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Impact of the stock market, major currencies, precious metals and central banks on the volatility of Bitcoin

Master's thesis in Industrial Economics and Technology
Management
Supervisor: Peter Molnár
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Faculty of Economics and Management
Department of Industrial Economics and Technology Management



Preface

This master's thesis is written as the fulfillment of our Master of Science in Industrial Economics and Technology Management at the Norwegian University of Science and Technology. The purpose is to investigate the volatility of Bitcoin.

We wish to sincerely thank our supervisor, Peter Molnár. He has provided us with crucial guidance and help during our work. His knowledge and input have been decisive for the fulfillment of the thesis. We are grateful for how he has constantly helped us improve our research, and the flexibility and presence he has shown.

Abstract

Volatility is one of the most important risk characteristics of an asset. Recently, the interest in Bitcoin has increased, but despite Bitcoin's large volatility, research in this field is limited. We therefore study how the volatility of Bitcoin is influenced by the volatility and returns of major currencies, the stock market, and gold and silver. Moreover, we investigate if central bank interest rate announcements affect the volatility of Bitcoin. We use the logarithmic HAR model in our study. Findings indicate that neither currencies, nor the stock market, nor precious metals can explain the volatility of Bitcoin. Furthermore, we find no evidence of central bank interest rate announcements having a systematic influence on the volatility of Bitcoin. This indicates that Bitcoin is a unique asset class unrelated to traditional financial markets.

Sammendrag

Volatilitet er en av de viktigste risikokarakteristikkene til en finansiell aktiva. Nylig har interessen for Bitcoin økt, men til tross for Bitcoins høye volatilitet er forskning på dette feltet begrenset. Vi studerer derfor hvordan volatiliteten til Bitcoin påvirkes av volatiliteten og avkastningen til valutaer, aksjemarkedet, gull og sølv. Videre undersøker vi påvirkningen fra rentekunngjøringer fra sentralbanker. I vår studie bruker vi den logaritmiske HAR-modellen. Resultatene indikerer at verken valutaer, aksjemarkedet eller edle metaller kan forklare volatiliteten til Bitcoin. Videre finner vi ikke noe bevis for at rentekunngjøringer har en systematisk innflytelse på volatiliteten til Bitcoin. Dette indikerer at Bitcoin er en unik aktivaklasse uten tilknytning til tradisjonelle finansmarkeder.

Contents

Preface	i
Abstract	iii
Sammendrag	v
List of Tables	ix
List of Figures	xi
1 Introduction	1
2 Literature Review	5
3 Data	9
3.1 Returns	9
3.2 Realized Variance	13
3.3 Central bank announcements	18
4 Methodology	19
4.1 HAR Models	19

4.1.1	Base HAR Model	19
4.1.2	HAR models with realized variance of other assets	20
4.1.3	HAR model with returns of Bitcoin and other assets	21
4.1.4	HAR model with central bank announcements	22
4.1.5	Forecasting with logarithmic HAR models	23
4.2	Methods for Model Comparison	23
4.2.1	Model comparison in-sample	24
4.2.2	Model comparison out-of-sample	24
4.3	Regression model for intra-day returns around interest rate announcements	26
5	Results	29
5.1	In-sample results	29
5.2	Out-of-sample results	34
5.3	Influence of interest rate announcements on realized volatility of Bitcoin	43
5.4	High-frequency response to interest rate announcements	44
6	Conclusion	49
	References	53

List of Tables

3.1	Descriptive statistics for returns series of the assets	12
3.2	Descriptive statistics for realized variance of Bitcoin	17
3.3	Correlation of realized variance of the assets	17
3.4	Central banks considered and number of announcements	18
5.1	Parameter values for HAR models extended with daily realized variance and daily, weekly, and monthly realized variance	31
5.2	Parameter values for HAR models extended with returns	33
5.3	Loss function values for one day, five days, and 22 days cumulative predictions using HAR models with daily RV	37
5.4	Loss function values for one day, five days, and 22 days cumulative predictions using HAR model with daily, weekly, and monthly RV	38
5.5	MCS results for one day, five days, and 22 days cumulative predictions using HAR models with daily RV	39
5.6	MCS results for one day, five days, and 22 days cumulative predictions using HAR models with daily, weekly, and monthly RV	39
5.7	Loss function values for one day, five days, and 22 days cumulative predictions using HAR models with returns	41

5.8	MCS results for one day, five days, and 22 days cumulative predictions using HAR models with returns	42
5.9	Parameter values for HAR model with central bank announcements	44
5.10	Parameter values for intra-day return regression on central bank announcements	48

List of Figures

3.1	Plot of RV for all assets	15
3.2	Plot of logarithmic RV for all assets	16
5.1	Realized variance of Bitcoin against fitted values from the base HAR model . . .	29
5.2	Plot of one day prediction using the base HAR model against true realize variance	34
5.3	Plot of cumulative five days prediction using the base HAR model against true realize variance	35
5.4	Plot of cumulative 22 days prediction using the base HAR model against true realize variance	35
5.5	Plot of intra-day logarithmic prices for certain interest rate announcement days for ECB, RBA, BoE, BoJ, BoC, and SNB	47

1

Introduction

Bitcoin was established in 2008 and is a form of digital payment medium that made way for a new class of assets known as cryptocurrencies. A cryptocurrency can formally be defined as "a digital asset designed to work as a medium of exchange using cryptography to secure the transactions and to control the creation of additional units of currency" (Tsai, Blower, Zhu, & Yu, 2016). Bitcoin is the cryptocurrency with the highest market capitalization, and its popularity has increased enormously over the last years, evident by the coin now being traded on more than 500 exchanges (Sedgwick, 2018). The cryptocurrency market as a whole has also experienced rapid growth. At the start of 2017, the market capitalization of cryptocurrencies was just above 19 billion USD. In January 2018, it reached an all-time high with a market capitalization of 800 billion USD, an increase of over 4100%. In April 2019, this number was down to 180 billion USD¹. The sizeable price movements this asset demonstrates over relatively short periods of time are unusual compared to traditional currencies, stock indices, and commodities. Increased knowledge about the volatility process of Bitcoin is essential in order to understand its place in risk management and portfolio optimization.

The main way Bitcoin differs from traditional assets is that it is decentralized, not being issued by a government and is not attached to a specific economy. The existing literature about the nature of cryptocurrencies often discuss whether cryptocurrencies should be classified as a medium of exchange or speculative investment (Baek & Elbeck, 2015; Dyhrberg, 2016; Glaser, Zimmermann, Haferkorn, Weber, & Siering, 2014). Some studies find that Bitcoin returns are not correlated with any of the major exchange rates, concluding that it is a unique asset class (Baur, Hong, & Lee, 2018; Yermack, 2015). Furthermore, Yermack (2015) finds that in 2013,

¹Market capitalization data can be extracted from <https://coinmarketcap.com/charts/>. History from 2013 is provided.

the yearly volatility of Bitcoin was much higher than the volatility of the exchange rates of euro, yen, British pound, and Swiss franc. Moreover, Dyhrberg (2016) and Baur, Dimpfl, and Kuck (2018), among others, have studied how Bitcoin behave compared to the US dollar and gold. Dyhrberg (2016) classifies Bitcoin between gold and the US dollar, while Baur, Dimpfl, and Kuck (2018) concludes that Bitcoin's return, volatility and correlation characteristics compared to the US dollar and gold, are distinctly different. This supports the suggestion that Bitcoin can be characterized as a distinct asset class with its own unique characteristics (Burniske & White, 2017).

Although the study of the price dynamics and volatility of Bitcoin has gained popularity, there are still many directions left to explore. The volatility of an asset tells the extent to which the price of the asset changes over time. In finance, it is common to develop volatility models in order to estimate and predict the price movements of an asset. One such model is the heterogeneous autoregressive (HAR) model, which utilizes the realized variance of the asset in question. The realized variance is calculated using high-frequency data. Today many assets, including Bitcoin, have tick-by-tick data readily available online. The availability of high-frequency data provides the opportunity to calculate more precise volatility estimates based on intra-day returns. HAR models have been found to have strong predictive power, due to high persistence in realized volatility. Vortelinos (2017) concludes that the HAR model outperforms both nonlinear models like Principal Components Combining, neural networks and GARCH for, among others, foreign exchange rates, bonds and commodities options.

This paper uses extensions of the HAR model together with high-frequency data for traditional currencies, S&P500 and precious metals in order to investigate how the volatility of these assets influences that of Bitcoin. Furthermore, we analyze how the returns of Bitcoin itself and that of these other assets affect the volatility of Bitcoin. We also investigate the claim made by Kristoufek (2013) that macroeconomic expectations do not influence Bitcoin by studying how interest rate announcements from central banks affect the Bitcoin volatility. The influence of the volatility and returns of these asset classes is a research area that has been explored only minimally. To the best of our knowledge, this paper is the first to utilize the HAR model to investigate the influence of other assets' volatility on the volatility of Bitcoin, as well as the effect of central bank interest rate announcements. This paper thereby contributes new information on the topic.

In our analysis, we consider six major FX rates: EUR-USD, AUD-USD, GBP-USD, JPY-USD, CAD-USD, and CHF-USD. The S&P00 index is used as a proxy for the stock market. The precious metals gold (XAU) and silver (XAG) are also considered. We investigate both the in-sample estimation and out-of-sample prediction of Bitcoin's volatility, and how including the volatility and returns of FX rates, S&P500, and precious metals can improve the Bitcoin volatility model. Furthermore, this paper investigates the influence of interest rate announcements made by seven central banks, the six associated with the aforementioned currencies, as well as the Federal Reserve. Our findings indicate that the volatility and returns of the considered assets do not have explanatory power for the volatility of Bitcoin. Furthermore, we find that interest rate announcements from central banks do not significantly affect the volatility of Bitcoin.

The rest of this paper is organized as follows: section 2 presents an overview of research on volatility estimation of Bitcoin, realized variance, volatility spillover and macroeconomic news announcements. In Section 3 our data is presented. Section 4 explains our methodology. Section 5 presents the results. Finally, section 6 will summarise and conclude.

2

Literature Review

Although cryptocurrencies are a relatively new phenomenon, some work has been conducted on volatility modelling of this market. Bitcoin is particularly popular, as it is the digital asset with the longest history. Letra (2016) estimates a GARCH(1,1) model on daily data where he includes content from Google Trends, Wikipedia and Twitter tweets and finds that Bitcoin returns are highly driven by popularity. Catania, Grassi, and Ravazzolo (2018) argue for more sophisticated volatility models with the inclusion of leverage effect and time-varying skewness. Chu, Chan, Nadarajah, and Osterrieder (2017) were the first to provide a paper on GARCH modelling on the seven most popular cryptocurrencies. Out of 12 GARCH type of models, they conclude that IGARCH and GJR-GARCH fit the data best based on information criteria. Bouoiyour and Selmi (2015a) find that the volatility of Bitcoin is more influenced by negative shocks than positive ones, giving evidence of leverage effects.

As high-frequency data has become more readily available, it has been used to study different financial markets, such as commodities (Baillie, Han, Myers, & Song, 2007; Birkelund, Haugom, Molnár, Opdal, & Westgaard, 2015; Cai, Cheung, & Wong, 2001; Haugom, Langeland, Molnár, & Westgaard, 2014; Lyócsa & Molnár, 2016, 2018; Martens & Zein, 2004), stocks and stock indices (Bonanno, Lillo, & Mantegna, 2001; Bugge, Guttormsen, Molnár, & Ringdal, 2016; Castura, Litzenberger, Gorelick, & Dwivedi, 2010; Dobrev & Szerszen, 2010; Horpestad, Lyócsa, Molnár, & Olsen, 2019; Lyócsa & Molnár, 2017) and currencies (Lyócsa, Molnár, & Fedorko, 2016). Andersen, Bollerslev, Diebold, and Labys (2001a) were some of the first to calculate realized variance and covariance for USD-DEM and YEN-DEM, finding a strong correlation between the two exchange rate volatilities. Sihabuddin, Subanar, and Winarko (2014) perform

a multivariate time series analysis, and study six FX rates' correlation with their respective country's interest rate and each other. They find that FX rates are highly correlated both with interest rates and with each other. They therefore conclude that one exchange rate can be used as an explanatory variable in the prediction of another. In this paper, we investigate if a similar predictive ability is present between exchange rates and Bitcoin.

There are a few examples of volatility modelling of Bitcoin using high-frequency data to calculate realized variance. Aalborg, Molnár, and de Vries (2018) combine the HAR-RV model with other explanatory variables, like Google trends and traded volume, to explain and predict the changes in Bitcoin's daily and weekly volatility. They find that the past daily, weekly, and monthly realized variance have high explanatory power in the HAR model. Kurka (2016) uses HAR and GARCH models to examine the patterns and drivers of volatility in Bitcoin, and find evidence of the leverage effect and high persistence of volatility shocks. Bergsli and Lind (2018) were some of the first to compare both several GARCH models and regular and logarithmic HAR models in- and out-of-sample. They conclude that the HAR models outperform GARCH models both in- and out-of-sample. Additionally, they find that these models have a superior predictive ability when considering shorter time horizons. This paper therefore utilizes the HAR model as a benchmark, and studies the effects of adding additional explanatory variables.

With the surge of activity in the cryptocurrency market, researchers have increasingly studied its movements in relation to other widely traded asset classes. Dyhrberg (2016) studies the market dynamics between Bitcoin and several other financial assets, finding that the USD-EUR and USD-GBP exchange rates have explanatory power for both returns and volatility, when using a GARCH(1,1) volatility model. Baur, Dimpfl, and Kuck (2018) oppose her findings. They conclude that there is no correlation between Bitcoin return and gold and fiat currencies. This is supported by Bouoiyour and Selmi (2015b), who find that the price of Bitcoin exhibits unpleasant speculative behaviour. van de Klashorst, Quaedvlieg, and Chalabi (2018) investigate the interaction between cryptocurrencies and the equity market, finding evidence of volatility spillover effects in the direction from S&P500 and Nikkei 225 to the five cryptocurrencies considered, but not vice versa. Trabelsi (2018) researches the connectedness across the Bitcoin index and other widely traded asset classes, finding no significant volatility spillover

effects between the cryptocurrency market and other financial markets, suggesting that cryptocurrencies truly are independent financial instruments. This is also studied by Bouri, Das, Gupta, and Roubaud (2018), who find that the Bitcoin market is not completely isolated, as the returns of Bitcoin are quite closely related to those of the other assets studied. The results also suggest that Bitcoin receives more volatility than it transfers, in line with the findings of van de Klashorst et al. (2018). Given that the research provides contradicting results, we believe there is still room for further analysis in this area.

Several studies have linked macroeconomic news surprises to increases in the FX and stock market volatility (Bauwens, Omrane, & Giot, 2005; Hussain, 2011; Lyócsa, Molnár, & Plíhal, 2019; Omrane & Hafner, 2015). For example, Omrane and Hafner (2015) use high-frequency data to study the effect of scheduled and unscheduled macroeconomic news surprises related to US, UK, Europe and Japan, on the exchange rate volatility of EUR/USD, GBP/USD and USD/JPY. They find significant effects from some European and US news surprises on the volatility of both the Pound and the Yen.

There are also some studies on the topic of macroeconomic news and Bitcoin. However, this area of research is rather limited. Corbet, McHugh, and Meegan (2017) investigate the effects of international monetary policy changes on Bitcoin. The results indicate that interest rate decisions in the US significantly impact Bitcoin returns and that quantitative easing announcements made by the US, EU, UK and Japan have an effect on volatility. Al-Khazali, Elie, Roubaud, et al. (2018) compared Bitcoin and gold with regard to the impact of macroeconomic news surprises from large developed economies on returns and volatility. They find that gold reacts in a manner consistent with its role as a safe haven, whereas Bitcoin behaves mostly in a manner not similar to that of gold. Corbet, Larkin, Lucey, Meegan, and Yarovaya (2018) examine the relationship between Bitcoin returns and four types of macroeconomic news announcements, finding that news regarding unemployment and durable goods have a significant impact, while news relating to GDP and CPI do not. Corbet, Larkin, Lucey, Meegan, and Yarovaya (2017) study the reactions of several cryptocurrencies to announcements regarding the US Federal Fund interest rate and quantitative easing. They classify each digital asset as either a currency, protocol or decentralized application, finding that the reactions of cryptocurrencies are linked

to their classification. Moreover, they find that monetary policy shocks affect currency-based digital assets more than others. As Bitcoin can be bought and sold using traditional currencies, this paper aims to investigate if factors that affect the volatility of the FX market also have an impact on Bitcoin. In particular, we consider interest rate announcements.

3

Data

3.1 Returns

We have gathered tick-by-tick high-frequency data for the FX rates and gold and silver from Dukascopy, a Swiss online bank. The data was extracted using the tool Quant Data Manager. We study six major exchange rates: EUR-USD, AUD-USD, GBP-USD, JPY-USD, CAD-USD, and CHF-USD. The Bitcoin data was collected from the Bitstamp exchange. This exchange was founded in 2011, making it one of the oldest Bitcoin exchanges (Shin, 2016). Through the exchange's API, we were able to retrieve high-frequency data of relatively high quality. For S&P500 we downloaded five-minute realized variance directly¹. Daily S&P500 prices were downloaded from Yahoo! Finance in order to calculate daily returns.

We used the rules proposed by Barndorff-Nielsen, Hansen, Lunde, and Shephard (2009) to clean the high-frequency datasets for the FX rates and precious metals:

- Delete entries where bid or ask is zero.
- Remove entries where the ask is lower than the bid.
- If multiple entries have the same timestamp, replace them with a single entry using the median bid and median ask.
- Remove entries where the spread is more than 50 times the median spread for that day.

¹Can be downloaded from the Realized Library at <https://realized.oxford-man.ox.ac.uk/>

The Bitcoin dataset contains transaction prices, and therefore no bid and ask. We deleted all transaction prices that were zero and replaced multiple entries with the same timestamp with the median transaction price, in accordance with rule one and three above.

For all the assets, we extracted data for the time period 01-Jan-14 to 05-Feb-19. During the weekends, the activity slows to a halt for all assets except Bitcoin, and the weekends are therefore excluded from all the data samples (Bollerslev & Domowitz, 1993). Furthermore, traditional assets lack transaction data for specific holidays. Such dates were therefore also excluded from our datasets. In total, each dataset contains price data for 1274 days. We consider this time frame representative, and since Bitcoin is a relatively new phenomenon, data before this period is not of the desired quality.

The datasets for the FX rates and precious metals contain both bid and ask quotes. Therefore, we use the logarithmic middle price. Gençay, Dacorogna, Muller, Pictet, and Olsen (2001) consider this the most relevant price of study and a better approximation of the true price than using either only the bid or ask price. Moreover, the logarithmic middle price is perfectly asymmetric, and therefore statistical results based on absolute differences of the price and volatility will be identical and independent of whether we, for example, look at USD-EUR or EUR-USD (Gençay et al., 2001). The logarithmic middle price at time t is computed as:

$$p_t = \frac{\log(p_{\text{bid},t}) + \log(p_{\text{ask},t})}{2} \quad (1)$$

Where $p_{\text{bid},t}$ and $p_{\text{ask},t}$ are the bid and ask price, respectively. From this transformation, returns for the FXs rates and the precious metals are calculated as:

$$R_t = p_t - p_{t-1} \quad (2)$$

For S&P500 we downloaded daily prices directly, while for Bitcoin we retrieved the last quoted price for each day from the high-frequency dataset. Returns are calculated using these prices:

$$R_t = \log\left(\frac{p_t}{p_{t-1}}\right) \quad (3)$$

Where p_t is the price of the asset at time t .

Table 3.1 gives a summary of the descriptive statistics for the returns of Bitcoin (BTC), EUR-USD, AUD-USD, GBP-USD, CAD-USD, JPY-USD, CHF-USD, S&P500, XAU, and XAG. All the FX rates are left-skewed, except EUR-USD, which is right-skewed. S&P500 returns, XAG returns, and BTC returns also exhibit left-skewness, while XAU returns are right-skewed. All returns series are characterized by excess kurtosis. Combined, these factors indicate non-normality for all the assets' returns series, which is confirmed by the Jarque-Bera test. The test concludes that none of the returns series is normally distributed. Moreover, none include a unit root, shown by the rejection of the null hypothesis in the Augmented Dickey-Fuller (ADF) test.

Asset	Statistic										
	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	p-value	ADF Test statistics	p-value
<i>BTC</i>	1.16×10^{-3}	1.98×10^{-3}	2.38×10^{-1}	-2.81×10^{-1}	4.65×10^{-2}	-0.22	8.08	1.38×10^3	0.00	-9.86	< 0.01
<i>EUR-USD</i>	-1.42×10^{-4}	-6.08×10^{-4}	2.86×10^{-2}	-2.36×10^{-2}	5.32×10^{-3}	1.41×10^{-3}	5.17	250.65	0.00	-10.88	< 0.01
<i>AUD-USD</i>	-1.63×10^{-4}	1.90×10^{-4}	2.06×10^{-2}	-2.18×10^{-2}	6.13×10^{-3}	-9.50×10^{-2}	3.57	19.35	0.00	-11.40	< 0.01
<i>GBP-USD</i>	-1.88×10^{-4}	1.53×10^{-4}	2.26×10^{-2}	-6.26×10^{-2}	5.78×10^{-3}	-0.12	15.26	827.38	0.00	-11.38	< 0.01
<i>JPY-USD</i>	3.73×10^{-5}	1.56×10^{-4}	2.79×10^{-2}	-3.12×10^{-2}	5.69×10^{-3}	-0.29	5.95	478.93	0.00	-10.44	< 0.01
<i>CAD-USD</i>	1.63×10^{-4}	3.00×10^{-4}	1.87×10^{-2}	-1.96×10^{-2}	4.94×10^{-3}	-0.11	3.86	44.08	0.00	-10.55	< 0.01
<i>CHF-USD</i>	8.33×10^{-5}	3.60×10^{-4}	2.36×10^{-2}	-1.76×10^{-1}	7.11×10^{-3}	-12.08	301.28	4.75×10^6	0.00	-12.75	< 0.01
<i>S&P500</i>	3.16×10^{-4}	4.52×10^{-4}	4.84×10^{-2}	-4.18×10^{-2}	8.40×10^{-3}	-0.47	6.78	802.55	0.00	-11.70	< 0.01
<i>XAU</i>	5.65×10^{-5}	3.55×10^{-5}	3.74×10^{-2}	-3.38×10^{-2}	8.05×10^{-3}	0.19	5.06	232.85	0.00	-11.15	< 0.01
<i>XAG</i>	-1.83×10^{-4}	-6.64×10^{-5}	5.75×10^{-2}	-7.00×10^{-2}	1.33×10^{-2}	-0.11	6.29	575.55	0.00	-11.78	< 0.01

Table 3.1: Descriptive statistics for returns of BTC, EUR-USD, AUD-USD, GBP-USD, CAD-USD, JPY-USD, CHF-USD, S&P500, XAU, and XAG, for the time period 01-Jan-14 to 05-Feb-19.

3.2 Realized Variance

The availability of high-frequency data makes it possible to estimate realized variance (RV) as a variance proxy for the assets. FX rates are traded 24 hours a day Monday to Thursday, and on Friday the market is closed from 21:00 (summer time) or 22:00 (winter time). Gold and silver are traded 23 hours a day, excluding weekends (FOREX.com, 2019). The New York Stock Exchange is open between 09:30 and 16:00 Monday to Friday. Bitcoin is traded 24-hours a day, seven days a week. Since we compare the different assets, we exclude weekends and bank holidays from all datasets, see the section above about data cleaning.

For the FX rates, precious metals, and Bitcoin, we calculate the realized variance. Christoffersen (2011) estimates daily variance from m evenly spaced intraday squared returns defined as:

$$RV_{t+1}^m = \sum_{j=1}^m R_{t+j/m}^2 \quad (4)$$

With m observations within a day, the realized variance can be calculated as the daily variance using the following formula:

$$RV_{t+1}^m = \sum_{j=1}^m R_{t+j/m}^2 \quad (5)$$

The FX rates have 24-hours with trading Monday to Thursday, but only 21 or 22 hours on Fridays, depending on the season. For these assets, we therefore scale realized variance for Fridays to get 24 hours realized variance for each day. This method has been utilized in previous research (Angelidis & Degiannakis, 2008; Koopman, Jungbacker, & Hol, 2005; Martens, 2002).

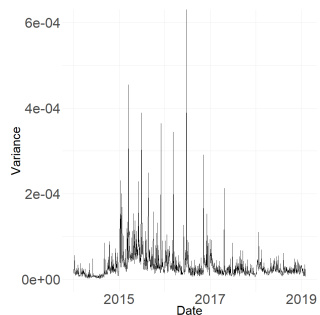
For the traditional currencies and the precious metals, we use a five-minute grid to compute the realized variance. Andersen, Bollerslev, Diebold, and Labys (2001b) explain that using a five-minute grid will make sure that RVs for the FX rates are largely free of measurement errors and microstructure biases will not be a major concern. Khalifa, Miao, and Ramchander (2011) conclude that a five-minute grid has low error for precious metals, including gold and silver. Using a five-minute grid to calculate realized variance for traditional assets is a popular choice in academic literature. Bitcoin returns are much noisier, and to make microstructure biases a minor concern, we estimate an average realized variance (Patton & Sheppard, 2009). Here we use grids of 10-, 15-, and 30-minutes, and find the average realized variance. For all cases, the

grid is computed by taking the last observation for each of the periods.

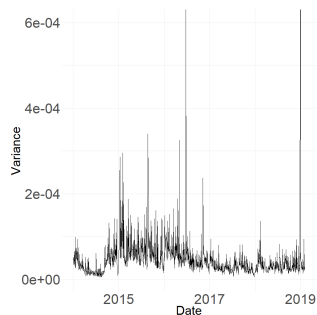
For S&P500 we downloaded the five-minute realized variance directly from the Oxford-Man Institute of Quantitative Finance².

Figure 3.1 shows the plots of the realized variance for the FX rates, S&P500, XAU, XAG, and Bitcoin. Figure 3.1a to 3.1f plot the realized variance for each of the traditional currencies. Figure 3.1g plots it for S&P500, and figure 3.1h to 3.1i plot the series for gold and silver, respectively. Figure 3.1j plots RV for Bitcoin. Notice the different scales of the plots. Bitcoin is considerably more volatile than the other currencies, requiring a larger scale. Figure 3.2 provides the same plots, only for the logarithmic transformation of the realized variances.

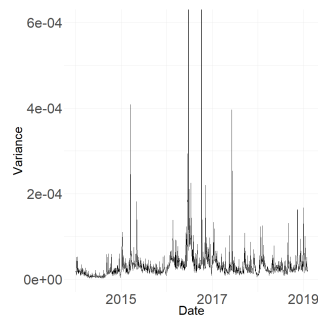
²Can be downloaded from the Realized Library at <https://realized.oxford-man.ox.ac.uk/>



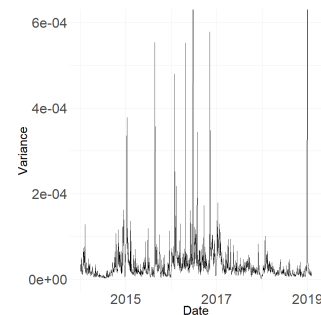
(a) RV EUR-USD



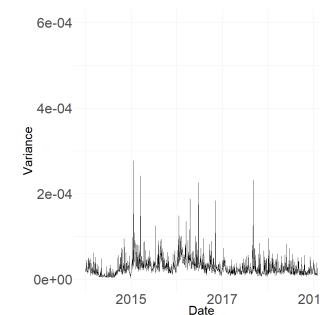
(b) RV AUD-USD



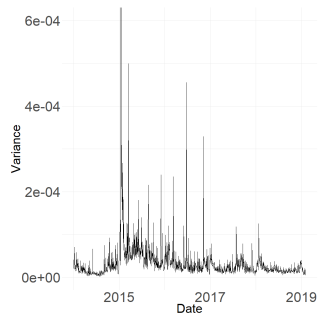
(c) RV GBP-USD



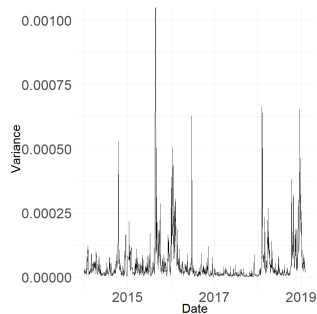
(d) RV JPY-USD



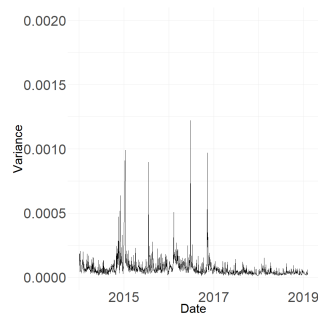
(e) RV CAD-USD



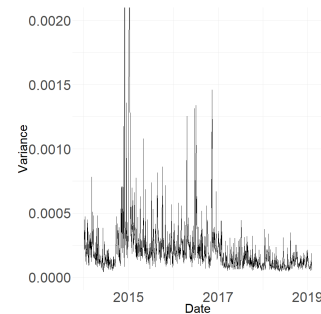
(f) RV CHF-USD



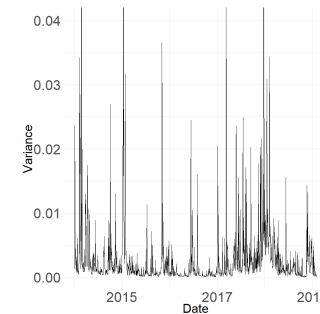
(g) RV S&P500



(h) RV XAU



(i) RV XAG



(j) RV BTC

Figure 3.1: Plot of realized variance. 5-min. grid used for EUR-USD, AUD-USD, GBP-USD, JPY-USD, CAD-USD, CHF-USD, S&P500, XAU, and XAG, and the average of 10, 15, and 30-minute grids used for BTC. Data for the period 01-Jan-14 to 05-Feb-19.

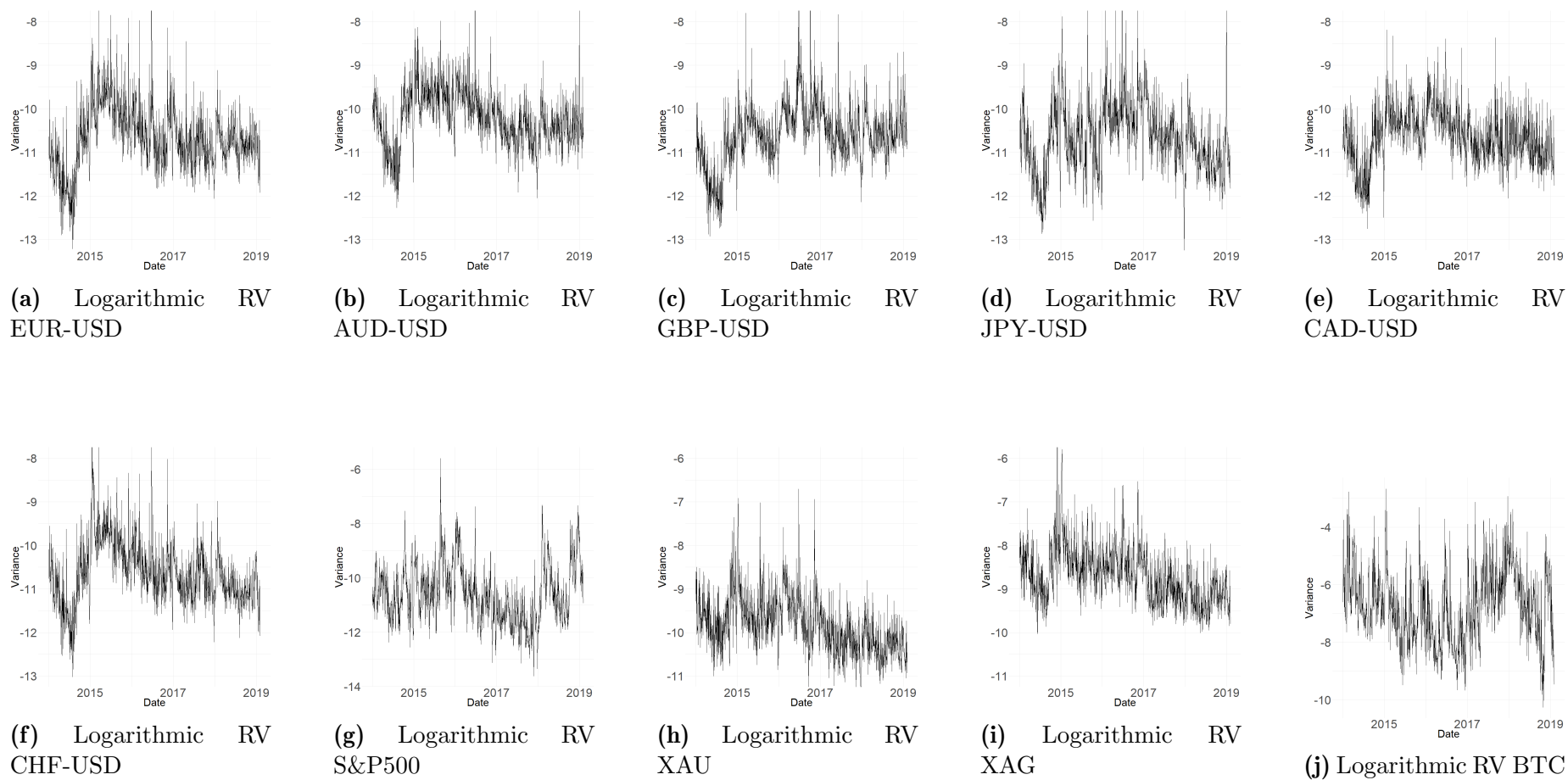


Figure 3.2: Plot of logarithmic realized variance. 5-min. grid used for EUR-USD, AUD-USD, GBP-USD, JPY-USD, CAD-USD, CHF-USD, S&P500, XAU, and XAG, and the average of 10, 15, and 30-minute grids used for BTC. Data for the period 01-Jan-14 to 05-Feb-19.

Table 3.2 provides the descriptive statistics for the realized variance of Bitcoin and its logarithmic transformation. Based on the descriptive statistics and the plots in figures 3.1 and 3.2, we observe that the logarithmic version of the realized variance has superior statistical properties compared to the raw version of the RV, providing more precise coefficient estimates when using OLS (Christoffersen, 2011; Gonçalves & Meddahi, 2011). In the estimation of the HAR models, we will therefore use the logarithmic transformation of the realized variance.

Statistic	<i>RV</i>	<i>LogRV</i>
<i>Mean</i>	-2.67×10^{-3}	-6.80
<i>Median</i>	1.05×10^{-3}	-6.86
<i>Max</i>	0.07	-2.66
<i>Min</i>	3.50×10^{-5}	-10.26
<i>Std. Dev.</i>	5.28×10^{-3}	1.28
<i>Skewness</i>	5.91	0.27
<i>Kurtosis</i>	52.82	2.78
<i>Jarque-Bera</i>	1.39×10^5	18.07
<i>p-value</i>	0.00	0.00
<i>ADF Test statistics</i>	-6.74	-4.86
<i>p-value</i>	< 0.01	< 0.01

Table 3.2: Descriptive statistics for raw realized variance and logarithmic realized variance of Bitcoin for the time period 01-Jan-14 to 05-Feb-19.

Table 3.3 shows the unconditional correlation of the realized variances of the considered assets. We observe that Bitcoin's realized variance seems not to be correlated with the other assets' realized variances. The CHF-USD RV is the one with the highest correlation with Bitcoin's RV, but it is nevertheless very low.

<i>Correlation</i>	<i>EUR-USD</i>	<i>AUD-USD</i>	<i>GBP-USD</i>	<i>JPY-USD</i>	<i>CAD-USD</i>	<i>CHF-USD</i>	<i>S&P500</i>	<i>XAU</i>	<i>XAG</i>	<i>BTC</i>
<i>EUR-USD</i>	1	0.54	0.34	0.53	0.53	0.17	0.29	0.53	0.29	0.01
<i>AUD-USD</i>		1	0.36	0.79	0.49	0.08	0.30	0.48	0.31	-0.01
<i>GBP-USD</i>			1	0.53	0.25	0.01	0.09	0.34	0.14	0.01
<i>JPY-USD</i>				1	0.39	0.04	0.30	0.55	0.26	0.03
<i>CAD-USD</i>					1	0.10	0.22	0.41	0.25	-0.03
<i>CHF-USD</i>						1	0.02	0.08	0.06	0.14
<i>S&P500</i>							1	0.20	0.13	0.04
<i>XAU</i>								1	0.13	0.04
<i>XAG</i>									1	0.04
<i>BTC</i>										1

Table 3.3: Correlation between the realized variance of the different assets in the time period 01-Jan-14 to 05-Feb-19.

3.3 Central bank announcements

As we wish to study the short term volatility effects of monetary policy announcements, we will look at target interest rate announcements by central banks. The purpose of target interest rates is to influence short term interest rates. The central banks considered are presented in table 3.4.

<i>Country</i>	<i>Central Bank</i>	<i>Abbreviation</i>	<i>Observations</i>
Canada	Bank of Canada	BoC	41
United Kingdom	Bank of England	BoE	50
Japan	Bank of Japan	BoJ	25
Eurozone	European Central Bank	ECB	45
United States	Federal Reserve	FED	41
Australia	Reserve Bank of Australia	RBA	56
Switzerland	Swiss National Bank	SNB	21

Table 3.4: Central banks considered and number of announcements made by each bank in the time period 01-Jan-14 to 05-Feb-19.

Announcement dates are easily collected from press releases for each central bank, and for most banks there is a consistent number of announcements each year. The exception is Japan, that on April 4, 2013 introduced the "Quantitative and Qualitative Monetary Easing". In this phase of monetary easing, the Bank of Japan would target a doubling of the monetary base through Japanese government bonds. A target interest rate was reintroduced on January 29, 2016, when the Bank of Japan decided to apply a negative interest rate to current accounts. Due to these changes in policy, there is no target interest announcements for the Bank of Japan in the period before January 29, 2016.

4

Methodology

4.1 HAR Models

This paper examines if the volatility or returns of traditional currencies, S&P500, gold, or silver have an influence on the volatility of Bitcoin. The currencies studied are EUR-USD, AUD-USD, GBP-USD, JPY-USD, CAD-USD, and CHF-USD. All of these assets will be referred to as the relevant assets. In all the HAR model specifications below, RV represents the logarithmic transformation of the realized variance.

4.1.1 Base HAR Model

Bergsli and Lind (2018) find that the heterogeneous autoregressive (HAR) model has a superior ability both in- and out-of-sample when modelling the volatility of Bitcoin. HAR models have the ability to capture the long-memory features of realized variance (Corsi, 2009). It can be estimated using simple ordinary least square (OLS) where daily, weekly, and monthly realized variances are used as the explanatory variables. In our data, we have excluded weekends, resulting in five-day weeks and 22-day months.

We define the simple moving averages of realized variance for the assets as:

$$\begin{aligned}RV_{D,t}^{(x)} &= RV_t^{(x)} \\RV_{W,t}^{(x)} &= RV_{t-4,t}^{(x)} = \frac{RV_{t-4}^{(x)} + RV_{t-3}^{(x)} + \dots + RV_t^{(x)}}{5} \\RV_{M,t}^{(x)} &= RV_{t-21,t}^{(x)} = \frac{RV_{t-21}^{(x)} + RV_{t-20}^{(x)} + \dots + RV_t^{(x)}}{22}\end{aligned}\tag{6}$$

Where x denotes the asset.

We can specify the HAR model by Corsi (2009) for Bitcoin as:

$$RV_{t+1}^{(BTC)} = \phi_0^{(BTC)} + \phi_D^{(BTC)} RV_{D,t}^{(BTC)} + \phi_W^{(BTC)} RV_{W,t}^{(BTC)} + \phi_M^{(BTC)} RV_{M,t}^{(BTC)} + \varepsilon_{t+1}^{(BTC)} \quad (7)$$

Equation (7) will be our benchmark volatility model for Bitcoin. All other models will be compared to this one.

4.1.2 HAR models with realized variance of other assets

Our first extension of the HAR model includes the realized variance of another asset in order to see whether there is evidence of volatility spillovers from the included asset to Bitcoin. Let $RV_t^{(BTC)}$ be the realized variance of Bitcoin at time t , and $RV_t^{(x)}$ be the realized variance of asset x at time t . x is a placeholder for EUR-USD, AUD-USD, GBP-USD, JPY-USD, CAD-USD, CHF-USD, S&P500, XAU, or XAG.

We first consider the HAR model extended with only the daily realized variance of another asset:

$$RV_{t+1}^{(BTC)} = \phi_0^{(BTC)} + \phi_D^{(BTC)} RV_{D,t}^{(BTC)} + \phi_W^{(BTC)} RV_{W,t}^{(BTC)} + \phi_M^{(BTC)} RV_{M,t}^{(BTC)} + \phi_D^{(x)} RV_{D,t}^{(x)} + \varepsilon_{t+1}^{(BTC)} \quad (8)$$

Furthermore, we also extend the model with both the daily, weekly, and monthly realized variance of the aforementioned assets:

$$\begin{aligned} RV_{t+1}^{(BTC)} = & \phi_0^{(BTC)} + \phi_D^{(BTC)} RV_{D,t}^{(BTC)} + \phi_W^{(BTC)} RV_{W,t}^{(BTC)} + \phi_M^{(BTC)} RV_{M,t}^{(BTC)} \\ & + \phi_D^{(x)} RV_{D,t}^{(x)} + \phi_W^{(x)} RV_{W,t}^{(x)} + \phi_M^{(x)} RV_{M,t}^{(x)} + \varepsilon_{t+1}^{(BTC)} \end{aligned} \quad (9)$$

This extension is made in order to also account for weekly and monthly volatility spillovers, as well as daily ones.

4.1.3 HAR model with returns of Bitcoin and other assets

We also consider how the returns of Bitcoin and other assets affect the volatility of Bitcoin. The HAR model is extended with simple moving averages of daily, weekly, and monthly returns for assets:

$$R_{D,t}^{(x)} = R_t^{(x)} \quad (10)$$

$$R_{W,t}^{(x)} = R_{t-4,t}^{(x)} = \frac{R_{t-4}^{(x)} + R_{t-3}^{(x)} + \dots + R_t^{(x)}}{5} \quad (11)$$

$$R_{M,t}^{(x)} = R_{t-21,t}^{(x)} = \frac{R_{t-21}^{(x)} + R_{t-20}^{(x)} + \dots + R_t^{(x)}}{22} \quad (12)$$

$$(13)$$

Here, $R_t^{(x)}$ is the return for asset x at time t .

We extend the HAR model with daily, weekly, and monthly absolute returns and absolute negative returns. The inclusion of both regular and negative returns is done to investigate if negative and positive returns have different impacts on the volatility of Bitcoin.

The HAR model including absolute returns and absolute negative returns is defined as:

$$\begin{aligned} RV_{t+1}^{(BTC)} &= \phi_0^{(BTC)} + \phi_D^{(BTC)} RV_{D,t}^{(BTC)} + \phi_W^{(BTC)} RV_{W,t}^{(BTC)} + \phi_M^{(BTC)} RV_{M,t}^{(BTC)} \\ &+ \lambda_D^{(x)} |R_{D,t}^{(x)}| + \lambda_W^{(x)} |R_{W,t}^{(x)}| + \lambda_M^{(x)} |R_{M,t}^{(x)}| \\ &+ \alpha_D^{(x)} I \left(R_{D,t}^{(x)} < 0 \right) |R_{D,t}^{(x)}| + \alpha_W^{(x)} I \left(R_{W,t}^{(x)} < 0 \right) |R_{W,t}^{(x)}| + \alpha_{M,t}^{(x)} I \left(R_{M,t}^{(x)} < 0 \right) |R_{M,t}^{(x)}| \\ &+ \varepsilon_{t+1}^{(BTC)} \end{aligned} \quad (14)$$

Here I is the indicator function which is 1 if and only if the boolean function inside it returns True. x will be BTC, EUR-USD, AUD-USD, GBP-USD, JPY-USD, CAD-USD, CHF-USD, S&P500, XAU, or XAG. BTC is included to investigate if the returns of Bitcoin itself have explanatory power for the volatility of Bitcoin.

4.1.4 HAR model with central bank announcements

As Bitcoin has many similarities with currencies, we study the effect of monetary policy announcements, more precisely target interest rate announcements made by central banks. The banks considered are presented in section 3.3. We follow the general approach of Lyócsa et al. (2019), using a regression with dummy variables for the day before, the day after and the day of an announcement, see equation (16). As Bitcoin is traded 24/7, and we in this dataset do not have any explanatory variables with missing values for weekends or holidays, we change the specification from five-day weeks and 22-day months in equation (6), to seven-day weeks and 30-day months, see equation (15). We let $B_{t+1}^{(x)}$, $N_{t+1}^{(x)}$ and $A_{t+1}^{(x)}$ be dummy variables for the day before an announcement, the day of an announcement and the day after an announcement made by bank x , respectively. The $B_{t+1}^{(x)}$ dummies are multiplied with the lagged realized variance, i.e. the realized variance two days prior to the announcement, $RV_t^{(BTC)}$, to capture the relative change in volatility. With the same reasoning, the dummies $N_{t+1}^{(x)}$ and $A_{t+1}^{(x)}$ are multiplied with the realized variance the day before the announcement, i.e., $RV_t^{(BTC)}$ and $RV_{t-1}^{(BTC)}$, respectively. We also control for day-of-the-week effects. This is done by adding dummy variables for the days of the week, which are multiplied with the lagged realized variance. We also make a version of equation (16) where x does not refer to a specific central bank, but rather any of the seven central banks considered. In this case, we do not distinguish which bank makes an announcement.

$$\begin{aligned}
RV_{D,t}^{(x)} &= RV_t^{(x)} \\
RV_{W,t}^{(x)} &= RV_{t-6,t}^{(x)} = \frac{RV_{t-6}^{(x)} + RV_{t-5}^{(x)} + \dots + RV_t^{(x)}}{7} \\
RV_{M,t}^{(x)} &= RV_{t-29,t}^{(x)} = \frac{RV_{t-29}^{(x)} + RV_{t-28}^{(x)} + \dots + RV_t^{(x)}}{30}
\end{aligned} \tag{15}$$

$$\begin{aligned}
RV_{t+1}^{(BTC)} &= \phi_0^{(BTC)} + \phi_D^{(BTC)} RV_{D,t}^{(BTC)} + \phi_W^{(BTC)} RV_{W,t}^{(BTC)} + \phi_M^{(BTC)} RV_{M,t}^{(BTC)} \\
&+ \lambda_B^{(x)} B_{t+1}^{(x)} RV_t^{(BTC)} + \lambda_N^{(x)} N_{t+1}^{(x)} RV_t^{(BTC)} + \lambda_A^{(x)} A_{t+1}^{(x)} RV_{t-1}^{(BTC)} \\
&+ \mu_{Mon} Mon_{t+1} RV_t^{(BTC)} + \mu_{Tue} Tue_{t+1} RV_t^{(BTC)} + \mu_{Thu} Thu_{t+1} RV_t^{(BTC)} \\
&+ \mu_{Fri} Fri_{t+1} RV_t^{(BTC)} + \mu_{Sat} Sat_{t+1} RV_t^{(BTC)} + \mu_{Sun} Sun_{t+1} RV_t^{(BTC)} + \varepsilon_{t+1}^{(BTC)}
\end{aligned} \tag{16}$$

To be able to compare this model to a base HAR model, we need to make an alternative specification of the model in equation (7). We now use seven-day weeks and 30-day months, as specified in equation (15), as well as dummy variables for the day of the week. Equation (17) specifies the new base HAR model.

$$\begin{aligned}
RV_{t+1}^{(BTC)} &= \phi_0^{(BTC)} + \phi_D^{(BTC)} RV_{D,t}^{(BTC)} + \phi_W^{(BTC)} RV_{W,t}^{(BTC)} + \phi_M^{(BTC)} RV_{M,t}^{(BTC)} \\
&+ \mu_{Mon} Mon_{t+1} RV_t^{(BTC)} + \mu_{Tue} Tue_{t+1} RV_t^{(BTC)} + \mu_{Thu} Thu_{t+1} RV_t^{(BTC)} \\
&+ \mu_{Fri} Fri_{t+1} RV_t^{(BTC)} + \mu_{Sat} Sat_{t+1} RV_t^{(BTC)} + \mu_{Sun} Sun_{t+1} RV_t^{(BTC)} + \varepsilon_{t+1}^{(BTC)}
\end{aligned} \tag{17}$$

4.1.5 Forecasting with logarithmic HAR models

As the exponential function is not linear, we have to transform the logarithmic RV using the assumption of normality of the error terms in order to forecast with the logarithmic HAR model. The normality assumption of the error terms implies:

$$\varepsilon_{t+1} (0, \sigma_\varepsilon^2) \Rightarrow E_t [\exp(\varepsilon_{t+1})] = \exp(\sigma_\varepsilon^2/2) \tag{18}$$

Using this assumption, we get the following transformation for K -days ahead:

$$\begin{aligned}
RV_{t+K|t} &= \exp(\varphi_0 + \varphi_{D,K} \ln(RV_{D,t}) + \varphi_{W,K} \ln(RV_{W,t}) + \varphi_{M,K} \ln(RV_{M,t}) + \varepsilon_{t+1}) \\
&= (RV_{D,t})^{\varphi_{D,K}} (RV_{W,t})^{\varphi_{W,K}} (RV_{M,t})^{\varphi_{M,K}} \exp\left(\varphi_{0,K} + \frac{\sigma_\varepsilon^2}{2}\right)
\end{aligned} \tag{19}$$

In equation (19) RV is the true realized variance, as opposed to the logarithmic one, as in the HAR model equations.

4.2 Methods for Model Comparison

Models are compared and evaluated using AIC in-sample, and loss functions and Model Confidence Set procedure out-of-sample.

4.2.1 Model comparison in-sample

Information criteria are a common way to compare models in-sample. The Akaike information criterion (AIC) estimates the relative quality of statistical models. We let k denote the number of parameters in the model, \hat{L} the value of the maximum likelihood function, and n the number of observations. Then the Akaike information criterion, developed by Akaike (1974), is defined as:

$$AIC = 2k - 2 \ln (\hat{L}) \quad (20)$$

The model with the lowest value of AIC is preferred. The information criterion itself does not say anything about the absolute quality of the model, only the relative quality compared to other models.

4.2.2 Model comparison out-of-sample

Loss functions

In order to evaluate the extended HAR models against the base HAR model, equation (7), we use several loss functions. The general rule is that the model producing the lowest loss function value fits the data the best. Each loss function is calculated using the fitted values of the OLS regression and the true values. Let T denote the number of observations, $\hat{\sigma}_{t,i}^2$ be the fitted variance value for asset i at day t , and $\sigma_{t,i}^2$ be the variance proxy for asset i at day t , in our case, realized variance. We consider the loss functions Mean Square Error (MSE), QLIKE, Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE).

The loss functions are calculated using the following formulas:

$$MSE_i = \frac{1}{T} \sum_{t=1}^T (\hat{\sigma}_{t,i}^2 - \sigma_{t,i}^2)^2 \quad (21)$$

$$QLIKE_i = \frac{1}{T} \sum_{t=1}^T \left(\ln (\hat{\sigma}_{t,i}^2) + \frac{\sigma_{t,i}^2}{\hat{\sigma}_{t,i}^2} \right) \quad (22)$$

$$MAE_i = \frac{1}{T} \sum_{t=1}^T |\hat{\sigma}_{t,i}^2 - \sigma_{t,i}^2| \quad (23)$$

$$MAPE_i = \frac{1}{T} \sum_{t=1}^T \left| \frac{\sigma_{t,i}^2 - \hat{\sigma}_{t,i}^2}{\sigma_{t,i}^2} \right| \quad (24)$$

Model Confidence Set

In order to be able to say that a volatility model is more accurate in its predictions than another model, its loss function value has to be statistically less than the other model's. An approach for choosing the best model is the Model Confidence Set (MCS) procedure developed by Hansen, Lunde, and Nason (2011). When using MCS, the models are evaluated using a user-specified loss function. It is based on several statistic tests, which makes the user able to construct a set of superior models. Let $e_{i,t}$ be the loss function value for model i at time t , and $d_{ij,t}$ the difference between the loss function values for model i and j , $d_{ij,t} = e_{i,t} - e_{j,t}$. The relative loss of model i relative to model j can then be described by:

$$d_{i,t} = (m - 1) \sum_{j \in M} d_{ij,t}, \quad i = 1, \dots, m, \quad (25)$$

where M is a set of models of dimension m . Then, the null and alternative hypothesis of equal predictive ability of a model set M can be formulated as:

$$\begin{aligned} H_{0,M} &: E[d_{ij}] = 0, \quad \text{for all } i, j = 1, \dots, m \\ H_{1,M} &: E[d_{ij}] \neq 0, \quad \text{for some } i, j = 1, \dots, m \end{aligned}$$

Hansen et al. (2011) show that these hypothesis can be tested using two test statistics:

$$t_{ij} = \frac{\bar{d}_{ij}}{\sqrt{\hat{\sigma}^2(\bar{d}_{ij})}} \quad \text{and} \quad t_i = \frac{\bar{d}_i}{\sqrt{\hat{\sigma}^2(\bar{d}_i)}}, \quad \text{for } i, j \in M \quad (26)$$

Here \bar{d}_{ij} gives the relative sample loss between model i and j , given by $\bar{d}_{ij} = \frac{1}{m} \sum_{t=1}^m d_{ij,t}$. Then $\bar{d}_{i,\cdot} = \frac{1}{m-1} \sum_{j \in M} \bar{d}_{ij}$ gives the simple loss of model i relative to the average of losses for all models in M . $\hat{\sigma}^2(\bar{d}_{ij})$ and $\hat{\sigma}^2(\bar{d}_{i,\cdot})$ are bootstrapped estimates of $\sigma^2(\bar{d}_{ij})$ and $\sigma^2(\bar{d}_{i,\cdot})$. The test statistics are then constructed as:

$$T_{R,M} = \max_{i,j \in M} |t_{ij}| \quad \text{and} \quad T_{\max,M} = \max_{i \in M} t_i. \quad (27)$$

The relevant distribution under the null hypothesis has to be estimated using bootstrapping since it is asymptotic and nonstandard. If the test statistics are larger than the bootstrapped estimates, the null hypothesis is rejected, and the models compared have different predictive abilities.

4.3 Regression model for intra-day returns around interest rate announcements

In order to evaluate if central bank interest rate announcements have an effect on asset's returns, we utilize a regression model. The purpose of the model is to capture the effects of an announcement in the immediate time around the announcement. We let the announcement time-interval go from five minutes before to five minutes after the announcement.

For central bank x we extract all five minute returns for asset y three hours before and after an announcement, and run the following regression:

$$R_t^{(y)} = \gamma_0 + \gamma_1 D0_t^{(x)} + \gamma_2 D+_t^{(x)} + \gamma_3 D-_t^{(x)} + \varepsilon_t \quad (28)$$

$R_t^{(y)}$ is the five-minutes return for asset y at time t . $D0$, $D+$, and $D-$ are dummy variables that take the following values:

- $D0_t = 1$ if t is in the announcement time-interval and the interest rate is unchanged.
- $D+_t = 1$ if t is in the announcement time-interval and the interest is increased.
- $D-_t = 1$ if t is in the announcement time-interval and the interest is decreased.

If the regression gives significant γ_1 , it indicates that when bank x announces to keep interest rate unchanged, it has a significant influence on the returns of asset y at the time of the announcement. Significant γ_2 indicates that increasing the interest rate influences the return of asset y at the time of announcement, while significant γ_3 implies the same for an interest rate decrease.

5

Results

5.1 In-sample results

Using equation (7) we estimate the base HAR model for the realized variance of Bitcoin. Figure 5.1 plots the base HAR model's fitted realized variance against the variance proxy; the average realized variance for Bitcoin, as explained in section 3.2. All extended HAR in-sample models will be compared to this base HAR model.

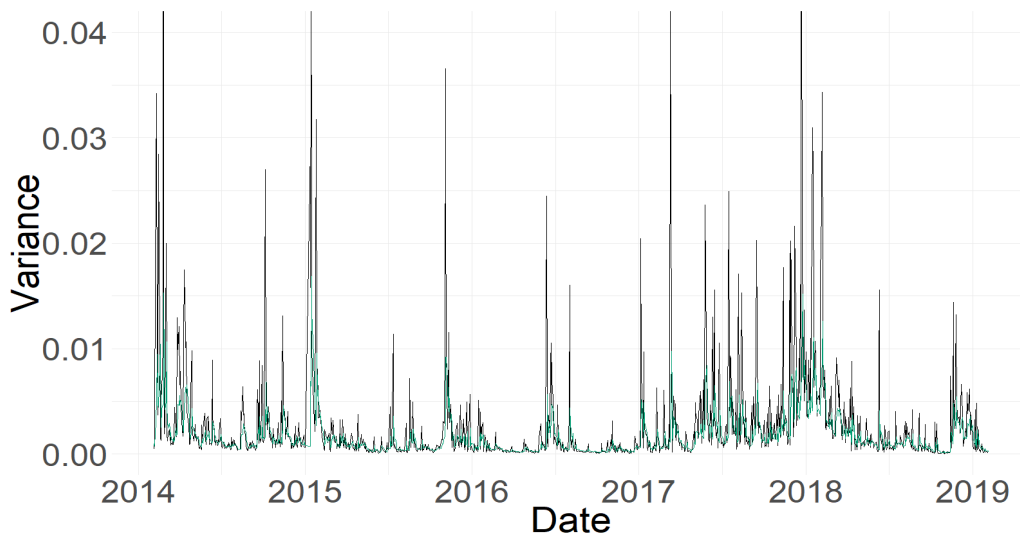


Figure 5.1: Plot of the realized variance of Bitcoin (black) against the fitted realized variance (green) from the base HAR model. Data for the time period 01-Jan-14 to 05-Feb-19.

For each of the FX rates, the S&P500, and the two precious metals, we estimate two HAR models extended with the realized variance of other assets. One model contains only the daily realized variance of other assets, while the other contains daily, weekly, and monthly realized variances of other assets. The models are specified in equations (8) and (9), respectively. We

let x be EUR-USD, AUD-USD, GBP-USD, JPY-USD, CAD-USD, CHF-USD, S&P500, XAU, or XAG in the equations. Table 5.1 presents the coefficients of the models, R^2 , adjusted R^2 , and AIC. The first column includes the estimates of the base HAR model.

From table 5.1, we observe that none of the coefficients for the daily realized variance of the assets is significant for the HAR models extended with only daily realized variance of the assets. However, this change for the HAR models extended with the daily, weekly, and monthly realized variance of the assets. For these models, the coefficients for daily realized variances of the FX rates are all significant at a 5%-level or more. These findings indicate that the current level of the variance of the considered asset does not contain much information about the Bitcoin volatility. However, including also weekly and monthly variance provides information about how the volatility of the considered asset changed relatively to the previous week/month, and as it turns out, this information is improving the Bitcoin volatility model. However, the improvement is very small.

To evaluate the models compared to the base HAR model, we consider adjusted R^2 and AIC. R^2 will always improve when including more exogenous variables, and is therefore not used to compare the models. We have marked adjusted R^2 and AIC in bold for models where the values improve. Considering adjusted R^2 , all of the HAR models extended with the daily, weekly, and monthly realized variance of the assets improve compared to the base HAR model. However, the improvements are minimal. None of the HAR models extended with daily realized variance improves when considering adjusted R^2 .

AIC does not improve for any of the HAR models extended with the daily realized variance of the assets compared to the base HAR. For HAR models extended with daily, weekly, and monthly realized variance of the assets, we find that models with the realized variances of the FX rates and the S&P500 improve. However, they improve only marginally.

We conclude that the variance of FX rates, S&P500, and precious metals does not improve the Bitcoin volatility model.

	x																						
	Base HAR	EUR-USD			AUD-USD			GBP-USD			JPY-USD			CAD-USD		CHF-USD		S&P500		XAU		XAG	
$\phi_0^{(BTC)}$	-1.07 ***	-0.80 *	-1.97 ***	-1.22 **	-2.70 ***	-1.25 **	-1.96 ***	-0.86 *	-1.87 ***	-0.72	-2.29 ***	-0.86 *	-1.25 **	-1.26 ***	-1.67 ***	-0.97 *	-1.76 **	-1.25 **	-1.60 **				
$\phi_D^{(BTC)}$	0.38 ***	0.38 ***	0.38 ***	0.38 ***	0.38 ***	0.38 ***	0.38 ***	0.38 ***	0.37 ***	0.38 ***	0.38 ***	0.37 ***	0.37 ***	0.38 ***	0.37 ***	0.38 ***	0.38 ***	0.38 ***	0.38 ***	0.38 ***	0.38 ***	0.38 ***	0.38 ***
$\phi_W^{(BTC)}$	0.35 ***	0.35 ***	0.33 ***	0.35 ***	0.33 ***	0.35 ***	0.35 ***	0.35 ***	0.33 ***	0.35 ***	0.34 ***	0.35 ***	0.34 ***	0.35 ***	0.34 ***	0.35 ***	0.35 ***	0.35 ***	0.35 ***	0.34 ***	0.35 ***	0.35 ***	0.35 ***
$\phi_M^{(BTC)}$	0.14 **	0.14 ***	0.14 ***	0.13 **	0.14 ***	0.13 **	0.13 **	0.14 ***	0.15 ***	0.14 ***	0.14 **	0.14 ***	0.16 ***	0.14 **	0.14 ***	0.14 **	0.14 ***	0.14 **	0.14 ***	0.13 **	0.14 **	0.14 **	0.14 **
$\phi_D^{(x)}$		0.02	0.19 **	-0.01	0.14 *	-0.02	0.14 *	0.02	0.12 *	0.03	0.16 **	0.02	0.18 **	-0.02	0.08	0.01	0.09	-0.02	0.08	0.01	0.09	-0.02	-0.01
$\phi_W^{(x)}$			-0.07		-0.03		-0.13		0.02		-0.04		-0.12		-0.08		-0.04		-0.08		-0.04		0.08
$\phi_M^{(x)}$			-0.20 *		-0.26 **		-0.09		-0.21 ***		-0.23 *		-0.09		-0.05		-0.13		-0.05		-0.13		-0.13
R^2	0.550	0.550	0.556	0.550	0.556	0.550	0.554	0.550	0.556	0.552	0.555	0.550	0.555	0.550	0.553	0.550	0.552	0.550	0.552	0.550	0.551	0.550	0.551
Adjusted R^2	0.549	0.549	0.554	0.549	0.554	0.549	0.552	0.549	0.554	0.549	0.552	0.549	0.553	0.549	0.551	0.549	0.550	0.549	0.549	0.549	0.549	0.549	0.549
AIC/100	31.76	31.78	31.65	31.78	31.65	31.78	31.71	31.78	31.65	31.78	31.70	31.78	31.69	31.78	31.75	31.78	31.77	31.78	31.77	31.78	31.78	31.78	31.80

Significance codes: $p \leq 0.001$ '***', $p \leq 0.01$ '**', $p \leq 0.05$ '*'

Table 5.1: Parameter values for HAR models with daily realized variance and daily, weekly, and monthly realized variance of EUR-USD, AUD-USD, GBP-USD, JPY-USD, CAD-USD, CHF-USD, S&P500, XAU, and XAG, for the time period 01-Jan-14 to 05-Feb-19.

Next, we estimate the HAR model with absolute regular and negative returns, as specified in equation (14). We let x be BTC, EUR-USD, AUD-USD, GBP-USD, JPY-USD, CAD-USD, CHF-USD, S&P500, XAU, or XAG in the equation. Table 5.2 presents the estimated coefficients. The coefficients of the base HAR model are included in the first column.

When including the absolute returns of Bitcoin itself, weekly and monthly absolute returns have significant coefficients, as well as negative daily returns. However, neither weekly nor monthly negative returns have significant coefficients. This indicates that the magnitude of weekly and monthly returns influence the variance of Bitcoin, and that negative returns do not have a significantly different impact than positive ones. For daily returns, negative returns have a significantly larger impact than positive ones. When considering the other assets' returns impact, we get significant coefficients for daily absolute returns of EUR-USD, daily negative returns of GBP-USD, weekly negative returns of JPY-USD and S&P500, and monthly negative returns of S&P500 and XAG.

Furthermore, we again consider adjusted R^2 and AIC in order to compare the extended HAR models against the base HAR model. The adjusted R^2 and AIC values that improve compared to the base HAR model are marked in bold in table 5.2. The largest improvement of adjusted R^2 is obtained when including regular and negative returns of Bitcoin itself. Other improvements of adjusted R^2 are minimal.

AIC is only improved for the HAR model extended with the returns of Bitcoin and S&P500. Including returns of S&P500 reduces AIC only minimally. However, when including the absolute returns of Bitcoin itself, AIC improves considerably. Based on this result, we find that the past returns of Bitcoin have explanatory power for the volatility of Bitcoin, indicating that including past regular and negative returns of Bitcoin in the volatility model could improve estimation compared to the base HAR model. Particularly, the magnitude of the returns improves the model.

	x										
	<i>Base HAR</i>	<i>BTC</i>	<i>EUR-USD</i>	<i>AUD-USD</i>	<i>GBP-USD</i>	<i>JPY-USD</i>	<i>CAD-USD</i>	<i>CHF-USD</i>	<i>S&P500</i>	<i>XAU</i>	<i>XAG</i>
$\phi_0^{(BTC)}$	-1.07***	-2.60***	-1.08***	-1.06***	-1.03***	-1.02***	-1.06***	-1.00***	-1.08***	-0.98***	-1.04***
$\phi_D^{(BTC)}$	0.38***	0.24***	0.38***	0.38***	0.38***	0.37***	0.38***	0.38***	0.37***	0.37***	0.37***
$\phi_W^{(BTC)}$	0.35***	0.28***	0.34***	0.35***	0.35***	0.33***	0.35***	0.35***	0.35***	0.34***	0.34***
$\phi_M^{(BTC)}$	0.14**	0.18***	0.14***	0.14**	0.13**	0.16***	0.14**	0.14**	0.15***	0.16***	0.15***
$\lambda_D^{(x)}$		1.97	22.77*	7.93	16.47	-0.69	-3.22	-9.05	1.77	-2.61	-3.58
$\lambda_W^{(x)}$		8.07***	-11.71	-6.27	-35.50	-26.12	6.05	-16.58	-23.60	17.33	7.39
$\lambda_M^{(x)}$		18.88***	-22.01	-0.76	-27.89	22.06	-11.06	0.67	38.72	71.19*	-30.94
$\alpha_D^{(x)}$		2.41*	-17.91	-8.00	-22.60*	3.27	7.05	12.67	3.59	1.27	5.35
$\alpha_W^{(x)}$		2.75	4.21	1.20	37.25	52.66*	2.37	8.76	38.02*	-9.20	-8.79
$\alpha_M^{(x)}$		-5.82	8.09	-13.55	-13.06	-110.71	-4.87	-17.18	-111.25**	47.57	43.97*
R^2	0.550	0.579	0.552	0.551	0.553	0.553	0.550	0.552	0.554	0.553	0.553
Adjusted R^2	0.549	0.576	0.549	0.547	0.550	0.550	0.547	0.548	0.551	0.549	0.549
$AIC/100$	31.76	31.06	31.82	31.87	31.80	31.80	31.88	31.84	31.76	31.81	31.81

Significance codes: $p \leq 0.001$ '***', $p \leq 0.01$ '**', $p \leq 0.05$ '*'

Table 5.2: Parameter values for HAR models extended with absolute returns and negative returns of BTC, EUR-USD, AUR-USD, GBP-USD, JPY-USD, CAD-USD, CHF-USD, S&P500, XAU, and XAG, for the time period 01-Jan-14 to 05-Feb-19.

5.2 Out-of-sample results

In this section, we investigate how the extended HAR models perform compared to the base HAR model in predicting the one, five, and 22 days ahead cumulative variance for Bitcoin. Even though extensions of the base HAR model with other assets did not prove much better in the in-sample comparison, we still proceed with the out-of-sample forecasting. The reason is that Bitcoin is a very dynamic system, and statistical properties of Bitcoin can change over time (Thies & Molnár, 2018). For example, if an impact of some variable on Bitcoin volatility changes gradually from positive to negative, this variable might be insignificant in a regression estimated for the whole sample, but might improve forecasts which are based on shorter estimation window.

We start by estimating a base HAR model using a rolling window of 500 in-sample observations and use these estimates to predict the cumulative variance over the N following days. Figures 5.2 to 5.4 visualize the estimated values for one, five, and 22 cumulative variance prediction, respectively, from the base HAR against the variance proxy.

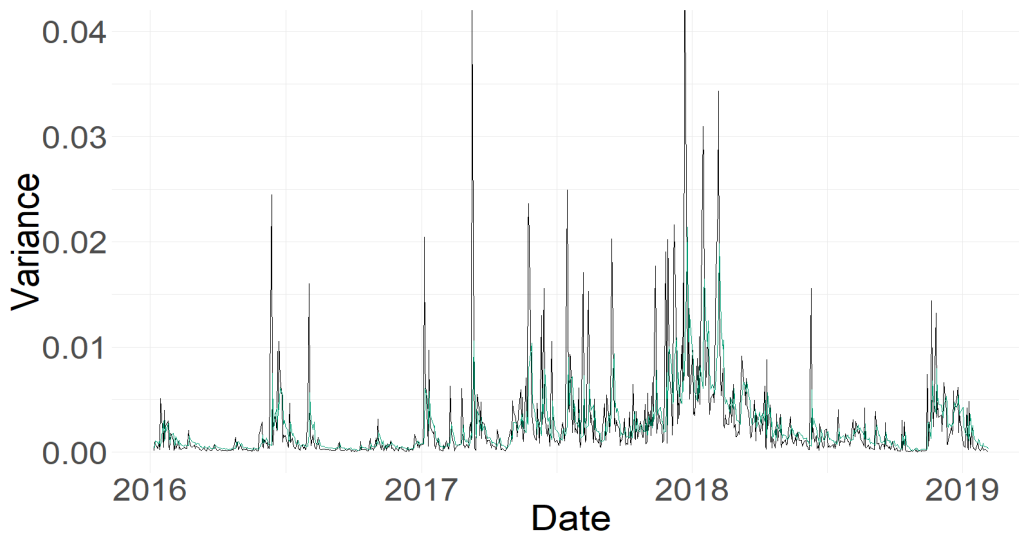


Figure 5.2: Plot of the one day prediction using base HAR (green) against true realized variance (black). Forecasts are based on a rolling window of the 500 most recent observations.

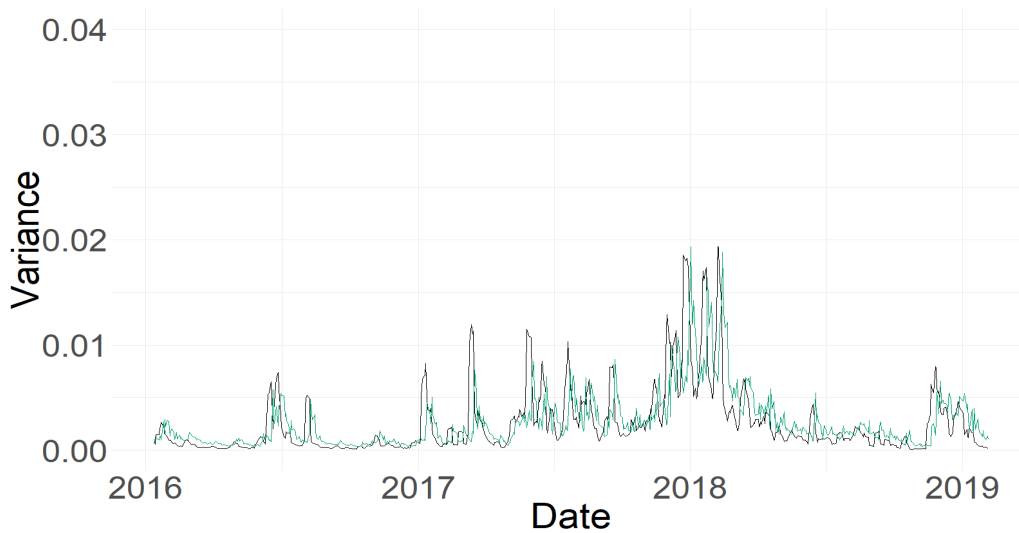


Figure 5.3: Plot of the cumulative five days prediction using the base HAR model (green) against true realized variance (black). Forecasts are based on a rolling window of the 500 most recent observations.

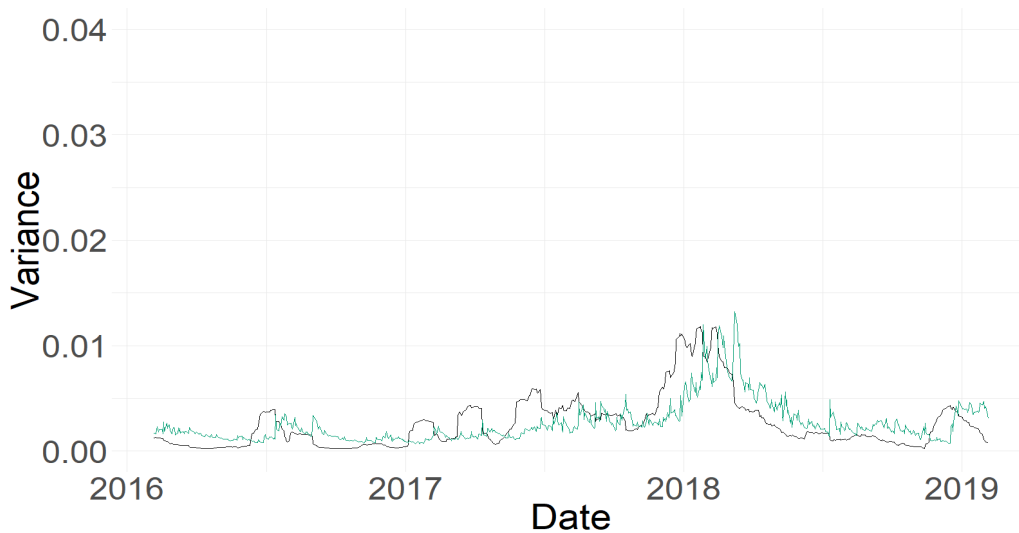


Figure 5.4: Plot of the cumulative 22 days prediction using the base HAR model (green) against true realized variance (black). Forecasts are based on a rolling window of the 500 most recent observations.

Again, we begin with extending the HAR model using the realized variance of other assets. One version is extended with only daily realized variance, as specified in equation (8), while another is extended using daily, weekly, and monthly realized variance, as in equation (9). As with the base HAR, we use a rolling window of 500 in-sample observations to predict the cumulative realized variance one, five, and 22 days ahead.

Table 5.3 provides the loss function values calculated using equation (21) to (24) for the HAR models extended with daily realized variance. In the first row, the loss functions for the base

HAR model are included. Table 5.4 gives the loss functions for the HAR models extended with daily, weekly, and monthly realized variance of the assets. In both tables, loss functions less than the corresponding loss function of the base HAR model are marked in bold. We observe that several of the extended HAR models improve compared to the base HAR model, but most of them improve only marginally.

In order to determine if any of the models are deemed significantly better than the base HAR model in predicting the variance of Bitcoin, we use the Model Confidence Set procedure by Hansen et al. (2011) with a significance level of 5%. Table 5.5 shows which HAR models extended with daily realized variance the test determines significantly better than the base HAR model for the different loss functions and the different horizons. Table 5.6 provides the same, but for HAR models extended with daily, weekly, and monthly realized variance.

The test deems a few HAR models significantly better when considering one loss function and time horizon at a time. However, we do not find that any of the models are significantly better when considering several loss functions or several horizons. Moreover, the MCS procedure concludes in some cases that the base HAR model is significantly better than the extended versions. These results indicate that the inclusion of the variance of the FX rates, the S&P500, and gold and silver do not systematically improve the forecasting of Bitcoin's volatility. This applies to all horizons, and especially for longer ones.

	1 day				5 days				22 days			
	MSE	QLIKE	MAE	MAPE	MSE	QLIKE	MAE	MAPE	MSE	QLIKE	MAE	MAPE
<i>Base HAR</i>	1.69×10^{-5}	-5.32	1.80×10^{-3}	1.21	1.88×10^{-4}	-3.61	8.27×10^{-3}	1.10	1.98×10^{-3}	-1.95	3.41×10^{-2}	1.19
<i>EUR-USD</i>	1.69×10^{-5}	-5.32	1.79×10^{-3}	1.19	1.90×10^{-4}	-3.61	8.33×10^{-3}	1.11	1.95×10^{-3}	-1.95	3.44×10^{-2}	1.26
<i>AUD-USD</i>	1.71×10^{-5}	-5.32	1.81×10^{-3}	1.23	2.00×10^{-4}	-3.62	8.43×10^{-3}	1.13	1.95×10^{-3}	-1.97	3.34×10^{-2}	1.22
<i>GBP-USD</i>	1.69×10^{-3}	-5.32	1.80×10^{-3}	1.22	1.89×10^{-4}	-3.61	8.27×10^{-3}	1.08	1.85×10^{-3}	-1.95	3.34×10^{-2}	1.12
<i>JPY-USD</i>	1.72×10^{-5}	-5.32	1.82×10^{-3}	1.25	2.09×10^{-4}	-3.61	8.64×10^{-3}	1.15	2.17×10^{-3}	-1.94	3.52×10^{-2}	1.25
<i>CAD-USD</i>	1.69×10^{-5}	-3.32	1.79×10^{-3}	1.19	1.89×10^{-4}	-3.62	8.35×10^{-3}	1.11	1.92×10^{-3}	-1.96	3.32×10^{-2}	1.20
<i>CHF-USD</i>	1.69×10^{-5}	-5.32	1.79×10^{-3}	1.19	1.92×10^{-4}	-3.61	8.35×10^{-3}	1.10	1.93×10^{-3}	-1.96	3.44×10^{-2}	1.24
<i>S&P500</i>	1.72×10^{-5}	-5.32	1.79×10^{-3}	1.20	1.88×10^{-4}	-3.60	8.06×10^{-3}	1.06	1.75×10^{-3}	-1.95	3.15×10^{-2}	1.15
<i>XAU</i>	1.70×10^{-5}	-5.32	1.81×10^{-3}	1.23	1.94×10^{-4}	-3.62	8.44×10^{-3}	1.14	1.91×10^{-3}	-1.96	3.44×10^{-2}	1.25
<i>XAG</i>	1.71×10^{-5}	-5.32	1.82×10^{-3}	1.24	1.87×10^{-4}	-3.61	8.41×10^{-3}	1.14	1.90×10^{-3}	-1.95	3.45×10^{-2}	1.23

Table 5.3: Loss function values for one day, five days, and 22 days cumulative predictions using HAR models extended with daily realized variance of EUR-USD, AUD-USD, GBP-USD, JPY-USD, CAD-USD, CHF-USD, S&P500, XAU, and XAG, for the time period 01-Jan-14 to 05-Feb-19.

	<i>1 day</i>				<i>5 days</i>				<i>22 days</i>			
	<i>MSE</i>	<i>QLIKE</i>	<i>MAE</i>	<i>MAPE</i>	<i>MSE</i>	<i>QLIKE</i>	<i>MAE</i>	<i>MAPE</i>	<i>MSE</i>	<i>QLIKE</i>	<i>MAE</i>	<i>MAPE</i>
<i>Base HAR</i>	1.69×10^{-5}	-5.32	1.80×10^{-3}	1.21	1.88×10^{-4}	-3.61	8.27×10^{-3}	1.10	1.98×10^{-3}	-1.95	3.41×10^{-2}	1.19
<i>EUR-USD</i>	1.68×10^{-5}	-5.33	1.81×10^{-3}	1.24	1.85×10^{-4}	-3.61	8.36×10^{-3}	1.17	1.98×10^{-3}	-1.92	3.51×10^{-2}	1.46
<i>AUD-USD</i>	1.68×10^{-5}	-5.34	1.81×10^{-3}	1.24	1.78×10^{-4}	-3.64	8.24×10^{-3}	1.18	1.96×10^{-3}	-1.97	3.24×10^{-2}	1.32
<i>GBP-USD</i>	1.69×10^{-5}	-5.32	1.79×10^{-3}	1.20	1.87×10^{-4}	-3.60	8.23×10^{-3}	1.07	1.86×10^{-3}	-1.84	3.39×10^{-2}	1.09
<i>JPY-USD</i>	1.69×10^{-5}	-5.33	1.85×10^{-3}	1.27	1.95×10^{-4}	-3.60	8.74×10^{-3}	1.18	2.33×10^{-3}	-1.92	3.53×10^{-2}	1.24
<i>CAD-USD</i>	1.67×10^{-5}	-5.34	1.79×10^{-3}	1.24	1.75×10^{-4}	-3.63	8.24×10^{-3}	1.19	1.76×10^{-3}	-1.98	3.30×10^{-2}	1.35
<i>CHF-USD</i>	1.68×10^{-5}	-5.34	1.81×10^{-3}	1.24	1.79×10^{-4}	-3.63	8.25×10^{-3}	1.15	1.79×10^{-3}	-1.94	3.37×10^{-2}	1.26
<i>S&P500</i>	1.70×10^{-5}	-5.32	1.77×10^{-3}	1.19	1.77×10^{-4}	-3.60	7.90×10^{-3}	1.07	1.73×10^{-3}	-1.92	3.17×10^{-2}	1.22
<i>XAU</i>	1.69×10^{-5}	-5.33	1.84×10^{-3}	1.28	1.84×10^{-4}	-3.61	8.56×10^{-3}	1.21	1.96×10^{-3}	-1.95	3.49×10^{-2}	1.34
<i>XAG</i>	1.69×10^{-5}	-5.33	1.85×10^{-3}	1.29	1.86×10^{-4}	-3.62	8.71×10^{-3}	1.20	1.93×10^{-3}	-1.94	3.49×10^{-2}	1.22

Table 5.4: Loss function values for one day, five days, and 22 days cumulative predictions using HAR model extended with daily, weekly, and monthly realized variance of EUR-USD, AUD-USD, GBP-USD, JPY-USD, CAD-USD, CHF-USD, S&P500, XAU, and XAG, for the time period 01-Jan-14 to 05-Feb-19.

	<i>1 day</i>				<i>5 days</i>				<i>22 days</i>			
	<i>MSE</i>	<i>QLIKE</i>	<i>MAE</i>	<i>MAPE</i>	<i>MSE</i>	<i>QLIKE</i>	<i>MAE</i>	<i>MAPE</i>	<i>MSE</i>	<i>QLIKE</i>	<i>MAE</i>	<i>MAPE</i>
<i>EUR-USD</i>				X								
<i>AUD-USD</i>										X		
<i>GBP-USD</i>												
<i>JPY-USD</i>												
<i>CAD-USD</i>												X
<i>CHF-USD</i>			X	X								
<i>S&P500</i>												
<i>XAU</i>												
<i>XAG</i>												

Table 5.5: Model Confidence Set procedure results for one day, five days, and 22 days cumulative predictions using HAR models extended with daily realized variance of EUR-USD, AUD-USD, GBP-USD, JPY-USD, CAD-USD, CHF-USD, S&P500, XAU, and XAG, for the time period 01-Jan-14 to 05-Feb-19. Significance level of 5% is used.

	<i>1 day</i>				<i>5 days</i>				<i>22 days</i>			
	<i>MSE</i>	<i>QLIKE</i>	<i>MAE</i>	<i>MAPE</i>	<i>MSE</i>	<i>QLIKE</i>	<i>MAE</i>	<i>MAPE</i>	<i>MSE</i>	<i>QLIKE</i>	<i>MAE</i>	<i>MAPE</i>
<i>EUR-USD</i>												
<i>AUD-USD</i>		X										
<i>GBP-USD</i>												
<i>JPY-USD</i>												
<i>CAD-USD</i>												X
<i>CHF-USD</i>												X
<i>S&P500</i>												
<i>XAU</i>												X
<i>XAG</i>												

Table 5.6: Model Confidence Set procedure results for one day, five days, and 22 days cumulative predictions using HAR models extended with daily, weekly, and monthly realized variance of EUR-USD, AUD-USD, GBP-USD, JPY-USD, CAD-USD, CHF-USD, S&P500, XAU, and XAG, for the time period 01-Jan-14 to 05-Feb-19. Significance level of 5% is used.

We also investigate if the returns of Bitcoin, the FX rates, the S&P500, and the precious metals improve the prediction of Bitcoin's variance. Again, we use equation (14), and compare the predictions to that of the base HAR model using a rolling window of 500 in-sample observations for horizons of one, five, and 22 days. Table 5.7 provides the loss functions for the models, with the first row providing the loss functions for the base HAR model. Bold values indicate that the loss function is less than the corresponding loss function from the base HAR model. We observe that several models improve compared to the base HAR, but most of them only minimally.

Table 5.8 provides the results from the MCS procedure for the HAR models extended with returns. Based on these results, we are not able to find that including returns of Bitcoin, the FX rates, S&P500, XAU, or XAG systematically provides better predictions for Bitcoin's variance compared to the base HAR model.

Overall, we are not able to find that out-of-sample prediction of Bitcoin's variance can be improved by including variances nor returns of FX rates, S&P500, gold or silver, further supporting the in-sample findings that these assets can not explain the variance process of Bitcoin.

	<i>1 day</i>				<i>5 days</i>				<i>22 days</i>			
	<i>MSE</i>	<i>QLIKE</i>	<i>MAE</i>	<i>MAPE</i>	<i>MSE</i>	<i>QLIKE</i>	<i>MAE</i>	<i>MAPE</i>	<i>MSE</i>	<i>QLIKE</i>	<i>MAE</i>	<i>MAPE</i>
<i>Base HAR</i>	1.69×10^{-5}	-5.32	1.80×10^{-3}	1.21	1.88×10^{-4}	-3.61	8.27×10^{-3}	1.10	1.98×10^{-3}	-1.95	3.41×10^{-2}	1.19
<i>BTC</i>	5.14×10^{-5}	-5.34	2.09×10^{-3}	1.22	4.86×10^{-4}	-3.62	9.38×10^{-3}	1.06	3.57×10^{-3}	-1.83	3.51×10^{-2}	1.10
<i>EUR-USD</i>	1.67×10^{-5}	-5.33	1.79×10^{-3}	1.21	1.83×10^{-4}	-3.60	8.19×10^{-3}	1.10	2.13×10^{-3}	-1.92	3.58×10^{-2}	1.23
<i>AUD-USD</i>	1.71×10^{-5}	-5.32	1.81×10^{-3}	1.23	1.84×10^{-4}	-3.61	8.24×10^{-3}	1.11	2.14×10^{-3}	-1.97	3.39×10^{-2}	1.14
<i>GBP-USD</i>	1.73×10^{-5}	-5.33	1.84×10^{-3}	1.23	1.91×10^{-4}	-3.61	8.35×10^{-3}	1.09	2.16×10^{-3}	-1.92	3.56×10^{-2}	1.22
<i>JPY-USD</i>	1.70×10^{-5}	-5.31	1.80×10^{-3}	1.22	1.86×10^{-4}	-3.61	8.31×10^{-3}	1.09	1.83×10^{-3}	-1.95	3.33×10^{-2}	1.13
<i>CAD-USD</i>	1.73×10^{-5}	-5.30	1.81×10^{-3}	1.22	2.01×10^{-4}	-3.61	8.45×10^{-3}	1.10	2.49×10^{-3}	-1.93	3.73×10^{-2}	1.20
<i>CHF-USD</i>	1.69×10^{-5}	-5.32	1.81×10^{-3}	1.22	1.88×10^{-4}	-3.61	8.29×10^{-3}	1.10	2.21×10^{-3}	-1.94	3.60×10^{-2}	1.20
<i>S&P500</i>	1.73×10^{-5}	-5.31	1.79×10^{-3}	1.19	1.85×10^{-4}	-3.60	8.16×10^{-3}	1.11	2.12×10^{-3}	-1.94	3.41×10^{-2}	1.28
<i>XAU</i>	1.71×10^{-5}	-5.32	1.79×10^{-3}	1.20	2.05×10^{-4}	-3.61	8.45×10^{-3}	1.11	2.00×10^{-3}	-1.93	3.48×10^{-2}	1.29
<i>XAG</i>	1.69×10^{-5}	-5.31	1.79×10^{-3}	1.18	1.98×10^{-4}	-3.60	8.32×10^{-3}	1.07	2.04×10^{-3}	-1.93	3.43×10^{-2}	1.19

Table 5.7: Loss function values for one day, five days, and 22 days cumulative predictions using HAR models extended with absolute regular and negative returns of EUR-USD, AUD-USD, GBP-USD, JPY-USD, CAD-USD, CHF-USD, S&P500, XAU, and XAG, for the time period 01-Jan-14 to 05-Feb-19.

	<i>1 day</i>				<i>5 days</i>				<i>22 days</i>			
	<i>MSE</i>	<i>QLIKE</i>	<i>MAE</i>	<i>MAPE</i>	<i>MSE</i>	<i>QLIKE</i>	<i>MAE</i>	<i>MAPE</i>	<i>MSE</i>	<i>QLIKE</i>	<i>MAE</i>	<i>MAPE</i>
<i>BTC</i>												X
<i>EUR-USD</i>												
<i>AUD-USD</i>												
<i>GBP-USD</i>												
<i>JPY-USD</i>												
<i>CAD-USD</i>												
<i>CHF-USD</i>												
<i>S&P500</i>												
<i>XAU</i>												
<i>XAG</i>								X				

Table 5.8: Model Confidence Set procedure results for one day, five days, and 22 days cumulative predictions using HAR models extended with absolute regular and negative returns of BTC, EUR-USD, AUD-USD, GBP-usd, JPY-USD, CAD-USD,CHF-USD, S&P500, XAU, and XAG, for the time period 01-Jan-14 to 05-Feb-19. Significance level of 5% is used.

5.3 Influence of interest rate announcements on realized volatility of Bitcoin

Table 5.9 presents the coefficient estimates for the base HAR model specified in equation (17) and the extended HAR model specified in equation (16). The coefficients have been estimated for each individual bank and for the case when we do not distinguish which particular bank makes the announcement. As explained in section 4.1.4, contrary to previous models presented in this paper, this model is estimated using seven-day weeks and 30-day months. This is due to Bitcoin being traded around the clock, and our attempt is to capture the effects the day before and after the announcement, regardless of those days being on the weekend or not, e.g., if there is an announcement on Monday, we wish to look at the effect on Sunday, rather than the Friday before. Due to the difference in the estimation, we compare these models to a new base HAR model, as specified in equation (17).

From the coefficients, we see that interest rate announcements do not appear to have any impact on the daily volatility of Bitcoin. If Bitcoin reacted to announcements in the way we would expect exchange rates to do, based on an extensive body of literature, there would be an increase in volatility on the day before and the day of a news announcement and a bounce back to the previous level the day after. Instead, Bitcoin seems unaffected by new information from the markets. However, there is a statistically significant negative coefficient on the day of announcements from the Bank of Japan. This would suggest a decrease in volatility the day new information reaches the market from the Bank of Japan, rather than the increase we would expect. Also, the day of the week coefficients are mostly insignificant, except for Saturday, where the positive coefficient implies an increase in volatility. When considering all announcements regardless of bank, there is no statistically significant impact on volatility the day before, at or after announcements. This is further evidence that Bitcoin is disconnected from traditional financial markets.

In table 5.9, adjusted R^2 and AIC values that improve compared to the base HAR, are marked in bold. When comparing the models that include central bank announcements with the benchmark model using adjusted R^2 , we see that the differences are insignificant, and conclude that the effects of interest announcements are negligible. We arrive at the same conclusion when looking at AIC.

	<i>Base HAR</i>	<i>BoC</i>	<i>BoE</i>	<i>BoJ</i>	<i>ECB</i>	<i>FED</i>	<i>RBA</i>	<i>SNB</i>	<i>All</i>
$\phi_0^{(BTC)}$	-0.76 ***	-0.76 ***	-0.76 ***	-0.76 ***	-0.76 ***	-0.76 ***	-0.76 ***	-0.76 ***	-0.76 ***
$\phi_D^{(BTC)}$	0.52 ***	0.52 ***	0.52 ***	0.53 ***	0.52 ***	0.52 ***	0.53 ***	0.53 ***	0.53 ***
$\phi_W^{(BTC)}$	0.25 ***	0.25 ***	0.25 ***	0.25 ***	0.26 ***	0.26 ***	0.26 ***	0.25 ***	0.26 ***
$\phi_M^{(BTC)}$	0.12 ***	0.12 ***	0.12 ***	0.12 ***	0.12 ***	0.12 ***	0.12 ***	0.12 ***	0.12 *
$\lambda_B^{(x)}$		0.01	0.02	3.5×10^{-3}	2.4×10^{-3}	-0.01	-1.6×10^{-3}	-0.02	-8.3×10^{-4}
$\lambda_N^{(x)}$		5.0×10^{-3}	4.6×10^{-3}	-0.06 **	0.03	4.6×10^{-3}	-1.2×10^{-3}	-0.02	4.7×10^{-3}
$\lambda_A^{(x)}$		-5.8×10^{-3}	-0.03	0.02	9.0×10^{-4}	-0.03	-0.01	-0.04	-0.01
μ_{Mon}	-2.2×10^{-3}	-1.4×10^{-3}	9.6×10^{-4}	-2.9×10^{-3}	-1.6×10^{-3}	-1.7×10^{-3}	-4.2×10^{-3}	-3.8×10^{-3}	-4.0×10^{-3}
μ_{Tue}	-1.6×10^{-3}	-2.6×10^{-3}	1.7×10^{-3}	-4.1×10^{-4}	-9.9×10^{-4}	9.9×10^{-4}	-3.7×10^{-3}	-3.2×10^{-3}	-4.4×10^{-3}
μ_{Thu}	5.2×10^{-4}	2.2×10^{-3}	2.9×10^{-3}	1.1×10^{-3}	-3.6×10^{-3}	5.8×10^{-3}	-1.8×10^{-3}	5.3×10^{-4}	1.2×10^{-3}
μ_{Fri}	-4.1×10^{-3}	-3.3×10^{-3}	4.2×10^{-3}	-4.1×10^{-3}	-3.6×10^{-3}	-3.3×10^{-3}	-6.5×10^{-3}	-2.7×10^{-3}	-1.4×10^{-3}
μ_{Sat}	0.03 **	0.03 **	0.03 **	0.03 **	0.03 **	0.03 **	0.02 *	0.03 **	0.02 *
μ_{Sun}	8.7×10^{-3}	9.5×10^{-3}	8.2×10^{-3}	8.2×10^{-3}	9.4×10^{-3}	9.2×10^{-3}	6.4×10^{-3}	-7.2×10^{-3}	6.8×10^{-3}
R^2	0.644	0.644	0.644	0.645	0.644	0.644	0.644	0.644	0.644
Adjusted R^2	0.642	0.641	0.642	0.643	0.642	0.642	0.641	0.642	0.642
$AIC/100$	40.55	40.60	40.57	40.52	40.58	40.55	40.60	40.57	40.58

Significance codes: $p \leq 0.001$ '***', $p \leq 0.01$ '**', $p \leq 0.05$ '*'

Table 5.9: Parameter values for the HAR model extended with central bank announcements from BoC, BoE, BoJ, ECB, FED, RBA, SNB, and all banks combined, for the time period 01-Jan-14 to 05-Feb-19.

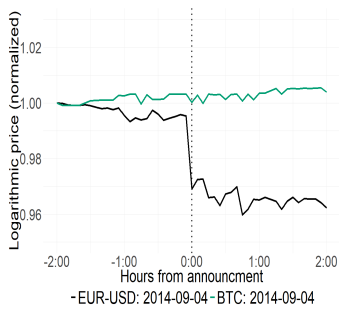
5.4 High-frequency response to interest rate announcements

To further investigate these results, we study the intra-day prices and returns for the FX rates and Bitcoin on announcement days. In figure 5.5, we have selected certain days when the currencies' national banks have increased, kept, or decreased the interest rate. For each bank, the figures show the normalized logarithmic middle intra-day price for the respective national currency (black) and the normalized logarithmic intra-day price for Bitcoin (green) two hours before and after the announcement. ECB, RBA, BoJ, and SNB have not increased the interest rate during the time period considered, and therefore these have no graphs showing the effect of an interest rate increase. The figures illustrate that Bitcoin does not show the same change around an interest rate announcement as we see is evident for the FX rates.

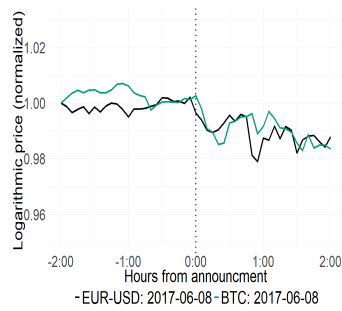
Furthermore, we run a regression on the returns of the FX rates and Bitcoin, as specified in equation (28). We run the regression for each of the currencies' representative central banks. Regression coefficients are shown in table 5.10. For all the FX rates, we find significant coef-

ficients for some or all of the dummies representing an increase, decrease or no change in the interest rate. For banks with no increase in the time period, $D+$ has no coefficient. None of the dummies have significant coefficients for any of the bank announcements when conducting the regression on Bitcoin. This indicate that the mean of Bitcoin's return in the three hours before and after the announcement do not change systematically around the banks' announcements.

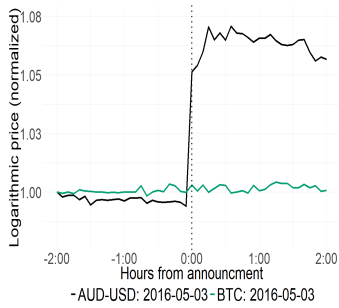
Overall, the analysis indicate that Bitcoin is not influenced systematically by interest rate announcements of these central banks, further supporting that Bitcoin is a independent financial instrument.



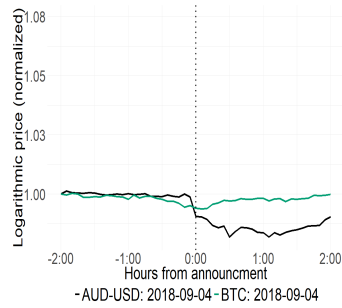
(a) ECB: interest rate decrease



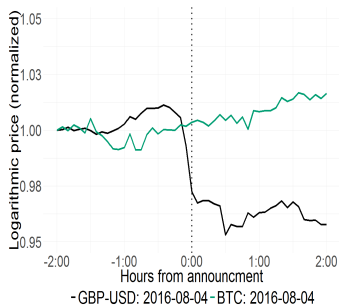
(b) ECB: interest rate unchanged



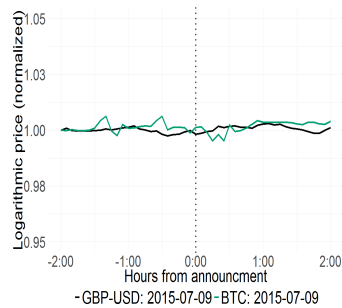
(c) RBA: interest rate decrease



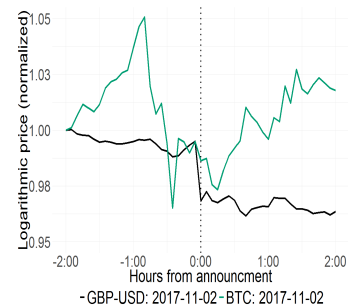
(d) RBA: interest rate unchanged



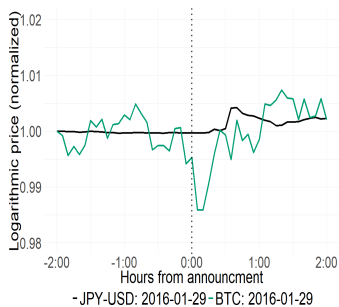
(e) BoE: interest rate decrease



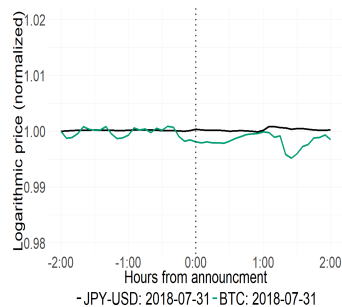
(f) BoE: interest rate unchanged



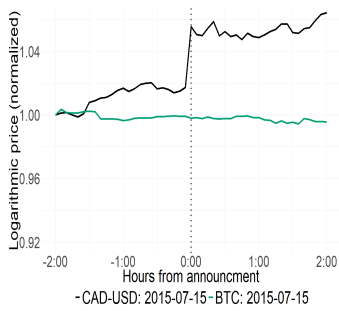
(g) BoE: interest rate increase



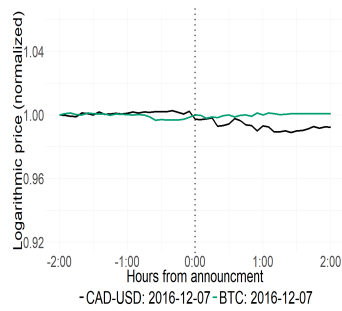
(h) BoJ: interest rate decrease



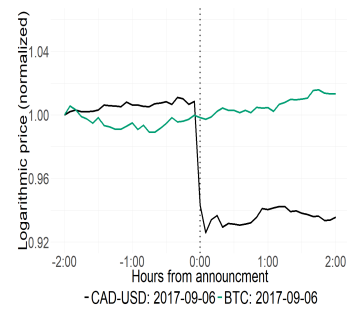
(i) BoJ: interest rate unchanged



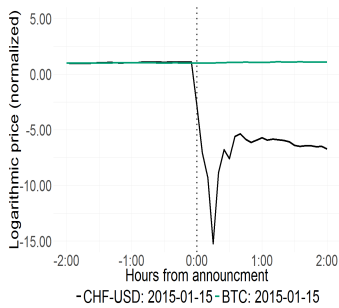
(j) BoC: interest rate decrease



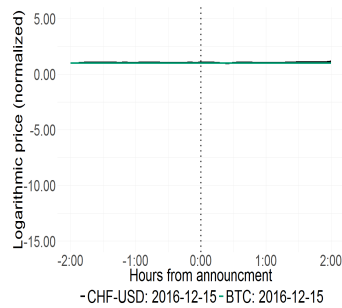
(k) BoC: interest rate unchanged



(l) BoC: interest rate increase



(m) SNB: interest rate increase



(n) SNB: interest rate unchanged

Figure 5.5: Plot of intra-day logarithmic price for EUR-USD, AUD-USD, GBP-USD, JPY-USD, CAD-USD, and CHF-USD and Bitcoin for selected days of interest rate announcements from ECB, RBA, BoE, BoJ, BoC, and SNB. Figures show the returns 2 hours before and after interest rate announcements on selected days. FX prices are shown in black and Bitcoin's price is shown in green.

<i>Currencies</i>	<i>ECB</i>	<i>RBA</i>	<i>BoE</i>	<i>BoJ</i>	<i>BoC</i>	<i>SNB</i>
	<i>EUR-USD</i>	<i>AUD-USD</i>	<i>GBP-USD</i>	<i>JPY-USD</i>	<i>CAD-USD</i>	<i>CHF-USD</i>
γ_0	-1.70×10^{-5}	1.65×10^{-5}	0.20×10^{-5}	-0.07×10^{-5}	0.56×10^{-5}	1.30×10^{-5}
γ_1	1.05×10^{-4}	5.32×10^{-4} ***	1.37×10^{-4} *	-3.62×10^{-4} **	-2.01×10^{-4} *	-0.34×10^{-4} ***
γ_2			-1.15×10^{-3} ***		-2.28×10^{-3} ***	
γ_3	-3.22×10^{-3} ***	-1.18×10^{-3} ***	-4.76×10^{-3} ***	-5.20×10^{-5}	5.96×10^{-3} ***	-5.86×10^{-4}
<i>Bitcoin</i>						
γ_0	4.96×10^{-5}	-1.04×10^{-5}	-1.58×10^{-5}	-3.98×10^{-5}	-5.45×10^{-5}	0.83×10^{-5}
γ_1	-1.80×10^{-4}	1.67×10^{-4}	0.48×10^{-4}	1.50×10^{-4}	6.97×10^{-4}	7.76×10^{-5}
γ_2			-1.06×10^{-3}		-1.51×10^{-3}	
γ_3	-1.18×10^{-3}	0.59×10^{-3}	5.76×10^{-4}	-2.62×10^{-3}	-6.87×10^{-4}	1.76×10^{-3}

Significance codes: $p \leq 0.001$ '***', $p \leq 0.01$ '**', $p \leq 0.05$ '*'

Table 5.10: Parameters for intra-day returns of EUR-USD, AUD-USD, GBP-USD, JPY-USD, CAD-USD, CHF-USD, and Bitcoin regressed on ECB, RBA, BoE, BoJ, BoC, and SNB interest rate announcements in the time period 01-Jan-14 to 05-Feb-19. Explanatory variables are dummies for unchanged, increased, and decreased interest rate.

6

Conclusion

This paper explores whether the volatility of Bitcoin is affected by the volatility and returns of other assets, as well as the effect of central bank announcements on the volatility. The logarithmic HAR model is used as the basis for all analysis and this model is extended with additional explanatory variables. Firstly, we extend the HAR model of Bitcoin with only the daily, as well as both the daily, weekly, and monthly realized variance of the EUR-USD, AUD-USD, GBP-USD, JPY-USD, CAD-USD, and CHF-USD exchange rates, the S&P500, gold (XAU), and silver (XAG). By including the RV of these assets, we can study how the volatility of these influence that of Bitcoin. Secondly, we extend the HAR model with past daily, weekly, and monthly absolute regular and negative returns of the aforementioned assets. Thirdly, we compare all models to the base HAR model in- and out-of-sample. For the out-of-sample estimation, we consider the cumulative RV one, five, and 22 days ahead.

As the literature has shown that exchange rates are highly affected by interest rate decisions made by central banks, we also consider how such announcements affect the volatility of Bitcoin. This paper investigates if Bitcoin's volatility is influenced on the day before, the day of, or the day after interest rate announcements from Bank of Canada, Bank of England, Bank of Japan, European Central Bank, Federal Reserve, Reserve Bank of Australia, and Swiss National Bank. We also explore the intra-day effect of interest rate announcements, comparing the reaction of Bitcoin to that of exchange rates.

When the HAR model is extended with the daily, weekly, and monthly realized variance of an exchange rate, these variables are significant, for some currencies. However, when considering

AIC, we conclude that none of the extended HAR models are significantly better than the base HAR model. When including absolute regular and negative returns of the considered assets, as well as Bitcoin, we conclude that only the HAR model extended with the returns of Bitcoin provides a better in-sample fit of the Bitcoin volatility model.

We use loss functions and the Model Confidence Set procedure to investigate how the models perform out-of-sample. We do not find that any of the models are consistently superior to the base HAR, making us unable to conclude that these models in general have significantly better predictive ability.

Based on the results, we do not find evidence that the variance or returns of exchange rates, the S&P500, or precious metals can explain the variance of Bitcoin or improve out-of-sample predictions, compared to only using the variance of Bitcoin itself.

When considering central bank interest rate announcements and the daily volatility of Bitcoin, we find no significant effects. We arrive at the same conclusion when considering intra-day returns in the three hours preceding and following an announcement. This is further evidence that the dynamics of Bitcoin are fundamentally different from that of traditional currencies.

Our work focusing on the volatility connectedness of Bitcoin and other financial market has the following contributions to the literature. Firstly, our paper complements the existing research on the movements of Bitcoin in relation to other widely traded asset classes. There is a lack of research on the use of realized variance as a volatility proxy to explore the direct effect of the volatility of FX rates, stock indices, and precious metals on the volatility of Bitcoin. Secondly, we provide empirical evidence that Bitcoin is unaffected by interest rate announcements, advancing the literature on the implications of macroeconomic news on cryptocurrencies. Our findings provide new information for users of Bitcoin and cryptocurrency investors who are building risk management strategies. Furthermore, this paper adds further weight to the argument that Bitcoin is a unique asset class.

As possible further research, it would be interesting to explore if movements in the Bitcoin market are completely independent of government actions. This could be done by investigating

the effect of announcements and expectations regarding major macroeconomic indicators.

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