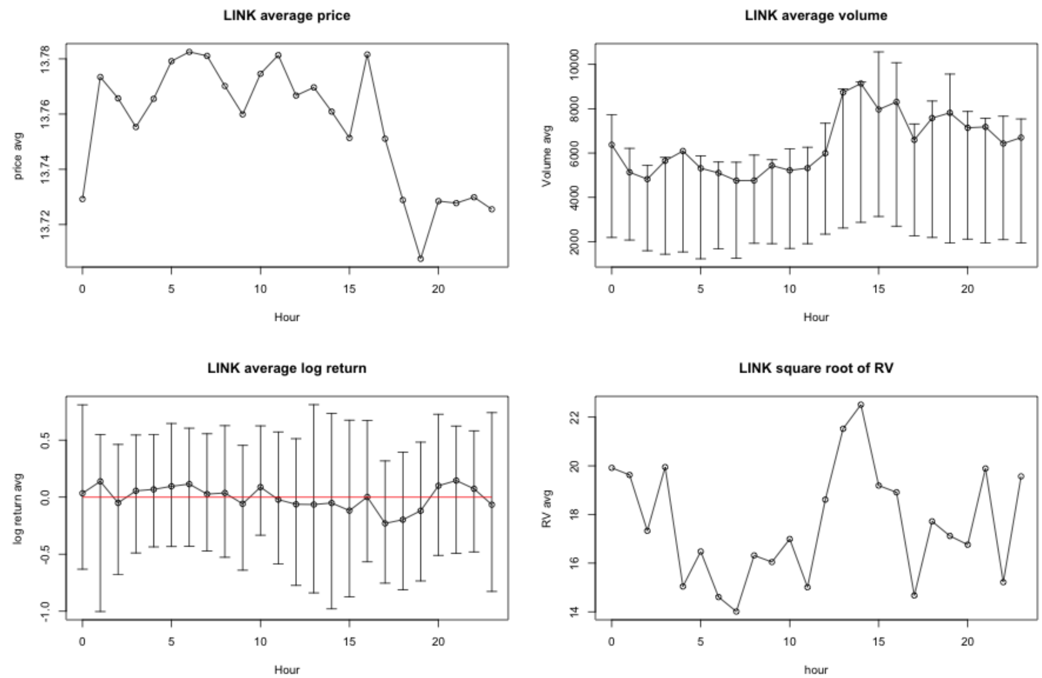
A the opening time of Hang Seng, some of the DeFi Platforms and Tokens and Blockchain-Based Gaming, such as SAND, CRV, GALA, YFI, and AXS, display their all-day high price. Other DeFi and Blockchain-Based Game and Music tokens, such as MATIC, AUDIO, SNX, GALA, COMP and BAT, display their maximum daily price at UTC hour 8:00, which corresponds to the opening of LSE.

Most of the tokens, show negative hourly average returns after LSE closes at UTC hour 16:00, except for SNX, YFI and GALA. GRT and MKR have positive hourly average returns between UTC hours 4:00 to 9:00, i.e. during the second part of the Hang Seng trading day until the opening of LSE.

Many tokens, including LINK, UNI, SAND, GALA, MKR, and COMP attain their top hourly average volumes and volatility during the period of overlap of LSE and NYSE trading between UTC hours 13:00 and 16:00. At UTC hour 14:00 , we observe a daily peak in volatility and volume of several tokens. For COMP and MKR, the peak in volume and volatility occurs earlier at UTC hour 13:00. CHZ, AUDIO and GRT display multiple peaks in volume, not all of the them being associated with increased return variances. Similarly, the volatility of SAND and AVE peaks at UTC hour 14:00, although the all-day maximum volume is observed later in the day at UTC hours 16:00 and 19:00, respectively. We observe that the patterns of KNC are quite different from those observed in other tokens.

The intraday patterns of other frequently traded tokens are displayed in Figures 43 to 59, Online Appendix.

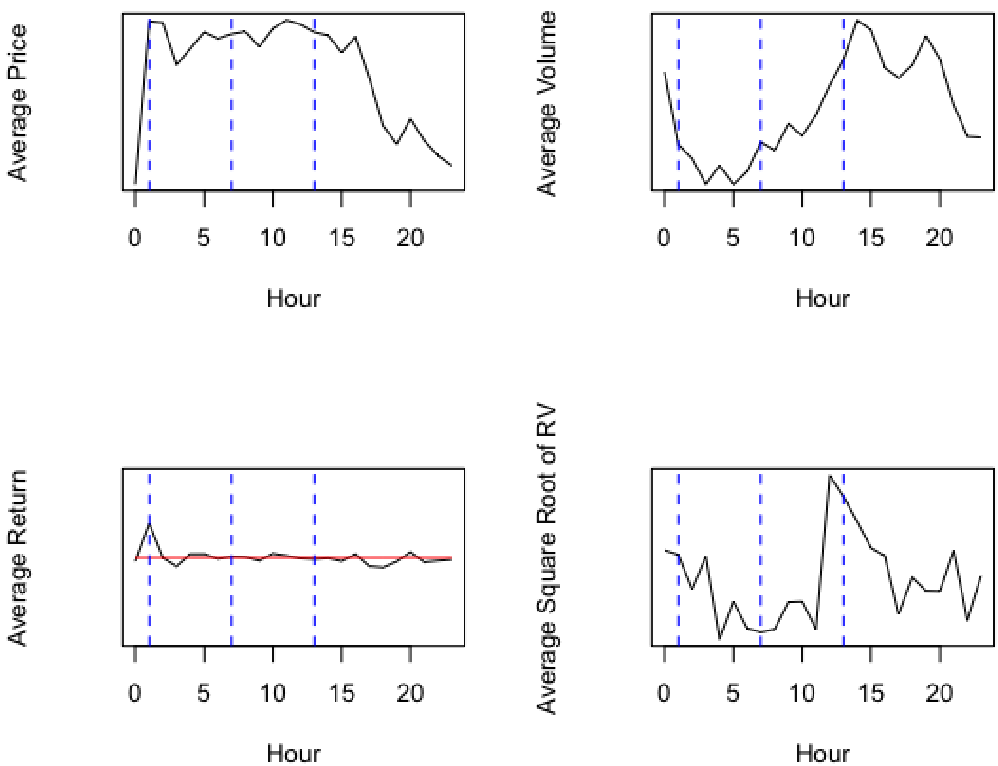
Figure 3: LINK



The top left graph displays the average prices of Chainlink at each hour of the day. The top right graph displays the average volumes of Chainlink at each hour of the day. The bottom left displays the average return of Chainlink at each hour of the day. The bottom right graph displays the volatility of Chainlink at each hour of the day. The vertical lines in the average volumes and log returns plots indicate the 25th and 75th percentiles of sample density. The red line in average log returns is at zero.

We conclude that native cryptocurrencies and frequently traded tokens share common patterns in hourly averages. Their intraday averages of prices, returns, volatility and volumes are influenced by the openings of major trading markets, as illustrated in Figure 4.

Figure 4: Typical Intraday Pattern of Native Coins and Tokens



The top left graph displays the typical intraday pattern of the average price of native coins and tokens. The top right graph displays the typical intraday pattern of the average volume of native coins and tokens. The bottom left displays the typical intraday pattern of the average return of native coins and tokens. The bottom right graph displays the typical intraday pattern of the volatility of native coins and tokens. The red line in average log returns is at zero.

The typical intraday pattern of price, return, volume, and RV is calculated by averaging the series of prices, volumes and volatilities. The returns are calculated from the average price series of natives and tokens. The openings of Hang Seng, LSE and NYSE are marked by the vertical lines in Figure 4.

After UTC hour 14:00 corresponding to the opening of NYSE, most native coins and tokens have lower prices, volumes and volatility. The prices increase at the opening of Hang Seng at UTC hour 1:00, tend to be associated with positive returns. There is another small positive return at UTC hour 20:00 corresponding to the closure of NYSE.

4.1.3 Stablecoins

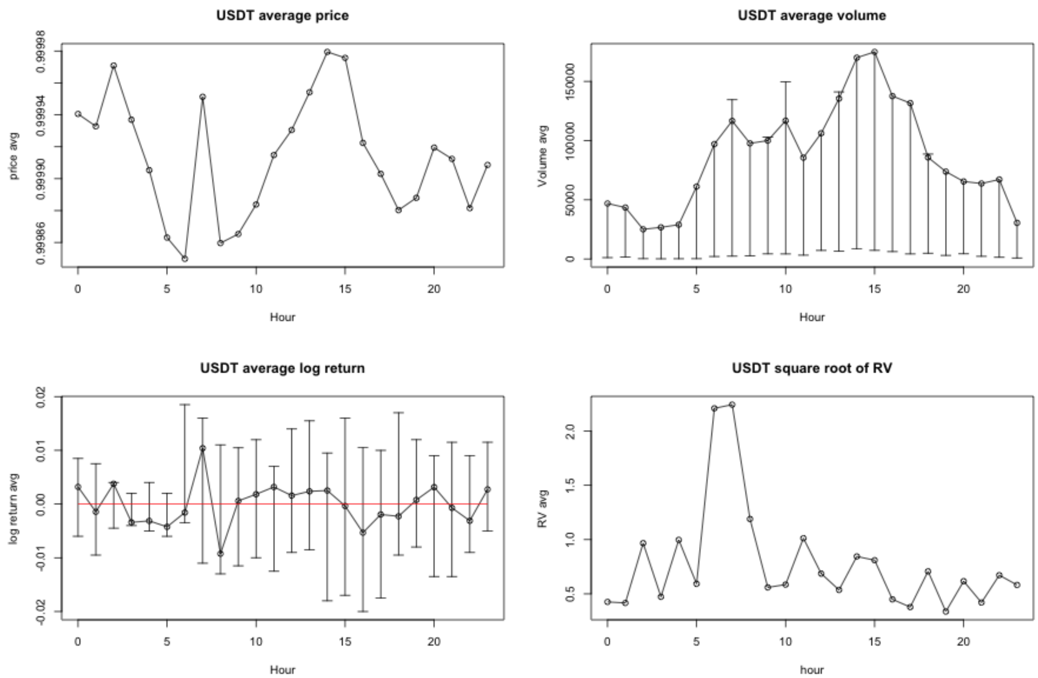
The stablecoins have lower price volatility than the native cryptocurrencies. For example, we can compare the coefficient of variation (CV) of BTC, a native cryptocurrency with the CV of Tether (UTSD), a stablecoin by computing the two following statistics:

$$CV_1 = \frac{\sigma}{\bar{x}} \text{ and } CV_2 = \frac{x_{max} - x_{min}}{\bar{x}}$$

We find that CV_1 is 19.41% for BTC as compared to 0.11% for USDT. Similarly, CV_2 is 81.41% for BTC and 3.91% for USDT.

The prices of stablecoins do not share much common periodic patterns, unlike the native cryptocurrencies and tokens. Figure 5 displays the patterns of USDT as an example of stablecoin intraday behavior. The intraday changes in prices and returns are very small and need to be interpreted with caution. The hourly average price of USDT is high after the opening of Hang Seng at UTC hour 2:00 and one hour before Hang Seng closes at UTC hour 7:00. Later on, it rises again after the opening of NYSE to its daily maximum between hours 14:00 and 15:00 . The average return of USDT is positive and at its all-day high at UTC hour 7:00, before the closing of Hang Seng. It remains positive between UTC hours 9:00 to 14:00 when LSE is operating. The hourly average volume of USDT is high over the LSE trading day between UTC hours 8:00 and 14:00 and peaks at the opening hour of NYSE at UTC hour 14:00. The hourly average RV of USDT is high between UTC hours 6:00 and 7:00. For comparison, the hourly average price of USDC (Figure 60, Online Appendix) attains its top level at UTC hour 0:00, i.e. one hour before the opening of Hang Seng. The hourly average volume of USDC is high at UTC hour 10:00 and after the closure of NYSE at UTC hour 20:00. The hourly average RV of USDC peaks between UTC hours 13:00 and 14:00 when LSE is operating and NYSE is about to open. That RV peak is associated with low prices and positive returns at UTC hour 14:00 when NYSE opens.

Figure 5: USDT

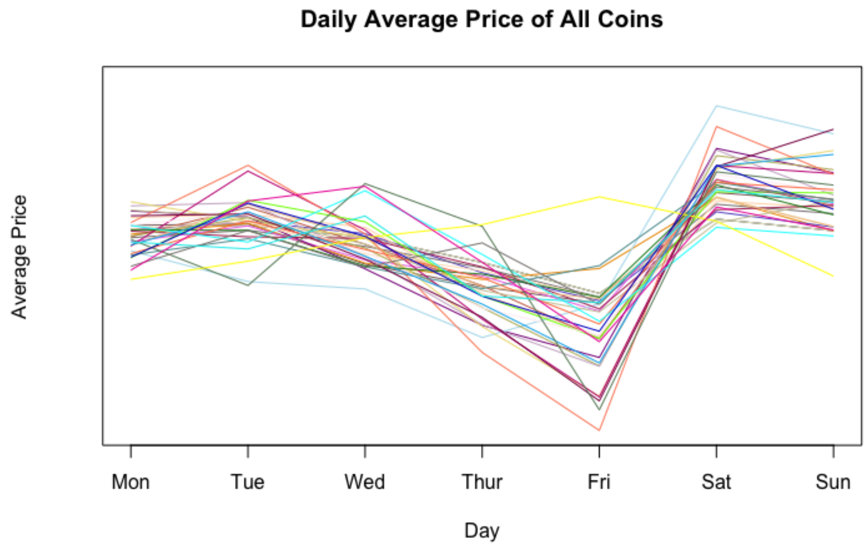


The top left graph displays the average prices of Tether at each hour of the day. The top right graph displays the average volumes of Tether at each hour of the day. The bottom left displays the average return of Tether at each hour of the day. The bottom right graph displays the volatility of Tether at each hour of the day. The vertical lines in average volumes and log returns plots indicate the 25th and 75th percentiles of sample density. The red line in average log returns is at zero.

4.2 Intraweek Patterns

This Section examines the intraweek patterns in native cryptocurrency, stablecoins and tokens. The analysis is motivated by the price behavior illustrated in Figure 6. The curves represent the prices of all frequently traded natives and tokens rescaled by their own weekly price averages over 7 days of the week.

Figure 6: Daily Average Price of All Coins (No Stablecoins)



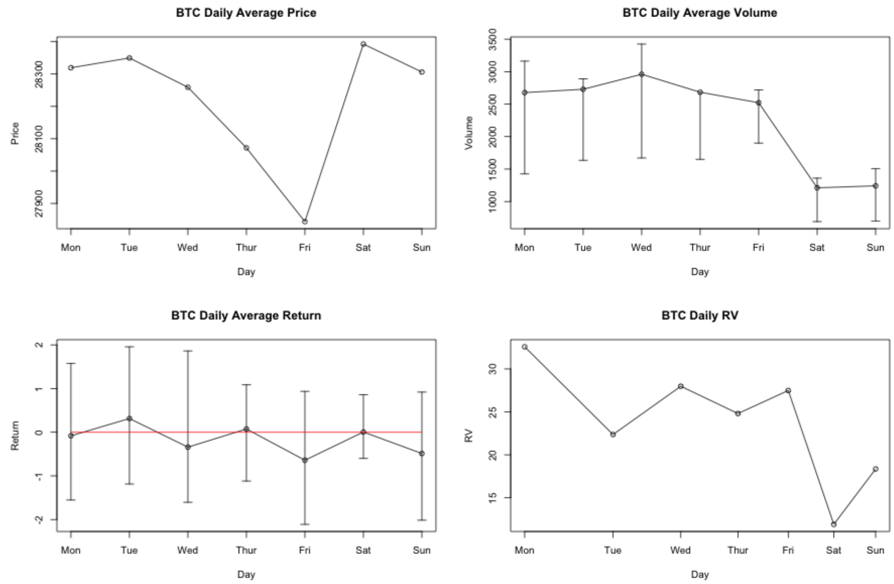
All coin's daily average prices are rescaled (but not demeaned) by their own average prices, e.g., BTC's daily average prices are rescaled (but not demeaned) by the average price of BTC on days 1 to 7 (Monday to Sunday)

We observe that the coin prices are on average relatively steady during the working days and decrease on Fridays. The highest average prices tend to be recorded on Saturdays.

4.2.1 Native Cryptocurrency

There is a common pattern in the intraweek average prices of native cryptocurrency, with daily averages decreasing gradually over the working days down to their lowest level on Fridays. As an example, Figure 7 shows the intraweek pattern of Bitcoin (BTC). The daily average prices of BTC and other native coins rebound on the weekends and tend to be high on Saturdays. The daily average returns tend to be positive on Tuesdays when most natives also show low average volatility. The highest volumes are mostly recorded on Wednesdays or Thursdays. The average volatility and volumes are low on the weekends. There are some exceptions. For example, XRP displays its lowest price on Thursday, instead of Friday. The volume of ETH and ADA peak on Tuesdays and the RV of SGB is at its highest level on Fridays.

Figure 7: BTC



The top left graph displays the average daily prices of Bitcoin on each day of the week. The top right graph displays the average daily volumes of Bitcoin on each day of the week. The bottom left graph displays the average daily return of Bitcoin on each day of the week. The bottom right graph displays the daily volatility of Bitcoin on each day of the week. The vertical lines in the average volumes and log returns plots indicate the 25th and 75th percentiles of sample density. The red line in average log returns is at zero.

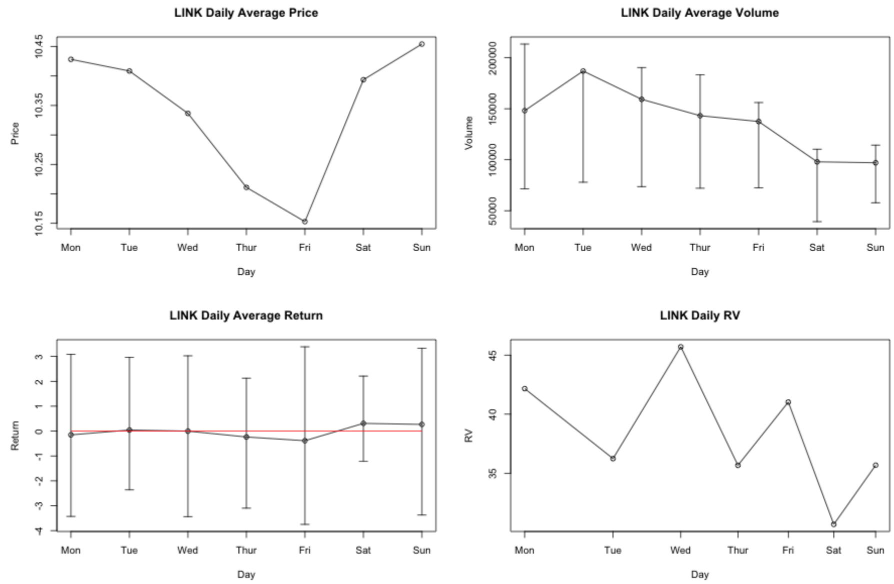
The intraweek patterns of other native cryptocurrencies are displayed in Figures 61 to 69 Online Appendix.

4.2.2 Tokens

Tokens display similar common intraweek patterns. The daily average price of tokens decrease over the week to its lowest level on Friday and jumps up on the weekends. CHZ is the only token in our sample with the lowest average price on Thursdays. Like in the intraday data, KNC also shows a different price pattern. Its price increases during the workweek, Monday through Friday, and falls on the weekends, Saturday through Sunday. The daily average volumes and volatilities of tokens decrease through the week as well and are at their lowest levels over the weekends. The daily average returns display low volatility and tend to be positive on Saturdays.

As an example, Figure 8 illustrates the intra-week pattern of the Chainlink (LINK).

Figure 8: LINK

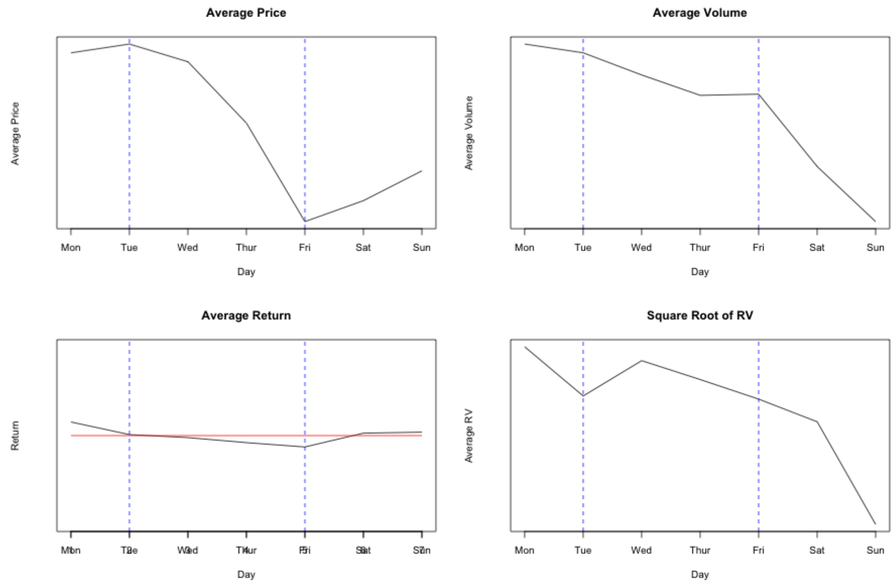


The top left graph displays the average daily prices of Chainlink on each day of the week. The top right graph displays the average daily volumes of Chainlink on each day of the week. The bottom left graph displays the average daily return of Chainlink on each day of the week. The bottom right graph displays the daily volatility of Chainlink on each day of the week. The vertical lines in the average volumes and log returns plots indicate the 25th and 75th percentiles of sample density. The red line in average log returns is at zero.

The intraweek patterns of tokens are displayed in Figures 70 to 91, Online Appendix.

We summarize the results of Sections 4.1 and 4.2 in Figure 9, which shows a typical intraweek pattern of native coins and tokens. The daily average prices decrease over the week to their lowest levels on Fridays. The weekends are characterized by high prices and low average volumes and volatility.

Figure 9: Typical Intraweek Pattern of Native Coins and Tokens



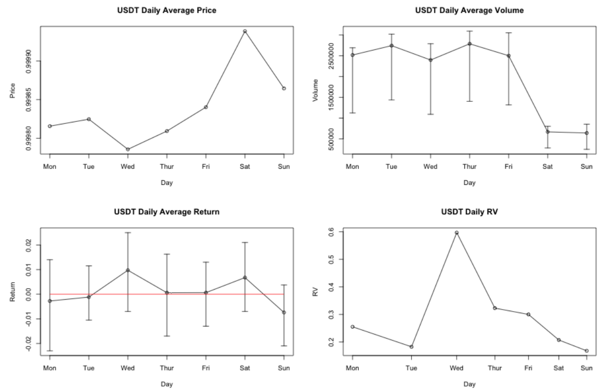
The top left graph displays the typical intraweek average daily price pattern of native coins and tokens. The top right graph displays the typical intraweek average daily volume pattern of native coins and tokens. The bottom left graph displays the typical intraweek average daily returns pattern of native coins and tokens. The bottom right graph displays the typical intraweek daily volatility pattern of native coins and tokens. The red line in average log returns is at zero

The typical intraweek pattern of price, return, volume, and RV is calculated by averaging over the series of daily prices, returns volumes, and RV of several cryptocurrencies. The vertical lines indicate Tuesdays and Fridays associated to the maximum and minimum intraweek average prices, respectively.

4.2.3 Stablecoins

Stablecoins do not share much common intraweek patterns. The daily average prices of stablecoins tend to be lower in the middle of the week. They attain their weekly maximum at the end of the week. Figure 10 show the intraweek patterns of Tether (USDT).

Figure 10: USDT



The top left graph displays the average daily prices of Tether on each day of the week. The top right graph displays the average daily volumes of Tether on each day of the week. The bottom left graph displays the average daily return of Tether on each day of the week. The bottom right graph displays the daily volatility of Tether on each day of the week. The vertical lines in the average volumes and log returns plots indicate the 25th and 75th percentiles of sample density. The red line in average log returns is at zero.

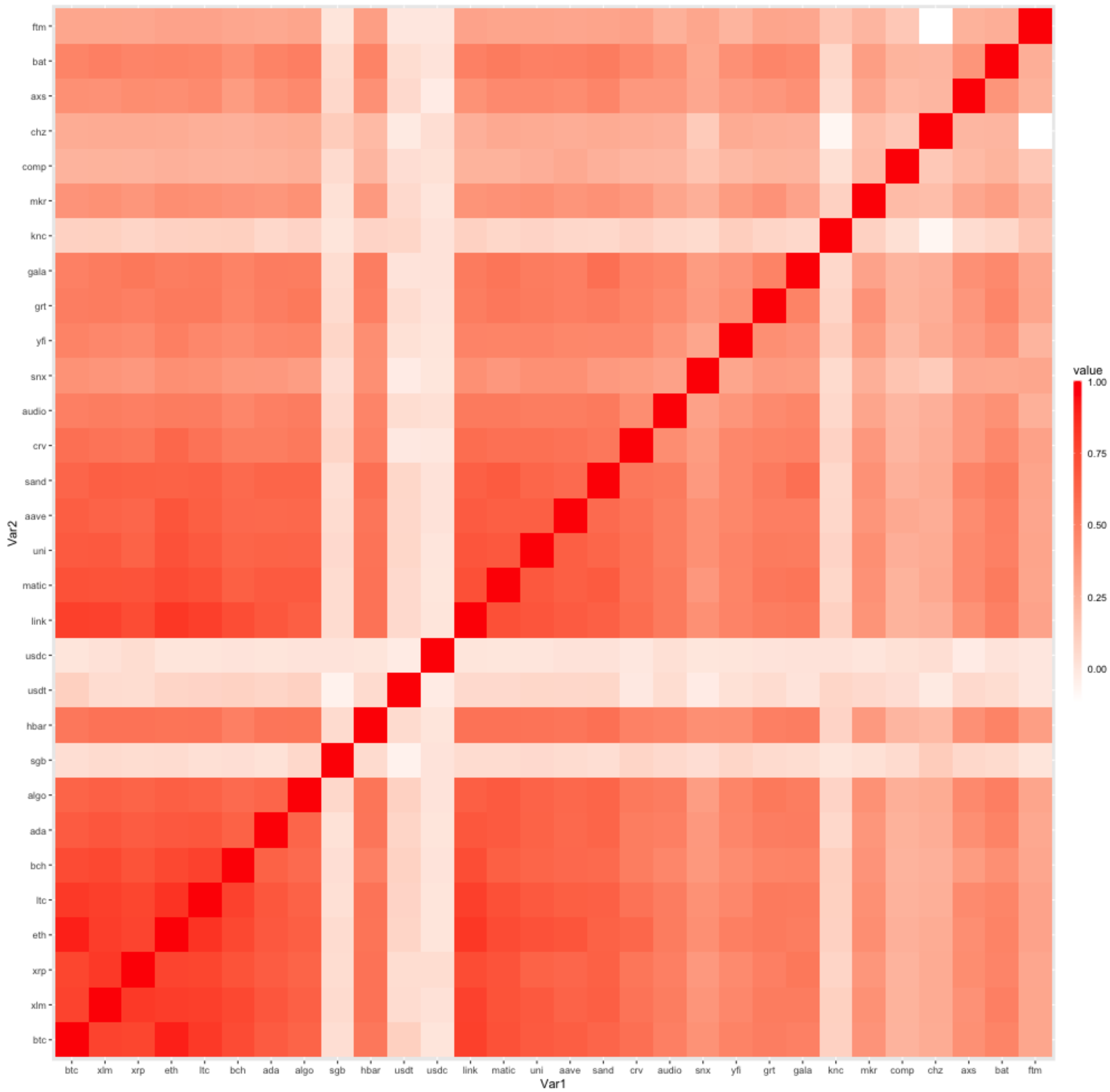
The daily average volumes of USDT and USDC tend to decrease over the working days down to their lowest levels on the weekends. The intraweek patterns of USDC are given in Figure 92, Online Appendix. The intraweek patterns of DAI are quite distinct from USDT and USDC. For comparison, they are are displayed in Figure 94, Online Appendix.

5 Cryptocurrency Market Portfolio

5.1 Correlation of hourly cryptocurrency returns

The correlation matrix is a basic measure of cross-sectional dependence of returns on coins over the sampling period. The contemporaneous cross-correlation analysis of hourly returns is applied to 30 hourly frequently traded coins. Figure 11 shows the heatmap of hourly return correlations of these cryptocurrencies.

Figure 11: The Heatmap of Hourly Return Correlation



A darker colour indicates that the two coins are more correlated. A lighter colour indicates that the two coins are less correlated. We observe that the stablecoins are uncorrelated with other coins and with one another.

The correlation matrix is computed from the returns on natives, stables and tokens, displayed on the axis of Figure 11 in this order. Starting from the origin, the coins in each group are ranked with respect to the percentages of daily non-zero volumes, which are decreasing from left to right. Hence, the coins located on the right side of the figure are traded less often than other coins and have more zero values of returns, which can bias the correlations down and may explain why they appear less correlated with the remaining coins. The dark color represents a strong correlation, while the light color depicts correlations close to 0. The return correlations are positive and high, especially for the natives and some tokens. The exceptions are SGB (native coin), and KNC, (token) which are not highly correlated with other coins [7]. The returns on stablecoins USDT and USDC show little correlation with the returns on other coins (columns 11 to 12 on the horizontal axis). These correlations are close to zero and appear almost white in Figure 11.

5.2 PCA analysis of hourly returns

The PCA is applied to the variance of return matrix of dimension 4296 by 30, with each column containing the demeaned and rescaled returns on one particular coin [8].

Table 2 displays the eigenvalues associated with each principal component. We observe that the eigenvalues cut-off, in the sense that the first one is much larger than the remaining ones. We calculate the variance percentage explained by each principal component, $h_i = \lambda_i / \sum_1^{30} \lambda_i$, and the cumulative variance percentage explained by the first n principal components, $h_n = \sum_1^n \lambda_i / \sum_1^{30} \lambda_i$, which are reported in columns 2 and 3, respectively. The first principal component captures 44.55% of the variability among the hourly cryptocurrency returns. The first 10 (resp. 20) principal components explain 73.83% (resp. 91.40%) of the hourly return variation.

[7]Recall that KNC displays distinct periodic patterns as pointed out in Secion 4.1.2.

[8]The row dimension 4296 is 179 days times 24 observations per day. Each column of the matrix is demeaned by subtracting the global mean and rescaled by dividing the demeaned columns by their standard deviation.

Table 2: Hourly PCA Eigenvalue, Variance Percentage Explained by Each PC and Cumulative Variance Percentage

	Eigenvalue	Variance Percent	Cumulative Variance Percent
Dim.1	13.36	44.55	44.55
Dim.2	1.29	4.31	48.86
Dim.3	1.26	4.19	53.05
Dim.4	1.05	3.52	56.57
Dim.5	1.02	3.41	59.98
Dim.6	0.98	3.27	63.25
Dim.7	0.87	2.91	66.16
Dim.8	0.84	2.81	68.97
Dim.9	0.74	2.47	71.44
Dim.10	0.72	2.39	73.83
Dim.11	0.65	2.15	75.98
Dim.12	0.62	2.07	78.04
Dim.13	0.59	1.95	80.00
Dim.14	0.58	1.93	81.92
Dim.15	0.53	1.75	83.68
Dim.16	0.52	1.73	85.40
Dim.17	0.49	1.65	87.05
Dim.18	0.47	1.58	88.63
Dim.19	0.44	1.46	90.09
Dim.20	0.39	1.30	91.40
Dim.21	0.37	1.22	92.62
Dim.22	0.36	1.19	93.81
Dim.23	0.34	1.13	94.93
Dim.24	0.31	1.04	95.97
Dim.25	0.28	0.95	96.92
Dim.26	0.27	0.89	97.81
Dim.27	0.22	0.73	98.54
Dim.28	0.18	0.60	99.13
Dim.29	0.17	0.57	99.70
Dim.30	0.09	0.30	100.00

Table 3 displays the computed connectedness measures $PCAS_{i,n}$ for n = 20. As mentioned earlier, the $PCAS_{i,n}$ of an individual coin i illustrates its risk contribution, or exposure to the system (Billio et al., 2012). We notice that the stablecoins (USDT and USDC) have a much lower contribution to the system, compared to natives and tokens. This is consistent with the objective of stablecoins, as they are supposed to remain strongly correlated with the US Dollar, to maintain the peg, rather than with the cryptocurrency market. Hence, the stablecoins seem immune to the cryptocurrency market risk.

We also find that Bitcoin has the lowest risk exposure to the system among the natives and frequently traded tokens. Moreover, SGB has the highest PCAS (0.0026) among the natives and KNC has the highest PCAS (0.0050) among the tokens.

Table 3: Hourly $PCAS$ for Each Cryptocurrency

Coin	$PCAS_{i,n}$	Coin	$PCAS_{i,n}$
btc	0.000910	xlm	0.001200
xrp	0.001100	eth	0.001200
ltc	0.001200	bch	0.001100
ada	0.001300	algo	0.001500
sgb	0.002600	hbar	0.001800
usdt	0.000094	usdc	0.000069
link	0.001500	matic	0.001400
uni	0.001400	aave	0.002000
sand	0.001600	crv	0.002200
audio	0.002500	snx	0.002700
yfi	0.001800	grt	0.002200
gala	0.002400	knc	0.005000
mkr	0.002300	comp	0.003600
chz	0.003100	axs	0.002400
bat	0.001900	ftm	0.003200

The first principal component associated with the largest eigenvalue explains the highest percentage of the variance. The big difference between the first and the second largest eigenvalues suggests the relevance of one market factor [Dunbar, Owusu-Amoako (2022), Tavares et al. (2021)]. The coefficients of the first principal component are used to build the eigenportfolio [Avellaneda et al. (2022)], which approximates the cryptocurrency market portfolio. The allocations of that eigenportfolio are the coin i's value of the first eigenvector (principal component coefficients) divided by the standard deviation of its return.

The allocations of the hourly market portfolio are displayed in Table 4 below. The stablecoins with returns that were found uncorrelated with the returns on other coins are not contributing to the risk on cryptocurrency market. Hence, they are removed from the market portfolio.

Table 4: Allocation of Hourly Eigenportfolio (without Stablecoins)

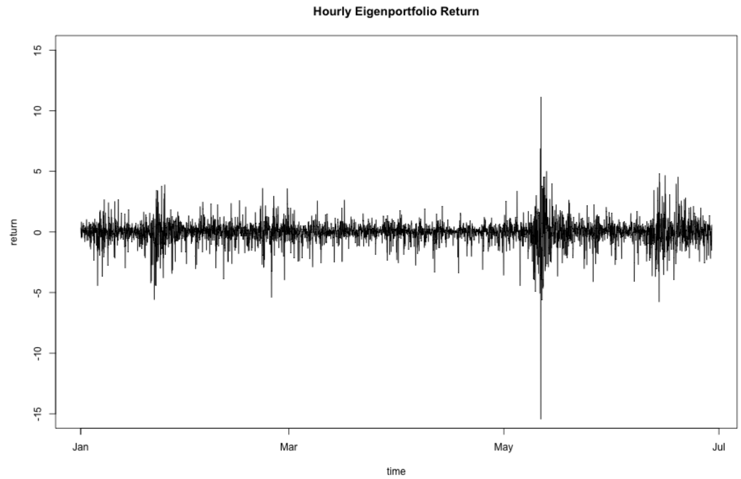
Coin	Allocation	Coin	Allocation
btc	0.08065	xlm	0.06152
xrp	0.05989	eth	0.06360
ltc	0.05981	bch	0.05425
ada	0.04529	algo	0.04243
sgb	0.00265	hbar	0.03806
link	0.04723	matic	0.04340
uni	0.04390	aave	0.03563
sand	0.03704	crv	0.03187
audio	0.02573	snx	0.01931
yfi	0.03356	grt	0.03057
gala	0.02716	knc	0.00239
mkr	0.02276	comp	0.00957
chz	0.01170	axs	0.02314
bat	0.03372	ftm	0.01318

Table 5: Daily PCA Eigenvalue, Variance Percentage Explained by Each PC and Cumulative Variance Percentage

	Eigenvalue	Variance Percent	Cumulative Variance Percent
Dim.1	21.39	59.41	59.41
Dim.2	1.33	3.69	63.09
Dim.3	1.14	3.17	66.27
Dim.4	1.03	2.87	69.14
Dim.5	0.95	2.65	71.79
Dim.6	0.86	2.39	74.18
Dim.7	0.70	1.96	76.13
Dim.8	0.64	1.79	77.92
Dim.9	0.63	1.74	79.66
Dim.10	0.61	1.70	81.36
Dim.11	0.53	1.47	82.83
Dim.12	0.47	1.32	84.15
Dim.13	0.46	1.27	85.41
Dim.14	0.43	1.19	86.60
Dim.15	0.38	1.06	87.66
Dim.16	0.35	0.97	88.64
Dim.17	0.34	0.94	89.57
Dim.18	0.33	0.92	90.49
Dim.19	0.32	0.88	91.37
Dim.20	0.29	0.81	92.18
Dim.21	0.28	0.77	92.95
Dim.22	0.27	0.74	93.69
Dim.23	0.25	0.68	94.37
Dim.24	0.22	0.61	94.98
Dim.25	0.22	0.60	95.58
Dim.26	0.20	0.56	96.15
Dim.27	0.19	0.52	96.67
Dim.28	0.18	0.51	97.18
Dim.29	0.17	0.46	97.64
Dim.30	0.16	0.43	98.07
Dim.31	0.15	0.41	98.48
Dim.32	0.15	0.40	98.88
Dim.33	0.12	0.34	99.22
Dim.34	0.12	0.32	99.55
Dim.35	0.09	0.25	99.79
Dim.36	0.08	0.21	100.00

The dynamic of the hourly returns on the cryptocurrency market portfolio (eigenportfolio) built by using the allocations given in Table 6 is plotted in Figure 12.

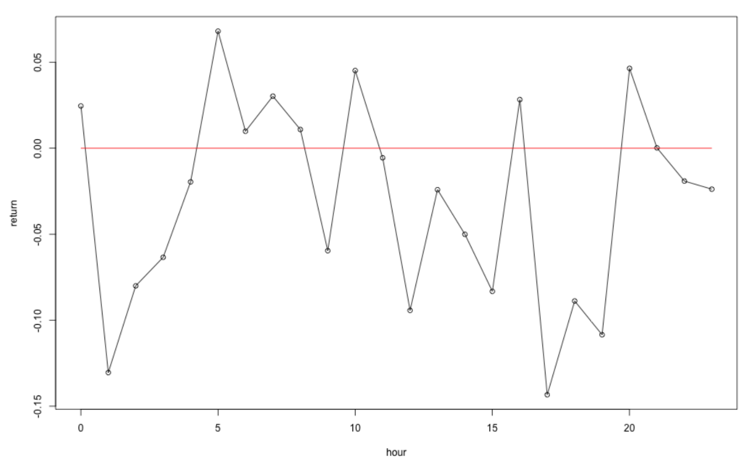
Figure 12: Hourly Cryptocurrency Market (Eigenportfolio) Return



This plot shows the hourly return of the eigenportfolio.

Figure 13 shows the average hourly patterns in the cryptocurrency market returns. We observe on average positive returns at UTC hours 5:00, 16:00 and 20:00. These times correspond to the effects of Hang Seng and closing of LSE and NYSE, respectively.

Figure 13: Average Hourly Eigenportfolio Return



This plot shows the average hourly eigenportfolio return

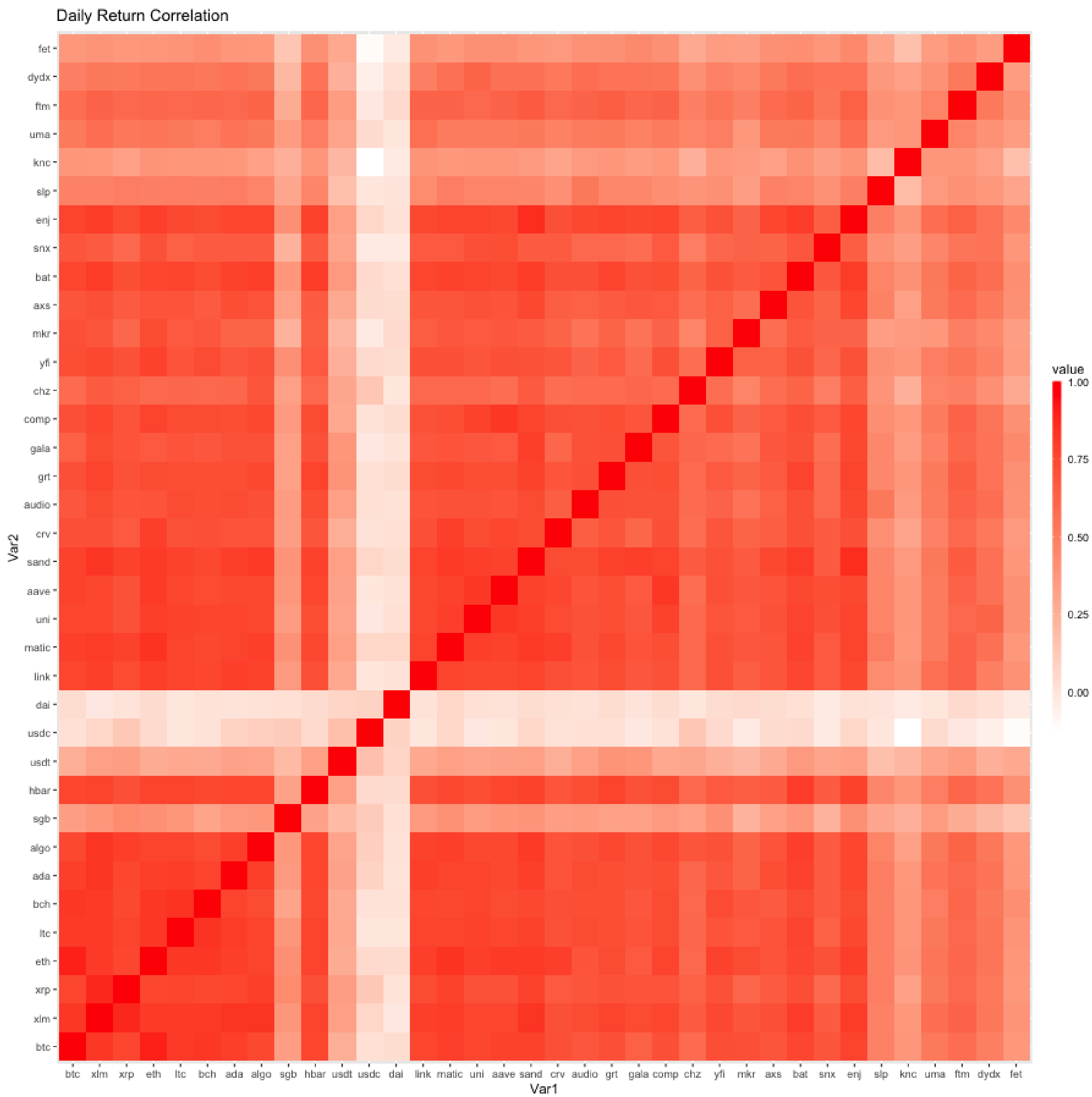
These intraday patterns are consistent with those revealed in the returns on native cryptocurrency and tokens in Sections 4.1.1 and 4.1.2, and illustrated in Figure 4, Section 4.1.2.

5.3 Correlation of daily cryptocurrency returns

The cross-sectional correlations of cryptocurrency returns are computed from 36 frequently traded coins. The correlation heatmap of daily returns is displayed in Figure 14. Starting from the origin, the return correlations of native coins, stablecoins and tokens are shown in this order and ranked with respect to the percentages of daily non-zero volumes of each type of cryptocurrency, which are decreasing from left to right. As explained in Section 5.2, the coins located on the right side of the figure are relatively less frequently traded, which may explain why they appear less correlated.

We find that the daily returns of native coins and tokens are positively and highly correlated except for SGB. Moreover, there is no evidence of return correlation for stablecoins in columns 11 to 13 (USDC, USDT and DAI), which is consistent with the results from Section 5.1. The correlation between the returns on stablecoins and other cryptocurrencies (i.e. natives and tokens) is close to 0. Moreover, the correlation between the returns on stablecoins themselves is very weak too.

Figure 14: The Heatmap of Daily Return Correlation



A darker colour indicates that the two coins are more correlated. A lighter colour indicates that the two coins are less correlated. We observe that the stablecoins are uncorrelated with other coins and with one another.

The daily returns on KNC show more correlation with the returns on other coins than in the hourly correlation matrix, as indicated by the darker shade in the heatmap.

5.4 PCA analysis of daily returns

The PCA is applied to the variance of daily return matrix of dimension 364 by 36, where each column is demeaned and rescaled by dividing the demeaned columns by the standard deviation. The results of PCA analysis of daily returns are given in Table 6.

Table 6: Daily PCA Eigenvalue, Variance Percentage Explained by Each PC and Cumulative Variance Percentage

	Eigenvalue	Variance Percent	Cumulative Variance Percent
Dim.1	21.39	59.41	59.41
Dim.2	1.33	3.69	63.09
Dim.3	1.14	3.17	66.27
Dim.4	1.03	2.87	69.14
Dim.5	0.95	2.65	71.79
Dim.6	0.86	2.39	74.18
Dim.7	0.70	1.96	76.13
Dim.8	0.64	1.79	77.92
Dim.9	0.63	1.74	79.66
Dim.10	0.61	1.70	81.36
Dim.11	0.53	1.47	82.83
Dim.12	0.47	1.32	84.15
Dim.13	0.46	1.27	85.41
Dim.14	0.43	1.19	86.60
Dim.15	0.38	1.06	87.66
Dim.16	0.35	0.97	88.64
Dim.17	0.34	0.94	89.57
Dim.18	0.33	0.92	90.49
Dim.19	0.32	0.88	91.37
Dim.20	0.29	0.81	92.18
Dim.21	0.28	0.77	92.95
Dim.22	0.27	0.74	93.69
Dim.23	0.25	0.68	94.37
Dim.24	0.22	0.61	94.98
Dim.25	0.22	0.60	95.58
Dim.26	0.20	0.56	96.15
Dim.27	0.19	0.52	96.67
Dim.28	0.18	0.51	97.18
Dim.29	0.17	0.46	97.64
Dim.30	0.16	0.43	98.07
Dim.31	0.15	0.41	98.48
Dim.32	0.15	0.40	98.88
Dim.33	0.12	0.34	99.22
Dim.34	0.12	0.32	99.55
Dim.35	0.09	0.25	99.79
Dim.36	0.08	0.21	100.00

We observe a cut-off point in the eigenvalues and conclude that there is one cryptocurrency market factor [Dunbar, Owusu-Amoako (2022), Tavares et al. (2021)]. The cumulated variance percentages-based connectedness measures of Billio et al. (2012) are shown in the third column of Table 6.

Table 7: Daily $PCAS$ for Each Cryptocurrency

Coin	$PCAS_{i,n}$	Coin	$PCAS_{i,n}$
btc	0.0001200	xlm	0.0001200
xrp	0.0001700	eth	0.0001800
ltc	0.0001700	bch	0.0001700
ada	0.0001800	algo	0.0001900
sgb	0.0002800	hbar	0.0001700
usdt	0.0000019	usdc	0.0000021
dai	0.0000140	link	0.0001900
matic	0.0002300	uni	0.0002000
aave	0.0002300	sand	0.0002200
crv	0.0002800	audio	0.0002400
grt	0.0002300	gala	0.0002600
comp	0.0002300	chz	0.0002800
yfi	0.0002200	mkr	0.0002100
axs	0.0002500	bat	0.0001800
snx	0.0003100	enj	0.0002100
slp	0.0003300	knc	0.0003400
uma	0.0002800	ftm	0.0003200
dydx	0.0003100	fet	0.0003100

Table 7 shows the $PCAS$ for daily returns. We find that the results from daily data are similar to those obtained from the hourly analysis. The stablecoins have much less risk contribution compared to the natives and tokens. SGB has the largest risk contribution/exposure to the daily cryptocurrency system among the natives. We observe that like in the hourly data, in daily data KNC also has the largest risk contribution among the tokens.

We proceed as in Section 5.2 and compute the daily market portfolio allocations without the stablecoins. Table 8 displays the allocations of the market portfolio (Avellaneda et al., 2022)

Table 8: Daily Eigenportfolio Allocation (without Stablecoins)

Coin	Allocation	Coin	Allocation
btc	0.0559	xlm	0.0476
xrp	0.0411	eth	0.0424
ltc	0.0412	bch	0.0414
ada	0.0390	algo	0.0361
sgb	0.0141	hbar	0.0398
link	0.0351	matic	0.0312
uni	0.0335	aave	0.0297
sand	0.0335	crv	0.0251
audio	0.0262	grt	0.0286
gala	0.0236	comp	0.0310
chz	0.0225	yfi	0.0294
mkr	0.0308	axs	0.0277
bat	0.0369	snx	0.0208
enj	0.0346	slp	0.0156
knc	0.0122	uma	0.0204
ftm	0.0205	dydx	0.0186
fet	0.0140		

The market portfolio computed from daily data contains 6 more coins than the one computed from hourly data: YFI, FET, ENJ, DYDX, UMA and SLP. Hence the allocations of the 30 initial coins are lower at the daily frequency, except for native SGB and tokens MKR, KNC and COMP, whose allocations in the daily portfolio are higher.

The daily market portfolio can be compared to the S&PCBD index, lunched in July 2021. ”The S&P Cryptocurrency Broad Digital Market (BDM) Index is designed to track the performance of digital assets listed on recognized open digital exchanges that meet minimum liquidity and market capitalization criteria that are covered by (our) price provider Lukka” The index is meant to reflect a broad investable universe.” [see, https://www.spglobal.com/spdji/en/indices/digital-assets/sp-cryptocurrency-broad- digital-market-index/#overview].

The index is part of an expansion of S&P DJI’s series of digital asset benchmarks, the S&P Digital Market Indices. All these indices use pricing data from Lukka, a crypto software and data provider, to determine the eligibility universe and pricing of individual constituents.

The main difference between these indexes and our market portfolio is that the indexes are available only daily between Monday and Friday, while the computed eigenportfolio is available for all days and hours. Moreover, the index allocations are determined by Lukka, while our approach follows from the financial theory [Avelanada et al. (2022)]. Nevertheless, we can select the returns on market portfolio over the workdays to compare them to the

S&PCBD. The linear regression results suggest that two variables are practically collinear. The estimated intercept is not statistically significant (-0.1000 with standard error 0.1827) and the estimated coefficient is 0.95674 with standard error 0.0427. The asymptotically valid confidence interval at level 0.95 contains the value 1. The scatterplot and the regression line are given in Figude 16.

Figure 15: The Scatter Plot of the BDM Index and Eigenportfolio

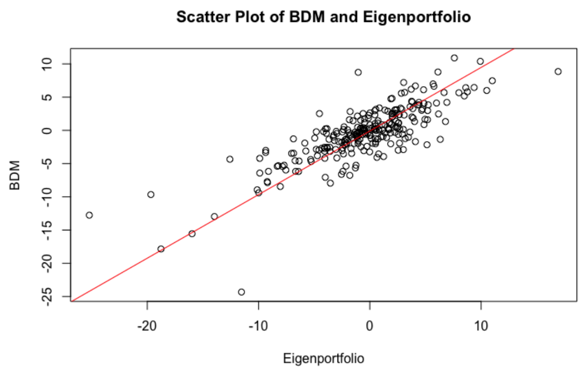
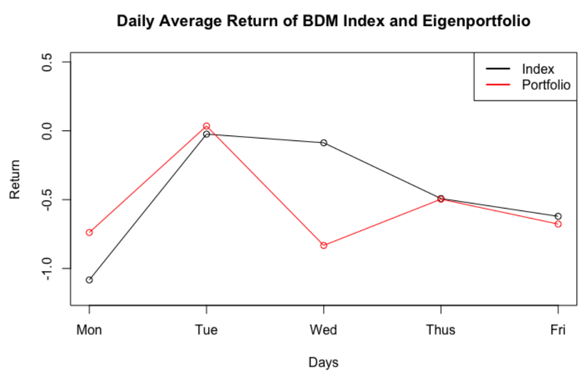


Figure 16 compares the daily patterns of S&PCBDM index with the daily market portfolio.

Figure 16: The Average Return of the BDM index and Eigenportfolio



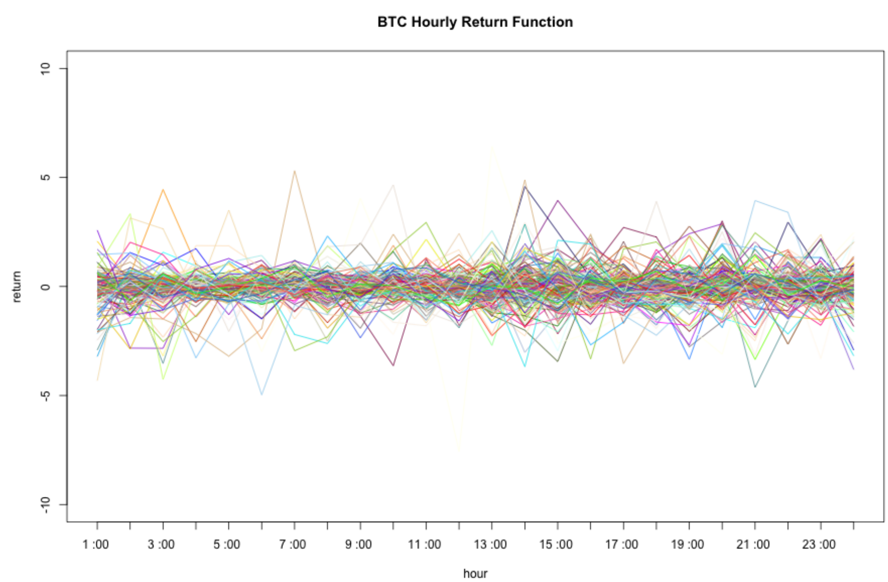
The black line shows the average return of BDM Index and the red line shows the average return of the Eigenportfolio

We find that both return series have similar daily patterns, except for Wednesdays when the returns on the index are higher than on the market portfolio.

6 Functional CAPM Regression

The relationship between the returns on individual coins and the cryptocurrency market portfolio reflects the systemic risk on the cryptocurrency market, according to the CAPM model. This Section estimates the relationships between the functions of daily and weekly returns on cryptocurrency and the returns on market factor to capture the periodic intraday and intraweek patterns in systemic risk. This allows us to determine the "betas" of the functional CAPM model and interpret them as the coins' exposure to the cryptocurrency market risk that varies across the day and week. We consider the returns on BTC as the first example and compute the excess returns by using the US Three-Month Treasury Bond as the risk-free asset [9]. Figures 17 and 18 below present 178 functions of returns on BTC over 24 hours, and 178 functions of return on the cryptocurrency market factor over 72 hours, respectively.

Figure 17: The Hourly Return Function of BTC

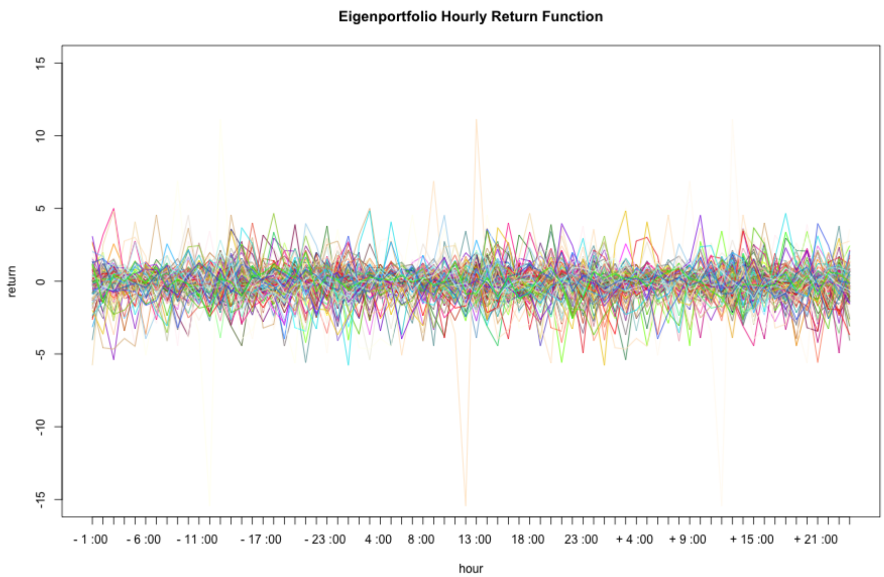


Each line represents the function of BTC hourly returns over one day.

[9] The hourly excess returns are calculated by the log return minus the three-month T-bill. The T-bill rates are divided by 365 × 24 to convert to an hourly rate. The data are downloaded from https://www.marketwatch.com/investing/bond/tmubmusd03m?countrycode=bx&mod=mw_quote_tab

Figure 19 presents the "dependent" variable functions of excess hourly returns on the current day.

Figure 18: The Market Factor Hourly Return Functions



Each line represents the function of market factor hourly returns over three days.

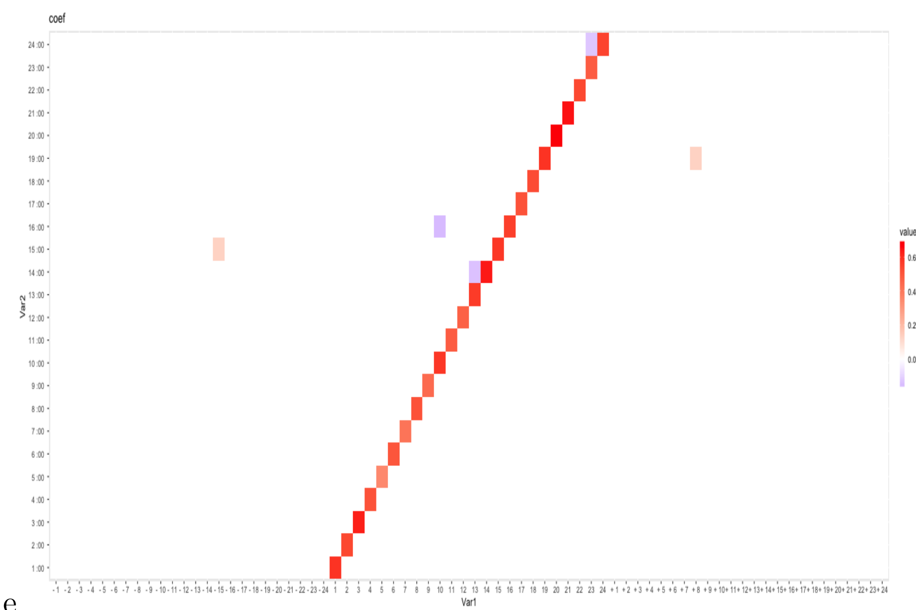
Figure 20 shows the "regressor" functions over the past, current and next day. We observe that the curves of the dependent variable functions and regressor functions overlap on each plot indicating an absence of trend. The functional regression extends the static CAPM model as follows. It provides us the hourly (and daily) values of betas, which are considered equal under the static CAPM model. Therefore, the variation of betas across the day (week) can be interpreted as the evidence against the CAPM model. In addition, the functional regression contains the lagged returns on the market factor among the regressors. The statistical significance of coefficients on these lagged market returns can also be seen as the evidence against the static CAPM.

6.1 Hourly Functional Regression

In the functional CAPM model, the excess returns on a coin are regressed on the market return on the current, previous and next day to capture the lead and lag effects in the "betas".

Figure 19 presents the statistically significant components of the estimated integral operator Π of BTC returns. We observe an affine relation over the current day. This is consistent with the CAPM model, suggesting a linear relationship between the contemporaneous excess returns on an asset and on the market. The dark red points on the line indicate the times of the day when the relationship is positive and high, whereas the lighter points indicate lower values of "betas". The difference in colors across the day suggests that the betas vary. In addition, we observe some lagged "betas", such as the one depicting the dependence of current (excess) returns on Bitcoin at UTC hour 15:00 on yesterdays (excess) returns on the market portfolio at UTC hour 15, which is one hour before LSE closes and after NYSE opens and is in line with Long (2020).

Figure 19: The Heatmap of Hourly Functional Regression Coefficients for BTC



angle

The red and light red areas indicate that the coefficients are positive or slightly positive. The light blue areas indicate that the coefficients are slightly negative. The time label on the horizontal and vertical axes are labelled with hours of UTC. The "-" and "+" on the horizontal axis indicate that the hours are from the previous day and the future day

To check the validity of the functional CAPM model, we estimate the intercepts of the functional regression. The estimated intercepts values reported in Table 9 are not statistically significant, except for UTC hours 19:00.

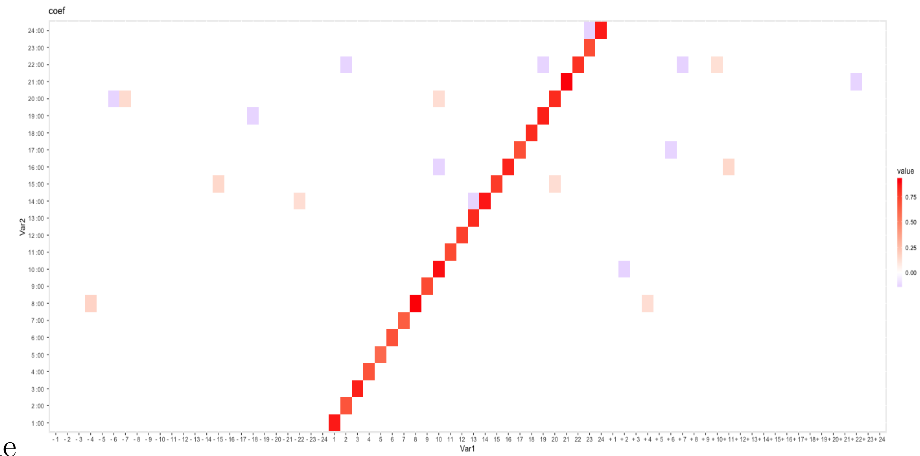
Table 9: The Intercept of Hourly Functional Regression

Hour	Estimate	Std. Error	t value	P-value
1	-0.043	0.036	-1.216	0.227
2	0.038	0.041	0.941	0.349
3	-0.034	0.042	-0.814	0.417
4	0.030	0.030	1.015	0.313
5	-0.010	0.025	-0.386	0.700
6	-0.027	0.034	-0.783	0.435
7	0.018	0.028	0.636	0.526
8	0.016	0.028	0.557	0.579
9	0.030	0.025	1.196	0.235
10	-0.015	0.031	-0.476	0.635
11	0.010	0.028	0.365	0.716
12	-0.018	0.032	-0.567	0.572
13	0.054	0.037	1.455	0.149
14	0.001	0.041	0.031	0.975
15	0.004	0.040	0.100	0.921
16	-0.036	0.040	-0.889	0.376
17	0.034	0.038	0.892	0.375
18	-0.047	0.036	-1.310	0.193
19	0.095	0.036	2.645	0.009
20	0.038	0.043	0.893	0.374
21	0.039	0.027	1.431	0.155
22	0.043	0.041	1.060	0.292
23	-0.026	0.032	-0.810	0.420
24	-0.068	0.036	-1.907	0.059

We conclude that Bitcoin returns at each hour satisfy a CAPM model with slightly different beta, except for hours 19:00 when the intercept is statistically significant and hours 14:00-16:00 and 0:00 when BTC returns depend not only on the current but also on the lagged market factor returns. The stability of the functional CAPM model is verified by estimating the model over three subsamples (see Figures 31 to 33, Appendix A).

The affine relationship of the the excess returns on individual cryptocurrency and market portfolio exists for most natives and tokens. It is illustrated in Figure 20 for ETH and Figure 21 for LINK.

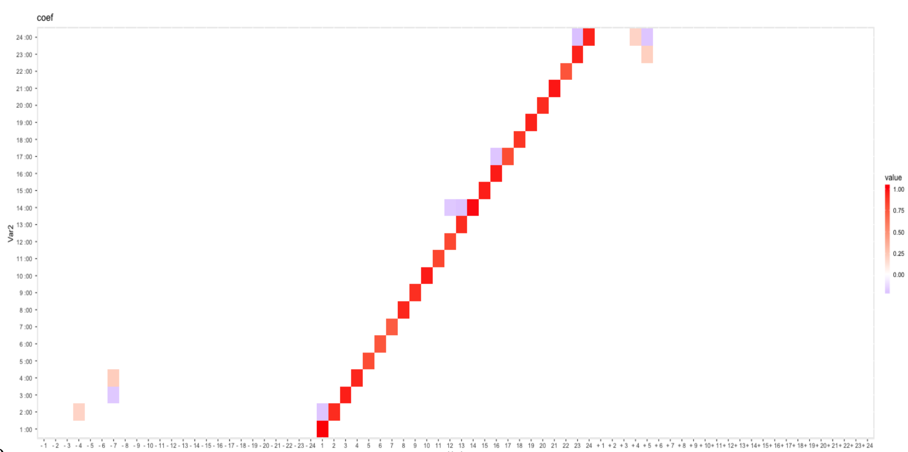
Figure 20: The Heatmap of Hourly Functional Regression Coefficients for ETH



angle

The red and light red areas indicate that the coefficients are positive or slightly positive. The light blue areas indicate that the coefficients are slightly negative. The time label on the horizontal and vertical axes are labelled with hours of UTC. The "-" and "+" on the horizontal axis indicate that the hours are from the previous day and the future day

Figure 21: The Heatmap of Hourly Functional Regression Coefficients for LINK



angle

The red and light red areas indicate that the coefficients are positive or slightly positive. The light blue areas indicate that the coefficients are slightly negative. The time label on the horizontal and vertical axes are labelled with hours of UTC. The "-" and "+" on the horizontal axis indicate that the hours are from the previous day and the future day

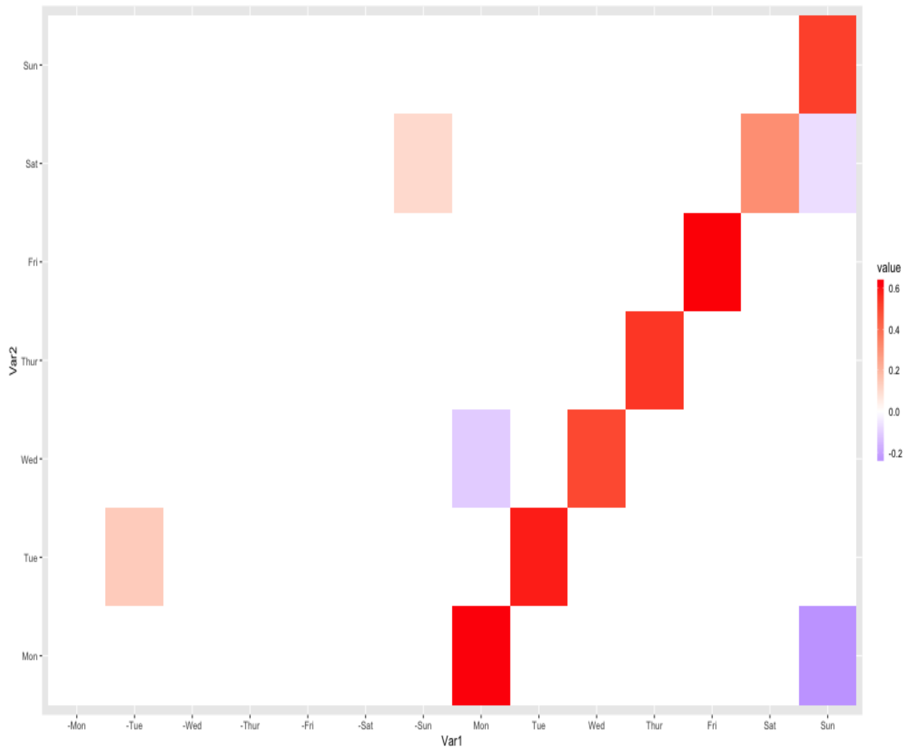
We find that the betas also vary across the day in both Figures 20 and 21. In comparison to BTC, the returns on ETH seem more affected by the lagged and future market returns after hour 14:00, i.e. after the opening of NYSE. The effects of future market returns can be explained by the trades of derivatives on ETH platform. The return on LINK resemble BTC more in that there are less times of the day when we observe the impact of lagged market returns, except at 14:00 (NYSE) and between hours 0:00 and 5:00 when Hang Seng is open. The affine relationship with the cryptocurrency market portfolio is not found in hourly returns on stablecoins, SGB and KNC that were reported uncorrelated with other coins in Section 5 (see, Online Appendix).

6.2 Daily Functional Regression

The daily functional CAPM regressions provide the values of "betas" on each day of the week. We regress 52 functions of weekly excess returns on a coin on the functions of weekly returns on the market portfolio over the past and current week to capture the lag effects in the "betas".

Figure 22 presents the estimator of daily integral operator of the functional regression of excess BTC returns on the market portfolio.

Figure 22: The Heatmap of Daily Functional Regression Coefficients for BTC



The red and light red areas indicate that the coefficients are positive or slightly positive. The light blue areas indicate that the coefficients are slightly negative

We observe an affine relationship between the current excess returns on BTC and the cryptocurrency market. The "betas" are positive and high on all days, except for Saturdays when they are slightly weaker. We do not observe any effects of lagged market returns on Thursdays, Fridays and Sundays. There are some lagged "betas", indicating, for example, the positive dependence of BTC Saturday returns on the market returns from the previous Sunday and negative dependence of BTC Monday returns on the current week's Sunday market returns.

To check the validity of the daily functional CAPM for BTC, we compute the intercepts and report them in Table 10. All the intercept terms are statistically not significant.

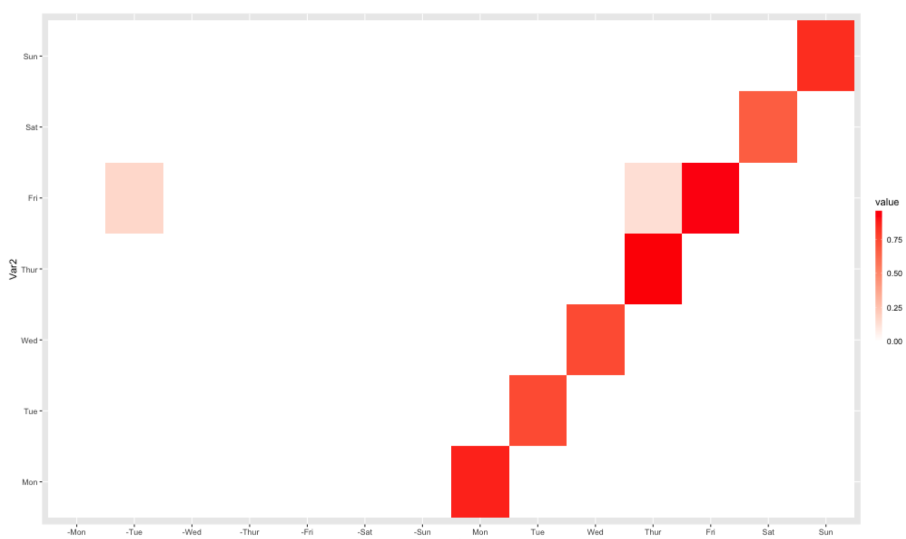
Table 10: The Intercept of Daily Functional Regression

Day	Estimate	Std. Error	t value	P-value
Monday	0.262	0.332	0.788	0.436
Tuesday	0.023	0.208	0.113	0.911
Wednesday	0.190	0.269	0.708	0.484
Thursday	-0.031	0.233	-0.135	0.894
Friday	0.085	0.291	0.293	0.772
Saturday	-0.202	0.133	-1.514	0.139
Sunday	0.085	0.159	0.537	0.595

Given these results, we conclude that the daily BTC returns are consistent with the static CAPM model on Thursdays, Fridays and Sundays and that BTC betas are different on each of these days.

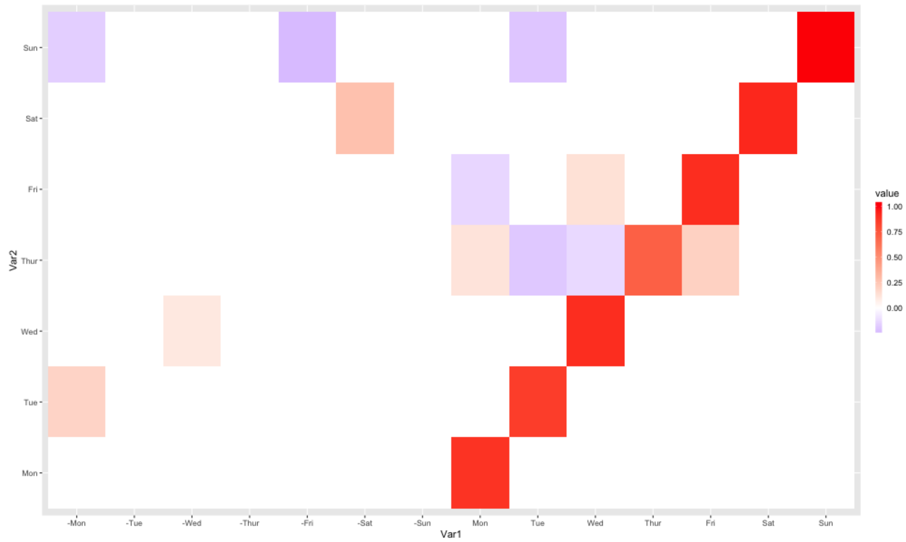
We find affine functional relations in daily returns on most natives and tokens. Figure 23 illustrates the functional "betas" for ETH and Figure 24 for Link. The affine relation with the market portfolio is weaker on Saturday in excess daily returns on BTC and ETH. IN LINK the lowest coefficient is associated to Thursday returns.

Figure 23: The Heatmap of Daily Functional Regression Coefficients for ETH



The red and light red areas indicate that the coefficients are positive or slightly positive.

Figure 24: The Heatmap of Daily Functional Regression Coefficients for LINK



The red and light red areas indicate that the coefficients are positive or slightly positive. The light blue areas indicate that the coefficients are slightly negative

There are also some lagged effects revealed in Figures 23 and 24. The Friday returns on ETH seem impacted by the market factor returns from Thursday and past week's Tuesday. The LINK's returns on Thursdays and Fridays show dependence on market factor returns from the previous days of the same week with either positive or negative coefficients. On Sundays, Link shows negative coefficients on past week's Friday and Monday market returns.

The affine relationship is not found in all coins and on all days of the weeek. In SGB returns, the betas are non-zero only over selected days of the week as shown in Figure 32, Appendix A. We observe an affine relation in daily excess returns on SGB between Wednesday and Friday. Although we did not find a linear relation of KNC hourly returns with the market return, there is a weak affine relation with market returns in KNC daily returns during the weekdays, as shown in Figure 101, Online Appendix. The daily returns on stablecoins show no relation with the daily market returns, which is consistent with the results from the hourly regression.

7 Summary and Conclusions

Common periodic intra-day and intra-week patterns are detected in prices, returns, volumes and volatility of native cryptocurrency and tokens. In general, the investors can benefit from lower prices by trading between 4 pm and 10 pm Eastern Standard Time, i.e. between the closing time of NYSE and the opening time of Hang Seng, and on Thursdays and Fridays, when the price volatility is the lowest as well. Stablecoins have distinct intra-day and intra-week dynamics. The correlation analysis shows a strong contemporaneous dependence between the returns on native cryptocurrencies and tokens. Stablecoin returns are uncorrelated with other cryptocurrencies and are uncorrelated with one another. The PCA applied to daily returns suggests the presence of one factor in the cryptocurrency market to which the stablecoins do not contribute. Therefore, they are immune to the systemic risk associated with the cryptocurrency market. The functional "CAPM" regression shows an affine relation of cryptocurrency excess returns with the excess returns on the market portfolio. The "betas" are weaker or stronger, depending on the time of day and day of the week. This suggests that the exposure to systemic risk displays periodic intraday and intraweek patters. There also exist some lagged dependence of coins' excess returns on past market excess returns, pointing to lagged effects of systemic risk. The affine relation is not found in the stablecoins and coins that are uncorrelated with the cryptocurrency market.

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Appendix A

Table 11: Hourly Data Summary of Cryptocurrencies Traded on Bitstamp

Type	Name	Symbol	No. of zero volumes	No. of Non-zero volumes	Average volume	% Non-zero volumes
Native Coins						
	Bitcoin	BTC	1	4295	101.34	99.98
	Stellar	XLM	1	4295	339781.2	99.98
	XRP	XRP	1	4295	1532195	99.98
	Ethereum	ETH	2	4294	703.12	99.95
	Litecoin	LTC	2	4294	934.12	99.95
	Bitcoin Cash	BCH	3	4293	242.5	99.93
	Cardano	ADA	471	3825	17301.84	89.04
	Algorand	ALGO	534	3762	12247.75	87.57
	Songbird	SGB	965	3331	50529.02	77.54
	Hedera Hashgraph	HBAR	986	3310	14643.05	77.05
Stable Coins						
	Tether	USDT	342	3954	87010.29	92.04
	USD Coin	USDC	581	3715	75208.69	86.48
	Dai	DAI	3332	964	1518.4	22.44
	Paxos Standard Token	PAX	3700	596	529.31	13.87
	Gemini Dollar	GUSD	4178	118	71.01	2.75
	Tether EURt	EURT	4218	78	26.59	1.82
Token						
	Chainlink	LINK	5	4291	6397.82	99.88
	Ploygon	MATIC	320	3976	17771.6	92.55
	Uniswap	UNI	461	3835	1324.7	89.27
	AAVE	AAVE	588	3708	66.77	86.31
	The Sandbox	SAND	596	3700	3345.1	86.13
	Curve	CRV	803	3493	3194.93	81.31
	Audius	AUDIO	1021	3275	3736.59	76.23
	Synthetix	SNX	1225	3071	435.63	71.49
	yearn.finance	YFI	1266	3030	0.21	70.53
	The Graph	GRT	1380	2916	10618	67.88
	Gala	GALA	1415	2881	13816.68	67.06
	Kyber Network	KNC	1615	2681	938.58	62.41
	Maker	MKR	1623	2673	2.03	62.22
	Compound	COMP	1884	2412	24.24	56.15
	Chiliz	CHZ	2004	2292	5043.76	53.35
	Axie Infinity	AXS	2043	2253	24.53	52.44
	Basic Attention Token	BAT	2055	2241	3884.54	52.16
	Fantom	FTM	2142	2154	3091.13	50.14
	UMA	UMA	2150	2146	170.93	49.95
	Enjin Coin	ENJ	2166	2130	1147.14	49.58
	Smooth Love Potion	SLP	2225	2071	76900.81	48.21
	Alpha Finance	ALPHA	2826	1470	1199.12	34.22
	Fetch.ai	FET	2833	1463	1960.78	34.05
	dYdX	DYDX	3067	1229	152.44	28.61
	SKALE Network	SKL	3127	1169	3413.58	27.21
	Storj	STORJ	3163	1133	261.95	26.37
	Perpetual Protocol	PERP	3431	865	88.17	20.14
	Swipe	SXP	3941	355	28.39	8.26
	Shiba Inu	SHIB	3962	334	43043614	7.77

Hourly average volumes over the period 2022-01-01 until 2022-06-28 (179 days) in numbers of transactions

Table 12: Daily Data Summary of Selected Cryptocurrencies Traded on Bitstamp

Type	Name	Symbol	No. of Observation	No. of zero volumes	No. of Non-zero volumes	Average volume	% Non-zero volumes
Native Coins							
	Bitcoin	BTC	364	0	364	2,289.05	100
	Stellar	XLM	364	0	364	6,882,900	100
	XRP	XRP	364	0	364	46,593,153	100
	Ethereum	ETH	364	0	364	16,487.85	100
	Litecoin	LTC	364	0	364	19,418.21	100
	Bitcoin Cash	BCH	364	0	364	5,184.64	100
	Cardano	ADA	364	0	364	469,651.9	100
	Algorand	ALGO	364	0	364	366,720.4	100
	Songbird	SGB	364	0	364	1,354,903	100
	Hedera Hashgraph	HBAR	364	0	364	715,269.8	100
Stable Coins							
	Tether	USDT	364	0	364	2,038,350	100
	USD Coin	USDC	364	0	364	146,280	100
	Dai	DAI	364	23	341	2,6096.82	93.68
	Paxos Standard Token	PAX	364	93	271	7,349.53	74.45
	Gemini Dollar	GUSD	364	247	117	1,185.03	32.14
	Tether EURt	EURT	364	286	78	374.92	21.43
Token							
	Chainlink	LINK	364	0	364	138,562.8	100
	Ploygon	MATIC	364	0	364	42,4164.5	100
	Uniswap	UNI	364	0	364	24,334.5	100
	AAVE	AAVE	364	0	364	1,169.16	100
	The Sandbox	SAND	364	0	364	75,935.64	100
	Curve	CRV	364	0	364	58,694.55	100
	Audius	AUDIO	364	0	364	95,783.09	100
	The Graph	GRT	364	0	364	241,152.1	100
	Gala	GALA	364	0	364	270,816.6	100
	Compound	COMP	364	0	364	467.91	100
	Chiliz	CHZ	364	0	364	11,472.7	100
	yearn.finance	YFI	364	1	363	4.12	99.73
	Maker	MKR	364	1	363	64.64	99.73
	Axie Infinity	AXS	364	1	363	826.11	99.73
	Basic Attention Token	BAT	364	1	363	6,6084.45	99.73
	Synthetix	SNX	364	3	361	7,58.75	99.18
	Enjin Coin	ENJ	364	7	357	17,460.33	98.08
	Smooth Love Potion	SLP	364	7	357	134,7507	98.08
	Kyber Network	KNC	364	9	355	14,314.1	97.53
	UMA	UMA	364	10	354	2,352.08	97.25
	Fantom	FTM	364	13	351	67,143.95	96.43
	dYdX	DYDX	364	17	347	3,393.68	95.33
	Fetch.ai	FET	364	28	336	34,016.57	92.31
	SKALE Network	SKL	364	35	329	101,611.7	90.38
	Storj	STORJ	364	55	309	4,560.35	84.89
	Alpha Finance	ALPHA	364	59	305	17,436.55	83.79
	Perpetual Protocol	PERP	364	117	247	1,431.04	67.86
	Shiba Inu	SHIB	364	156	208	2,725,982,421	57.14
	Swipe	SXP	364	220	144	425.39	39.56

Daily average volumes over the period 2022-01-01 to 2022-12-30 of 52 weeks in numbers of transactions

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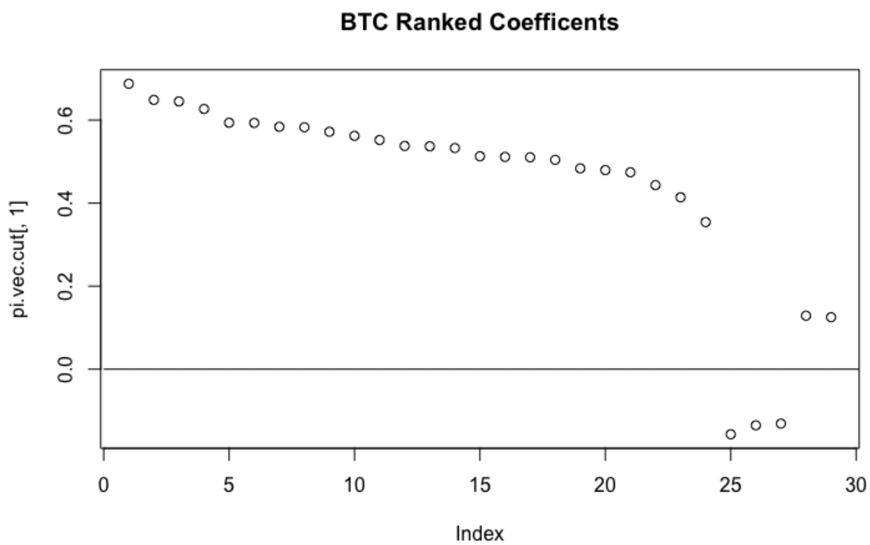
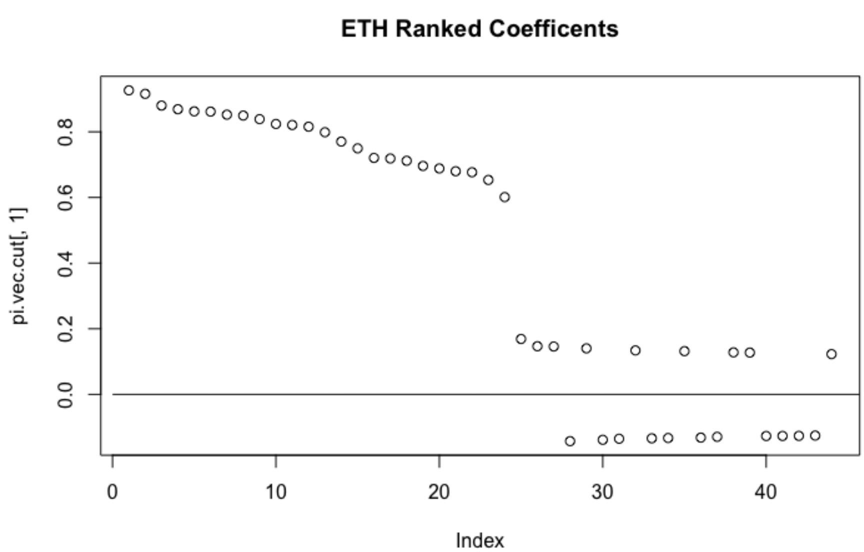
Figure 25: The Ordered Hourly Functional Regression Coefficients for BTC



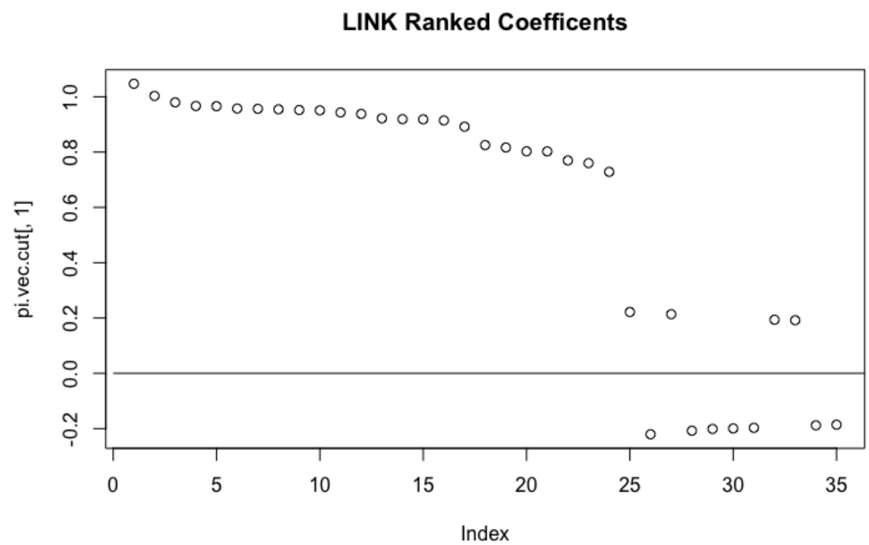
The coefficients are ordered by their absolute values

Figure 26: The Ordered Hourly Functional Regression Coefficients for ETH



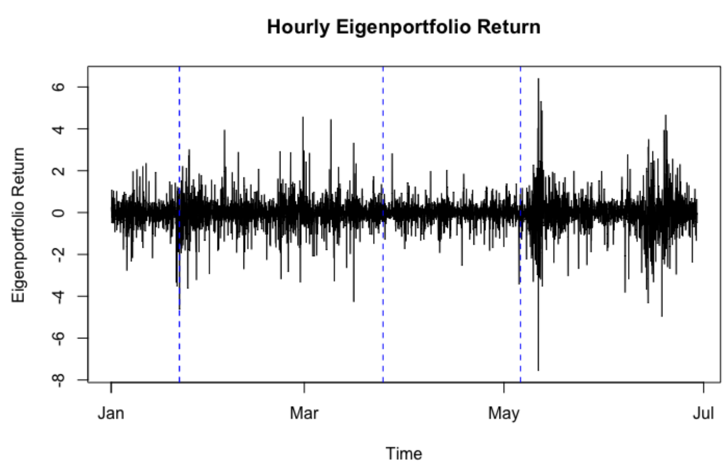
The coefficients are ordered by their absolute values

Figure 27: The Ordered Hourly Functional Regression Coefficients for LINK



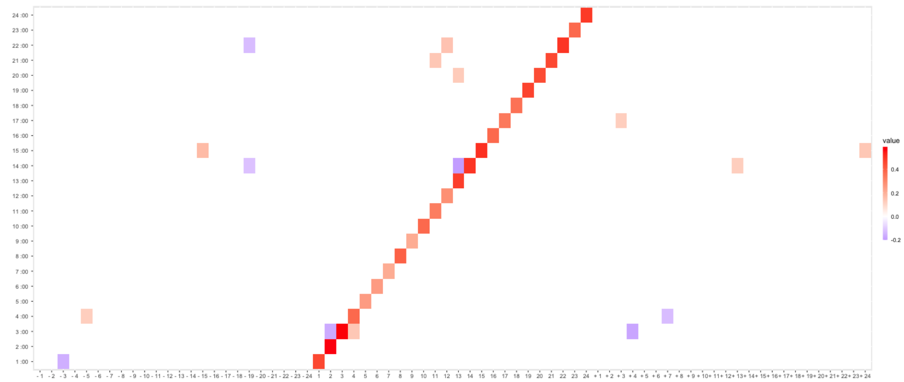
The coefficients are ordered by their absolute values

Figure 28: Hourly Cryptocurrency Market (Eigenportfolio) Return



This plot shows the hourly return of the eigenportfolio.

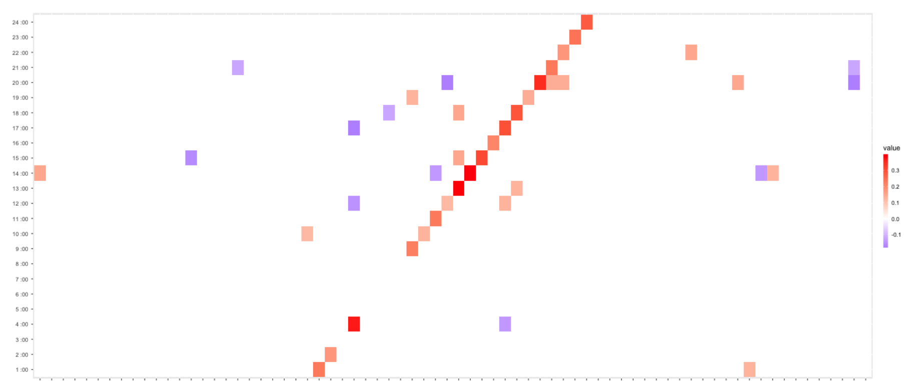
Figure 29: The Heatmap of Hourly Functional Regression Coefficients for BTC in First Period



The red and light red areas indicate that the coefficients are positive or slightly positive. The light blue areas indicate that the coefficients are slightly negative. The time label on the horizontal and vertical axes are labelled with hours of UTC. The "-" and "+" on the horizontal axis indicate that the hours are from the previous day and the future day

This hourly functional regression for the period between January/23/2022 and March/24/2022. (Second period in Figure 28)

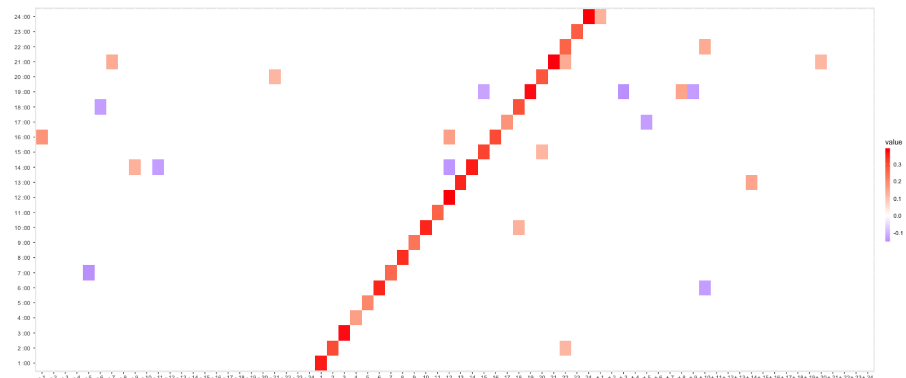
Figure 30: The Heatmap of Hourly Functional Regression Coefficients for BTC in The More Stable Period



The red and light red areas indicate that the coefficients are positive or slightly positive. The light blue areas indicate that the coefficients are slightly negative. The time label on the horizontal and vertical axes are labelled with hours of UTC. The "-" and "+" on the horizontal axis indicate that the hours are from the previous day and the future day

This hourly functional regression for the period between March/26/2022, and April/26/2022. (Third period in Figure 28)

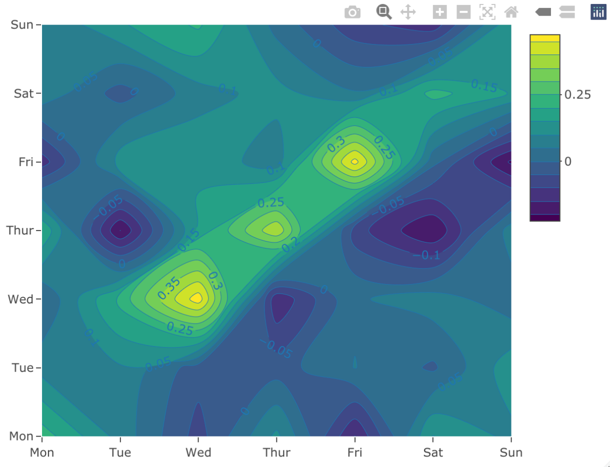
Figure 31: The Heatmap of Hourly Functional Regression Coefficients for BTC in More Volatilize Period



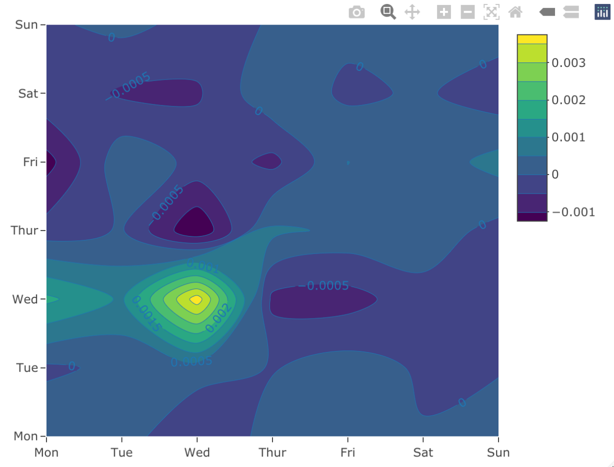
The red and light red areas indicate that the coefficients are positive or slightly positive. The light blue areas indicate that the coefficients are slightly negative. The time label on the horizontal and vertical axes are labelled with hours of UTC. The "-" and "+" on the horizontal axis indicate that the hours are from the previous day and the future day

This hourly functional regression for the period between May/07/2022 and June/28/2022. (Last period in Figure 28)

Figure 32: The Contour Plot of Daily Functional Regression Coefficients of SGB and USDT



(a) SGB



(b) USDT

The left figure shows the regression of the excess returns on SGB on excess market return of the current week. The right figure shows the regression of excess market return on UTSD. The blue and dark blue areas indicate that the coefficients are zeros or slightly negative. The light green and yellow areas indicate that the coefficients are positive.

Online Appendix

Table 13: Description of Cryptocurrencies (sourced from Chatgdp and www. coinmarketcap.com)

Bitcoin	BTC	It's the first and well-known decentralized digital currency used for peer-to-peer transactions and as a store of value..
Stellar	XLM	It focuses on facilitating fast and low-cost cross-border transactions and remittances. It aims to connect financial institutions and enable seamless money transfers.
XRP	XRP	It is designed for efficient cross-border payments and partnerships with financial institutions. It aims to improve international money transfers and settlement systems.
Ethereum	ETH	A versatile blockchain platform that allows developers to craft various smart contracts and decentralized applications (DApps).
Litecoin	LTC	It offers quicker transaction confirmations, especially for smaller transactions, and employ a distinct hashing algorithm.
Bitcoin Cash	BCH	A fork of Bitcoin, Bitcoin Cash strives to amplify scalability and transaction speed by enlarging the block size. It centers its efforts on serving as a digital currency suited for everyday spending.
Cardano	ADA	A blockchain platform recognized for its meticulous research-driven strategy and emphasis on security and scalability. It tries to establish a robust groundwork for constructing smart contracts and DApps.
Algorand	ALGO	A blockchain platform with high rapidity and scalability focuses on creating decentralized applications and provides a blockchain foundation with elevated processing capabilities.
Songbird	SGB	canary network for Flare, the blockchain built for universal connectivity.
Hedera Hashgraph	HBAR	is favoured by its high throughput and low-latency consensus. It targets applications that require both swift and secure transactional processes.
Tether	USDT	is one of the earliest and most well-known stablecoins. It's pegged 1:1 to the US Dollar and is designed to maintain a 1:1 value ratio.

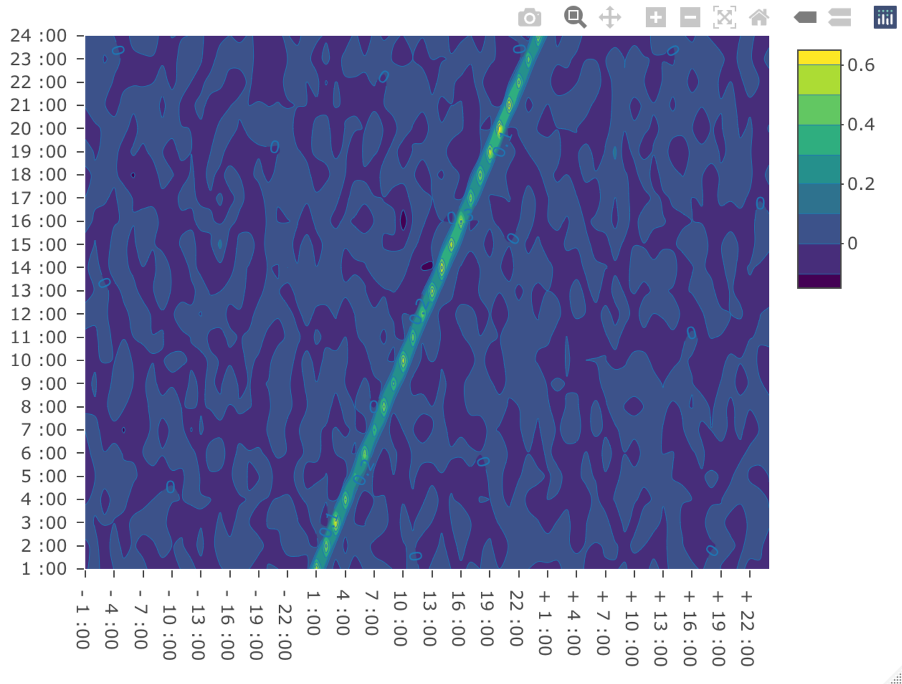
USD Coin	USDC	is another popular stablecoin pegged 1:1 to the US Dollar. It's regulated and issued by several financial institutions, aiming to provide transparency and security.
Dai	DAI	A Ethereum blockchain decentralized stablecoin. It is generated through collateralized loans and algorithmic mechanisms to maintain its value at around 1 USD.
Paxos Standard Token	PAX	a stablecoin regulated by the New York State Department of Financial Services. It's pegged 1:1 to the US Dollar.
Gemini Dollar	GUSD	is issued by the Gemini cryptocurrency exchange. It is pegged 1:1 to the USD and fully backed by USD held in reserve accounts.
Tether EURt	EURT	EURT is a stablecoin pegged 1:1 to the Euro.
Chainlink	LINK	A decentralized oracle network that connects smart contracts on the blockchain with real-world data, events, and APIs. It aims to bridge the gap between blockchain and external data sources, enabling smart contracts to access and interact with information from the outside world in a secure and reliable manner.
Polygon	MATIC	Formerly known as Matic Network is a scaling solution for Ethereum that enhances its capabilities by providing a framework for building and connecting Ethereum-compatible blockchains. It seeks to address Ethereum's scalability issues and offers faster and cheaper transactions.
Uniswap	UNI	A decentralized exchange protocol built on the Ethereum blockchain. It enables users to trade Ethereum-based tokens directly from their wallets without the need for intermediaries. UNI is the governance token of the Uniswap protocol, allowing token holders to participate in decisions about its development and management.
AAVE	AAVE	A decentralized lending protocol built on the Ethereum blockchain. It allows users to lend, borrow, and earn interest on various cryptocurrencies in a peer-to-peer manner. AAVE is the native token of the Aave platform, used for governance and fee-sharing.

The Sandbox	SAND	A virtual world and gaming platform that operates on blockchain technology. It enables users to create, own, and monetize their gaming experiences and assets. SAND is the utility token used within The Sandbox ecosystem.
Curve	CRV	A decentralized exchange designed for stablecoin trading with low slippage. It focuses on providing efficient and low-risk trading of stablecoins like USDC, DAI, and USDT. CRV is the governance token of the Curve protocol.
Audius	AUDIO	A decentralized music-sharing and streaming platform that allows artists to directly share and monetize their music. AUDIO is the native token of the Audius platform, used for governance and rewarding network participants.
Synthetix	SNX	A decentralized synthetic asset platform built on Ethereum. It enables the creation and trading of synthetic assets that track the value of real-world assets like currencies, commodities, and cryptocurrencies. SNX is the token used to collateralize the creation of synthetic assets.
yearn.finance	YFI	A decentralized platform that aims to optimize yield farming strategies across different DeFi protocols. YFI is the governance token of the Yearn.finance ecosystem, allowing holders to participate in decisions about the platform's development.
The Graph	GRT	A decentralized indexing and query protocol for blockchain data. It allows developers to efficiently retrieve and index data from various blockchains, improving the functionality of decentralized applications. GRT is the native token used for protocol governance.
Gala	GALA	The native utility token of the Gala Games platform, which aims to empower game developers and players through blockchain technology. It allows players to participate in game development decisions and own in-game assets.
Kyber Network	KNC	A decentralized liquidity protocol that facilitates the exchange of tokens directly from wallets. It aims to provide a seamless and secure way to swap tokens without intermediaries.

Maker	MKR	The governance token of the MakerDAO platform, which is responsible for creating and managing the stablecoin DAI. MKR holders have the power to make decisions about the platform's parameters and upgrades.
Compound	COMP	The governance token of the Compound protocol, a decentralized lending platform. Users can lend and borrow cryptocurrencies, and COMP holders can propose and vote on changes to the platform.
Chiliz	CHZ	A cryptocurrency designed for sports and entertainment platforms, allowing fans to engage with their favorite teams through blockchain-based tokens and applications.
Axie Infinity	AXS	A blockchain-based game that enables players to collect, breed, and battle fantasy creatures known as Axies. AXS is the utility token used within the Axie Infinity ecosystem.
Basic Attention Token	BAT	The native token of the Brave browser ecosystem. It's designed to improve online advertising and content monetization by rewarding users for their attention and engagement.
Fantom	FTM	A high-performance blockchain platform that aims to supply fast and scalable smart contract capabilities. It's designed to address the limitations of existing blockchain networks.
UMA	UMA	A decentralized platform that allows users to create synthetic assets and financial contracts. It focuses on enabling decentralized finance (DeFi) innovations.
Enjin Coin	ENJ	Designed to facilitate the creation and management of non-fungible tokens (NFTs) for gaming and virtual goods. It aims to enable a thriving NFT ecosystem.
Smooth Love Potion	SLP	The in-game token used within the Axie Infinity game. Players earn SLP by participating in battles and breeding Axies.
Alpha Finance	ALPHA	The governance token of the Alpha Finance DeFi platform. It's used for voting on proposals and participating in the platform's development.
Fetch.ai	FET	An AI-driven blockchain platform that focuses on autonomous machine-to-machine communication and economic activity.

dYdX	DXDY	A decentralized exchange and DeFi platform that provides trading and lending services for various cryptocurrencies.
SKALE Network	SKL	A blockchain platform that offers high-performance and configurable sidechains to enhance Ethereum's scalability.
Storj	STORJ	A decentralized cloud storage platform that allows users to rent out their unused storage space and earn STORJ tokens in return.
Perpetual Protocol	PERP	A decentralized trading platform that delivers perpetual contracts for various cryptocurrencies.
Swipe	SXP	A multi-asset digital wallet and cryptocurrency payment platform aims to allow easy conversion between fiat currency and cryptocurrencies.
Shiba Inu	SHIB	Shiba Inu is a meme-inspired cryptocurrency that gained attention for its resemblance to other well-known cryptocurrencies. It's part of the broader "dogecoin" meme coin trend.

Figure 33: The Contour Plot of Hourly Functional Regression Coefficients for BTC



The blue and dark blue areas indicate that the coefficients are zeros or slightly negative. The light green and yellow areas indicate that the coefficients are positive.

A.1.1 Native Cryptocurrency

Figure 34: XLM

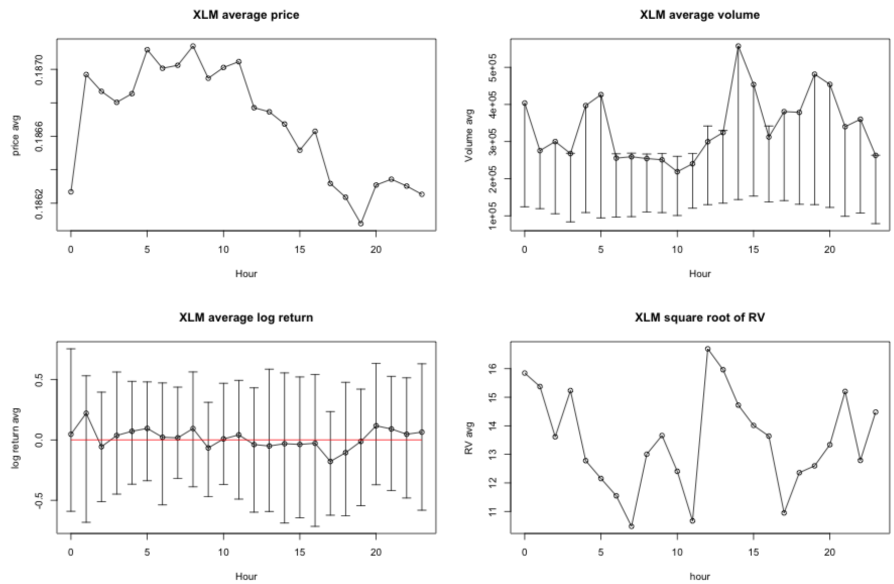


Figure 35: XRP

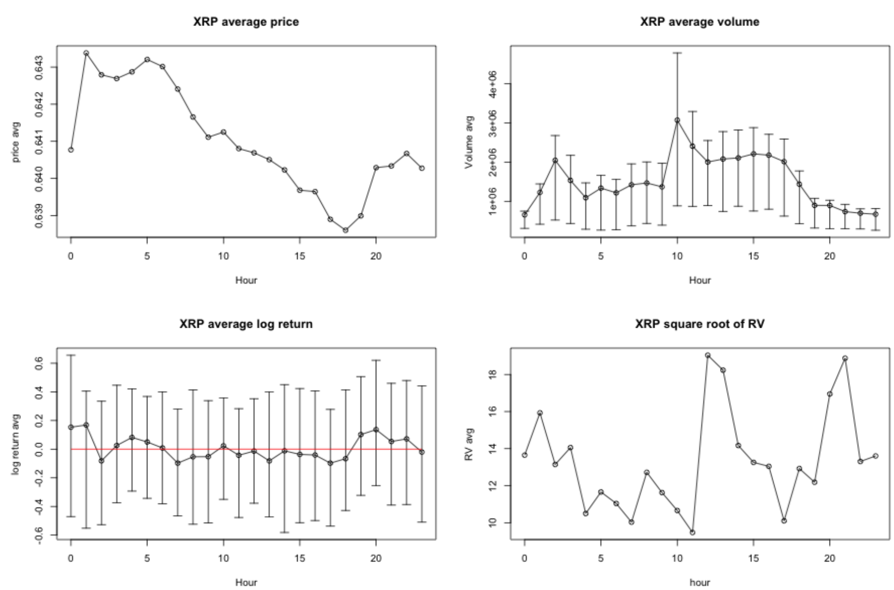


Figure 36: ETH

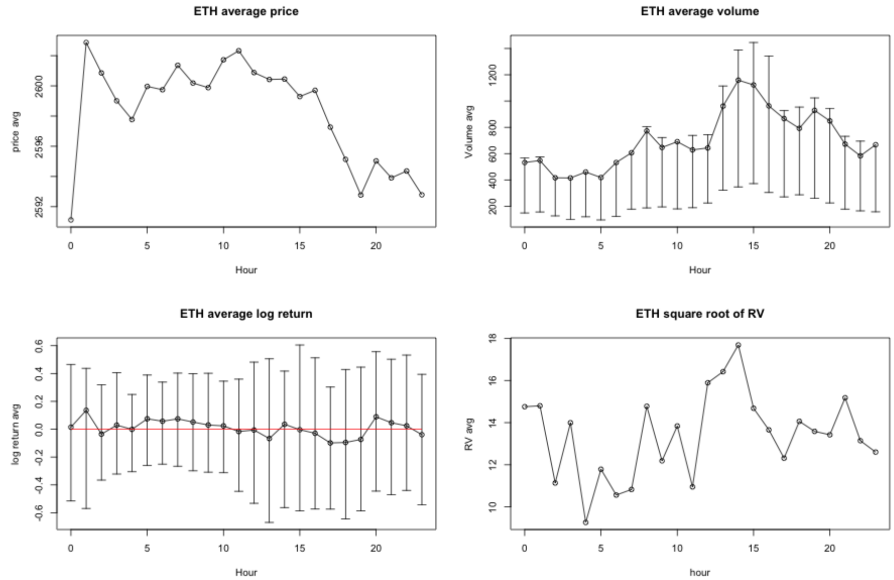


Figure 37: LTC

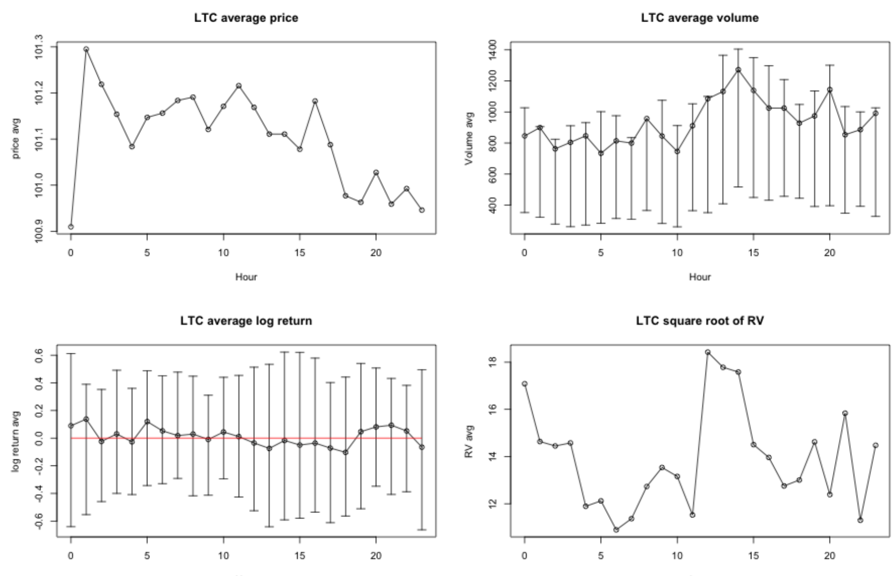


Figure 38: BCH

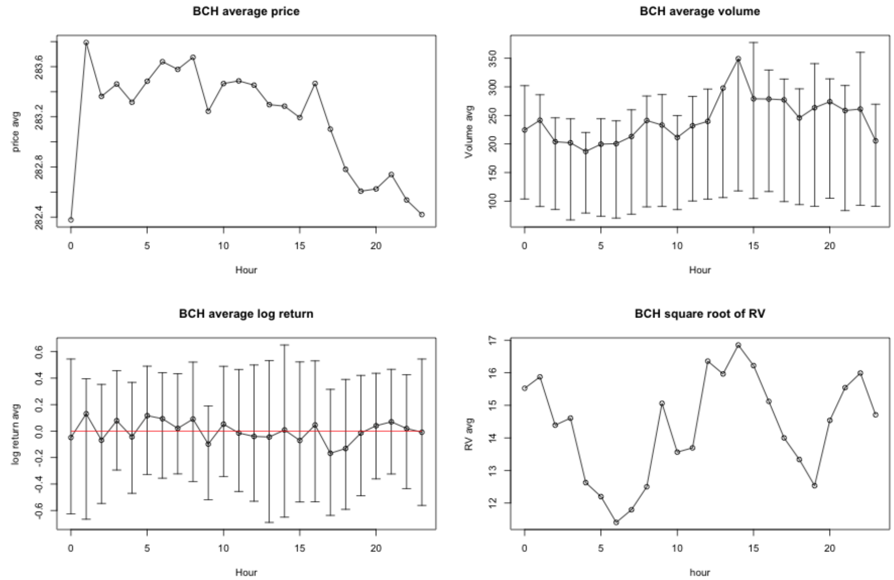


Figure 39: ADA

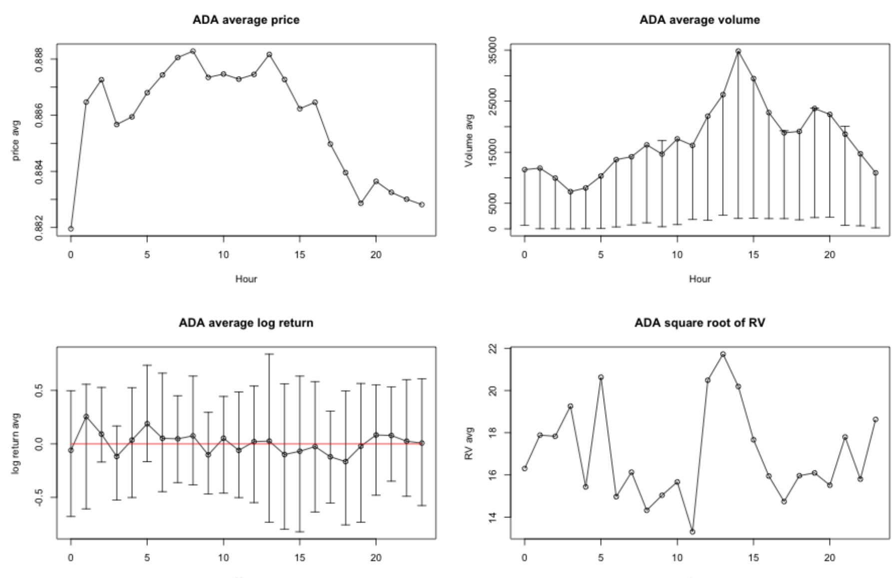


Figure 40: ALGO

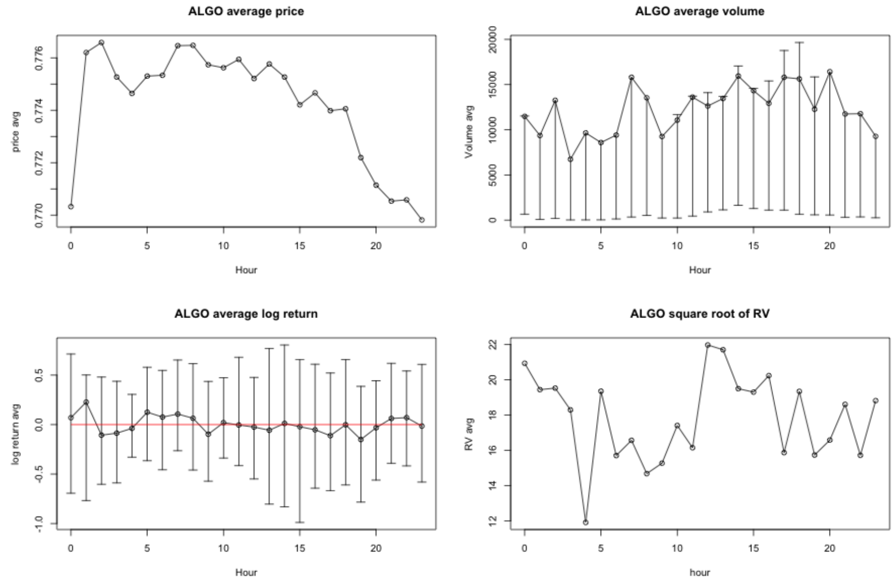


Figure 41: SGB

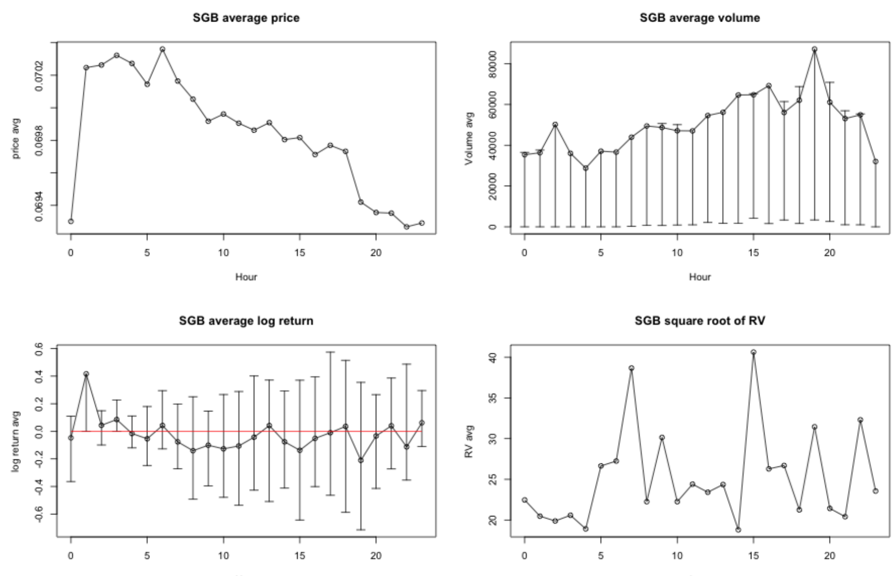
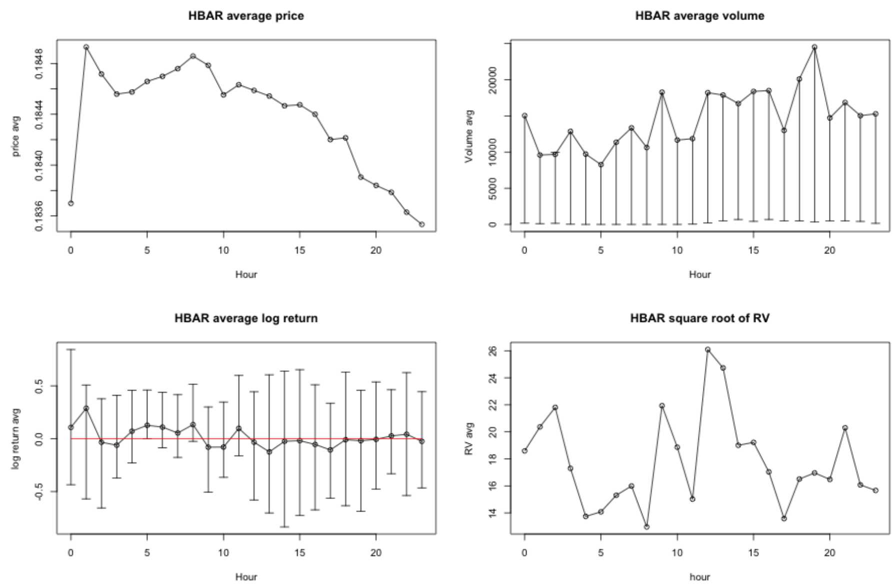


Figure 42: HBAR



A.1.2 Token

Figure 43: MATIC

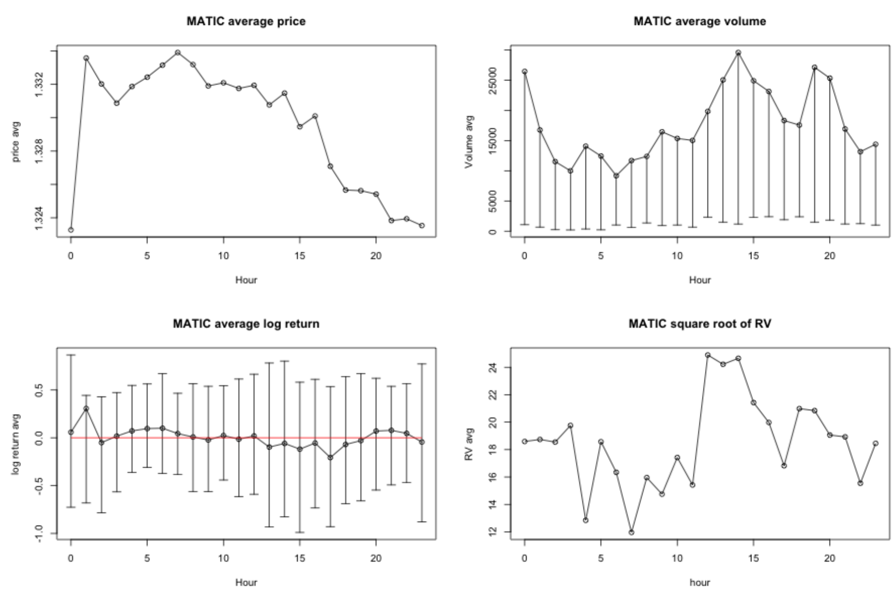


Figure 44: UNI

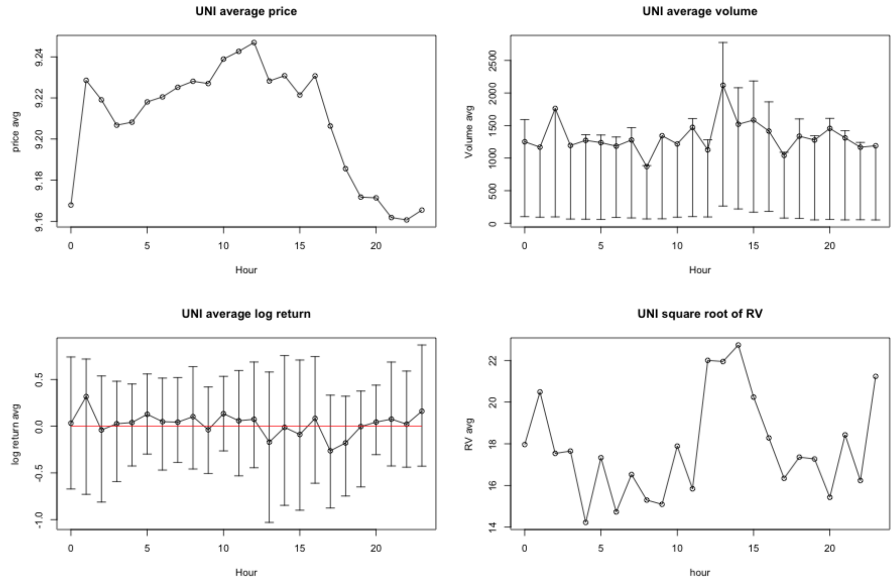


Figure 45: AAVE

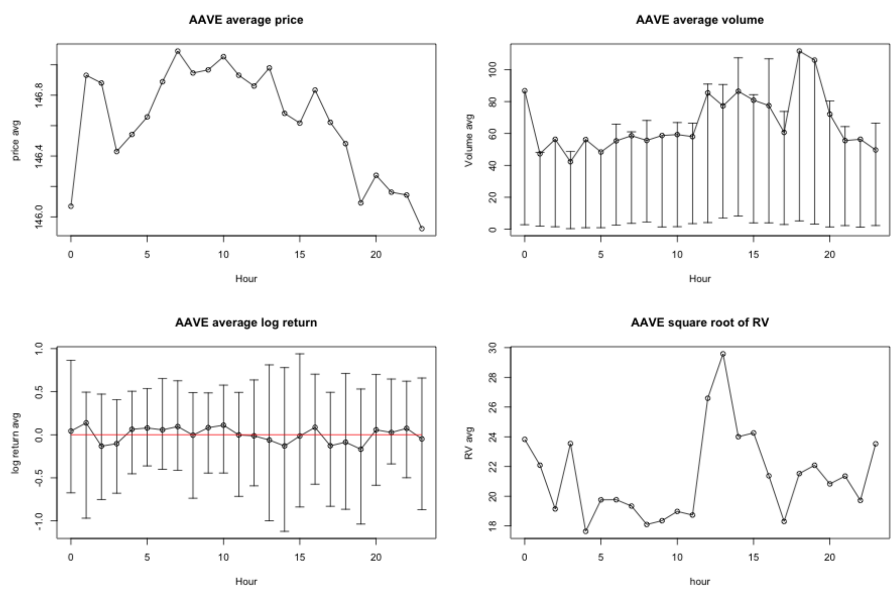


Figure 46: SAND

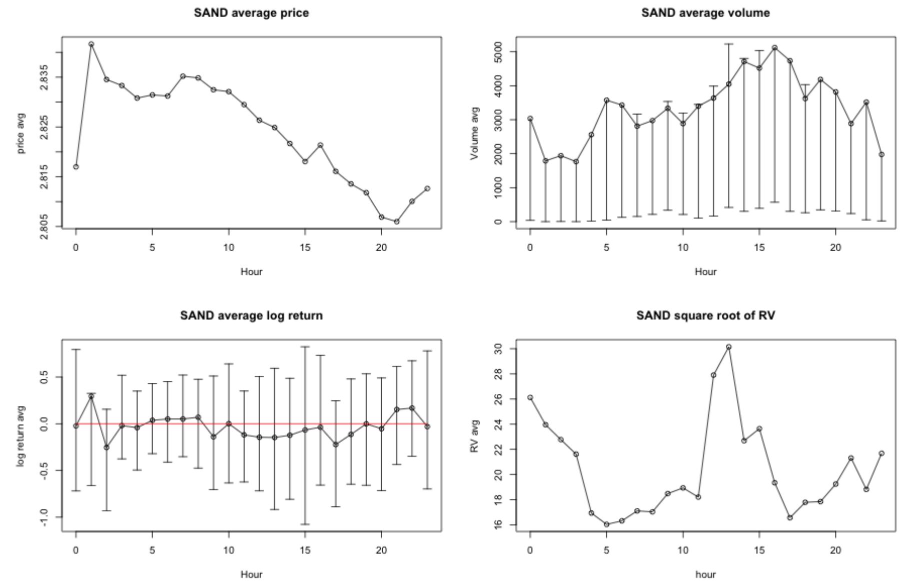


Figure 47: CRV

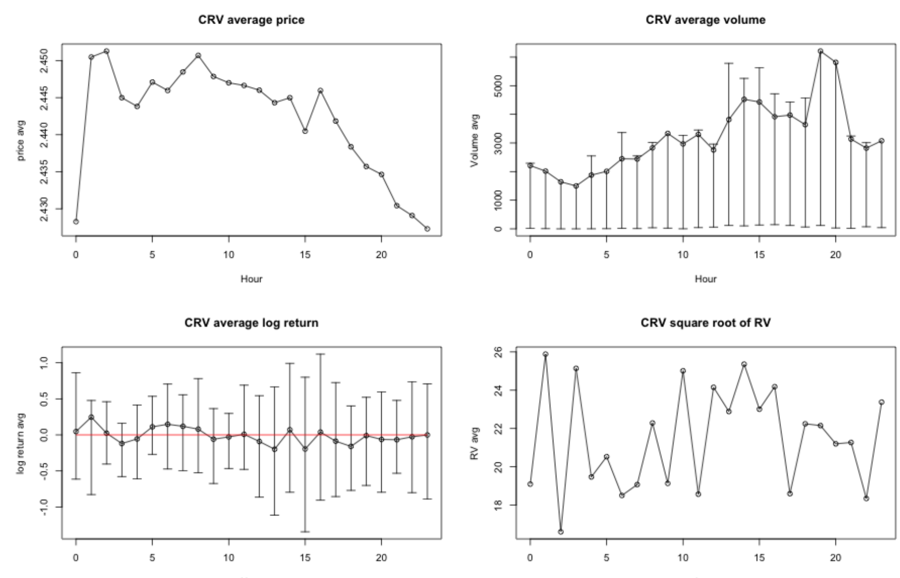


Figure 48: AUDIO

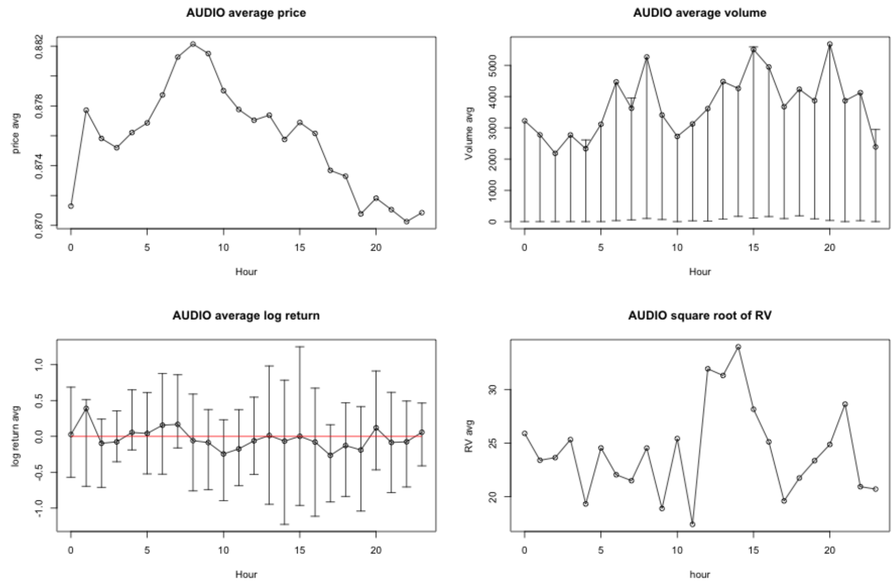


Figure 49: SNX

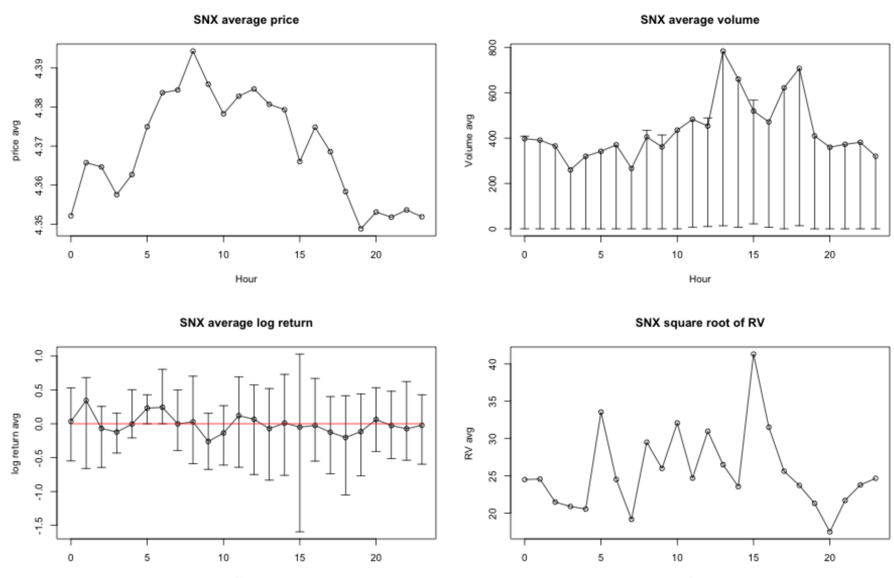


Figure 50: YFI

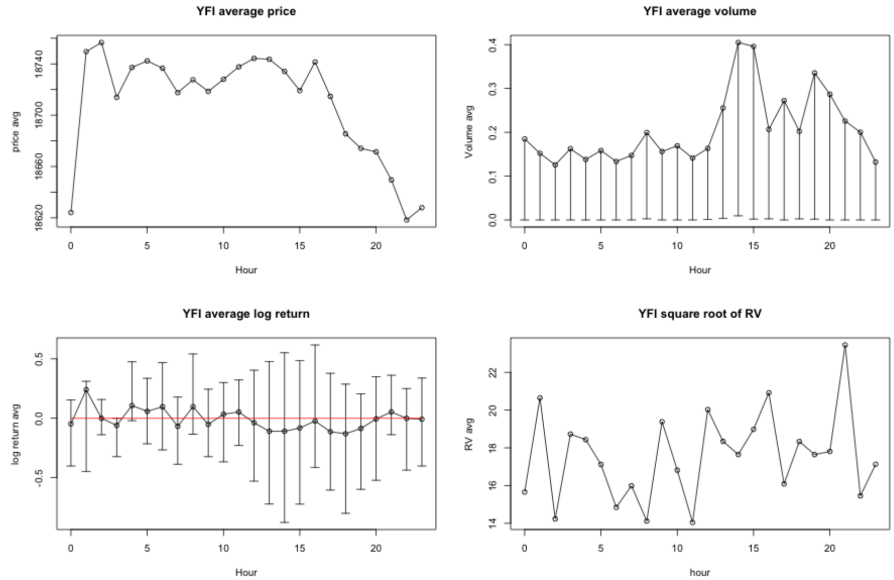


Figure 51: GRT

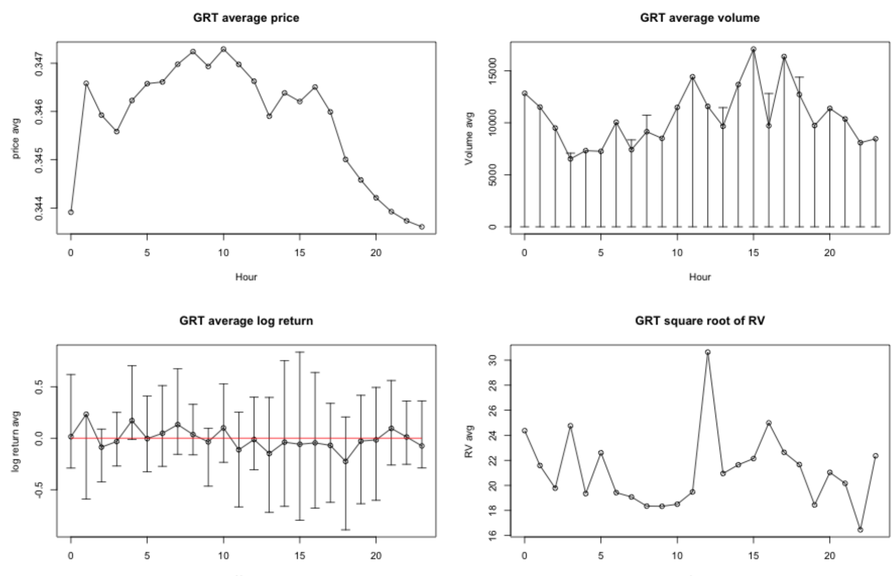


Figure 52: GALA

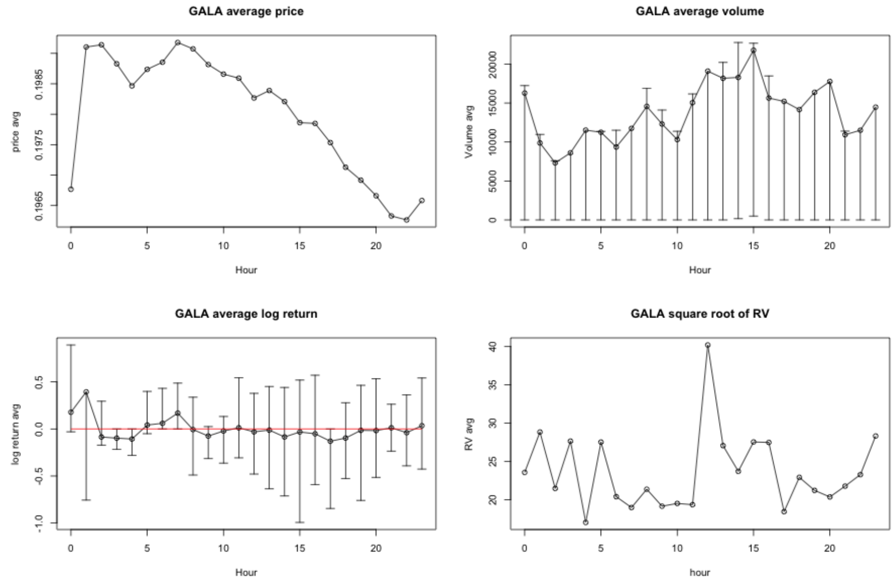


Figure 53: KNC

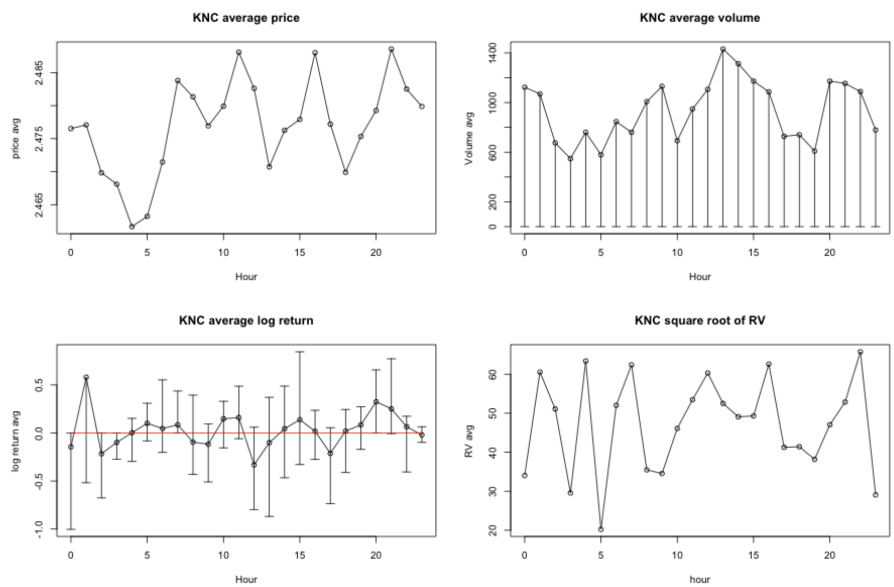


Figure 54: MKR

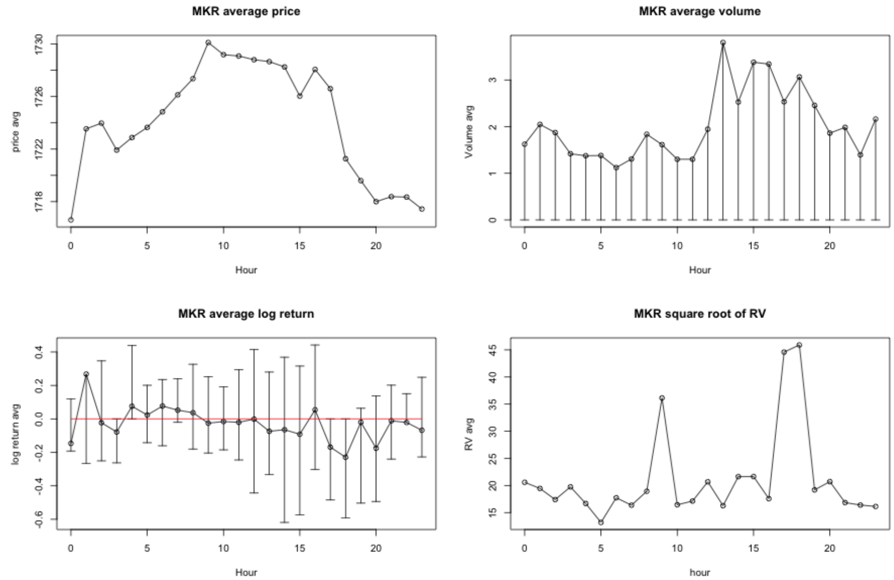


Figure 55: COMP

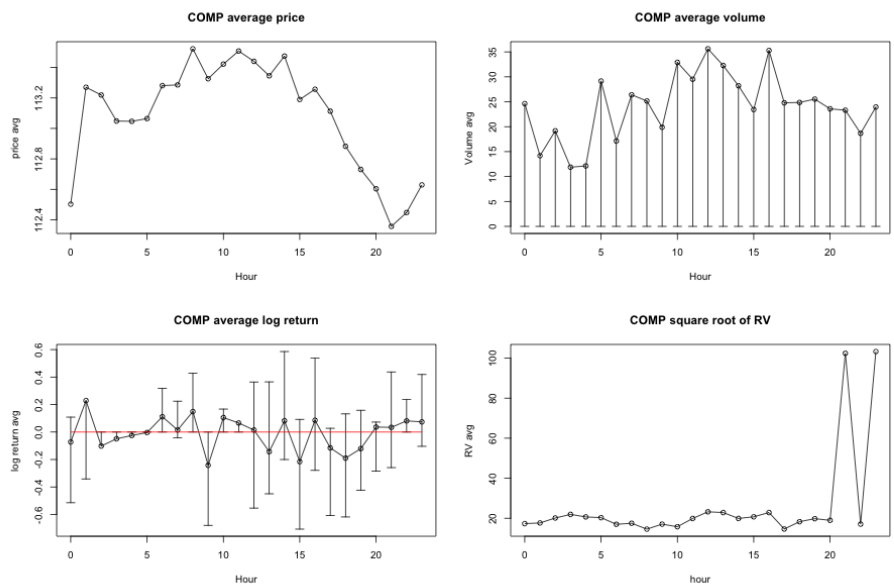


Figure 56: CHZ

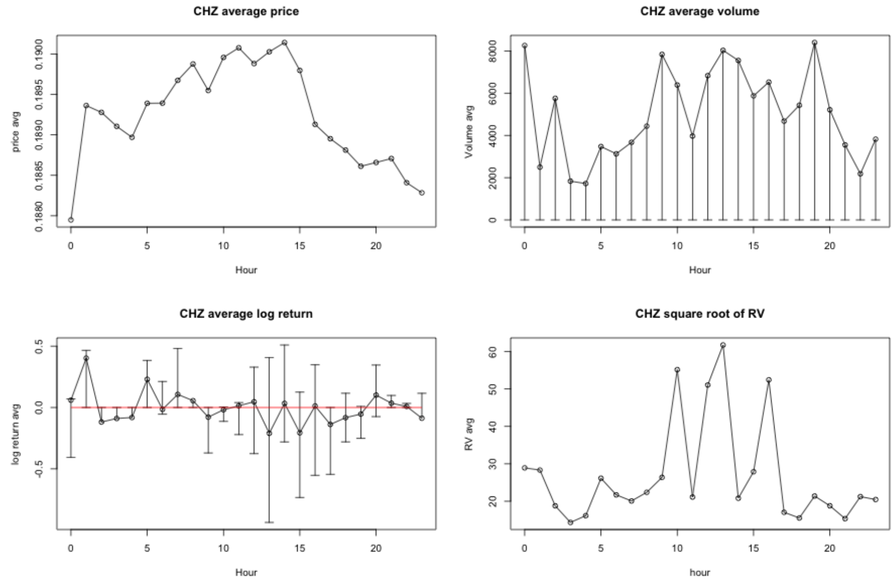


Figure 57: AXS

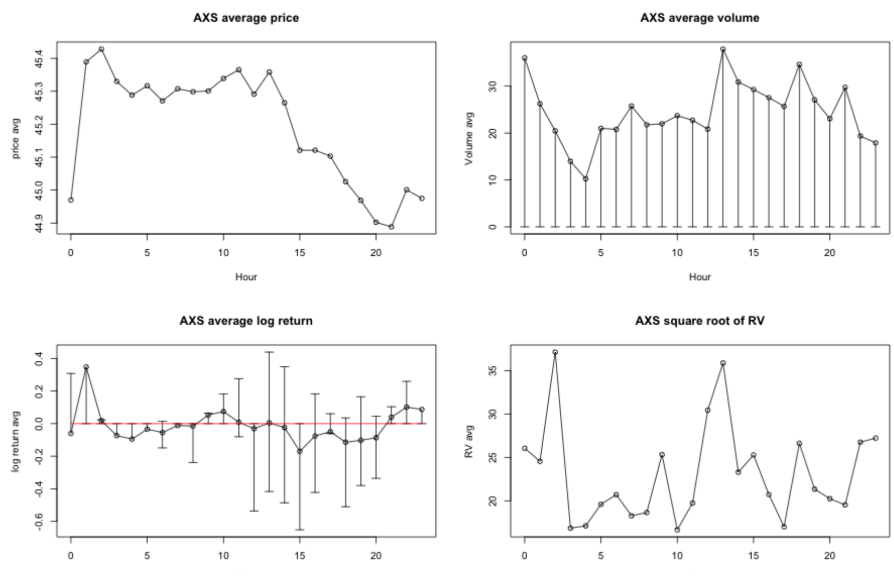


Figure 58: BAT

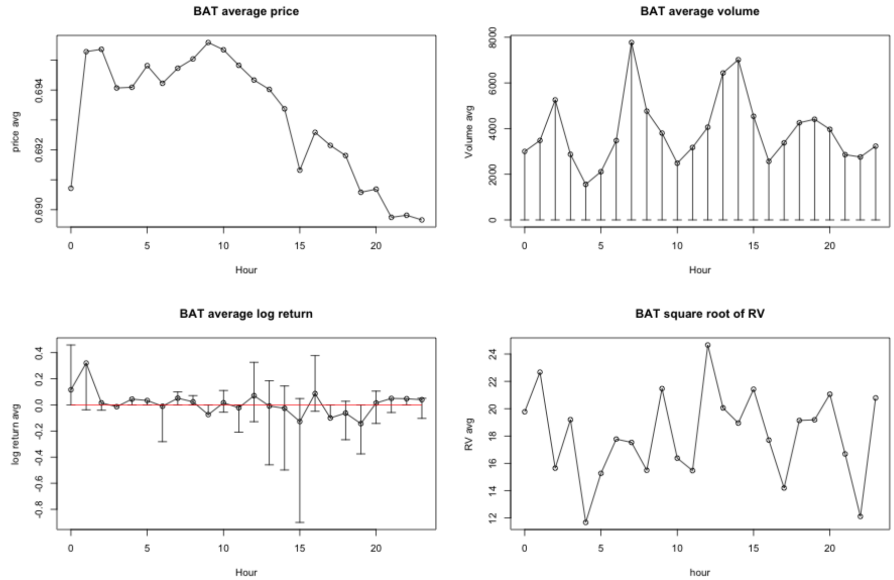
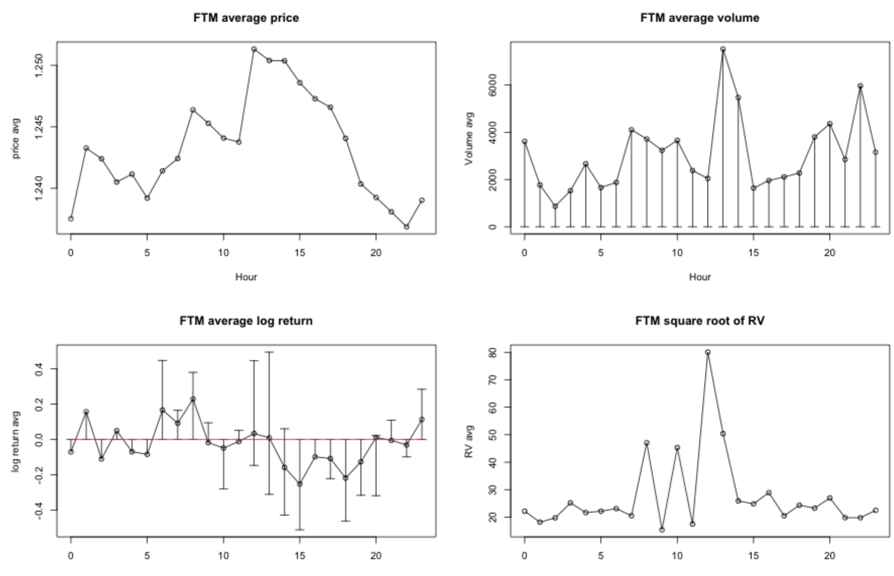
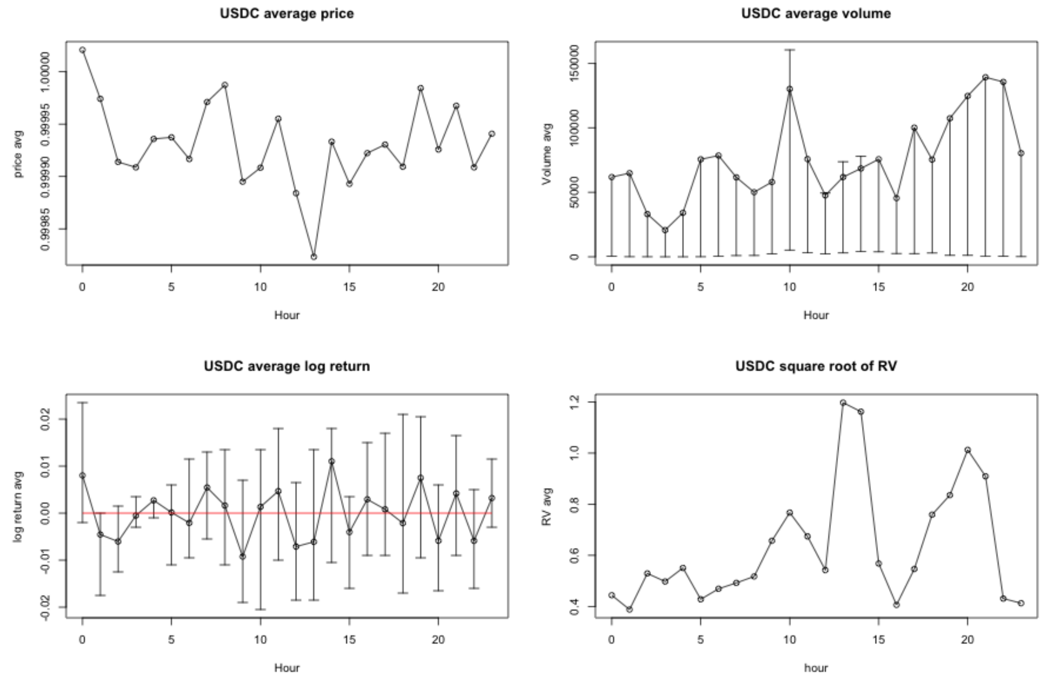


Figure 59: FTM



A.1.3 Stablecoins

Figure 60: USDC



The top left graph displays the average prices of USD Coin at each hour of the day. The top right graph displays the average volumes of USD Coin at each hour of the day. The bottom left displays the average return of USD Coin at each hour of the day. The bottom right graph displays the volatility of USD Coin at each hour of the day. The vertical lines in the average volumes and log returns plots indicate the 25th and 75th percentiles of sample density. The red line in average price is at 1 USD. The red line in average log returns is at zero.

Appendix 2

A.2.1 Native Cryptocurrencies

Table 14: Eigenportfolio Allocation Ratio (Hourly/Daily)

Coin	Ratio
btc	1.4428085
xlm	1.2929317
xrp	1.4586834
eth	1.4988991
ltc	1.4507012
bch	1.3097701
ada	1.1599586
algo	1.1769855
sgb	0.1877742
hbar	0.9572989
link	1.3474083
matic	1.3934029
uni	1.3092796
aave	1.1994453
sand	1.1062673
crv	1.2699811
audio	0.9834645
snx	0.9280566
yfi	1.1404238
grt	1.0671938
gala	1.1508426
knc	0.1962703
mkr	0.7379601
comp	0.3086797
chz	0.5198314
axs	0.8346204
bat	0.9136077
ftm	0.6434917

Figure 61: XLM

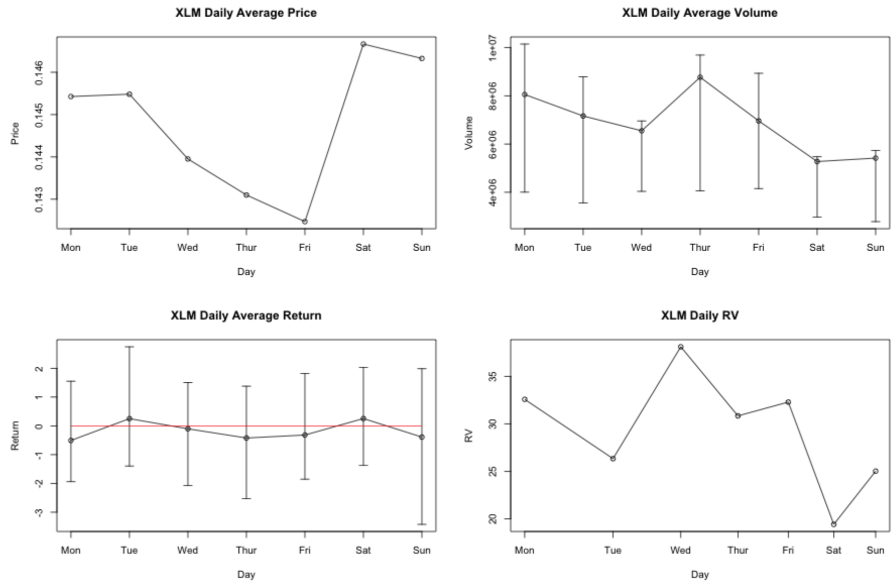


Figure 62: XRP

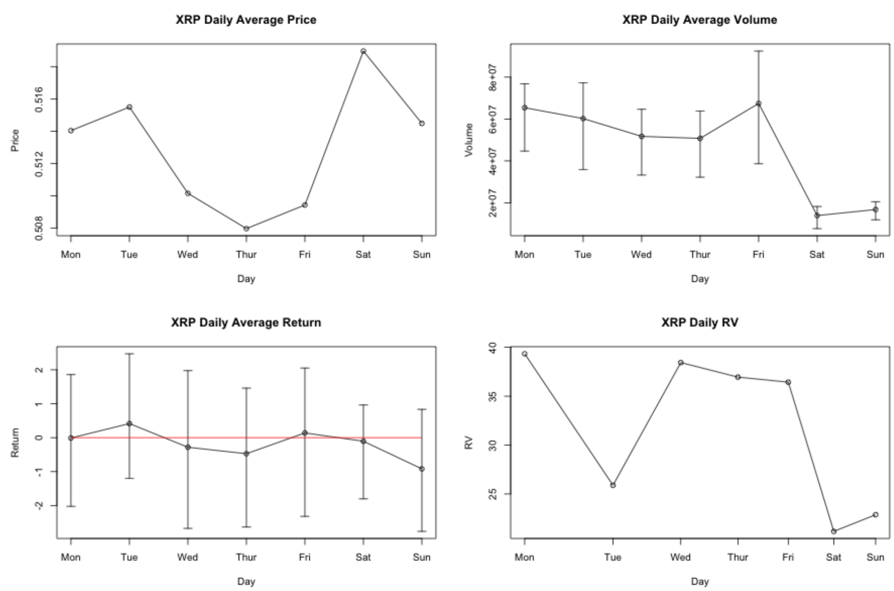


Figure 63: ETH

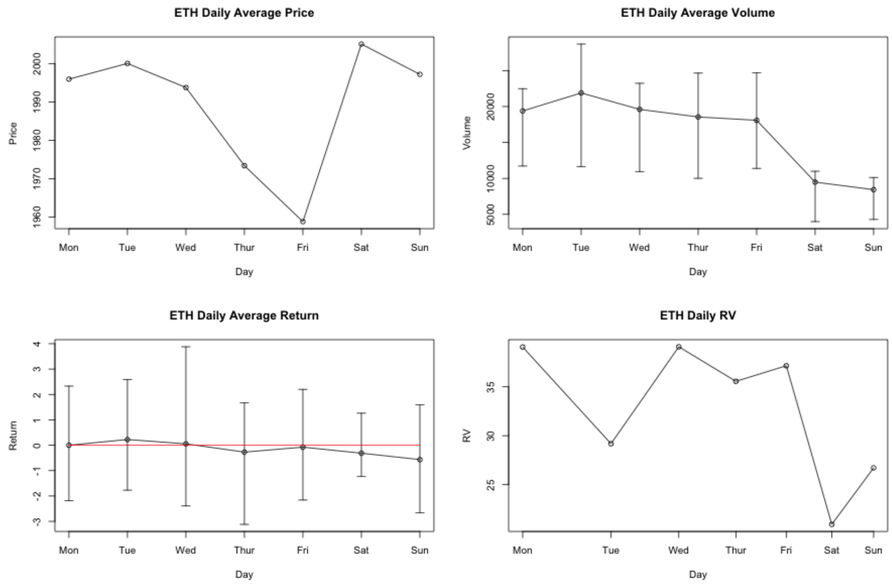


Figure 64: LTC

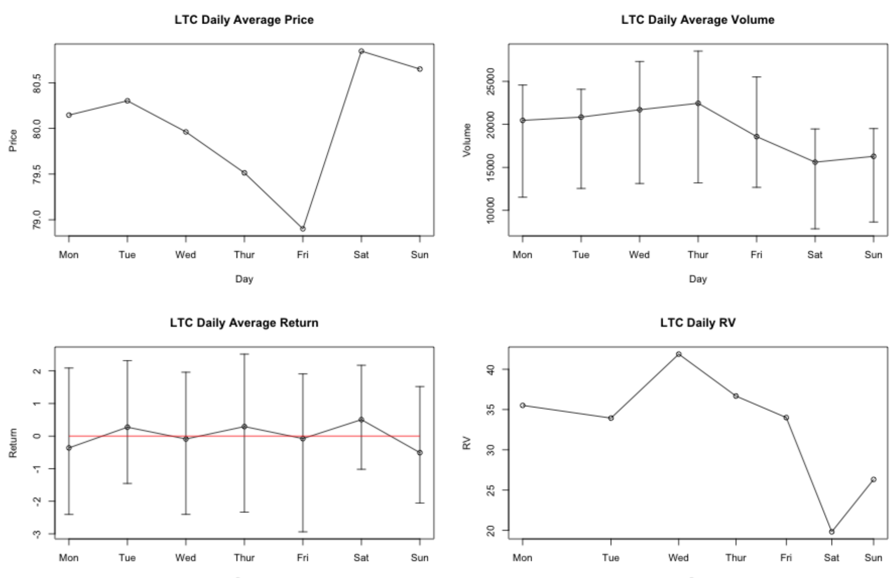


Figure 65: BCH

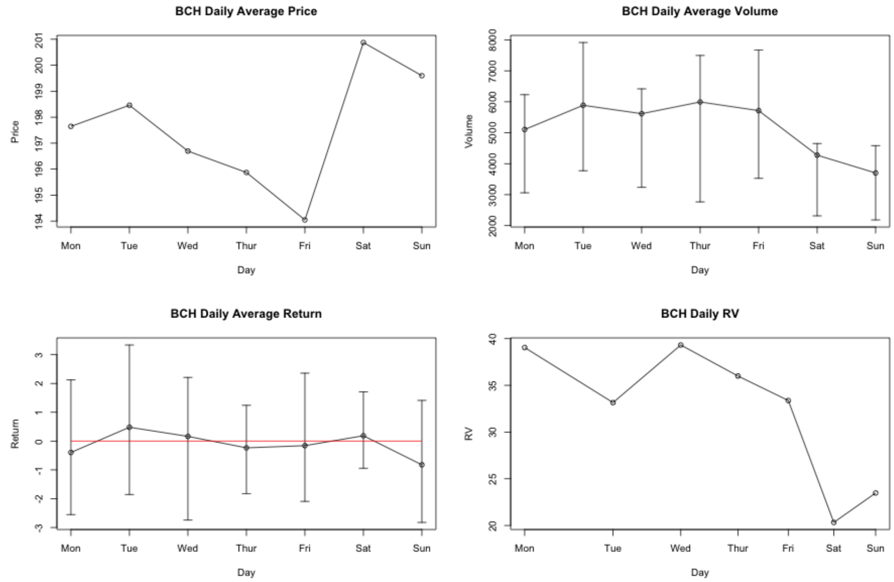


Figure 66: ADA

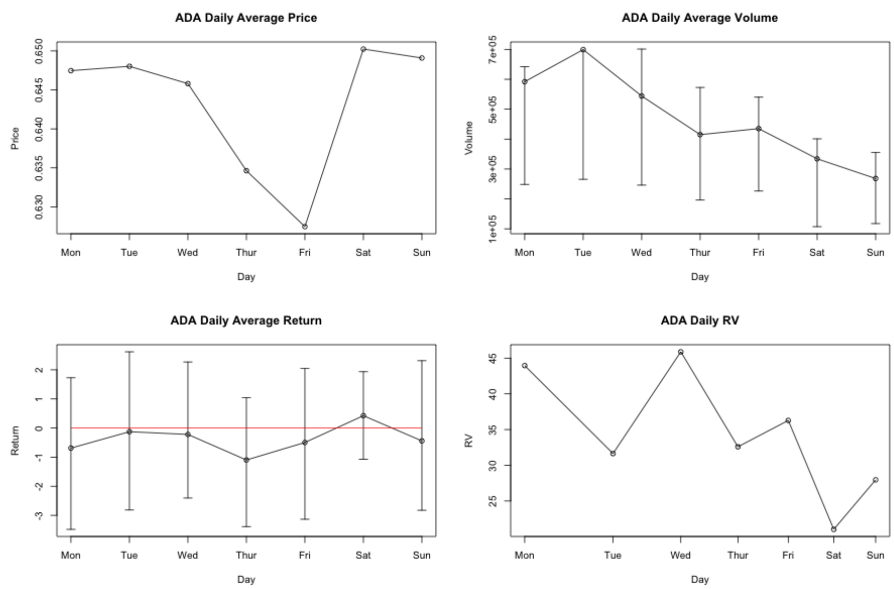


Figure 67: ALGO

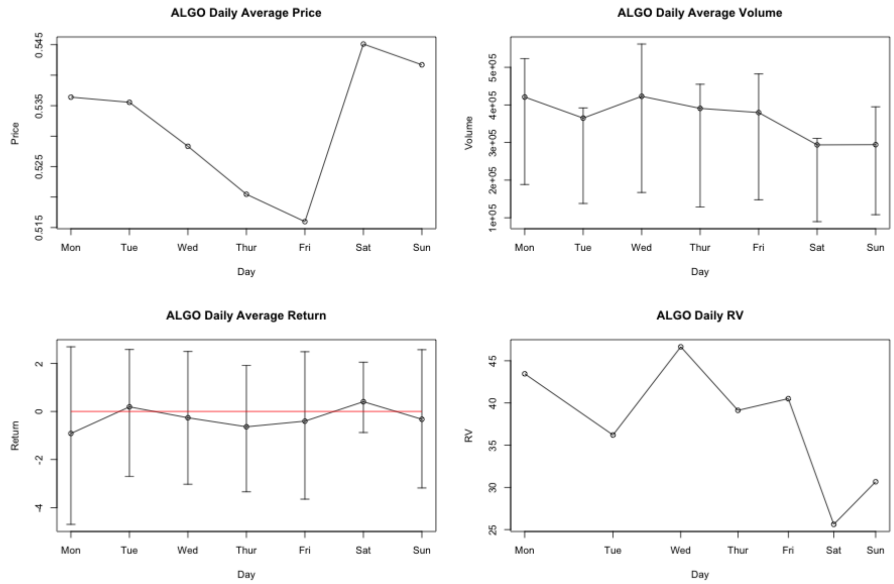


Figure 68: SGB

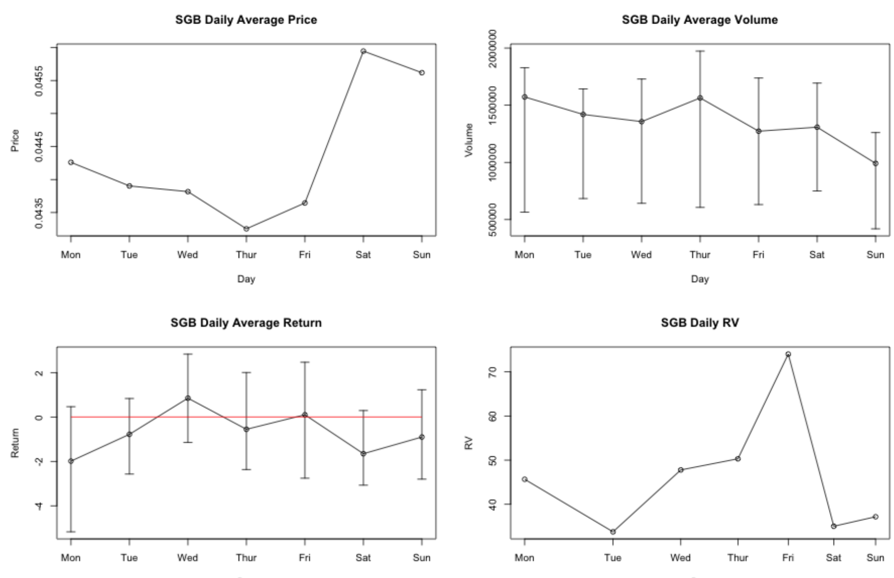
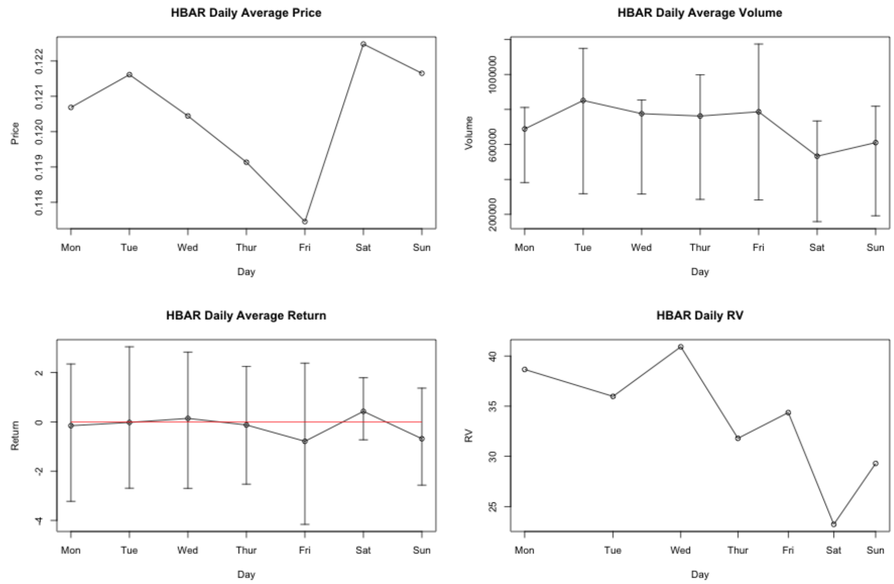


Figure 69: HBAR



7.1 A.2.2 Tokens

Figure 70: MATIC

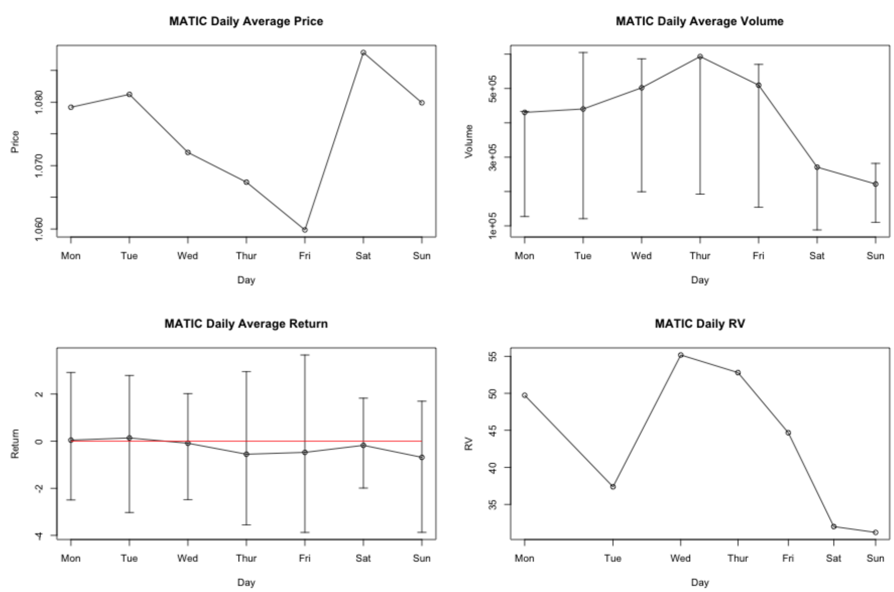


Figure 71: UNI

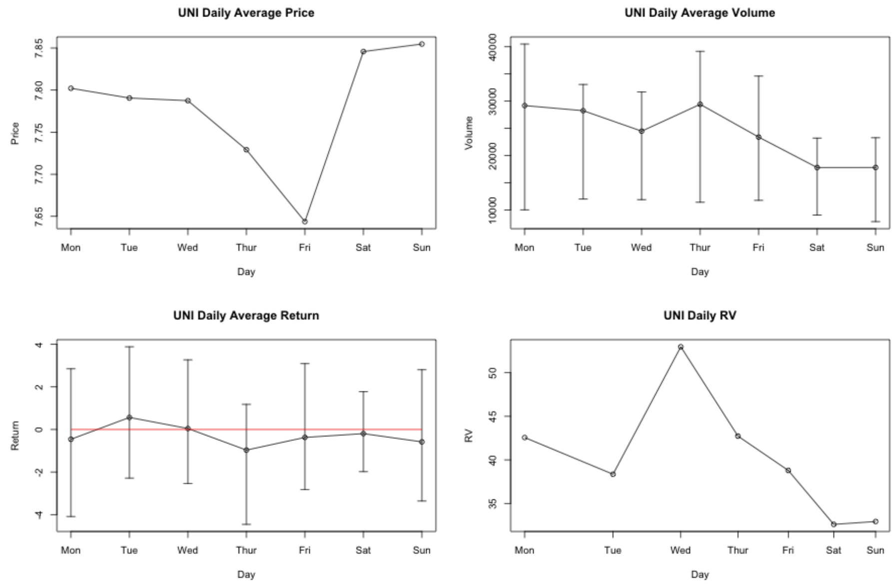


Figure 72: AAVE

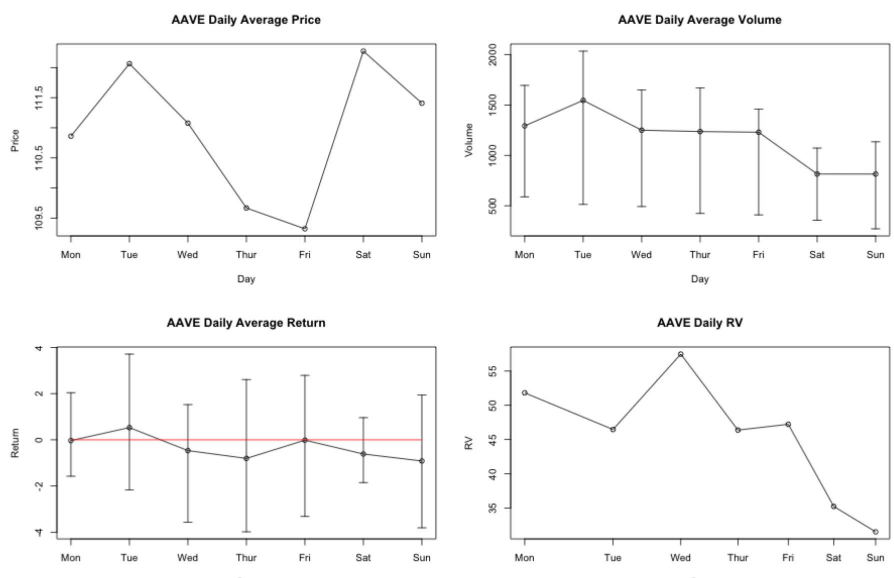


Figure 73: SAND

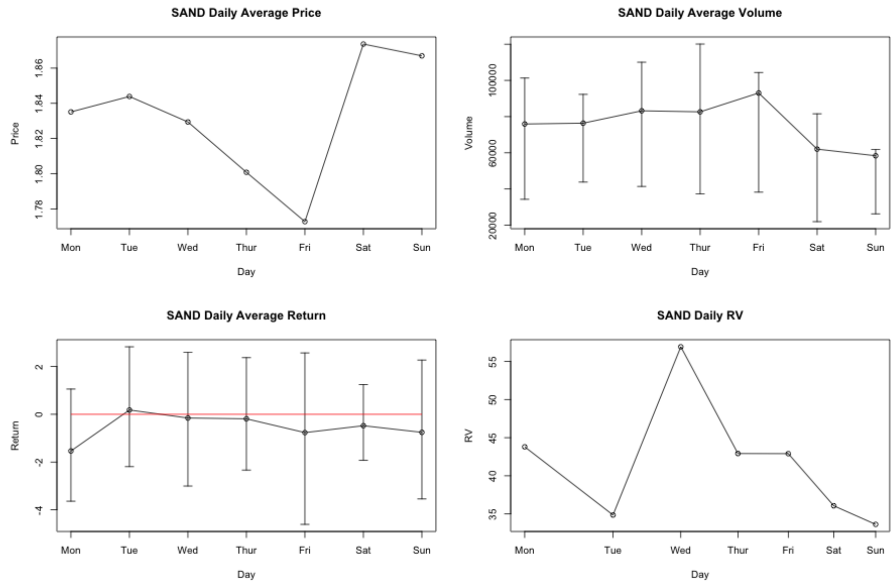


Figure 74: CRV

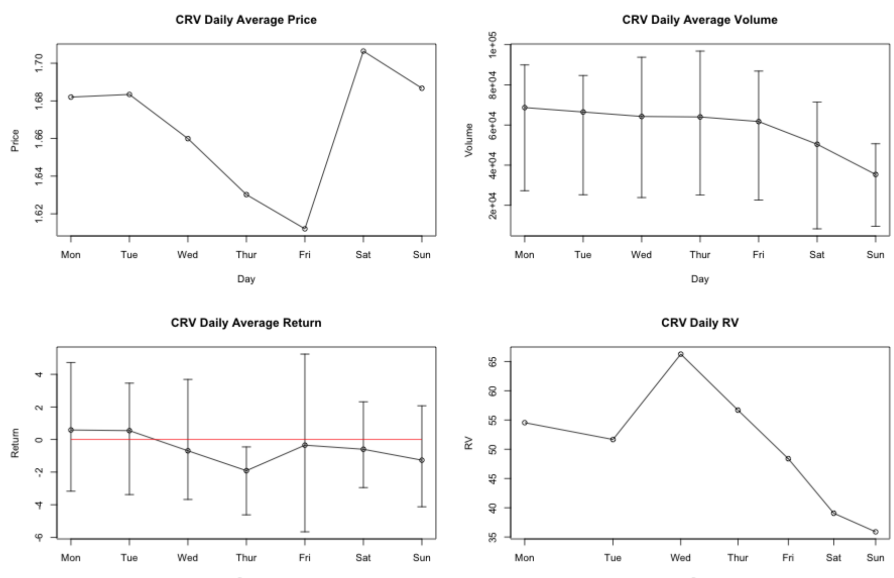


Figure 75: AUDIO

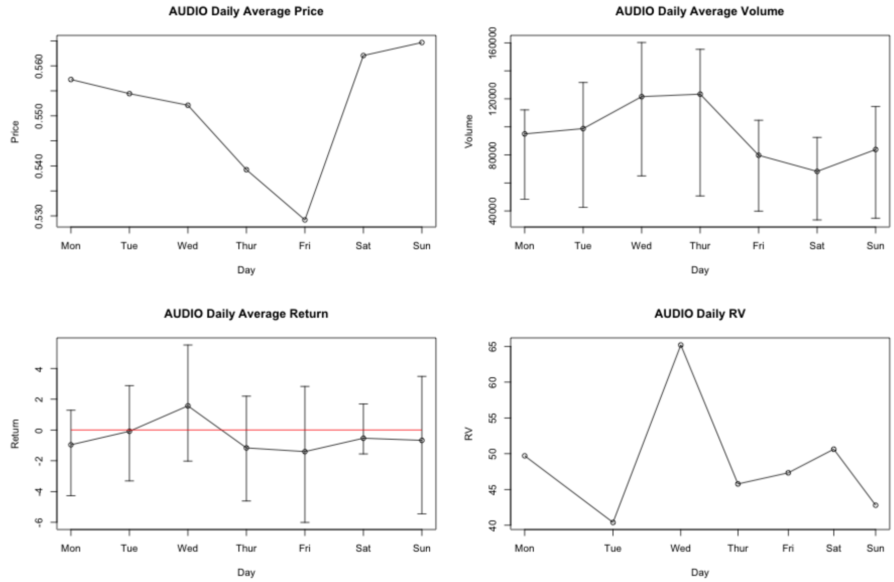


Figure 76: GRT

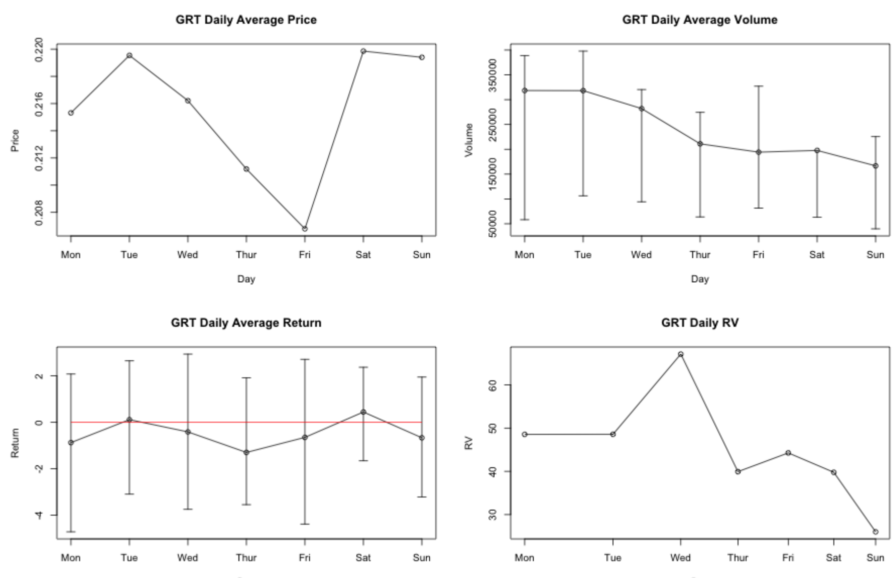


Figure 77: GALA

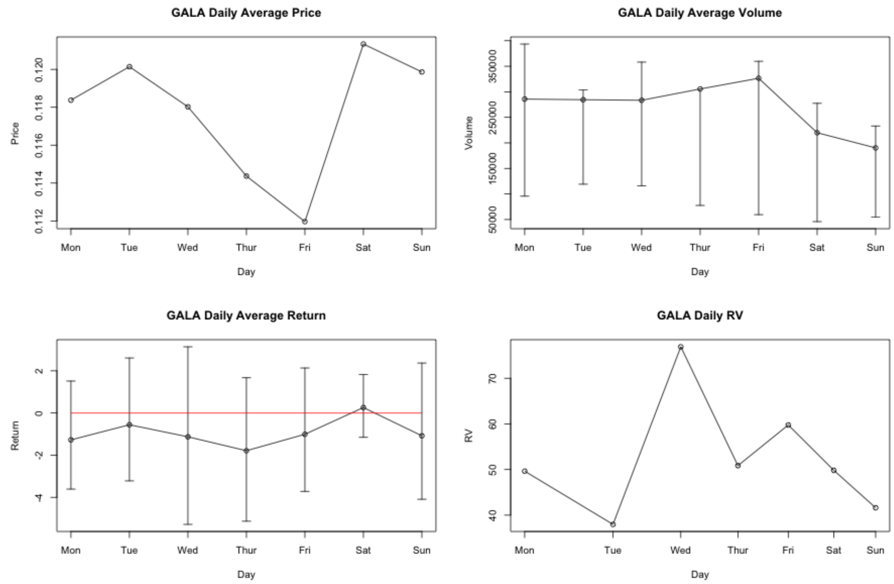


Figure 78: COMP

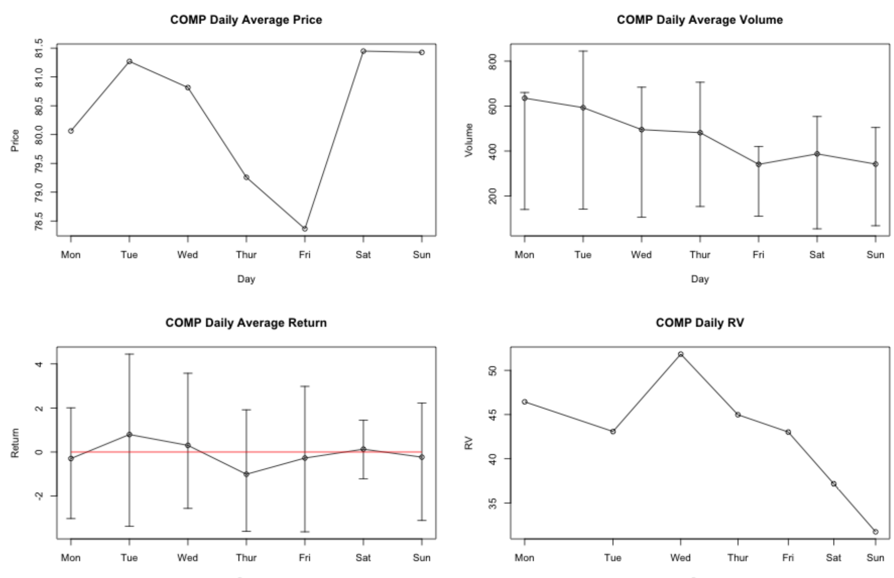


Figure 79: CHZ

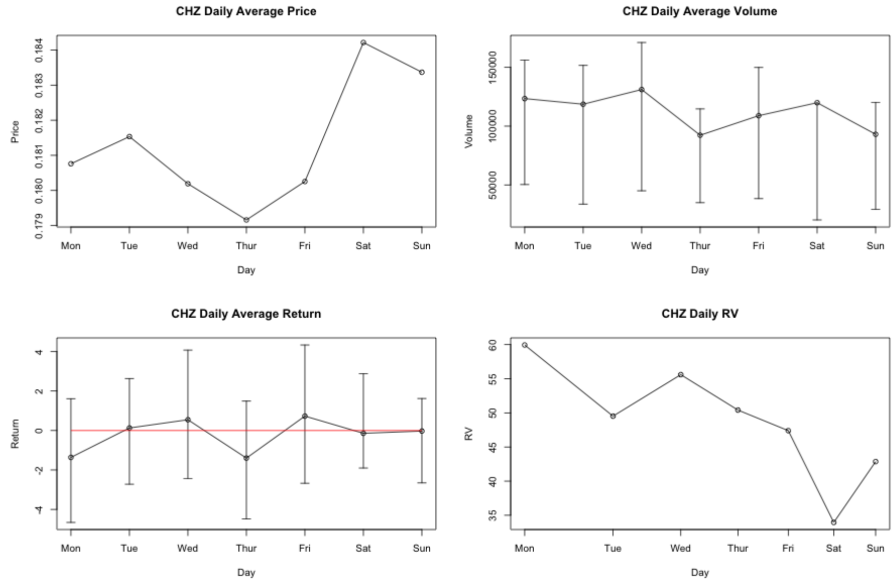


Figure 80: YFI

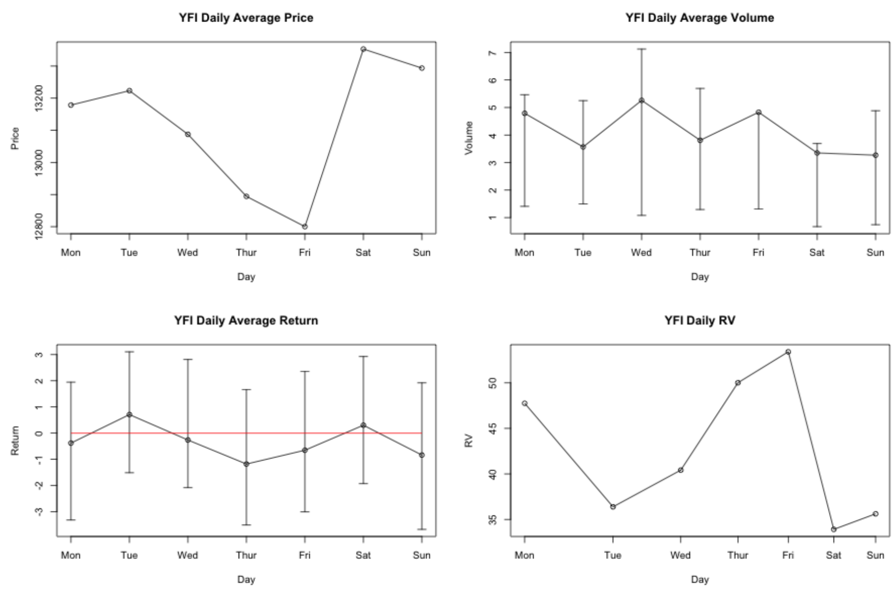


Figure 81: MKR

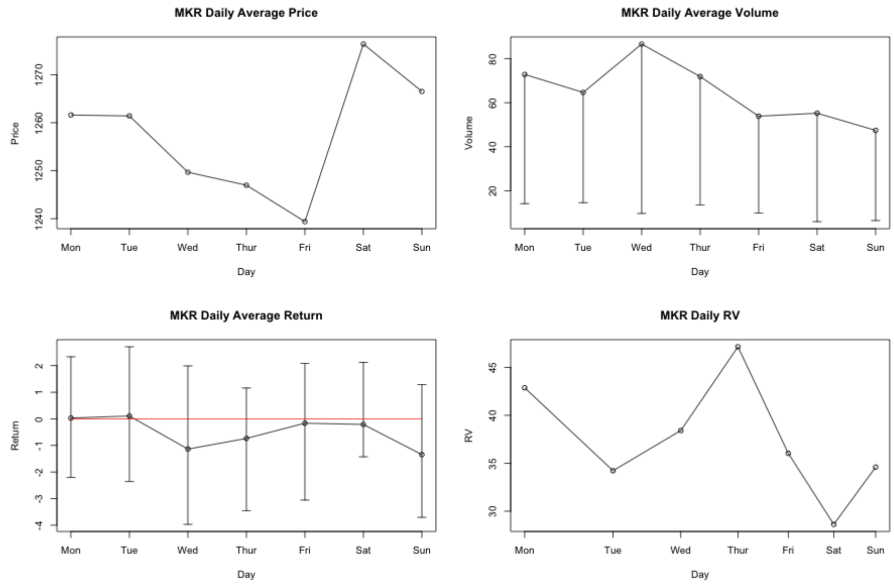


Figure 82: AXS

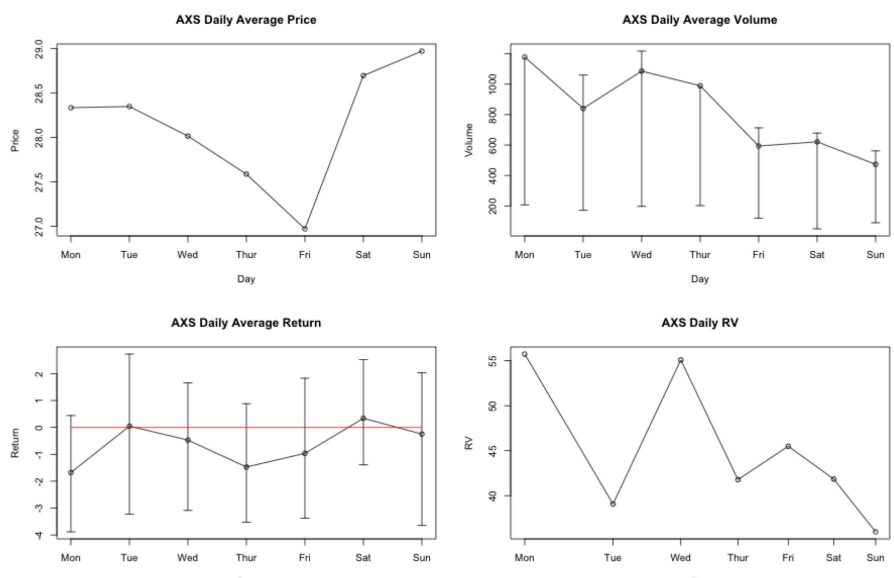


Figure 83: BAT

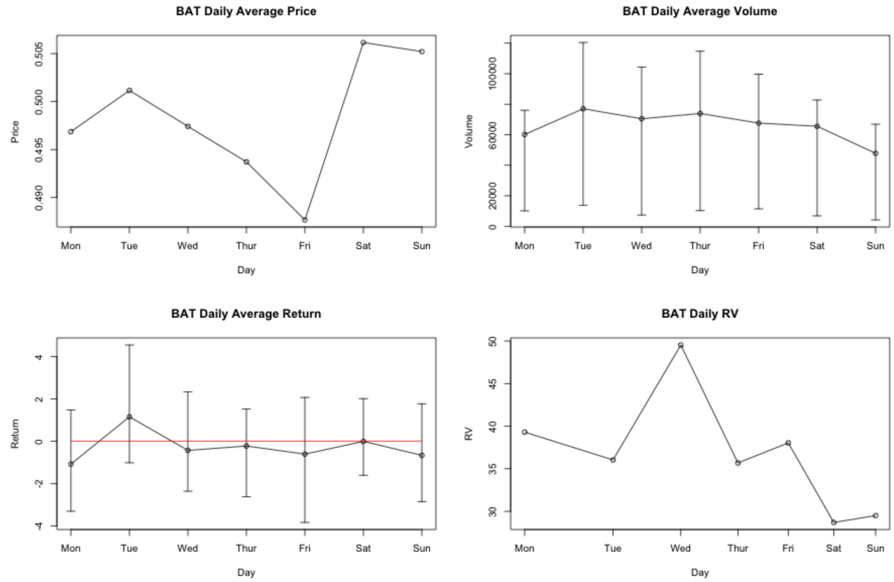


Figure 84: SNX

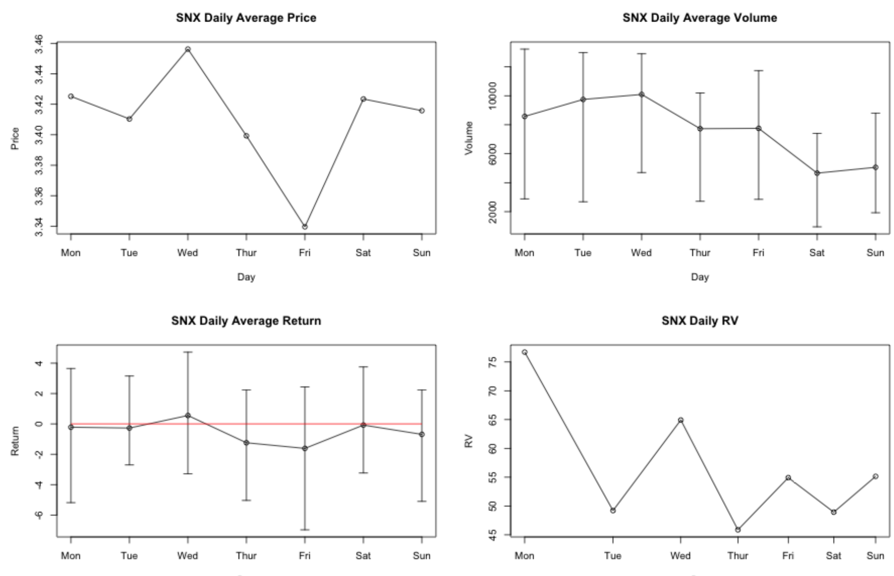


Figure 85: ENJ

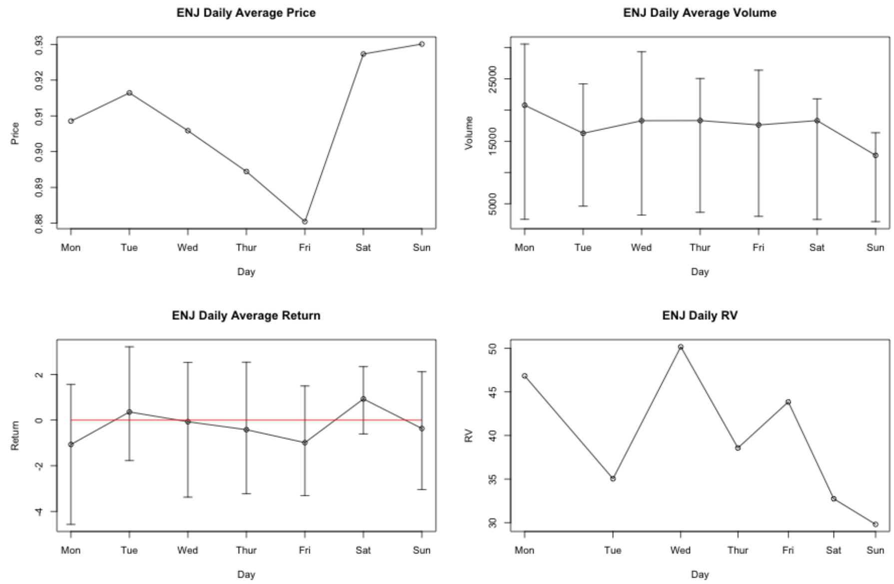


Figure 86: SLP

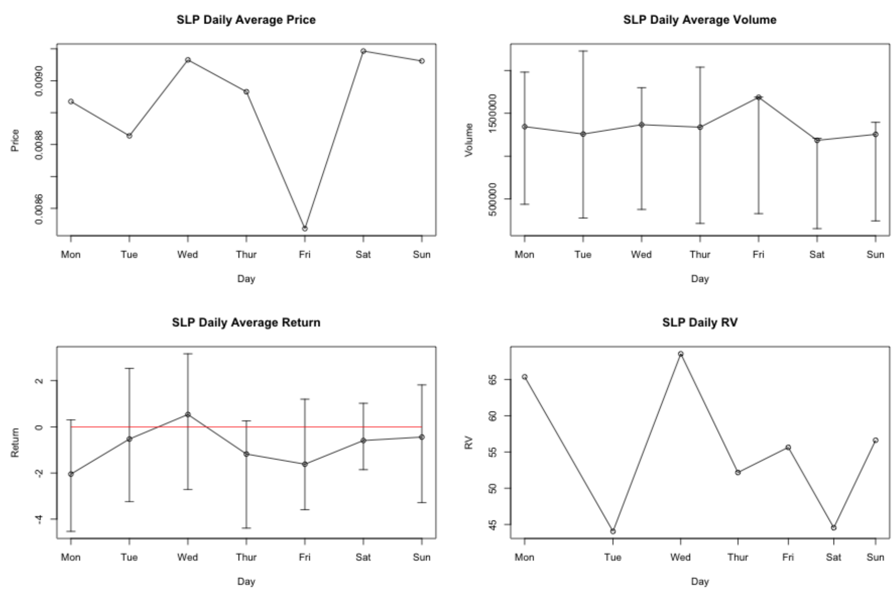


Figure 87: KNC

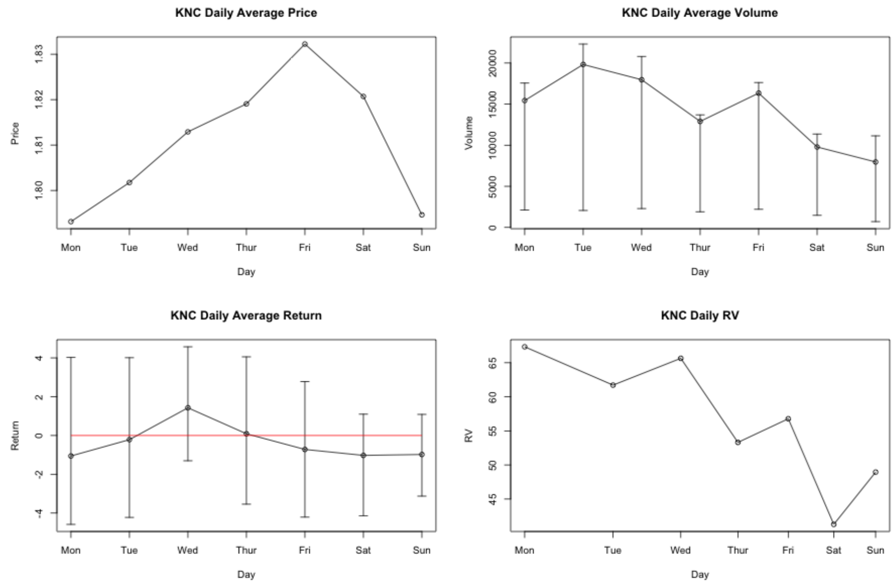


Figure 88: UMA

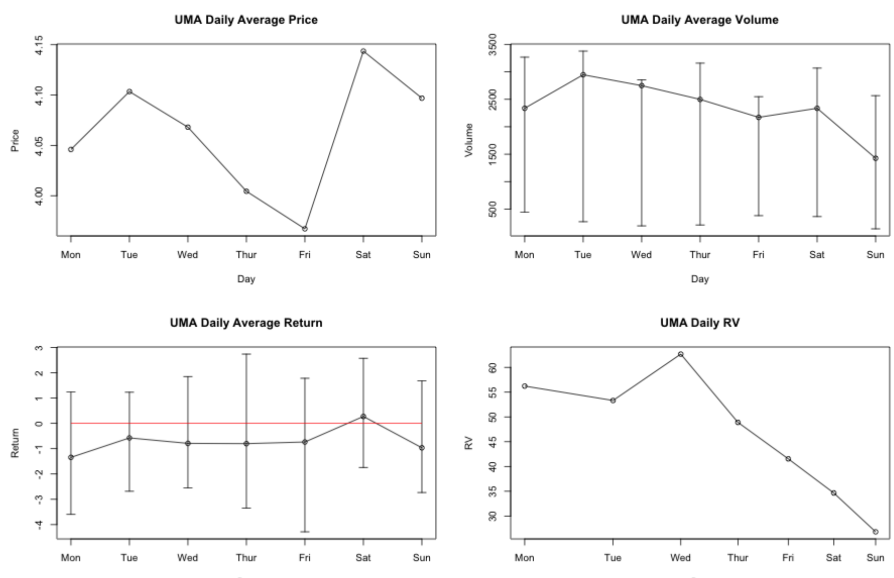


Figure 89: FTM

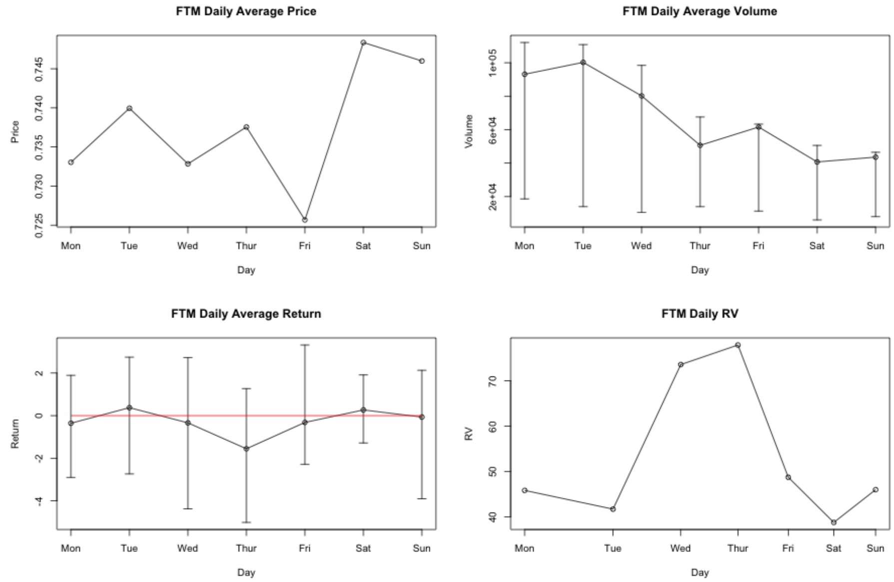


Figure 90: DYDX

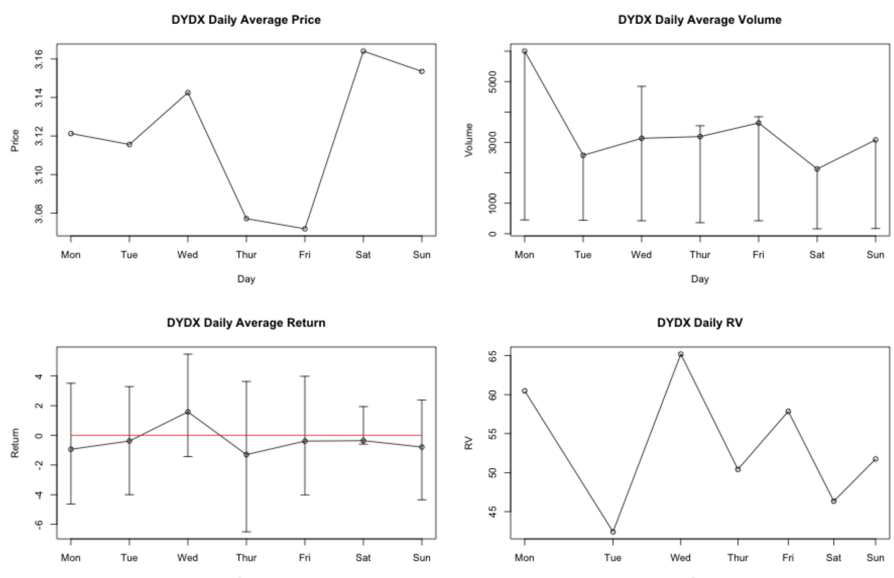
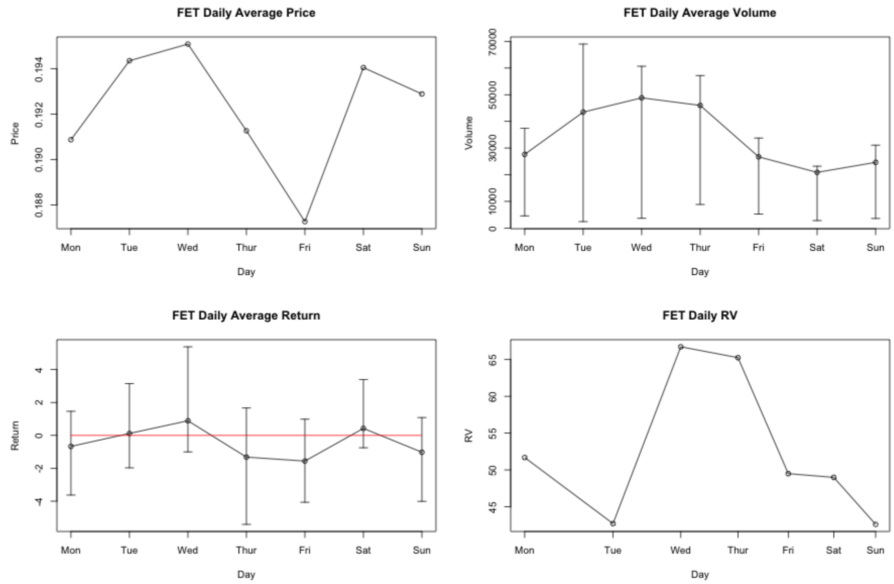
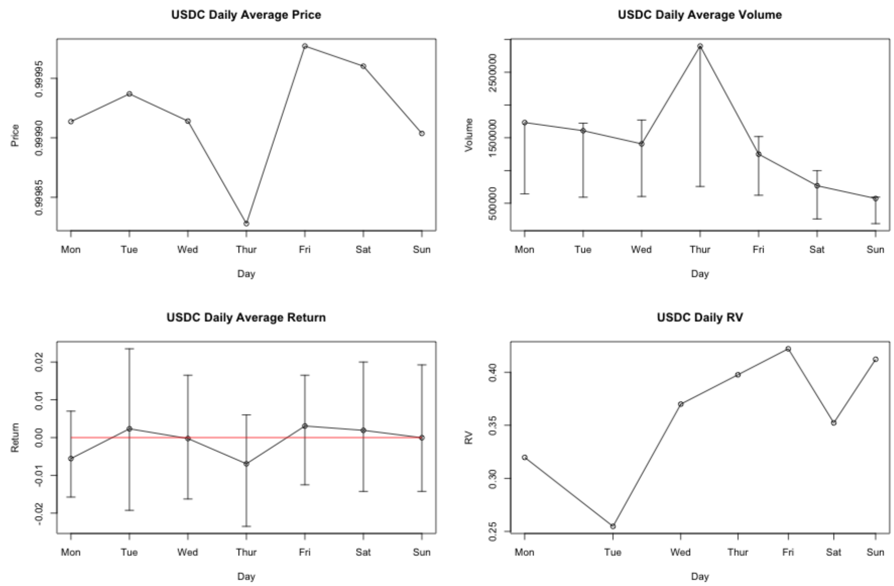


Figure 91: FET



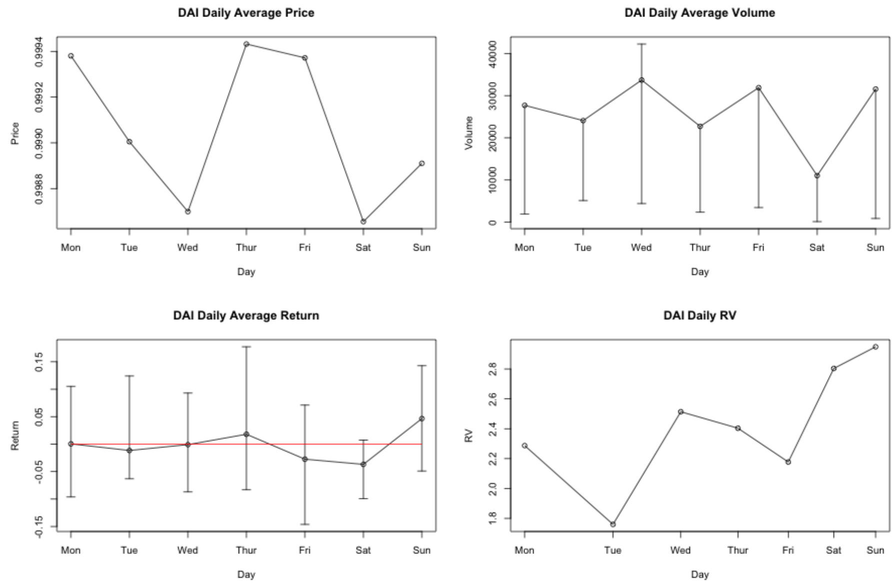
A.2.3 Stable Coins

Figure 92: USDC



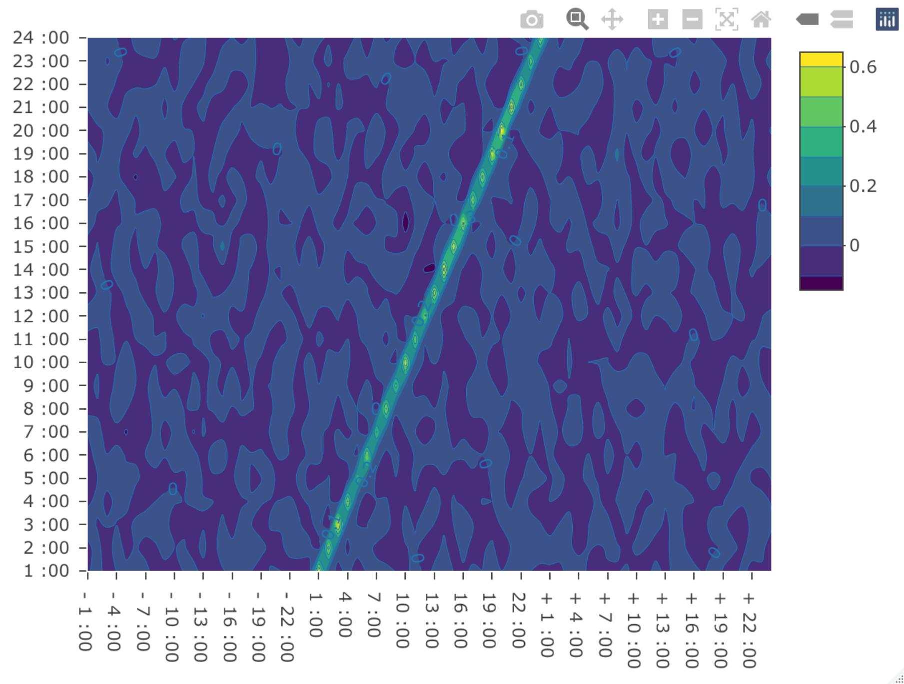
The top left graph displays the average daily prices of USD Coin on each day of the week. The top right graph displays the average daily volumes of USD Coin on each day of the week. The bottom left graph displays the average daily return of USD Coin on each day of the week. The bottom right graph displays the daily volatility of USD Coin on each day of the week. The vertical line in the average volumes and log returns plots indicate the 25th and 75th percentiles of sample density. The red line in average log returns is at zero

Figure 93: DAI



8 A.3 Functional Regression: Additional Figures

Figure 94: The Contour Plot of Hourly Functional Regression Coefficients for BTC



The blue and dark blue areas indicate that the coefficients are zeros or slightly negative. The light green and yellow areas indicate that the coefficients are positive.

Figure 95: The Contour Plot of Hourly Functional Regression Coefficients for ETH

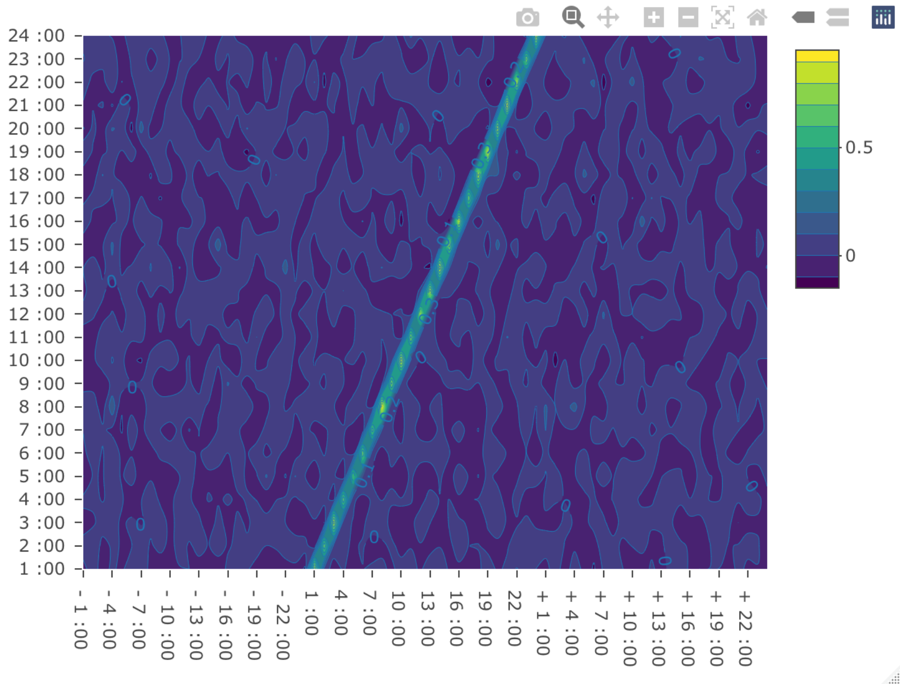


Figure 96: The Contour Plot of Hourly Functional Regression Coefficients for Link

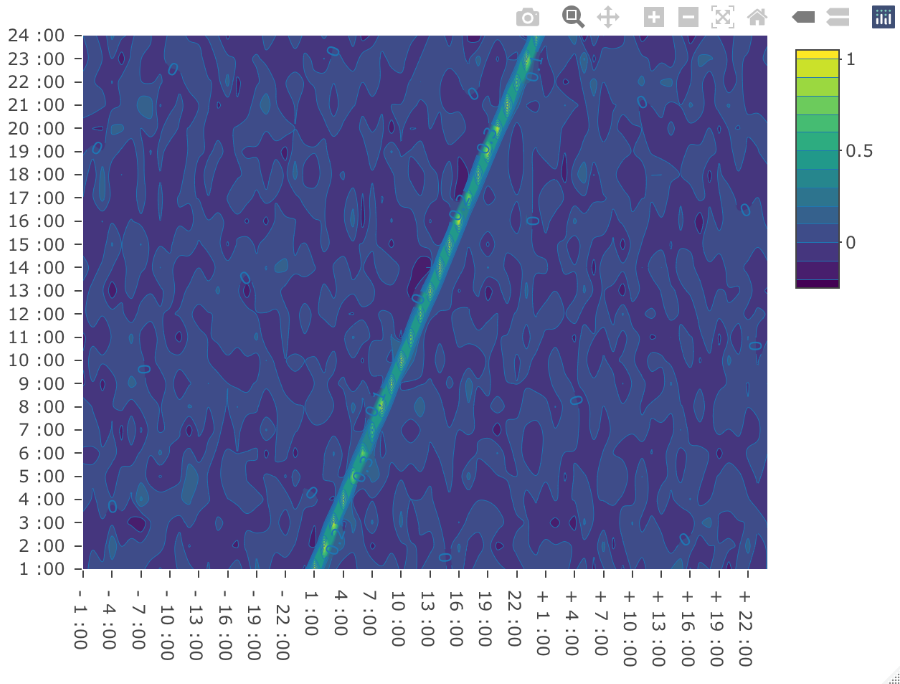


Figure 97: The Contour Plot of Hourly Functional Regression Coefficients of USDT

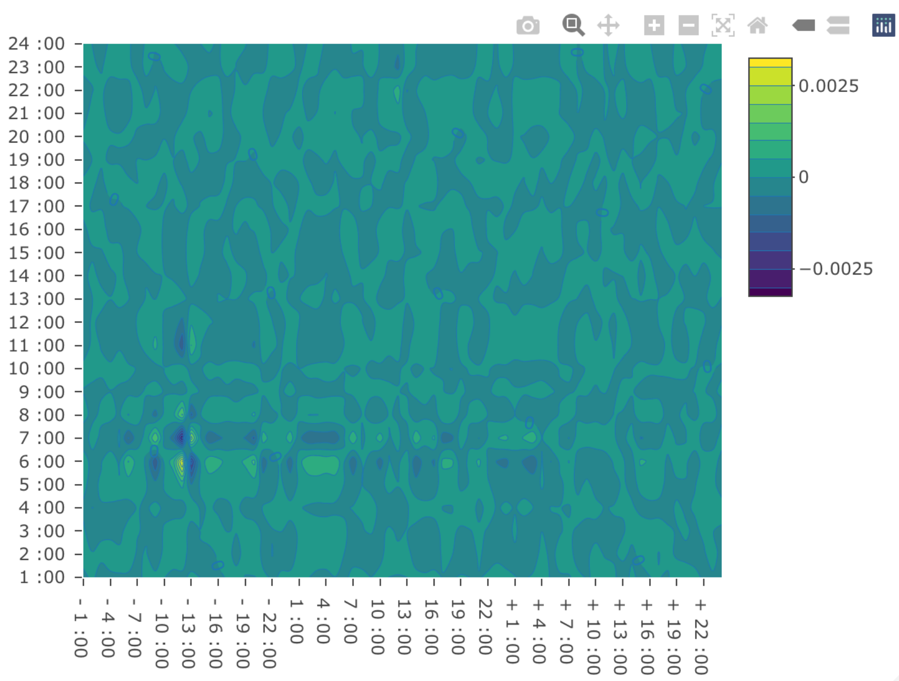


Figure 98: The Contour Plot of Hourly Functional Regression Coefficients of KNC

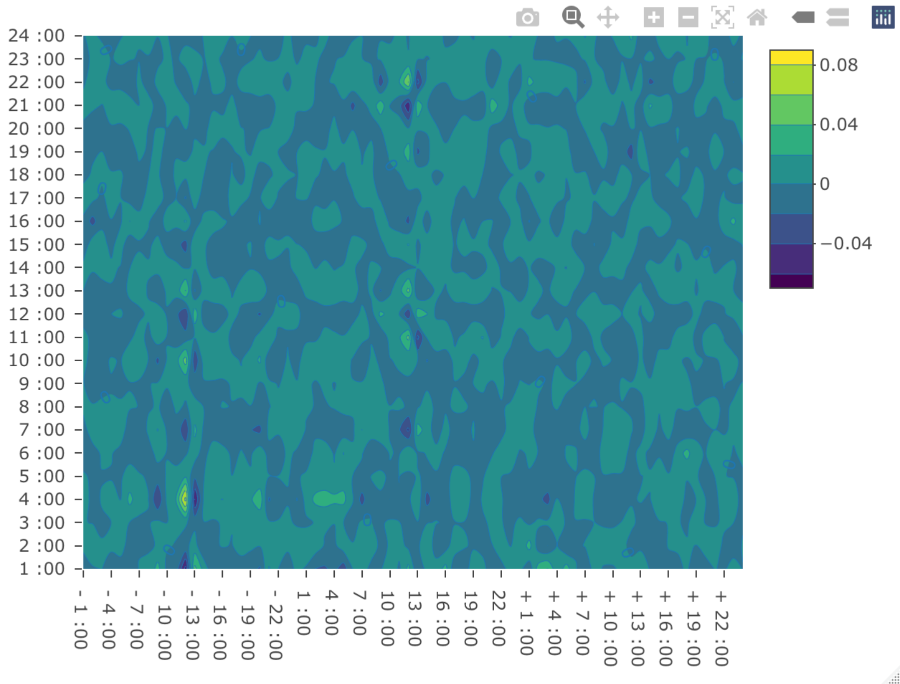
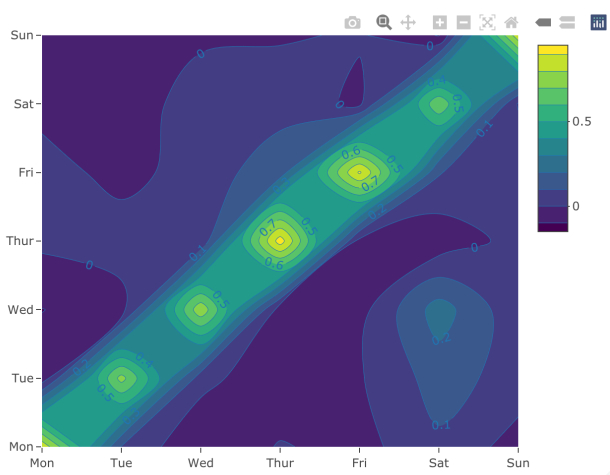
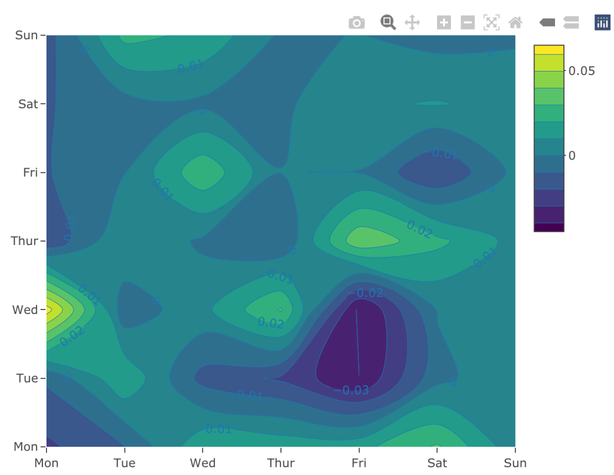


Figure 99: The Contour Plot of Daily Functional Regression Coefficients of ETH

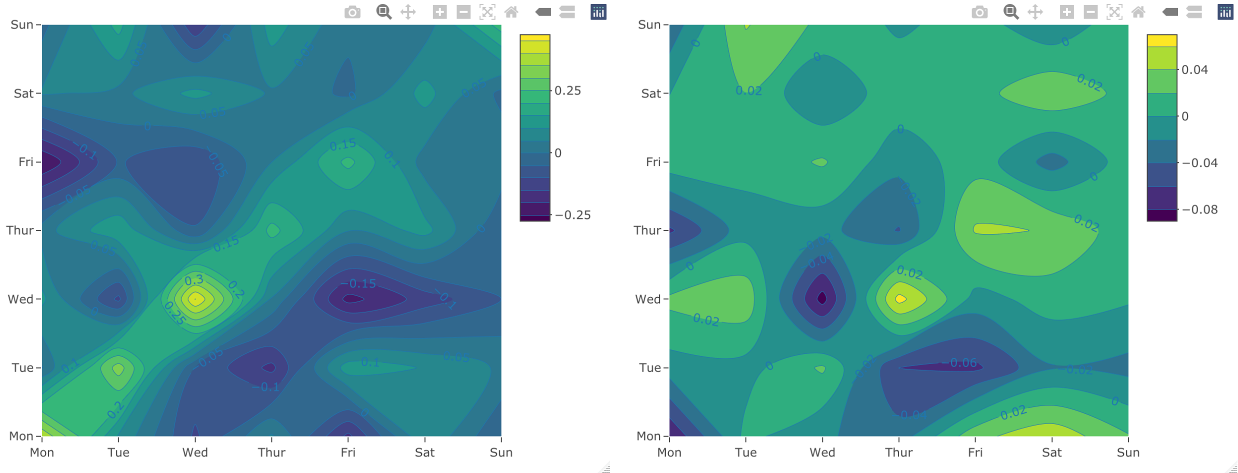


(a) Current Week



(b) Previous Week

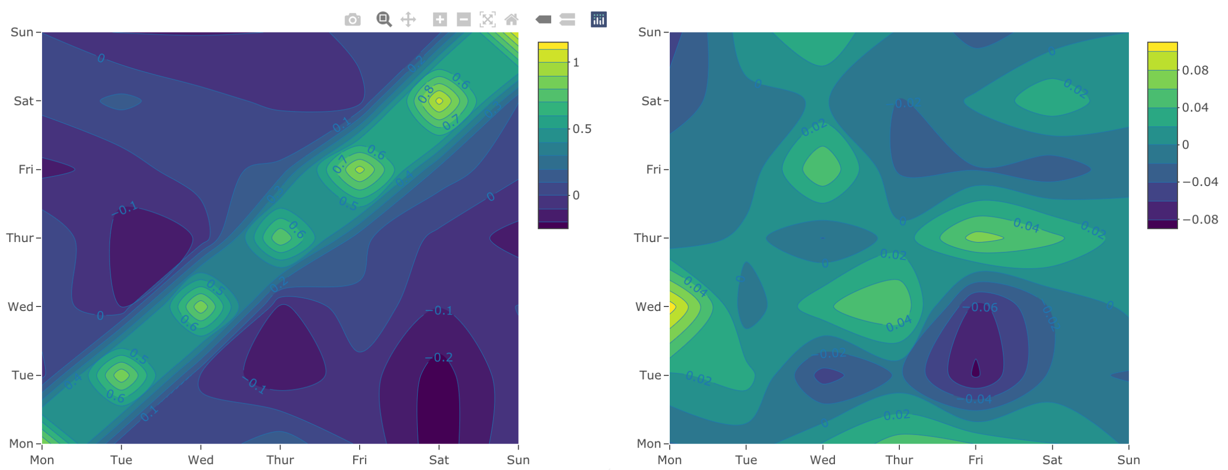
Figure 101: The Contour Plot of Daily Functional Regression Coefficients of KNC



(a) Current Week (b) Previous Week

The left figure shows the regression of the excess market return of the current week of KNC and the right figure shows the results for the previous week. The blue and dark blue areas indicate that the coefficients are zeros or slightly negative. The light green and yellow areas indicate that the coefficients are positive.

Figure 100: The Contour Plot of Daily Functional Regression Coefficients of LINK



(a) Current Week (b) Previous Week