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Master's thesis in Industrial Economics and Technology Management
Supervisor: Peter Molnar
June 2022

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Abstract

In this paper, we examine the impact the opening and closing of the New York Stock Exchange (NYSE), the London Stock Exchange (LSE), and the Tokyo Stock Exchange (TSE) have on Bitcoin in terms of return, volatility, volume and spread over the two most recent years using a high-frequency dataset.

We employ a model estimating mutual dependencies between the variables, and uncover positive autocorrelation on one-minute, one-hour and one-day granularities. Volatility is found to have the largest impact on the other variables. We find inter alia that the opening of the NYSE and the LSE positively impacts the trading volume of Bitcoin, and the lunchtime closure of the TSE impacts the volatility and spread. We did not discover an effect on return for either stock exchange. Our findings challenge the notion that Bitcoin is unrelated to traditional financial markets.

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List of Abbreviations

ADF Augmented Dickey-Fuller. 14

AGARCH Asymmetric Generalized Autoregressive Conditional Heteroskedasticity. 4

AR Autoregressive. 4

BST British Summer Time. 6

BTC Bitcoin. iii, 6–15, 19, 21, 23, 25, 27

EDT Eastern Daylight Time. 6

EST Eastern Standard Time. 6, 17, 18, 20, 22, 24, 26, 32–39

FOREX Foreign Exchange. 2, 4

GMT Greenwich Mean Time. 4, 6, 20, 22, 24, 26, 32–39

JST Japan Standard Time. 6, 18–20, 22–24, 26, 32–39

KPSS Kwiatkowski–Phillips–Schmidt–Shin. 14

LSE London Stock Exchange. i, 5, 8–11, 13, 17, 19, 20, 22–28, 32–39

MA Moving Average. 4

MLR Multiple Linear Regression. ii, 14, 17, 19, 28

NYSE New York Stock Exchange. i, 2, 5, 8–13, 17–20, 22–28, 32–39

RQS relative quoted spread. ii, iii, 6–8, 12–14, 16, 17, 26, 27

SFE Sydney Futures Exchange. 3, 10, 13, 27

TSE Tokyo Stock Exchange. i, 3, 5, 8–11, 13, 17–20, 22–28, 32–39

UTC Coordinated Universal Time. 6, 8, 11, 15

VAR Vector Autoregression. ii, 4, 5, 14, 15, 17, 18, 28

VARMA Vector Autoregressive Moving Average. 4

1 Introduction

This paper examines how Bitcoin market characteristics are affected by the opening and closing of major stock exchanges. Interrelations between return, volatility, volume and relative quoted spread are examined in order to model the behaviour of Bitcoin during stock exchange opening and closing times. We use one-second observations from the order book of Coinbase ranging over two years as the empirical foundation for the paper.

Since the publication of the Bitcoin whitepaper (Nakamoto, 2008), Bitcoin and other cryptocurrencies have grown from fascinating ideas to popular phenomena both as investment vehicles and as means of payment. The price of one Bitcoin was $0.023 in November 2010; ten years later, the asset had reached an all-time high of $68,521, with the total market capitalisation of the cryptocurrency world surpassing $3 trillion (Statmuse, 2021). Nonetheless, the cryptocurrency market still only constitutes a fraction of the volume comprised of stocks, commodities, FIAT currencies, derivatives, and other traditional financial assets. The increasing usage and value of Bitcoin have generated scholarly interest in the asset along the lines of the research on traditional financial markets.

It is possible to gain insight into the usage of cryptocurrencies for diversification, hedging, and potential arbitrage opportunities by researching the co-movement of Bitcoin and the stock market (Pichl and Kaizoji, 2017; Gil-Alana, Abakah and Rojo, 2020; Kumaran, 2022). Investing in cryptocurrencies has become a potentially realistic choice for diversification due to the advent of various cryptocurrency exchanges that offer services similar to those of the traditional financial markets. For example, according to Umar et al. (2020), there are similarities between stock market behaviour and cryptocurrencies, particularly related to Bitcoin price changes. Notably, during negative shocks, the stock and cryptocurrency markets appear to correlate to a greater extent than during positive shocks of the same magnitude. This correlation has also been documented by Klein, Thu and Walther (2018), demonstrating that Bitcoin tends to positively correlate with stock market downward movements.

As financial institutions are expanding their positions in Bitcoin compared to regular investors (DeVault and Wang, 2021), the cryptocurrency market may be impacted by institutional investors and their standardised trading hours. Traders on stock and futures exchanges are restricted by the opening hours of the respective exchanges - which are typically 7.5 hours throughout the day in their regional time zone on weekdays. The trading window for cryptocurrencies differs as trade is available both on and off the blockchain (i.e. through exchanges) 24 hours a day, seven days a week. Therefore, habits from traditional trading of institutional and retail investors could partly explain why the volume of cryptocurrency trading is lower on weekends and outside exchange opening hours (Eross et al., 2019). Moreover, several banks are closed during weekends, limiting FIAT transfers to cryptocurrency exchanges. This may also be a factor in explaining the lower volume.

Indriawan, Jiao and Tse (2019) examine the impact of the US stock market opening on government bond futures during the 30 minutes before and after opening. They find the US Treasury note, the German bund, and the UK gilt to have increased spillover effects during the opening of the NYSE. Their findings illuminate the importance of the US stock market opening as a structural break both in domestic and international government bond futures (Brandt and Kavajecz, 2004). As Bitcoin also trades 24 hours a day, we find it interesting to examine the spillover effect of global stock markets on Bitcoin.

In the financial literature, the stock market opening and closing effects are investigated for a variety of assets (Gerety and Mulherin, 1992; Webb and Smith, 1994). Related studies on intraday fluctuations in the FOREX- and stock futures markets have also been conducted (Taylor, 2011; Wang and Yang, 2011; Gau and Wu, 2017). Our research contributes to the literature by investigating the cross-market impact of the opening of three global stock exchanges on Bitcoin.

As the TSE closes during lunchtime, it is interesting to estimate the lunchtime closing and reopening effects of the stock market on Bitcoin. Frino, Grant and Johnstone (2008) state that the lunch break provides a dividing point in the daily trading cycle, possibly impacting trading behaviour. During the four-month lunchtime trading trial of the Sydney Futures Exchange (SFE), Frino and Winn (2001) conducted a natural laboratory experiment study. Their findings indicate that the lunchtime closure affected trading behaviour: at the reopening of the exchange, they observed abnormally high trading volumes, wide bid-ask spreads and higher volatility.

According to Brauneis et al. (2021), cryptocurrency markets have several characteristics that differ from traditional markets. For example, cryptocurrency markets are fragmented, always open, and allow direct market access for all traders. Most trading platforms allow transfers of FIAT currencies directly from bank accounts, and transactions are both handled and settled by the exchanges. As Brauneis et al. (2021) suggest, the contrasting characteristics imply that liquidity formation on cryptocurrency exchanges may vary from the traditional asset markets.

Bid-ask spread is often used to measure asset liquidity; a low spread characterises high liquidity and vice versa. The bid-ask spread is a regularly used metric when evaluating an exchange, as it characterises the costs of immediately trading an asset (Brauneis et al., 2021). For frequently traded assets - such as stocks, currencies and cryptocurrencies - there is substantial competition in trying to exploit spread discrepancies between different exchanges. Modern exchanges are required to handle high-frequency trading activity to a greater extent than before, as the number of investors and trades increases (Garay and Pulga, 2021). Trading volume and bid-ask spread are assumed to have an implied bidirectional relationship. It is expected to observe higher trading volumes with smaller spreads and lower trading volumes with larger spreads. However, when examining time series variability of liquidity in the cryptocurrency market using transaction-based liquidity measures - such as the Amihud (2002) illiquidity ratio and the Roll (1984) serial covariance estimator - Brauneis et al. (2021) find a positive relationship between trading volume and bid-ask spread in cryptocurrency markets. The positive relation between trading volume and bid-ask spreads of Bitcoin contradicts most academic studies on the matter (Copeland and Galai, 1983; Narayan, Mishra and Narayan, 2014). However, similar findings have also been documented by Bogousslavsky and Collin-Dufresne (2022) as they find trading volume and bid-ask spreads in large US stocks to be bidirectionally positive. The alleged discrepancy of cryptocurrency and traditional markets on the relationship between trading volume and spread invites further investigation on measuring the co-movement between the two variables in the case of Bitcoin.

Comparing liquidity and volatility for cryptocurrencies throughout the day is also of interest (Będowska-Sójka, Hinc and Kliber, 2020). For traditional financial markets, Będowska-Sójka, Hinc and Kliber (2020) find that if volatility is high, liquidity is high and vice versa. The relationship has been thoroughly researched in both modern and older literature on traditional financial markets but not as extensively for cryptocurrencies (Eross et al., 2019; Będowska-Sójka, Hinc and Kliber, 2020). This is also supported by Balcilar et al. (2017), who recommend further research into the relationships between Bitcoin behaviour in terms of volume, return, volatility and liquidity.

The findings of Będowska-Sójka, Hinc and Kliber (2020) indicate a similar relationship between volatility and spread for Bitcoin as for traditional asset markets. Będowska-Sójka, Hinc and Kliber (2020) state that the results of their study regarding such relationships within the cryptocurrency markets have important implications for both scholars and practitioners, and they recommend other scientific actors to research the inter-relationships further. Their research and findings illuminate dependencies that have previously been researched on traditional markets, demonstrating that cryptocurrencies act more like speculative assets than steady safe-haven assets.

Brauneis et al. (2021) states that a result of decentralisation is that cryptocurrency markets do not have an equivalent regulated data feed similar to the consolidated tape for U.S. equities. Therefore, although cryptocurrency trading is becoming increasingly popular, determining the exact liquidity of these markets is difficult. As there are many cryptocurrency exchanges and no centralised governing body providing data along the lines of a consolidated feed, calculating high-frequency bid-ask spreads is both costly and imprecise. This is a challenge for scholars when attempting to model and measure liquidity for cryptocurrencies. High-frequency intraday data, which is often expensive and time-consuming to process, is typically used to compute bid-ask spreads (Brauneis et al., 2021). This is perhaps the reason for the lack of papers studying liquidity of Bitcoin markets (Dyhrberg, Foley and Svec, 2018; Hautsch, Scheuch and Voigt, 2018; Makarov and Schoar, 2020). Since few papers use datasets with higher frequency than daily data, our paper's contribution using a dataset with one-second increments could be substantial.

Intraday stock market activity patterns have been extensively examined in recent decades, assisting investors in making short-term trading decisions based on empirical data. Intraday trading volume and volatility trends have been well documented for several stock exchanges worldwide (Jain and Joh, 1988; McInish and Wood, 1990; Andersen and Bollerslev, 1997). Cai, Hudson and Keasey (2004) find that stock price volatility shows M- and U-shaped patterns throughout the day, while trading volume exhibits M-shaped behaviour. In terms of Bitcoin market tendencies, Wang, Liu and Hsu (2020) find that volume and volatility are higher during American and European stock market trading hours, and lower on weekends. The volume of Bitcoin appears to be mostly unaffected by the Asian stock market, although volatility is somewhat affected. In the United States and Europe, a reverse U-shaped pattern is visible for volume during daytime trading hours. The same may be said about stock price volatility, which appears to be higher at the open and close than throughout the middle of the day. Eross et al. (2019) study interrelationships and intraday patterns for return, volatility, volume, and liquidity of Bitcoin on the Bitstamp exchange using 5-min frequency data. Trading volume and volatility appear to be relatively low until early morning (GMT) and are substantially higher during the opening hours of American and European stock markets. The correlation between volatility and volume is comparable to those found in the FOREX market. Furthermore, they find that volume reaches a peak between 14:00 and 15:00 (GMT), coinciding with the opening of East American stock markets. Therefore, they suggest that European and American markets are the main drivers of Bitcoin's volume (USD). This is consistent with the notion that European and American investors are trading within their respective stock market opening hours, thus being the main drivers of the volume of FIAT currencies. Regarding intraday liquidity, Eross et al. (2019) observe higher illiquidity (i.e. wider spread) throughout the morning (GMT). Liquidity is found to be highest (i.e. most narrow) and relatively stable from 10:00 until 22:00, coinciding with the opening hours of European and American stock markets. Wang, Liu and Hsu (2020) emphasise the lack of studies on co-movement between cryptocurrencies and the traditional stock markets, inviting new research using high-frequency data.

Aalborg, Molnár and De Vries (2019) study which variables are useful in explaining and predicting return, volatility and trading volume of Bitcoin using daily data. By studying the mutual relationships between return, volatility, and volume, the findings indicate similarities between Bitcoin and traditional assets in terms of predictability. Similar to several traditional assets, Bitcoin appears to be somewhat predictable in terms of volatility and volume, but not in terms of return. Additionally, they observe that trading volume is correlated with and can predict volatility using daily data.

Variants of AR- and MA-models are widespread tools used to model and forecast dynamics in econometrics with high-frequency datasets, both for the traditional stock market and cryptocurrencies. Arutunyan et al. (2018) model the dynamics of Bitcoin using a VAR-model, attempting to capture interconnections between media coverage, return, volatility and trading volume. Uzonwanne (2021) applies a multivariate VARMA-AGARCH model to capture transmission mechanisms of volatility and return spillovers between stock markets and Bitcoin. We use a vectorised model similar to that of Sathyanarayana and Gargesa (2019), thus allowing the inclusion of several evolving variables - return, volatility, volume and spread - to perform a multivariate linear regression. This allows for capturing interconnections between different variables describing the behaviour of Bitcoin.

In stock and FOREX transaction prices it is common to observe significant negative autocorrelation in high frequencies when investigating time series of return (Madhavan, 2000). Moreover, De Nicola (2021) finds the return of Bitcoin to be negatively autocorrelated on higher frequencies as well. This contradicts our findings, where the return is positively autocorrelated with one-second, one-hour and one-day lags of itself. This is in accordance with the observations of positive autocorrelation in return over short time horizons (Poterba and Lawrence H. Summers, 1988). We find the same to be valid for volatility and bid-ask spread. Concerning trading volume, we only find evidence for autocorrelation when using one-second and one-hour lags.

Following the recommendations of Wang, Liu and Hsu (2020) and Makarov and Schoar (2020), our paper attempts to document and analyse Bitcoin intraday behaviour. Specifically, we study the impact of stock exchange opening and closing on Bitcoin. This involves examining Bitcoin's return (i.e. price fluctuations), volatility, trading volume, and liquidity in the hours leading up to and following stock exchange opening and closing. The exchanges New York Stock Exchange (NYSE), Tokyo Stock Exchange (TSE), and London Stock Exchange (LSE) are taken into account for regional variations. We hypothesise that overall trading volume is higher during stock exchange opening times for all exchanges.

By employing a VAR-model, we discover positive autocorrelation on one-minute, one-hour and one-day granularities in all variables except for trading volume. The most relevant variables from the VAR-model are included in the regressions conducted on the stock exchange opening and closing time frames. We find that the stock market opening of the NYSE and the LSE positively impact volume. The lunch break of the TSE impacts Bitcoin's price volatility and spread. Return does not exhibit the same behaviour, remaining unpredictable in accordance with the findings of Aalborg, Molnár and De Vries (2019).

We describe the data and methodology in Section 2. Section 3 illustrates the behaviour of Bitcoin's return, volatility, volume, and spread, while Section 4 contains a discussion in the context of the statistical results. Section 5 concludes the discussion.

2 Data

The movements of return, volatility, trading volume, and spread are denoted in Eastern Standard Time (EST) local to New York, Greenwich Mean Time (GMT) local to London, and Japan Standard Time (JST) local to Tokyo. For New York and London, summer daylight savings are accounted for in the relevant periods (Eastern Daylight Time (EDT) and British Summer Time (BST)). The figures in Section 3 are all denoted in Coordinated Universal Time (UTC)+0 for consistency. The time intervals of primary interest are the opening and closing hours of the stock exchanges.

2.1 Data extraction

The trustworthiness and validity of several datasets utilised in the scientific Bitcoin environment are insufficient (Alexander and Dakos, 2020). Due to the lack of regulatory oversight on cryptocurrency exchanges and 'coin-ranking' websites, skewed, manipulated (e.g. wash trading) and inaccurate empirical data are prevalent. Empirical sciences are inherently dependent on precise and reliable observations; therefore, the data used in this paper is carefully chosen. We have extracted a large dataset from Coinbase. The chosen dataset contains second observations that span over two years, from 31.10.2019 to 30.10.2021. It contains information on *unix time, volume, bid price, bid size, ask price* and *ask size* for each second throughout the period. We extracted the dataset from Coinbase through an API supplied by Crypto Chassis[1].

2.2 Data cleaning

Before it could be analysed, the dataset needed to be cleaned and pre-processed. The extracted .csv file was saved as a dataframe using the Python module *Pandas* to speed up processing and data handling. The unix column strings were converted to Pandas *DateTime* objects to comply with Pandas' required time handling format. To avoid mismanagement of the row order, the dataset was sorted on date and time using the *datetime* objects. Furthermore, the Pandas function *day_name()* was utilised to link weekdays to their associated dates. New York time EST and EDT and London time GMT and BST vary between UTC-4 and UTC-5 and UTC+0 and UTC-1, depending on the time of year. To account for daylight saving time, the Pandas *localize*-function was applied to the dataset for each time zone.

2.3 Definition of price features

In this subsection, we present and define the subjects of study; return, volatility, volume, and relative quoted spread (RQS) of BTC. These four variables will be collectively referred to as "price features". We aggregate the one-second observations in the dataset to define 15- and 60-minute observations for Section 3, and one-minute observations for the regressions in Section 4. The price of BTC in a particular observation is calculated as the midpoint between the bid price and the ask price, denoted as p_i^{bid} and p_i^{ask}, as illustrated in Equation 1.

$$p_i = \frac{p_i^{ask} + p_i^{bid}}{2} \tag{1}$$

2.3.1 Return

We define return as seen in Equation 2. At second i, r_i is the logarithmic percentage return. The price in second i is denoted by p_i, and p_{i-1} denotes the price in the previous second. The one-second observations in the dataset are aggregated into quarter-hour and hourly observations

[1]https://github.com/crypto-chassis/cryptochassis-data-api-docsmarket-depth

when creating the figures in Section 3. For the regressions conducted on return in Section 4, we use one-minute observations.

$$r_i = \ln(\frac{p_i}{p_{i-1}}) \cdot 100\% \tag{2}$$

2.3.2 Volatility

We examine the historical volatility (now denoted volatility) of BTC to gain insight on the dispersion of BTC return. The one-second return is defined using Equation 2. The standard deviation is retrieved by using the integrated function *std()* from the Python *numpy*-library. Finally, as illustrated in Equation 3, we multiply the standard deviation by a factor $\sqrt{t}$ to obtain the volatility for a given time interval t.

$$\sigma_{t,i,n} = \sqrt{t} \cdot SD(r_i, r_{i+1}, ..., r_{i+n-1}, r_{i+n}) \tag{3}$$

where $\sigma_{t,i,n}$ denotes the time interval volatility, $SD(r_i, r_{i+1}, ..., r_{i+n-1}, r_{i+n})$ the standard deviation of the return in second i, and n indicates the number of observations. In Section 3, the figures are illustrated with quarter-hour and hourly observations, using Equation 3 for the respective time intervals. In Section 4, we use one-minute observations.

2.3.3 Volume

As illustrated in Equation 4, trading volume (USD) is defined by aggregating trading volume for each second over the relevant time interval.

$$V_{i,n} = \sum_{j=0}^{n} V_{i+j} \tag{4}$$

where n denotes the number of observations, V_i denotes volume at second i and $V_{i,n}$ denotes the time interval volume. In Section 3 we start by gathering volume observations for the period we wish to analyse. Then we apply Equation 4 and average the data to create the illustrations. The illustrations use quarter-hour and hourly observations. When performing the regressions in Section 4, we use Equation 4 to sum the one-second observations, and transform volume into a stationary series by applying Equation 5 which we denote as $\widehat{V}_{i,n}$. $\overline{V}_{i,n}$ denotes the average volume throughout the previous week.

$$\widehat{V}_{i,n} = \ln(V_{i,n}) - \ln(\overline{V}_{i,n}) \tag{5}$$

2.3.4 Relative Quoted Spread (RQS)

The bid-ask spread is the difference between limit orders from buyers and sellers, i.e. the highest bid price and the lowest ask price of the order book.

We calculate the RQS according to Equation 6. In Section 4, we calculate the spread for each minute. In Section 3 we averaged the minute observations to quarter-hour and hourly intervals.

$$RQS_i = (\frac{p_i^{ask} - p_i^{bid}}{p_i}) \cdot 100\% \tag{6}$$

where RQS_i denotes the relative quoted spread at second i.

3 Preliminary analysis

This section illustrates how the price features: return, volatility, volume, and relative quoted spread (RQS) of BTC behave throughout the week based on one-second observations of two years of data. The results displayed are retrieved prior to performing the regressions in Section 4. This paper's primary focus is to evaluate the impact of the opening and closing of stock markets on BTC. We use the results displayed in this section's figures to get a preliminary understanding of the behaviour of the variables. Throughout the following section, all illustrations are denoted in UTC+0 (herein UTC). The visualised results in this section are not evaluated regarding their statistical significance.

The following subsections examine how quarter-hour and hourly averages of return, volatility, volume, and RQS evolve throughout a 24-hour window. The opening hours of the NYSE, the LSE, and the TSE are included to see the behaviour of the price features in relation to the opening hours of the stock exchanges. In the figures, the opening hours of the NYSE, the LSE, and the TSE are illustrated in their standard opening hours, not considering daylight saving time. The NYSE is open 14:30-21:00 (UTC), the LSE is open 08:00-16:30 (UTC), the TSE is open 00:00-06:00 (UTC), with a lunch break from 02:30 to 03:30 (UTC). The LSE also has a lunch break from 12:00-12:02 (UTC), which is not accounted for due to being brief. These stock exchanges are chosen based on both dispersions of opening hours and their importance in the traditional stock markets.

3.1 Return

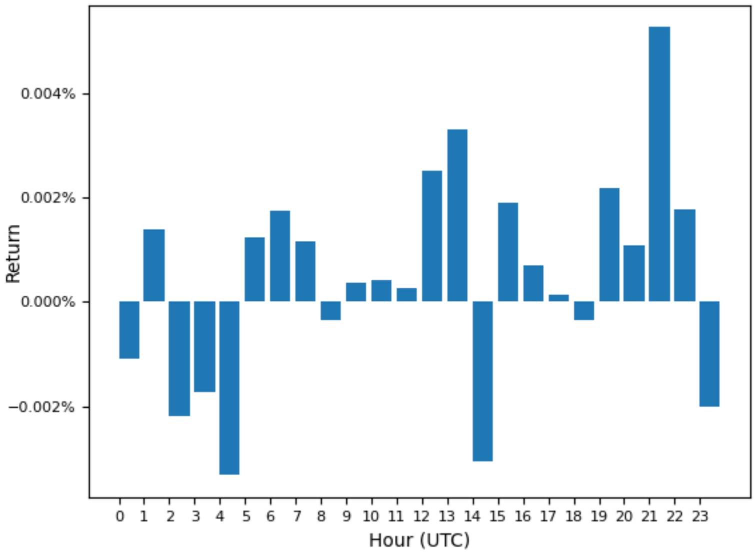

Figure 1: Hourly average return for BTC.

Figure 1 displays how the hourly average BTC return behaves during a 24-hour window. The figure shows that the BTC price frequently fluctuates between positive and negative return.

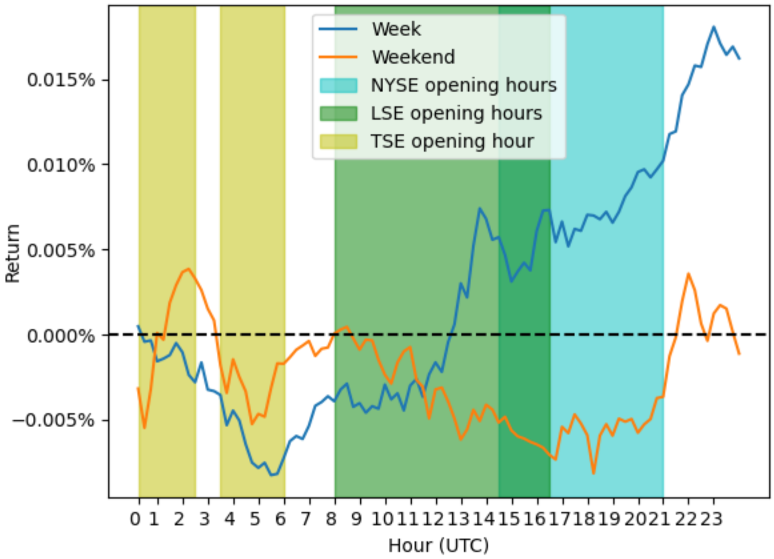

Figure 2: Cumulative quarter-hour average return for BTC.

Figure 2 displays the cumulative quarter-hour average return of BTC for both weekdays and weekends. The opening hours of the NYSE, the LSE, and the TSE are marked in their standard opening hours. One point in the graph represents the average return throughout the next quarter-hour, e.g. the point at 15:00 represents the period from 15:00 to 15:14. Weekdays and weekends do not seem to have the same sign or trend. We observe that return does not exhibit similar behaviour during weekdays and weekends.

3.2 Volatility

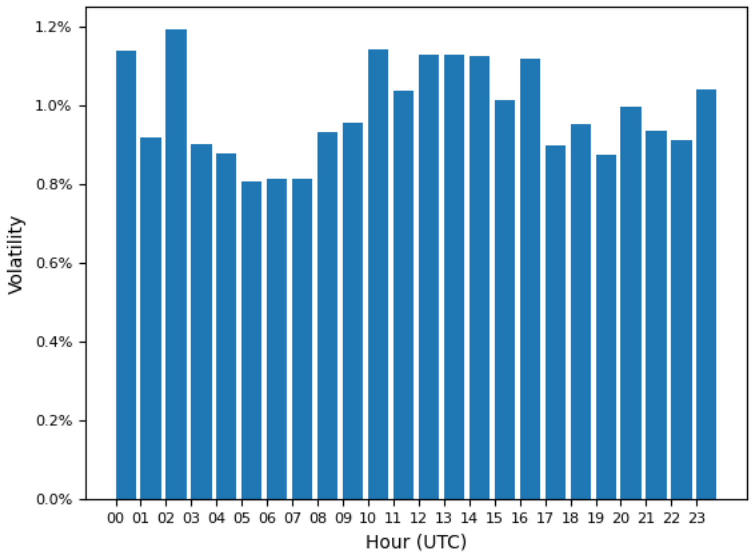

Figure 3: Hourly average volatility for BTC.

Figure 3 illustrates how the hourly average price volatility of BTC behaves during a 24-hour window throughout the week. The hourly average price volatility of BTC resides in the range of 0.8% to 1.2%.

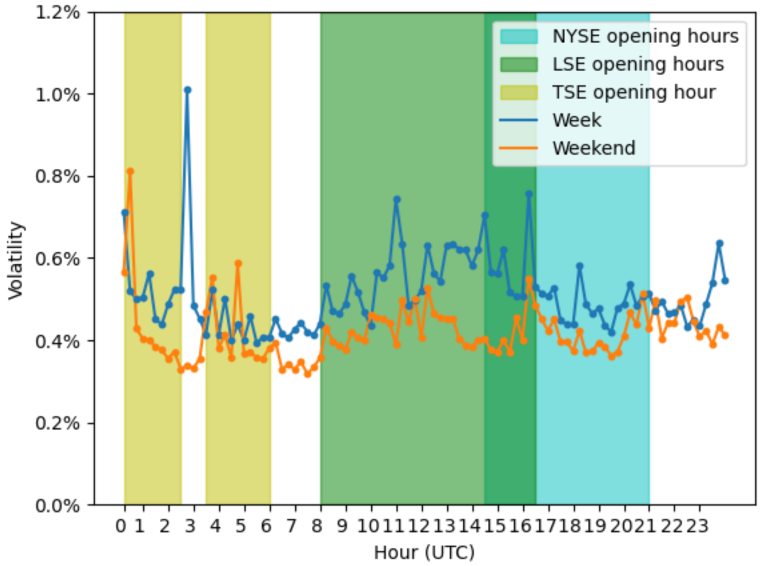

Figure 4: Quarter-hour average volatility for BTC.

Figure 4 displays the quarter-hour average price volatility of BTC during the weekdays and weekends. In addition, the opening hours of the NYSE, the LSE and the TSE are illustrated as in Figure 2. Each point in the graph displays the corresponding average price volatility throughout the next quarter of an hour. From Figure 4 it is apparent that volatility during weekdays and weekends display similar patterns, where the two graphs seem to be parallel shifted. The volatility pattern during weekends is shifted to a lower level than on weekdays. This is in accordance with the findings of Wang, Liu and Hsu (2020). Interestingly, one of the lowest volatility points during the weekends is the highest point during the weekdays, which corresponds to the moments after lunchtime closing in the TSE. This suggests that the utterance "Bitcoin's volatility is marginally affected by the opening of Asian stock markets" (Wang, Liu and Hsu, 2020, p. 4) could be an understatement. Frino and Winn (2001) find similar results for the SFE, where price volatility increases at lunchtime closure. Another seemingly interesting period is during the opening hour of the NYSE, where the volatility trends of the weekdays and weekends move in opposite directions. This may indicate that the lunch break of the TSE and the opening of the NYSE could impact the BTC price volatility.

3.3 Volume

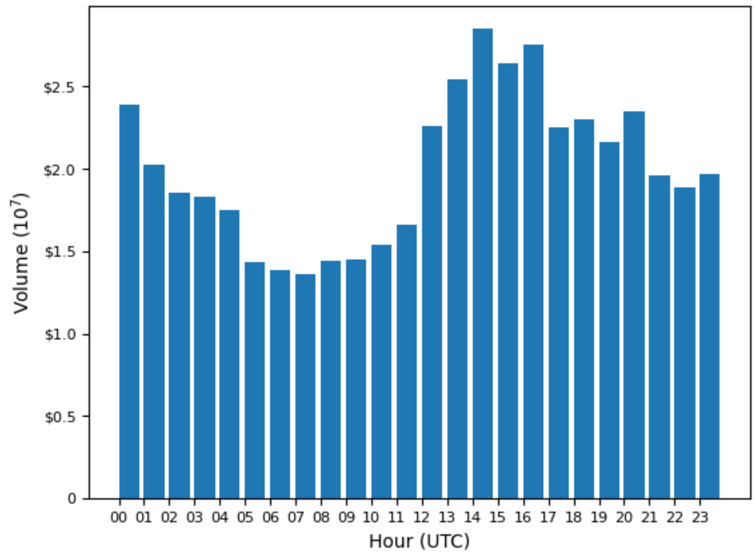

Figure 5: Hourly average volume for BTC.

Figure 5 displays how the average trading volume of BTC behaves during a 24-hour window. The figure shows that the hourly average trading volume (USD) of BTC is substantially different depending on the time of day, almost doubling from 07:00 to 14:00 UTC.

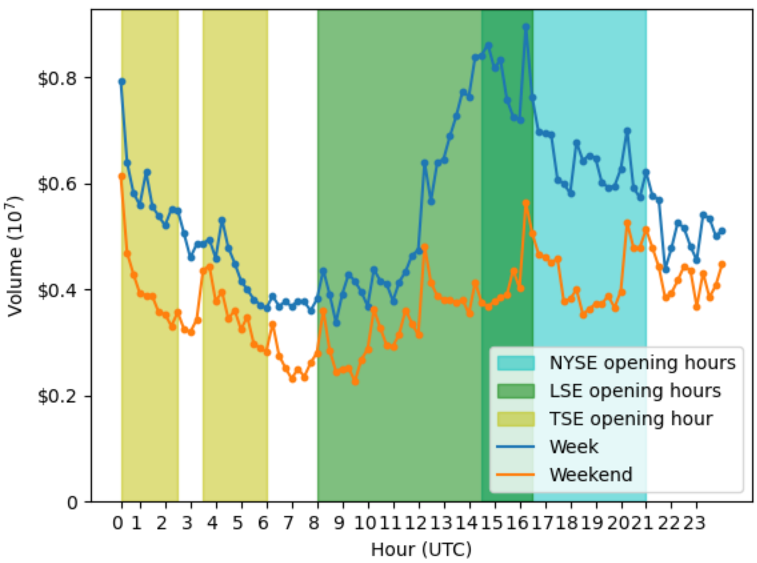

Figure 6: Quarter-hour average volume for BTC.

Figure 6 illustrates the quarter-hour average trading volume of BTC throughout weekdays and weekends, with stock exchange openings of the NYSE, the LSE, and the TSE emphasised. The volume seems to resemble a U-shape pattern from 00:00 until 12:30. During the opening hours of the TSE, the trading volume seems to be lower during weekends compared to weekdays. However, the graphs seem to be relatively similar, but parallel shifted. This is in accordance with the findings of Wang, Liu and Hsu (2020), stating that volume is fairly unaffected by the Asian stock market.

On weekdays after 12:30, the trading activity increases until its peak during the opening of the NYSE. During weekends after 12:30, the activity remains more stable. By comparing the overall volume of weekdays and weekends we see a similar pattern, but with lower volumes during the weekends. The exception is the period two hours before the opening of the NYSE, until the exchange closes. In this period, the weekdays trading volume resembles a reverse U-shape pattern. This pattern is also found by Eross et al. (2019) and Wang, Liu and Hsu (2020) for American and European markets. In particular, it seems as if the two-hour intervals before and after the opening of the NYSE are the periods in which the patterns of weekdays and weekends differ the most. This could indicate that the trading volume of BTC is affected by the opening of the NYSE.

3.4 Relative quoted spread (RQS)

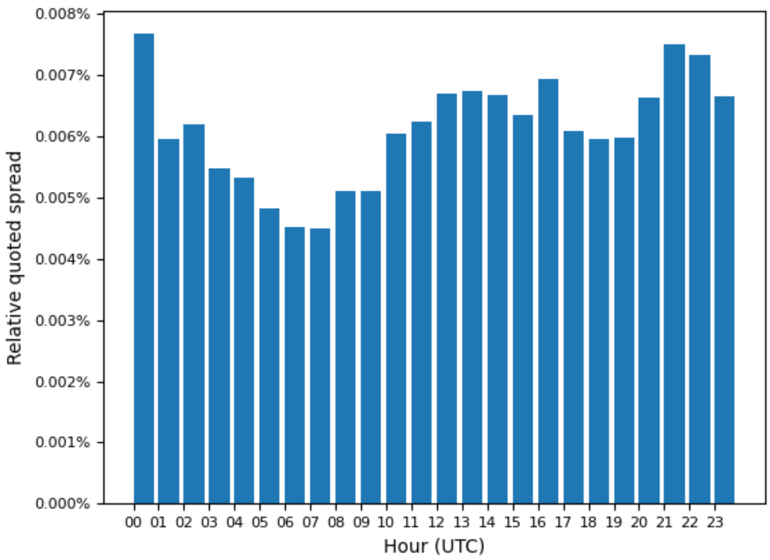

Figure 7: Hourly average relative quoted spread (RQS) for BTC.

Figure 7 displays how the average RQS of BTC's price behaves during a 24-hour window. The figure shows that the average RQS ranges between 0.0045% and 0.008%.

The observation regarding the trend-resemblance between Figure 7 and Figure 5 is noteworthy. This is in contrast to theoretical notions and intuition regarding the supposedly negative relation between RQS and volume (Copeland and Galai, 1983; Narayan, Mishra and Narayan, 2014). Our illustrations seem to align with the findings of Brauneis et al. (2021) for cryptocurrencies and Bogousslavsky and Collin-Dufresne (2022) for large US stocks; that the relationship between volume and RQS of BTC may be positive. Moreover, by comparing Figure 3 for volatility and Figure 7 for RQS, there is some visual pattern resemblance between the two.

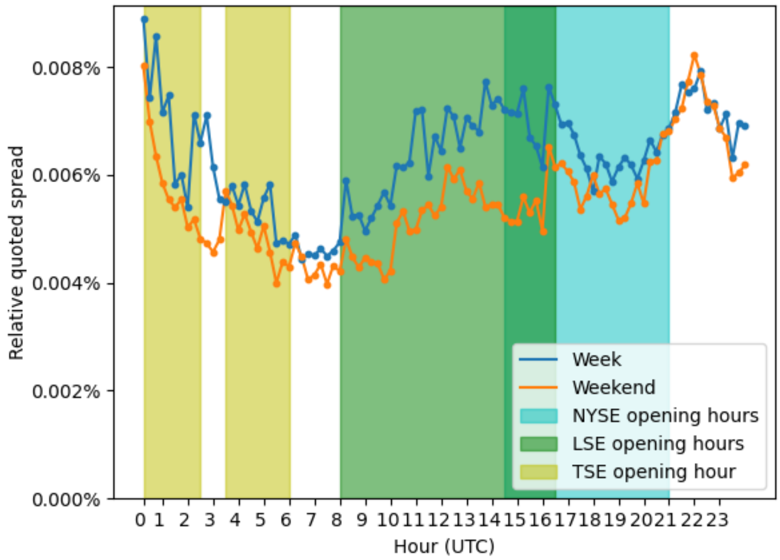

Figure 8: Quarter-hour average relative quoted spread (RQS) for BTC.

Figure 8 illustrates the quarter-hour average RQS in BTC's price throughout weekdays and weekends, with stock exchange opening hours of the NYSE, the LSE, and the TSE emphasised. Comparing the overall level of RQS for weekdays and weekends, we see a similar pattern, but with a slightly wider RQS during weekdays. Two exceptions to the pattern resemblance can be emphasised. Firstly, we observe an increase in the spread around the opening the NYSE. Secondly, an increase before the lunch break of the TSE is apparent. This could indicate that lunch break of the TSE impacts the spread of BTC. The observed lunch break effect on the spread of BTC resembles the findings of Frino and Winn (2001) reporting wider spreads at lunchtime closure on the SFE.

4 Results

This section is organized into two parts. First, in Section 4.1 we study the relationship between return, volatility, volume and RQS using a Vector Autoregression (VAR) model. In Section 4.2 we measure the effect of stock exchange opening and closing on BTC using a Multiple Linear Regression (MLR).

We use our findings in the VAR-regression to help construct the MLR-model measuring the impact of stock exchange opening and closing on BTC. The lags showing significance in the VAR-regression are added to the MLR-regression in order to improve the model.

4.1 Vector Autoregression (VAR)

4.1.1 Methodology

We use a VAR-model to estimate the co-movements of the four subjects of study: return, volatility, volume, and relative quoted spread (RQS). The model consists of lagged variables of all the price features. We conduct a regression with each price feature as dependent variables using minute observations. The definition is presented in Equation 13. $y_{t,p}$ is a placeholder for either return, volatility, volume or RQS, denoted by p = 1,2,3,4. In this section, t denotes an observation. In matrix form, the VAR-model is presented in Equation 14. To avoid confusion, in Equation 13 and Equation 14 the subscript p indexes the dependent variables, while f indexes the independent variables.

The lagged variable $y^{PO}_{t-1,p}$, describing the previous observation, is shown in Equation 7. $y^{H}_{t-1,p}$ describes the average value of the previous hour, as shown in Equation 8. $y^{D}_{t-1,p}$ describes the average of the previous day, as shown in Equation 9. Equation 10 defines $y^{DH}_{t-1,p}$, a lag containing the hourly average 24 hours ago. Lastly, $y^{W}_{t-1,p}$ as defined in Equation 11 is the average value of the preceding week.

$$y^{PO}_{t-1,p} = y_{t-1,p} \tag{7}$$

$$y^{H}_{t-1,p} = \frac{1}{60}\sum_{i=1}^{60} y_{t-i,p} \tag{8}$$

$$y^{D}_{t-1,p} = \frac{1}{24 \cdot 60}\sum_{i=1}^{24\cdot 60} y_{t-i,p} \tag{9}$$

$$y^{DH}_{t-1,p} = \frac{1}{60}\sum_{i=1}^{60} y_{t-24\cdot 60-i,p} \tag{10}$$

$$y^{W}_{t-1,p} = \frac{1}{7 \cdot 24 \cdot 60}\sum_{i=1}^{7\cdot 24\cdot 60} y_{t-i,p} \tag{11}$$

Before performing the regression, we tested the four price feature time series for stationarity using Augmented Dickey-Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS)-tests. Unsurprisingly, volume was deemed non-stationary as the BTC trading volume has increased substantially over the last two years. Therefore, we used Equation 5 to transform the time series, erasing the upward trend. The other time series were found to be stationary and required no similar transformation. As the regression is intended to compare the coefficient values of the different price features directly to each other, we standardise the time series to be able to compare results with different units of measurement (e.g. USD and percentages). Standardisation was conducted using

Equation 12, rescaling the time series so that the mean of the observed values is 0 and the standard deviation is 1. Thus, the coefficient values give a rough indication of the relative importance of the independent variables.

$$\beta^* = \frac{s_x}{s_y}\beta \tag{12}$$

$$y_{t,p} = \alpha_{t,p} + \sum_{f\ \in \{pricefeatures\}} \left(\beta_{1,p,f} \cdot y^{PO}_{t-1,f} + \beta_{2,p,f} \cdot y^{H}_{t-1,f} + \beta_{3,p,f} \cdot y^{D}_{t-1,f} + \beta_{4,p,f} \cdot y^{DH}_{t-1,f} + \beta_{5,p,f} \cdot y^{W}_{t-1,f} \right) + \epsilon_{t,p} \tag{13}$$

$$\begin{bmatrix} y_{t,1} \\ y_{t,2} \\ y_{t,3} \\ y_{t,4} \end{bmatrix} = \begin{bmatrix} \alpha_{t,1} \\ \alpha_{t,2} \\ \alpha_{t,3} \\ \alpha_{t,4} \end{bmatrix} + \sum_{f\ \in \{pricefeatures\}} \left(\begin{bmatrix} \beta_{1,1,f} & \beta_{2,1,f} & \beta_{3,1,f} & \beta_{4,1,f} & \beta_{5,1,f} \\ \beta_{1,2,f} & \beta_{2,2,f} & \beta_{3,2,f} & \beta_{4,2,f} & \beta_{5,2,f} \\ \beta_{1,3,f} & \beta_{2,3,f} & \beta_{3,3,f} & \beta_{4,3,f} & \beta_{5,3,f} \\ \beta_{1,4,f} & \beta_{2,4,f} & \beta_{3,4,f} & \beta_{4,4,f} & \beta_{5,4,f} \end{bmatrix} \begin{bmatrix} y^{PO}_{t-1,f} \\ y^{H}_{t-1,f} \\ y^{D}_{t-1,f} \\ y^{DH}_{t-1,f} \\ y^{W}_{t-1,f} \end{bmatrix} \right) + \begin{bmatrix} \epsilon_{t,1} \\ \epsilon_{t,2} \\ \epsilon_{t,3} \\ \epsilon_{t,4} \end{bmatrix} \tag{14}$$

4.1.2 Vector Autoregression (VAR)-results

The results from the VAR-model are presented in Table 1 and show the estimations of co-movements between the price features of BTC. As the regression is performed at the same time zone (UTC), we present the results in the four columns in Table 1.

Table 1: VAR-regression

	Dependent variables:			
	Return	Volatility	Volume	RQS
Independent variables:				
Intercept	0	0	0	0
	(0.001)	(0.001)	(0.001)	(0.001)
ReturnPreviousObservation	0.0170^{**}	-0.0149^{**}	-0.0081^{**}	-0.0057^{**}
	(0.001)	(0.003)	(0.001)	(0.001)
ReturnPreviousHourAverage	0.1295^{**}	-0.0409^{**}	-0.0084^{**}	-0.0448^{**}
	(0.001)	(0.001)	(0.001)	(0.001)
ReturnPreviousDayAverage	0.0051^{**}	-0.0061^{**}	0.0030^{*}	-0.0055^{**}
	(0.002)	(0.001)	(0.001)	(0.001)
ReturnPreviousDayHourAverage	-0.0005	0.0005	0.0004	0.0042^{**}
	(0.001)	(0.001)	(0.001)	(0.001)
ReturnPreviousWeekAverage	-0.0003	$-8.794 \cdot 10^{-5}$	0.0034^{**}	0.0019
	(0.002)	(0.001)	(0.001)	(0.001)
VolatilityPreviousObservation	0.0194^{**}	0.2604^{**}	0.0613^{**}	0.0868^{**}
	(0.002)	(0.001)	(0.001)	(0.001)
VolatilityPreviousHourAverage	0.0232^{**}	0.4328^{**}	-0.0497^{**}	-0.0149^{**}
	(0.003)	(0.002)	(0.003)	(0.002)
VolatilityPreviousDayAverage	-0.0425^{**}	0.0716^{**}	0.0379^{**}	-0.0077
	(0.006)	(0.004)	(0.004)	(0.004)
VolatilityPreviousDayHourAverage	0.0064^{*}	-0.0100^{**}	-0.0061^{*}	-0.0042
	(0.003)	(0.002)	(0.002)	(0.002)
VolatilityPreviousWeekAverage	0.0064	-0.0069^{*}	-0.0171^{**}	-0.0155^{**}
	(0.004)	(0.003)	(0.003)	(0.003)
VolumePreviousObservation	-0.0165^{**}	0.1935^{**}	0.2994^{**}	0.0600^{**}
	(0.002)	(0.001)	(0.001)	(0.001)
VolumePreviousHourAverage	0.0058^{**}	-0.1156^{**}	0.4279^{**}	-0.0400^{**}
	(0.002)	(0.002)	(0.002)	(0.002)
VolumePreviousDayAverage	0.0056^{*}	-0.0086^{**}	0.0038^{*}	-0.0002
	(0.002)	(0.002)	(0.002)	(0.002)
VolumePreviousDayHourAverage	-0.0015	0.0006	-0.0051^{**}	0.0002
	(0.002)	(0.001)	(0.001)	(0.001)
VolumePreviousWeekAverage	-0.0013	0.0040^{**}	0.0036^{*}	-0.0035^{*}
	(0.002)	(0.001)	(0.001)	(0.001)
RQSPreviousObservation	0.0324^{**}	0.0729^{**}	0.0153^{**}	0.2782^{**}
	(0.002)	(0.001)	(0.001)	(0.001)
RQSPreviousHourAverage	-0.0093^{**}	-0.0651^{**}	-0.0118^{**}	0.4335^{**}
	(0.003)	(0.002)	(0.002)	(0.002)
RQSPreviousDayAverage	-0.0027	-0.0048	-0.0128^{**}	0.0391^{**}
	(0.004)	(0.003)	(0.003)	(0.003)
RQSPreviousDayHourAverage	0.0063^{*}	-0.0046^{**}	0.0007	-0.0135^{**}
	(0.002)	(0.002)	(0.002)	(0.002)
RQSPreviousWeekAverage	-0.0083^{**}	0.0136^{**}	0.0045^{*}	0.0164^{**}
	(0.003)	(0.002)	(0.002)	(0.002)
Adj. R-squared	0.018	0.507	0.447	0.509
Durbin-Watson	1.964	2.054	2.063	2.085

Number of observations: 982084
Note: $p^{*} < 0.05$, $p^{**} < 0.01$.

We generally observe that the dependent variables' own previous hour average $y^{H}_{t-1,p}$ has the largest coefficient value. This seems sensible. For example, it is reasonable to suppose that the average volume for the preceding hour has strong explanatory power for the current volume. $y^{PO}_{t-1,p}$ also shows significance and relatively high coefficient values. $y^{D}_{t-1,p}$, $y^{DH}_{t-1,p}$ and $y^{W}_{t-1,p}$ generally have the least explanatory power and are insignificant in several instances. Thus, it seems that $y^{H}_{t-1,p}$ and $y^{PO}_{t-1,p}$ predict the subsequent observation of a price feature relatively well compared to the other lagged values. An observation is apparent for return, volatility and RQS concerning the lagged values within the last 24 hours. As these three variables have positive lags ($y^{PO}_{t-1,p}$, $y^{H}_{t-1,p}$ and $y^{D}_{t-1,p}$) during the preceding day, they display positive autocorrelation as they predict themselves positively. Volume displays positive autocorrelation for the lagged values within the preceding hour ($y^{PO}_{t-1,p}$ and $y^{H}_{t-1,p}$).

When comparing the coefficient values directly to each other, volatility consistently has the largest values compared to the other variables. Thus, we conclude that volatility has the most relative explanatory power for co-movements among the price features.

The statistically significant lags with $p < 0.01$ from the VAR-model are included in the MLR-model in Section 4.2.

4.2 Multiple Linear Regression (MLR)

4.2.1 Methodology

We apply a Multiple Linear Regression (MLR) model to estimate the outcome of four dependent variables; return, volatility, volume and RQS with multiple independent variables.

To capture the behaviour with different time granularities close to stock exchange opening and closing, we conduct separate regressions with different dummy time intervals using minute observations. Three separate regressions are modelled for each price feature - one with hourly dummies, one with half-hourly dummies and one with quarter-hour dummies. Furthermore, we conduct separate regressions according to the time zones of the selected stock exchanges, the NYSE, the LSE and the TSE. Thus, we model 36 regressions in total, as there are four price features, three time zones, and three dummy time intervals.

The regressions conducted with hourly dummy variables contain one intercept term, 23 hourly dummy variables (denoted H_i), one $marketOpen$-dummy variable (denoted mO), one $marketClose$-dummy variable (denoted mC), and one $isWeekend$-dummy variable (denoted iW) as shown in Equation 15. The lags that are included from Section 4.1 are displayed in the tables corresponding to each price feature regression.

The applied MLR-model with hourly dummies can be described as follows, where t is indexing a minute observation:

$$y_{t,p} = \beta_{0,p} + \sum_{i=1}^{23} (\beta_{i,p} \cdot H_i) + \beta_{24,p} \cdot mO_{t,p} + \beta_{25,p} \cdot mC_{t,p} + \beta_{26,p} \cdot iW_t + \sum_{\substack{f \in \{pricefeatures\} \\ j \in \{lags\}}} (\beta_{j,p,f} \cdot y^{j}_{t-1,f}) + \epsilon_{t,p} \tag{15}$$

The observations in the hourly model are represented as follows: the dummies $H_1, H_2, ..., H_{23}$ represent 23 of the 24 hour intervals in a day, where the remaining hour is omitted, and is thus represented by the intercept term. The 23 hour dummies are equal to 1 in the time interval they belong and 0 elsewhere. $marketOpen$ represents the dummy variable corresponding to whether or not the stock market is opening. For example, since the NYSE opens at 09:30 EST, $marketOpen$ is equal to 1 in the hour interval 09:00-09:59 EST from Mondays to Fridays, and 0 otherwise. The same logic applies to the $marketClose$-variable, representing each relevant stock exchange's closing hour.

All the stock exchanges have their opening or closing time between two hourly dummies, depending on their local time zones and opening hours. The hourly dummies are designed to capture the half-hour before, and the half-hour after the exact moment a stock exchange opens or closes. For instance, for the NYSE's opening hours (09:30 to 16:00 EST), the hourly dummies are defined from 09:00 to 09:59, 10:00 to 10:59 - all the way to 15:00. To achieve the same dummy interval span for the closing of the NYSE as for the opening, the periods 15:00-15:29 and 16:30-16:59 are omitted - and the hourly dummy designed to capture the closing interval is defined from 15:30 to 16:29. The $marketOpen$ and $marketClose$ dummies for the NYSE are defined in the interval 09:00-09:59 and 15:30-16:29, respectively. The remaining periods of the day are captured by hourly dummies defined from 00:00-00:59 until 23:00-23:59.

We include an $isWeekend$ variable to test whether there are overall differences between the patterns for weekdays and weekends. $isWeekend$ is equal to 1 for weekends and 0 for weekdays. The dummy variable is defined to include both weekends and all non-trading days. The last sum in Equation 15,

$$\sum_{\substack{f \in \{pricefeatures\} \\ j \in \{lags\}}} (\beta_{j,p,f} \cdot y^{j}_{t-1,f})$$

describes the lags that were found significant in the VAR-model. j describes the time frame to which the lagged variable belongs (i.e. Equation 7-11), and f indexes the independent variables.

As the TSE closes during lunchtime (11:30-12:29 (JST)), two dummy variables are included to represent the stock market closing and reopening in this particular period: namely $marketCloseLunch$ and $marketOpenLunch$. These dummies are only included in the regressions for the TSE and are defined over the time intervals 11:00-11:59 and 12:00-12:59, respectively.

When conducting the regression with hourly dummies, information on more granular levels is potentially lost. Our high-frequency dataset allows for more detail examining the stock market opening and closing effect, as the dependent variables probably experience fluctuations within the examined hours of the stock exchanges. Therefore we also conduct similar regressions with shorter dummy time intervals, i.e. half-hourly and quarter-hour dummies.

The models using half-hourly and quarter-hour dummies have similar setups to the hourly model. However, these models separate the potential effect *before* and *after* the openings and closings of the stock exchanges. The variables $preMarketOpen$ (denoted $preMO$) and $postMarketOpen$ (denoted $postMO$) represent the time intervals before and after stock exchange opening. The variables $preMarketClose$ (denoted $preMC$) and $postMarketClose$ (denoted $postMC$) represent the time intervals before and after stock exchange closing. For example, the half-hourly dummies for the NYSE are from 09:00 to 09:29 and from 09:30 to 10:00; namely $preMarketOpen$ and $postMarketOpen$. The corresponding quarter-hour model for the NYSE opening has dummies from 09:15 to 09:29, and from 09:30 to 09:44. The model with half-hourly dummies is shown in Equation 16. The half-hourly dummy model includes 47 of the 48 half-hour intervals in a day, and the quarter-hour includes 95 of the 96 quarter-hour intervals in a day. As in the hourly model, the remaining half-hour and quarter-hour are omitted, and are thus represented by the intercept term.

$$\begin{aligned} y_{t,p} =& \beta_{0,p} + \sum_{i=1}^{47} (\beta_{i,p} \cdot H_i) + \beta_{48} \cdot preMO_{t,p} + \beta_{49,p} \cdot postMO_{t,p} + \beta_{50,p} \cdot preMC_{t,p} \\ &+ \beta_{51,p} \cdot postMC_{t,p} + \beta_{52,p} \cdot iW_t + \sum_{\substack{f \in \{pricefeatures\} \\ j \in \{lags\}}} (\beta_{j,p,f} \cdot y^{j}_{t-1,f}) + \epsilon_{t,p} \end{aligned} \tag{16}$$

As the TSE also closes during lunchtime (11:30-12:29 (JST)), four similar dummy variables are included to represent before and after lunchtime closing and reopening for this particular stock exchange in the half-hourly and quarter-hour models. Thus, the models for the TSE include the same variables as in Equation 16 in addition to the following dummies; $preMarketCloseLunch$, $postMarketCloseLunch$, $preMarketOpenAfterLunch$, and $postMarketOpenAfterLunch$. In the half-hourly model, they are defined over the time intervals 11:00-11:29, 11:30-11:59, 12:00-

12:29 and 12:30-12:59 (JST). In the quarter-hour model, they are defined over the time intervals 11:15-11:29, 11:30-11:44, 12:15-12:29 and 12:30-12:44 (JST).

4.2.2 Multiple Linear Regression (MLR)-results

In this section, we present the results regarding the impact of stock exchange opening and closing on the price features of BTC. The results are displayed in twelve tables, three tables for each dependent variable. The table showing the outcome from the hourly dummy regressions is included in this section; the half-hourly and quarter-hour tables can be found in Appendix. Column 1 displays the regression results for the NYSE, and columns 2 and 3 display the results for the LSE and the TSE, respectively. The standard errors of the coefficients are included in parentheses beneath each table entry. We only mention the coefficients significant on a $p < 0.01$ level when discussing the tables.

4.2.3 Regression of return

Table 2: MLR-regression of return with hourly dummies

	Dependent variable: Return		
	EST (NYSE)	GMT (LSE)	JST (TSE)
Independent variables:			
Intercept	0	0	0
	(0.001)	(0.001)	(0.001)
MarketOpen	−0.0009	0.0010	0.0042
	(0.002)	(0.002)	(0.002)
MarketCloseLunch			0.0008
			(0.002)
MarketOpenLunch			−0.0011
			(0.002)
MarketClose	0.0004	−0.0003	0.0020
	(0.002)	(0.002)	(0.002)
IsWeekend	−0.0010	−0.0009	−0.0003
	(0.001)	(0.001)	(0.001)
ReturnPreviousObservation	0.0169**	0.0170**	0.0169**
	(0.001)	(0.001)	(0.001)
ReturnPreviousHourAverage	0.1282**	0.1282**	0.1282**
	(0.001)	(0.001)	(0.001)
ReturnPreviousDayAverage	0.0058**	0.0058**	0.0058**
	(0.001)	(0.001)	(0.001)
VolatilityPreviousObservation	0.0180**	0.0180**	0.0180**
	(0.002)	(0.002)	(0.002)
VolatilityPreviousHourAverage	0.0236**	0.0236**	0.0235**
	(0.003)	(0.003)	(0.003)
VolatilityPreviousDayAverage	−0.0284**	−0.0283**	−0.0283**
	(0.002)	(0.002)	(0.002)
VolumePreviousObservation	−0.0148**	−0.0149**	−0.0149**
	(0.002)	(0.002)	(0.002)
VolumePreviousHourAverage	0.0054**	0.0053**	0.0054**
	(0.002)	(0.002)	(0.002)
RQSPreviousObservation	0.0251**	0.0251**	0.0252**
	(0.002)	(0.002)	(0.002)
RQSPreviousHourAverage	−0.0093**	−0.0093**	−0.0093**
	(0.002)	(0.002)	(0.002)
RQSPreviousWeekAverage	−0.0036*	−0.0036*	−0.0036*
	(0.002)	(0.002)	(0.002)
Hourly dummy variables	Yes	Yes	Yes
Adj. R-squared	0.018	0.018	0.018
Durbin-Watson	1.964	1.964	1.964

Number of observations: 982084
Note: $p^{*} < 0.05$, $p^{**} < 0.01$.

The values of *marketOpen*, *marketOpenLunch*, *marketCloseLunch*, and *marketClose* in the hourly dummy regressions of return can be found in Table 2. Table 2 and Table 6 display the half-hourly and quarter-hour dummy models. None of the opening or closing variables from Table 2, Table 6, or Table 7 is statistically significant on any p-levels. This indicates that there is insufficient evidence to conclude that there exists a non-zero correlation between stock exchange opening/closing and return of BTC.

In Table 2, Table 6 and Table 7, the $isWeekend$-variable is non-significant. This is unsurprising, considering the pattern dissimilarity between the weekday and weekend graphs displayed in Figure 2. Our findings are supported by literature, as price changes are generally difficult to predict both for BTC and other traditional financial assets (Aalborg, Molnár and De Vries, 2019).

The Adjusted R-squared values in Table 2, Table 6, and Table 7 are low, all with a value of 0.018. This means that the regressions do not explain much of the movement of the return of BTC.

4.2.4 Regression of volatility

Table 3: MLR-regression of volatility with hourly dummies

	Dependent variable: Volatility		
	EST (NYSE)	GMT (LSE)	JST (TSE)
Independent variables:			
Intercept	0	0	0
	(0.001)	(0.001)	(0.001)
MarketOpen	0.0013	0.0021	0.0016
	(0.002)	(0.002)	(0.002)
MarketCloseLunch			0.0009
			(0.002)
MarketOpenLunch			-0.0047^{**}
			(0.002)
MarketClose	-0.0022	-0.0006	-0.0012
	(0.002)	(0.002)	(0.002)
IsWeekend	0.0026^{*}	0.0029^{**}	0.0022
	(0.001)	(0.001)	(0.001)
ReturnPreviousObservation	-0.0143^{**}	-0.0143^{**}	-0.0143^{**}
	(0.001)	(0.001)	(0.001)
ReturnPreviousHourAverage	-0.0406^{**}	-0.0406^{**}	-0.0406^{**}
	(0.001)	(0.001)	(0.001)
ReturnPreviousDayAverage	-0.0068^{**}	-0.0068^{**}	-0.0068^{**}
	(0.001)	(0.001)	(0.001)
VolatilityPreviousObservation	0.2560^{**}	0.2561^{**}	0.2559^{**}
	(0.001)	(0.001)	(0.001)
VolatilityPreviousHourAverage	0.4323^{**}	0.4322^{**}	0.4326^{**}
	(0.002)	(0.002)	(0.002)
VolatilityPreviousDayAverage	0.0627^{**}	0.0631^{**}	0.0629^{**}
	(0.003)	(0.003)	(0.003)
VolatilityPreviousDayHourAverage	-0.0073^{**}	-0.0077^{**}	-0.0075^{**}
	(0.002)	(0.002)	(0.002)
VolumePreviousObservation	0.1973^{**}	0.1973^{**}	0.1970^{**}
	(0.001)	(0.001)	(0.001)
VolumePreviousHourAverage	-0.1129^{**}	-0.1129^{**}	-0.1137^{**}
	(0.002)	(0.002)	(0.002)
VolumePreviousDayAverage	-0.0079^{**}	-0.0079^{**}	-0.0076^{**}
	(0.002)	(0.002)	(0.002)
VolumePreviousWeekAverage	0.0024	0.0024	0.0025
	(0.001)	(0.001)	(0.001)
RQSPreviousObservation	0.0719^{**}	0.0719^{**}	0.0717^{**}
	(0.001)	(0.001)	(0.001)
RQSPreviousHourAverage	-0.0642^{**}	-0.0645^{**}	-0.0643^{**}
	(0.002)	(0.002)	(0.002)
RQSPreviousDayHourAverage	-0.0057^{**}	-0.0057^{**}	-0.0059^{**}
	(0.001)	(0.001)	(0.001)
RQSPreviousWeekAverage	0.0106^{**}	0.0106^{**}	0.0105^{**}
	(0.001)	(0.001)	(0.001)
Hourly dummy variables	Yes	Yes	Yes
Adj. R-squared	0.502	0.502	0.502
Durbin-Watson	2.052	2.052	2.052

Number of observations: 982084
Note: $p^{*} < 0.05$, $p^{**} < 0.01$.

Table 3 shows how volatility is affected by the NYSE, the LSE, and the TSE in the hour intervals the stock exchanges open and close. Table 8 and Table 9 in the Appendix display the half-hourly and quarter-hour dummy models.

We can see that volatility is not significantly affected by the opening or closing of the NYSE or the LSE. In Table 3, the $marketOpenLunch$-variable for the TSE is statistically significant and negative. Similarly, as seen in Table 8 and Table 9, $preMarketOpenAfterLunch$ affects volatility negatively with significance. This means that BTC's volatility is affected by the half/quarter-hour period before reopening of the TSE in the time intervals 12:00-12:29 and 12:15-12:29 JST.

In Table 3, Table 8 and Table 9, we can see that the $isWeekend$-dummy is significant for all exchanges, but in different dummy time intervals.

4.2.5 Regression of volume

Table 4: MLR-regression of volume with hourly dummies

	Dependent variable: Volume		
	EST (NYSE)	GMT (LSE)	JST (TSE)
Independent variables:			
Intercept	0	0	0
	(0.001)	(0.001)	(0.001)
MarketOpen	0.0113**	0.0059**	−0.0007
	(0.002)	(0.002)	(0.002)
MarketCloseLunch			$-8.204 \cdot 10^{-5}$
			(0.002)
MarketOpenLunch			−0.0028
			(0.002)
MarketClose	−0.0027	−0.0044*	−0.0029
	(0.002)	(0.002)	(0.002)
IsWeekend	−0.0102**	−0.0109**	−0.0115**
	(0.001)	(0.001)	(0.001)
ReturnPreviousObservation	−0.0081**	−0.0081**	−0.0081**
	(0.001)	(0.001)	(0.001)
ReturnPreviousHourAverage	−0.0088**	−0.0087**	−0.0086**
	(0.001)	(0.001)	(0.001)
ReturnPreviousWeekAverage	0.0075**	0.0074**	0.0071**
	(0.001)	(0.001)	(0.001)
VolatilityPreviousObservation	0.0614**	0.0615**	0.0612**
	(0.001)	(0.001)	(0.001)
VolatilityPreviousHourAverage	−0.0459**	−0.0456**	−0.0453**
	(0.002)	(0.002)	(0.002)
VolatilityPreviousDayAverage	0.0442**	0.0435**	0.0414**
	(0.003)	(0.003)	(0.003)
VolatilityPreviousWeekAverage	−0.0206**	−0.0205**	−0.0194**
	(0.002)	(0.002)	(0.002)
VolumePreviousObservation	0.2944**	0.2945**	0.2945**
	(0.001)	(0.001)	(0.001)
VolumePreviousHourAverage	0.4175**	0.4181**	0.4196**
	(0.002)	(0.002)	(0.002)
VolumePreviousDayHourAverage	−0.0039**	−0.0042**	−0.0033**
	(0.001)	(0.001)	(0.001)
RQSPreviousObservation	0.0150**	0.0151**	0.0148**
	(0.001)	(0.001)	(0.001)
RQSPreviousHourAverage	−0.0137**	−0.0138**	−0.0134**
	(0.002)	(0.002)	(0.002)
RQSPreviousDayAverage	−0.0138**	−0.0136**	−0.0131**
	(0.002)	(0.002)	(0.002)
Hourly dummy variables	Yes	Yes	Yes
Adj. R-squared	0.449	0.449	0.449
Durbin-Watson	2.061	2.061	2.060

Number of observations: 982084
Note: $p^{*} < 0.05$, $p^{**} < 0.01$.

Table 4 shows how volume is affected by the NYSE, the LSE, and the TSE at the hour intervals the stock exchanges open and close. Table 10 and Table 11 display the half-hourly and quarter-hour models.

The results from the regressions on the NYSE indicate that the trading volume increases during opening, and decreases right after closing. The *marketOpen* and *postMarketOpen* variables are significant and positive, while the *postMarketClose* variables are negative. These observations support our initial hypothesis that stock exchange openings have a positive effect on the trading volume of BTC. The same effect is observed for the LSE. The period around the opening of the LSE has a positive impact on trading volume, while the period right before and after the exchange closing has a negative impact on volume. For the TSE, *preMarketOpen* is significant both with half-hourly dummies and quarter-hour dummies. Both values are negative, indicating that the trading volume is affected negatively before the opening of the TSE. *postMarketClose* is also negative and significant for the TSE in the quarter-hour model in Table 11. The findings related to the TSE contradict our initial hypothesis that stock exchange openings impact the volume positively. Thus, our initial hypothesis is valid only for the NYSE and the LSE. In accordance with the observations of Eross et al. (2019) and Wang, Liu and Hsu (2020), this may be explained by the European and American stock markets being more important than Asian stock markets in explaining the trading volume of BTC.

The *isWeekend*-dummy is significant in Table 4, Table 10 and Table 11 with a negative value. This indicates that the trading volume is higher during the weekdays compared to the weekends.

4.2.6 Regression of relative quoted spread (RQS)

Table 5: MLR-regression of RQS with hourly dummies

	Dependent variable: RQS		
	EST (NYSE)	GMT (LSE)	JST (TSE)
Independent variables:			
Intercept	0	0	0
	(0.001)	(0.001)	(0.001)
MarketOpen	0.0032	0.0007	−0.0006
	(0.002)	(0.002)	(0.002)
MarketCloseLunch			0.0064**
			(0.002)
MarketOpenLunch			−0.0044*
			(0.002)
MarketClose	−0.0008	0.0018	−0.0028
	(0.002)	(0.002)	(0.002)
IsWeekend	0.0016	0.0017	0.0011
	(0.001)	(0.001)	(0.001)
ReturnPreviousObservation	−0.0057**	−0.0057**	−0.0057**
	(0.001)	(0.001)	(0.001)
ReturnPreviousHourAverage	−0.0451**	−0.0451**	−0.0452**
	(0.001)	(0.001)	(0.001)
ReturnPreviousDayAverage	−0.0048**	−0.0049**	−0.0048**
	(0.001)	(0.001)	(0.001)
ReturnPreviousDayHourAverage	0.0046**	0.0045**	0.0045**
	(0.001)	(0.001)	(0.001)
VolatilityPreviousObservation	0.0867**	0.0868**	0.0866**
	(0.001)	(0.001)	(0.001)
VolatilityPreviousHourAverage	−0.0189**	−0.0190**	−0.0189**
	(0.002)	(0.002)	(0.002)
VolatilityPreviousWeekAverage	−0.0247**	−0.0247**	−0.0246**
	(0.002)	(0.002)	(0.002)
VolumePreviousObservation	0.0599**	0.0600**	0.0597**
	(0.001)	(0.001)	(0.001)
VolumePreviousHourAverage	−0.0415**	−0.0413**	−0.0416**
	(0.002)	(0.002)	(0.002)
RQSPreviousObservation	0.2779**	0.2779**	0.2779**
	(0.001)	(0.001)	(0.001)
RQSPreviousHourAverage	0.4359**	0.4358**	0.4356**
	(0.002)	(0.002)	(0.002)
RQSPreviousDayAverage	0.0327**	0.0327**	0.0332**
	(0.002)	(0.002)	(0.002)
RQSPreviousDayHourAverage	−0.0154**	−0.0153**	−0.0157**
	(0.001)	(0.001)	(0.001)
RQSPreviousWeekAverage	0.0219**	0.0219**	0.0218**
	(0.002)	(0.002)	(0.002)
Hourly dummy variables	Yes	Yes	Yes
Adj. R-squared	0.509	0.509	0.509
Durbin-Watson	2.085	2.085	2.085

Number of observations: 982084
Note: $p^{*} < 0.05$, $p^{**} < 0.01$.

Table 5 shows how RQS is affected by the NYSE, the LSE, and the TSE, the hour interval the stock exchanges open and close. The half-hourly and quarter-hour results are displayed in Table 12 and Table 13.

We can see that the closing at lunchtime in the TSE affects RQS positively, and the half-hour before reopening after lunchtime affects RQS negatively. Both the $marketCloseLunch$ and $preMarketCloseLunch$ for hourly and half-hourly dummies affect RQS positively, while $preMarketOpenAfterLunch$ affects RQS negatively. The lunch break effect we observe on the RQS of BTC resembles the findings of Frino and Winn (2001), who report wider spreads at lunchtime closure on the SFE. None of the other stock exchanges seems to have an impact on RQS.

The $isWeekend$-dummy is not significant in Table 5, Table 12 or Table 13. This means that we do not have significant results to conclude that there is a difference in RQS between the weekdays and weekends.

5 Conclusion

The emergence of cryptocurrencies as investment vehicles invites empirical research similar to that conducted on traditional financial markets. By studying interconnections between these markets, it is possible to produce valuable contributions both in academic and practical sense. The focus of this paper is twofold; the first objective is to estimate interrelationships within the return, volatility, volume and spread of Bitcoin. The second objective is to study the impact of the opening and closing of the NYSE, the LSE and the TSE on Bitcoin. By employing a VAR-regression we discover dependencies between the variables mentioned above. We include the variables with the most explanatory power in a MLR-model accounting for the stock exchange opening and closing hours. Using a dataset with one-second observations from the order book of Coinbase, our paper stands out in terms of observation frequency.

We uncover positive autocorrelation on one-minute, one-hour and one-day time frames for return, volatility and spread. Trading volume seems to be positively autocorrelated on one-minute and one-hour basis. The VAR-model suggests that volatility has the most explanatory power for the other variables. Our paper also finds Bitcoin behaviour to be significantly affected by stock exchange opening and closing. Particularly, the NYSE and the TSE are significant in explaining volatility, volume and spread. Most noteworthy, volume seems to increase during the opening of the NYSE and the LSE and later decrease during closing of the former. Lunchtime closure of the TSE is found to have explanatory power for volatility and spread. The spread seems to increase once the lunch break starts, whilst at reopening an hour later, both volatility and spread decrease. Bitcoin return does not seem explicable by any exchange opening or closing.

In terms of further work, we recommend conducting similar studies on other large-cap cryptocurrencies to expand upon the overall academic understanding of the entire cryptocurrency market.

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Appendix

A Return

Table 6: MLR-regression of return with half-hourly dummies

	Dependent variable: Return		
	EST (NYSE)	GMT (LSE)	JST (TSE)
Independent variables:			
Intercept	0	0	0
	(0.001)	(0.001)	(0.001)
PreMarketOpen	−0.0014	−0.0003	0.0025
	(0.002)	(0.002)	(0.002)
PostMarketOpen	0.0001	0.0017	0.0036
	(0.002)	(0.002)	(0.002)
PreMarketCloseLunch			0.0006
			(0.002)
PostMarketCloseLunch			0.0006
			(0.002)
PreMarketOpenAfterLunch			0.0009
			(0.002)
PostMarketOpenAfterLunch			-0.0025
			(0.002)
PreMarketClose	0.0015	0.0007	0.0013
	(0.002)	(0.002)	(0.002)
PostMarketClose	−0.0010	−0.0011	0.0016
	(0.002)	(0.002)	(0.002)
IsWeekend	−0.0011	−0.0010	−0.0003
	(0.001)	(0.001)	(0.001)
ReturnPreviousObservation	0.0169**	0.0169**	0.0169**
	(0.001)	(0.001)	(0.001)
ReturnPreviousHourAverage	0.1283**	0.1283**	0.1283**
	(0.001)	(0.001)	(0.001)
ReturnPreviousDayAverage	0.0058**	0.0058**	0.0058**
	(0.001)	(0.001)	(0.001)
VolatilityPreviousObservation	0.0180**	0.0180**	0.0181**
	(0.002)	(0.002)	(0.002)
VolatilityPreviousHourAverage	0.0237**	0.0236**	0.0235**
	(0.003)	(0.003)	(0.003)
VolatilityPreviousDayAverage	−0.0284**	−0.0283**	−0.0283**
	(0.002)	(0.002)	(0.002)
VolumePreviousObservation	−0.0148**	−0.0148**	−0.0147**
	(0.002)	(0.002)	(0.002)
VolumePreviousHourAverage	0.0053**	0.0052**	0.0054**
	(0.002)	(0.002)	(0.002)
RQSPreviousObservation	0.0251**	0.0251**	0.0252**
	(0.002)	(0.002)	(0.002)
RQSPreviousHourAverage	−0.0093**	−0.0093**	−0.0094**
	(0.002)	(0.002)	(0.002)
RQSPreviousWeekAverage	−0.0036*	−0.0037*	−0.0036*
	(0.002)	(0.002)	(0.002)
Half-hourly dummy variables	Yes	Yes	Yes
Adj. R-squared	0.018	0.018	0.001
Durbin-Watson	1.964	1.964	1.964

Number of observations: 982084
Note: $p^{*} < 0.05$, $p^{**} < 0.01$.

Table 7: MLR-regression of return with quarter-hour dummies

	Dependent variable: Return		
	EST (NYSE)	GMT (LSE)	JST (TSE)
Independent variables:			
Intercept	0	0	0
	(0.001)	(0.001)	(0.001)
PreMarketOpen	0.0022	−0.0018	0.0015
	(0.002)	(0.002)	(0.002)
PostMarketOpen	0.0002	0.0023	0.0044
	(0.002)	(0.002)	(0.002)
PreMarketCloseLunch			0.0011
			(0.002)
PostMarketCloseLunch			0.0024
			(0.002)
PreMarketOpenAfterLunch			0.0015
			(0.002)
PostMarketOpenAfterLunch			-0.0014
			(0.002)
PreMarketClose	0.0035	0.0013	0.0021
	(0.002)	(0.002)	(0.002)
PostMarketClose	−0.0008	−0.0022	0.0014
	(0.002)	(0.002)	(0.002)
IsWeekend	−0.0008	−0.0011	−0.0003
	(0.001)	(0.001)	(0.001)
ReturnPreviousObservation	0.0168**	0.0169**	0.0169**
	(0.001)	(0.001)	(0.001)
ReturnPreviousHourAverage	0.1283**	0.1283**	0.1283**
	(0.001)	(0.001)	(0.001)
ReturnPreviousDayAverage	0.0058**	0.0058**	0.0058**
	(0.001)	(0.001)	(0.001)
VolatilityPreviousObservation	0.0181**	0.0180**	0.0181**
	(0.002)	(0.002)	(0.002)
VolatilityPreviousHourAverage	0.0238**	0.0236**	0.0235**
	(0.003)	(0.003)	(0.003)
VolatilityPreviousDayAverage	−0.0285**	−0.0284**	−0.0283**
	(0.002)	(0.002)	(0.002)
VolumePreviousObservation	−0.0148**	−0.0148**	−0.0148**
	(0.002)	(0.002)	(0.002)
VolumePreviousHourAverage	0.0052**	0.0052**	0.0054**
	(0.002)	(0.002)	(0.002)
RQSPreviousObservation	0.0251**	0.0251**	0.0251**
	(0.002)	(0.002)	(0.002)
RQSPreviousHourAverage	−0.0093**	−0.0092**	−0.0093**
	(0.002)	(0.002)	(0.002)
RQSPreviousWeekAverage	−0.0036*	−0.0036*	−0.0036*
	(0.002)	(0.002)	(0.002)
Quarter-hour dummy variables	Yes	Yes	Yes
Adj. R-squared	0.018	0.018	0.018
Durbin-Watson	1.964	1.964	1.964

Number of observations: 982084
Note: $p^{*} < 0.05$, $p^{**} < 0.01$.

B Volatility

Table 8: MLR-regression of volatility with half-hourly dummies

	Dependent variable: Volatility		
	EST (NYSE)	GMT (LSE)	JST (TSE)
Independent variables:			
Intercept	0	0	0
	(0.001)	(0.001)	(0.001)
PreMarketOpen	0.0021	0.00016	0.0021
	(0.002)	(0.002)	(0.002)
PostMarketOpen	-0.0003	0.0014	0.0004
	(0.002)	(0.002)	(0.002)
PreMarketCloseLunch			0.0013
			(0.002)
PostMarketCloseLunch			$-7.853 \cdot 10^{-6}$
			(0.002)
PreMarketOpenAfterLunch			-0.0055^{**}
			(0.002)
PostMarketOpenAfterLunch			-0.0012
			(0.002)
PreMarketClose	-0.0040^{*}	0.0011	-0.0012
	(0.002)	(0.002)	(0.002)
PostMarketClose	0.0009	-0.0020	-0.0004
	(0.002)	(0.002)	(0.002)
IsWeekend	0.0026^{*}	0.0029^{**}	0.0023^{*}
	(0.001)	(0.001)	(0.001)
ReturnPreviousObservation	-0.0143^{**}	-0.0143^{**}	-0.0143^{**}
	(0.001)	(0.001)	(0.001)
ReturnPreviousHourAverage	-0.0408^{**}	-0.0407^{**}	-0.0407^{**}
	(0.001)	(0.001)	(0.001)
ReturnPreviousDayAverage	-0.0069^{**}	-0.0068^{**}	-0.0069^{**}
	(0.001)	(0.001)	(0.001)
VolatilityPreviousObservation	0.2555^{**}	0.2557^{**}	0.2553^{**}
	(0.001)	(0.001)	(0.001)
VolatilityPreviousHourAverage	0.4328^{**}	0.4325^{**}	0.4330^{**}
	(0.002)	(0.002)	(0.002)
VolatilityPreviousDayAverage	0.0623^{**}	0.0630^{**}	0.0619^{**}
	(0.003)	(0.003)	(0.003)
VolatilityPreviousDayHourAverage	-0.0070^{**}	-0.0076^{**}	-0.0064^{**}
	(0.002)	(0.002)	(0.002)
VolumePreviousObservation	0.1969^{**}	0.1970^{**}	0.1965^{**}
	(0.001)	(0.001)	(0.001)
VolumePreviousHourAverage	-0.1124^{**}	-0.1127^{**}	-0.1122^{**}
	(0.002)	(0.002)	(0.002)
VolumePreviousDayAverage	-0.0080^{**}	-0.0079^{**}	-0.0082^{**}
	(0.002)	(0.002)	(0.002)
VolumePreviousWeekAverage	0.0024	0.0024	0.0024
	(0.001)	(0.001)	(0.001)
RQSPreviousObservation	0.0718^{**}	0.0719^{**}	0.0717^{**}
	(0.001)	(0.001)	(0.001)
RQSPreviousHourAverage	-0.0642^{**}	-0.0646^{**}	-0.0641^{**}
	(0.002)	(0.002)	(0.002)
RQSPreviousDayHourAverage	-0.0057^{**}	-0.0057^{**}	-0.0061^{**}
	(0.001)	(0.001)	(0.001)
RQSPreviousWeekAverage	0.0106^{**}	0.0107^{**}	0.0106^{**}
	(0.001)	(0.001)	(0.001)
Half-hourly dummy variables	Yes	Yes	Yes
Adj. R-squared	0.502	0.502	0.502
Durbin-Watson	2.051	2.052	2.051

Number of observations: 982084
Note: $p^{*} < 0.05$, $p^{**} < 0.01$.

Table 9: MLR-regression of volatility with quarter-hour dummies

	Dependent variable: Volatility		
	EST (NYSE)	GMT (LSE)	JST (TSE)
Independent variables:			
Intercept	0	0	0
	(0.001)	(0.001)	(0.001)
PreMarketOpen	0.0031	0.0010	0.0033
	(0.002)	(0.002)	(0.002)
PostMarketOpen	0.0022	0.0002	0.0019**
	(0.002)	(0.002)	(0.002)
PreMarketCloseLunch			0.0010
			(0.002)
PostMarketCloseLunch			0.0022
			(0.002)
PreMarketOpenAfterLunch			−0.0045**
			(0.002)
PostMarketOpenAfterLunch			−0.0013
			(0.002)
PreMarketClose	−0.0019	0.0002	0.0010
	(0.002)	(0.002)	(0.002)
PostMarketClose	0.0007	−0.0028	−0.0006
	(0.002)	(0.002)	(0.002)
IsWeekend	0.0029**	0.0027*	0.0028**
	(0.001)	(0.001)	(0.001)
ReturnPreviousObservation	−0.0143**	−0.0143**	−0.0142**
	(0.001)	(0.001)	(0.001)
ReturnPreviousHourAverage	−0.0407**	−0.0407**	−0.0407**
	(0.001)	(0.001)	(0.001)
ReturnPreviousDayAverage	−0.0069**	−0.0068**	−0.0069**
	(0.001)	(0.001)	(0.001)
VolatilityPreviousObservation	0.2553**	0.2555**	0.2551**
	(0.001)	(0.001)	(0.001)
VolatilityPreviousHourAverage	0.4330**	0.4326**	0.4331**
	(0.002)	(0.002)	(0.002)
VolatilityPreviousDayAverage	0.0623**	0.0631**	0.0618**
	(0.003)	(0.003)	(0.003)
VolatilityPreviousDayHourAverage	−0.0070**	−0.0076**	−0.0063**
	(0.002)	(0.002)	(0.002)
VolumePreviousObservation	0.1966**	0.1968**	0.1962**
	(0.001)	(0.001)	(0.001)
VolumePreviousHourAverage	−0.1123**	−0.1125**	−0.1119**
	(0.002)	(0.002)	(0.002)
VolumePreviousDayAverage	−0.0080**	−0.0080**	−0.0081**
	(0.002)	(0.002)	(0.002)
VolumePreviousWeekAverage	0.0024	0.0024	0.0024
	(0.001)	(0.001)	(0.001)
RQSPreviousObservation	0.0717**	0.0719**	0.0717**
	(0.001)	(0.001)	(0.001)
RQSPreviousHourAverage	−0.0642**	−0.0646**	−0.0640**
	(0.002)	(0.002)	(0.002)
RQSPreviousDayHourAverage	−0.0057**	−0.0057**	−0.0061**
	(0.001)	(0.001)	(0.001)
RQSPreviousWeekAverage	0.0106**	0.0107**	0.0106**
	(0.001)	(0.001)	(0.001)
Quarter-hour dummy variables	Yes	Yes	Yes
Adj. R-squared	0.502	0.502	0.502
Durbin-Watson	2.051	2.051	2.051

Number of observations: 982084
Note: $p^{*} < 0.05$, $p^{**} < 0.01$.

C Volume

Table 10: MLR-regression of volume with half-hourly dummies

	Dependent variable: Volume		
	EST (NYSE)	GMT (LSE)	JST (TSE)
Independent variables:			
Intercept	0	0	0
	(0.001)	(0.001)	(0.001)
PreMarketOpen	0.0026	0.0046^{*}	-0.0048^{**}
	(0.002)	(0.002)	(0.002)
PostMarketOpen	0.0136^{**}	0.0038^{*}	0.0036
	(0.002)	(0.002)	(0.002)
PreMarketCloseLunch			$2.735 \cdot 10^{-6}$
			(0.002)
PostMarketCloseLunch			-0.0002
			(0.002)
PreMarketOpenAfterLunch			-0.0030
			(0.002)
PostMarketOpenAfterLunch			-0.0011
			(0.002)
PreMarketClose	0.0041^{*}	-0.0049^{**}	-0.0002
	(0.002)	(0.002)	(0.002)
PostMarketClose	-0.0079^{**}	-0.0014	-0.0041^{*}
	(0.002)	(0.002)	(0.002)
IsWeekend	-0.0103^{**}	-0.0109^{**}	-0.0119^{**}
	(0.001)	(0.001)	(0.001)
ReturnPreviousObservation	-0.0081^{**}	-0.0081^{**}	-0.0081^{**}
	(0.001)	(0.001)	(0.001)
ReturnPreviousHourAverage	-0.0089^{**}	-0.0088^{**}	-0.0087^{**}
	(0.001)	(0.001)	(0.001)
ReturnPreviousWeekAverage	0.0075^{**}	0.0075^{**}	0.0074^{**}
	(0.001)	(0.001)	(0.001)
VolatilityPreviousObservation	0.0608^{**}	0.0610^{**}	0.0604^{**}
	(0.001)	(0.001)	(0.001)
VolatilityPreviousHourAverage	-0.0452^{**}	-0.0451^{**}	-0.0448^{**}
	(0.002)	(0.002)	(0.002)
VolatilityPreviousDayAverage	0.0443^{**}	0.0436^{**}	0.0437^{**}
	(0.003)	(0.003)	(0.003)
VolatilityPreviousWeekAverage	-0.0207^{**}	-0.0206^{**}	-0.0206^{**}
	(0.002)	(0.002)	(0.002)
VolumePreviousObservation	0.2927^{**}	0.2931^{**}	0.2923^{**}
	(0.001)	(0.001)	(0.001)
VolumePreviousHourAverage	0.4185^{**}	0.4188^{**}	0.4191^{**}
	(0.002)	(0.002)	(0.002)
VolumePreviousDayHourAverage	-0.0039^{**}	-0.0041^{**}	-0.0038^{**}
	(0.001)	(0.001)	(0.001)
RQSPreviousObservation	0.0148^{**}	0.0150^{**}	0.0146^{**}
	(0.001)	(0.001)	(0.001)
RQSPreviousHourAverage	-0.0137^{**}	-0.0138^{**}	-0.0135^{**}
	(0.002)	(0.002)	(0.002)
RQSPreviousDayAverage	-0.0138^{**}	-0.0136^{**}	-0.0138^{**}
	(0.002)	(0.002)	(0.002)
Half-hourly dummy variables	Yes	Yes	Yes
Adj. R-squared	0.450	0.450	0.450
Durbin-Watson	2.059	2.059	2.058

Number of observations: 982084
Note: $p^{*} < 0.05$, $p^{**} < 0.01$.

Table 11: MLR-regression of volume with quarter-hour dummies

	Dependent variable: Volume		
	EST (NYSE)	GMT (LSE)	JST (TSE)
Independent variables:			
Intercept	0	0	0
	(0.001)	(0.001)	(0.001)
PreMarketOpen	0.0022	0.0025	-0.0059^{**}
	(0.002)	(0.002)	(0.002)
PostMarketOpen	0.0130^{**}	0.0029	0.0043^{*}
	(0.002)	(0.002)	(0.002)
PreMarketCloseLunch			-0.0011
			(0.002)
PostMarketCloseLunch			0.0007
			(0.002)
PreMarketOpenAfterLunch			-0.0022
			(0.002)
PostMarketOpenAfterLunch			-0.0013
			(0.002)
PreMarketClose	0.0078^{**}	0.0009	0.0018
	(0.002)	(0.002)	(0.002)
PostMarketClose	-0.0065^{**}	-0.0005^{**}	-0.0062^{**}
	(0.002)	(0.002)	(0.002)
IsWeekend	-0.0102^{**}	-0.0107^{**}	-0.0116^{**}
	(0.001)	(0.001)	(0.001)
ReturnPreviousObservation	-0.0082^{**}	-0.0082^{**}	-0.0081^{**}
	(0.001)	(0.001)	(0.001)
ReturnPreviousHourAverage	-0.0089^{**}	-0.0088^{**}	-0.0088^{**}
	(0.001)	(0.001)	(0.001)
ReturnPreviousWeekAverage	0.0075^{**}	0.0075^{**}	0.0074^{**}
	(0.001)	(0.001)	(0.001)
VolatilityPreviousObservation	0.0604^{**}	0.0608^{**}	0.0599^{**}
	(0.001)	(0.001)	(0.001)
VolatilityPreviousHourAverage	-0.0448^{**}	-0.0448^{**}	-0.0442^{**}
	(0.002)	(0.002)	(0.002)
VolatilityPreviousDayAverage	0.0438^{**}	0.0435^{**}	0.0430^{**}
	(0.003)	(0.003)	(0.003)
VolatilityPreviousWeekAverage	-0.0206^{**}	-0.0206^{**}	-0.0203^{**}
	(0.002)	(0.002)	(0.002)
VolumePreviousObservation	0.2913^{**}	0.2920^{**}	0.2906^{**}
	(0.001)	(0.001)	(0.001)
VolumePreviousHourAverage	0.4197^{**}	0.4195^{**}	0.4205^{**}
	(0.002)	(0.002)	(0.002)
VolumePreviousDayHourAverage	-0.0038^{**}	-0.0040^{**}	-0.0036^{**}
	(0.001)	(0.001)	(0.001)
RQSPreviousObservation	0.0147^{**}	0.0148^{**}	0.0145^{**}
	(0.001)	(0.001)	(0.001)
RQSPreviousHourAverage	-0.0138^{**}	-0.0138^{**}	-0.0136^{**}
	(0.002)	(0.002)	(0.002)
RQSPreviousDayAverage	-0.0137^{**}	-0.0136^{**}	-0.0135^{**}
	(0.002)	(0.002)	(0.002)
Quarter-hour dummy variables	Yes	Yes	Yes
Adj. R-squared	0.450	0.450	0.451
Durbin-Watson	2.058	2.058	2.057

Number of observations: 982084
Note: $p^{*} < 0.05$, $p^{**} < 0.01$.

D Relative Quoted Spread

Table 12: MLR-regression of RQS with half-hourly dummies

	Dependent variable: RQS		
	EST (NYSE)	GMT (LSE)	JST (TSE)
Independent variables:			
Intercept	0	0	0
	(0.001)	(0.001)	(0.001)
PreMarketOpen	0.0007	0.0002	0.0025
	(0.002)	(0.002)	(0.002)
PostMarketOpen	0.0038*	0.0009	−0.0032
	(0.002)	(0.002)	(0.002)
PreMarketCloseLunch			0.0064**
			(0.002)
PostMarketCloseLunch			0.0026
			(0.002)
PreMarketOpenAfterLunch			−0.0052**
			(0.002)
PostMarketOpenAfterLunch			−0.0010
			(0.002)
PreMarketClose	−0.0004	0.0014	−0.0010
	(0.002)	(0.002)	(0.002)
PostMarketClose	−0.0008	0.0011	−0.0030
	(0.002)	(0.002)	(0.002)
IsWeekEnd	0.0016	0.0017	0.0012
	(0.001)	(0.001)	(0.001)
ReturnPreviousObservation	−0.0057**	−0.0057**	−0.0057**
	(0.001)	(0.001)	(0.001)
ReturnPreviousHourAverage	−0.0451**	−0.0450**	−0.0452**
	(0.001)	(0.001)	(0.001)
ReturnPreviousDayAverage	−0.0048**	−0.0049**	−0.0048**
	(0.001)	(0.001)	(0.001)
ReturnPreviousDayHourAverage	0.0045**	0.0046**	0.0045**
	(0.001)	(0.001)	(0.001)
VolatilityPreviousObservation	0.0866**	0.0868**	0.0866**
	(0.001)	(0.001)	(0.001)
VolatilityPreviousHourAverage	−0.0187**	−0.0191**	−0.0187**
	(0.002)	(0.002)	(0.002)
VolatilityPreviousWeekAverage	−0.0248**	−0.0247**	−0.0247**
	(0.002)	(0.002)	(0.002)
VolumePreviousObservation	0.0599**	0.0600**	0.0597**
	(0.001)	(0.001)	(0.001)
VolumePreviousHourAverage	−0.0415**	−0.0413**	−0.0414**
	(0.002)	(0.002)	(0.002)
RQSPreviousObservation	0.2777**	0.2778**	0.2778**
	(0.001)	(0.001)	(0.001)
RQSPreviousHourAverage	0.4359**	0.4359**	0.4357**
	(0.002)	(0.002)	(0.002)
RQSPreviousDayAverage	0.0327**	0.0326**	0.0329**
	(0.002)	(0.002)	(0.002)
RQSPreviousDayHourAverage	−0.0153**	−0.0152**	−0.0156**
	(0.001)	(0.001)	(0.001)
RQSPreviousWeekAverage	0.0219**	0.0219**	0.0219**
	(0.002)	(0.002)	(0.002)
Half-hourly dummy variables	Yes	Yes	Yes
Adj. R-squared	0.509	0.509	0.509
Durbin-Watson	2.085	2.085	2.085

Number of observations: 982084
Note: $p^{*} < 0.05$, $p^{**} < 0.01$.

Table 13: MLR-regression of RQS with quarter-hour dummies

	Dependent variable: RQS		
	EST (NYSE)	GMT (LSE)	JST (TSE)
Independent variables:			
Intercept	0	0	0
	(0.001)	(0.001)	(0.001)
PreMarketOpen	$-1.362 \cdot 10^{-5}$	0.0003	0.0011
	(0.002)	(0.002)	(0.002)
PostMarketOpen	0.0039^{*}	0.0019	-0.0018
	(0.002)	(0.002)	(0.002)
PreMarketCloseLunch			0.0037^{*}
			(0.002)
PostMarketCloseLunch			0.0038^{*}
			(0.002)
PreMarketOpenAfterLunch			-0.0040^{*}
			(0.002)
PostMarketOpenAfterLunch			-0.0008
			(0.002)
PreMarketClose	0.0010	0.0015	-0.0008
	(0.002)	(0.002)	(0.002)
PostMarketClose	-0.0015	0.0003	-0.0017
	(0.002)	(0.002)	(0.002)
IsWeekEnd	0.0015	0.0016	0.0013
	(0.001)	(0.001)	(0.001)
ReturnPreviousObservation	-0.0057^{**}	-0.0057^{**}	-0.0057^{**}
	(0.001)	(0.001)	(0.001)
ReturnPreviousHourAverage	-0.0452^{**}	-0.0450^{**}	-0.0452^{**}
	(0.001)	(0.001)	(0.001)
ReturnPreviousDayAverage	-0.0048^{**}	-0.0049^{**}	-0.0048^{**}
	(0.001)	(0.001)	(0.001)
ReturnPreviousDayHourAverage	0.0045^{**}	0.0046^{**}	0.0045^{**}
	(0.001)	(0.001)	(0.001)
VolatilityPreviousObservation	0.0866^{**}	0.0868^{**}	0.0866^{**}
	(0.001)	(0.001)	(0.001)
VolatilityPreviousHourAverage	-0.0187^{**}	-0.0190^{**}	-0.0187^{**}
	(0.002)	(0.002)	(0.002)
VolatilityPreviousWeekAverage	-0.0248^{**}	-0.0247^{**}	-0.0247^{**}
	(0.002)	(0.002)	(0.002)
VolumePreviousObservation	0.0598^{**}	0.0599^{**}	0.0596^{**}
	(0.001)	(0.001)	(0.001)
VolumePreviousHourAverage	-0.0414^{**}	-0.0413^{**}	-0.0414^{**}
	(0.002)	(0.002)	(0.002)
RQSPreviousObservation	0.2775^{**}	0.2777^{**}	0.2777^{**}
	(0.001)	(0.001)	(0.001)
RQSPreviousHourAverage	0.4361^{**}	0.4361^{**}	0.4359^{**}
	(0.002)	(0.002)	(0.002)
RQSPreviousDayAverage	0.0326^{**}	0.0326^{**}	0.0329^{**}
	(0.002)	(0.002)	(0.002)
RQSPreviousDayHourAverage	-0.0153^{**}	-0.0152^{**}	-0.0155^{**}
	(0.001)	(0.001)	(0.001)
RQSPreviousWeekAverage	0.0219^{**}	0.0219^{**}	0.0219^{**}
	(0.002)	(0.002)	(0.002)
Quarter-hour dummy variables	Yes	Yes	Yes
Adj. R-squared	0.509	0.509	0.509
Durbin-Watson	2.085	2.085	2.085

Number of observations: 982084
Note: $p^{*} < 0.05$, $p^{**} < 0.01$.

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