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# EXOGENOUS DRIVERS OF CRYPTOCURRENCY VOLATILITY – A MIXED DATA SAMPLING APPROACH TO FORECASTING

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# Exogenous Drivers of Cryptocurrency Volatility – A Mixed Data Sampling Approach to Forecasting

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**Abstract**

We apply the GARCH-MIDAS framework to forecast the daily, weekly, and monthly volatility of four highly capitalized Cryptocurrencies (Bitcoin, Etherium, Litecoin, and Ripple) as well as the Cryptocurrency index CRIX. Based on the prediction quality, we determine the most important exogenous drivers of volatility in Cryptocurrency markets. We find that the Global Real Economic Activity outperforms all other economic and financial drivers under investigation. Only the average forecast combination results in lower loss functions. This indicates that the information content of exogenous factors is time-varying and the model averaging approach diversifies the impact of single drivers.

*Keywords:* Bitcoin, Cryptocurrencies, GARCH, Mixed Data Sampling, Volatility

*JEL classification:* C10; C58; G11

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## 1. Introduction

This study employs the Mixed Data Sampling (MIDAS, Ghysels et al., 2004, 2007) technique to identify important drivers of the conditional volatility of different Cryptocurrencies. However, we do not focus on the in-sample perspective and performance in terms of goodness-of-fit and other measures, which is carried out in Dyhrberg (2016), Catania & Grassi (2017), Chu et al. (2017), Corbet et al. (2018), Katsiampa (2017), Peng et al. (2018), Phillip et al. (2018), and Klein et al. (2018) for example. We rather investigate the usefulness and applicability of those exogenous drivers for forecasting and predicting the variance level for difference forecasting horizons.

Conrad et al. (2018) use GARCH-MIDAS to identify the drivers of long-term volatility of Bitcoin. We build on their study and investigate other Cryptocurrencies in addition to Bitcoin with a framework outlined in Engle et al. (2013). In view of the extreme movement of Cryptocurrencies in the recent months, the identification of factors driving this volatility is becoming an important branch of research in this field. Kristoufek (2015) analyses different types of drivers of Bitcoin prices and volatility based on a wavelet approach. It is found that Bitcoin shows signs of a classical currency with supply and price level as main drivers of volatility along with a sentiment component. These internal drivers are already found in Baek & Elbeck (2015) who do not identify any exogenous drivers in the early years of price development in Bitcoin markets. Cheah & Fry (2015) characterize Bitcoin as an speculative asset–prone to bubble formation–and present evidence that the fundamental value might be zero with little exogenous economic impact. Urquhart (2017) presents evidence that Bitcoin tends to cluster around round numbers. For more recent data, Conrad et al. (2018) and Klein et al. (2018) find a negative relationship of Bitcoin volatility and volatility of developed markets. The contrast of more recent studies to findings of earlier might be due to a transition of Cryptocurrency markets and a progressing maturing of these market. This article contributes to this observation by reviewing a broad range of possible factors and economic variable which influence the volatility of major Cryptocurrencies. We put the sole purpose on volatility prediction and compare the performance of those exogenous drivers.

The methodology is concisely outlined in Section 2. Price data is summarized in Section 3 while the results are discussed in Section 4. Important implications are presented in Section 5.

## 2. Methodology

The GARCH-MIDAS model (Engle et al., 2013) disentangles the volatility into a short-term ($g_{t,m}$) and a long-term component ($\tau_m$) and roots in the Component- and Spline-GARCH (Engle & Lee, 1999, Engle & Rangel, 2008). While the $g_{t,m}$ is a standard GARCH(1,1) process, $\tau_m$ is described by means of the MIDAS technique and involves data of lower frequency. The full model for the daily Cryptocurrency returns reads as follows:

$$r_{t,m} = \mu + \varepsilon_{t,m}, \tag{1}$$

$$\varepsilon_{t,m} = z_{t,m}\sqrt{\tau_m g_{t,m}} \quad \text{with } z_{t,m} \sim t_\nu(0,1) \text{ i.i.d.}, \tag{2}$$

$$g_{t,m} = (1-\alpha-\beta) + \alpha\left(\frac{\varepsilon^2_{t-1,m}}{\tau_m}\right) + \beta g_{t-1,m}, \tag{3}$$

$$\tau_m = \exp\left(c + \theta\sum_{k=1}^{K}\varphi_k\left(\omega_1,\omega_2\right)X_{m-k}\right), \tag{4}$$

$$\varphi_k\left(\omega_1,\omega_2\right) = \frac{\left(k/\left(K+1\right)\right)^{\omega_1-1}\left(1-k/\left(K+1\right)\right)^{\omega_2-1}}{\sum_{j=1}^{K}\left(j/\left(K+1\right)\right)^{\omega_1-1}\left(1-j/\left(K+1\right)\right)^{\omega_2-1}}, \tag{5}$$

where $\mu$ is the unconditional mean, $t$ and $m$ are the indices for the days and months, and $X_m$ is the explanatory variable at monthly frequency. For the GARCH process the standard non-negativity and stationarity constrains have to hold. As suggested by Klein et al. (2018), we use Student's $t$ distributed errors for the model to account for the non-normal returns of Cryptocurrencies. To weight the lagged low-frequency variables, we use the Beta-weighting scheme $\varphi_k\left(\omega_1,\omega_2\right)$ introduced by Ghysels et al. (2007). It is easy to see that the model decomposes to the standard GARCH model if $\theta = 0$. Here, we employ monthly explanatory variables to describe the long-term component of the daily conditional volatility of Cryptocurrencies and set $K = 12$.

We forecast the 1-day, 7-days, and 30-days ahead variance $h_{t,m} = \tau_m g_{t,m}$ by estimating the parameters of the model for a rolling window $t = 1, \ldots, T$ and predicting the next day's variance $\hat{h}_{T+1,m}$. We evaluate the forecast by means of the Heteroskedasticity-adjusted Mean Squared Error (HMSE)

$$\text{HMSE} = N^{-1} \sum_{i=1}^{N} \left(1 - \left(r_{i,m} - \hat{\mu}\right)^2 / \hat{h}_{i,m}\right)^2, \tag{6}$$

and the Heteroskedasticity-adjusted Mean Absolute Error (HMAE)

$$\text{HMAE} = N^{-1} \sum_{i=1}^{N} |1 - \left(r_{i,m} - \hat{\mu}\right)^2 / \hat{h}_{i,m}|. \tag{7}$$

The two measures are often used to evaluate GARCH models (e.g. Bollerslev & Ghysels, 1996, Patton, 2011). Based on the Model Confidence Set (MCS, Hansen et al., 2011), we derive a set of models with a sufficient prediction of the variance, outperforming models which are not an element of the respective MCS. We use the GARCH(1,1) model as a benchmark and also employ the average forecast combination of all GARCH-MIDAS models (1/n) as model averaging approach by $\hat{h}_{i,m} = |P|^{-1} \sum_{p \in P} \hat{h}^p_{i,m}$, where $P$ is the set of all models under investigation.

## 3. Data

We employ time series of prominent Cryptocurrencies, i.e. Bitcoin, Etherium, Litecoin, and Ripple. All Cryptocurrency time series are retrieved from `coinmarketcap.com`. In addition, we use the Cryptocurrency index CRIX available from `crix.hu-berlin.de` (Trimborn & Härdle, 2016). All daily price series are sampled until April 30, 2018 but vary in their starting point. An overview of the respective sampling period and resulting total number of observations is given in Panel A of Tab. 1 along with selected descriptive statistics. An in-depth statistical overview of Cryptocurrencies is given in Härdle et al. (2018).

In order to explain the long-term volatility component in the GARCH-MIDAS set-up, we utilize various financial and economic time series which are given in Panel B.

| | Start | OoS Start | End | OoS Obs. | Total Obs. | Mean | St.Dev. | ADF |
|---|---|---|---|---|---|---|---|---|
| Panel A: Cryptocurrencies (daily) | | | | | | | | |
| Bitcoin logRet | 01-May-2013 | 01-May-2014 | 30-Apr-2018 | 1460 | 1826 | 0.2298 | 4.5028 | $-42.5976^{***}$ |
| Etherium logRet | 01-Sep-2015 | 31-Aug-2016 | 30-Apr-2018 | 607 | 973 | 0.6372 | 6.9197 | $-29.7004^{***}$ |
| Litecoin logRet | 01-May-2013 | 01-May-2014 | 30-Apr-2018 | 1460 | 1826 | 0.1940 | 6.9335 | $-41.6256^{***}$ |
| Ripple logRet | 01-Sep-2013 | 01-Sep-2014 | 30-Apr-2018 | 1337 | 1703 | 0.2937 | 7.8816 | $-39.0844^{***}$ |
| CRIX logRet | 01-Aug-2014 | 01-Aug-2015 | 30-Apr-2018 | 1003 | 1369 | 0.2516 | 3.8992 | $-37.2988^{***}$ |
| Panel B: Explanatory Variables (monthly) | | | | | | | | |
| S&P500 logRET | 01-Jun-2012 | – | 01-Apr-2018 | – | 71 | 0.1075 | 0.3418 | $-9.2076^{***}$ |
| S&P500 RV | 01-Jun-2012 | – | 01-Apr-2018 | – | 71 | 0.1151 | 0.0495 | $-1.7107^{*}$ |
| VIX | 01-Jun-2012 | – | 01-Apr-2018 | – | 71 | 15.1754 | 3.5992 | $-1.1881$ |
| MSCI EM logRET | 01-Jun-2012 | – | 01-Apr-2018 | – | 71 | 0.0819 | 0.4886 | $-7.7978^{***}$ |
| MSCI EM RV | 01-Jun-2012 | – | 01-Apr-2018 | – | 71 | 0.1361 | 0.0432 | $-1.3393$ |
| GSCI logRET | 01-Jun-2012 | – | 01-Apr-2018 | – | 71 | $-0.1146$ | 0.6355 | $-7.1362^{***}$ |
| GSCI RV | 01-Jun-2012 | – | 01-Apr-2018 | – | 71 | 0.1705 | 0.0680 | $-1.2276$ |
| DJPM logRET | 01-Jun-2012 | – | 01-Apr-2018 | – | 71 | $-0.1076$ | 1.2539 | $-8.7420^{***}$ |
| DJPM RV | 01-Jun-2012 | – | 01-Apr-2018 | – | 71 | 0.3390 | 0.1257 | $-1.1863$ |
| GEPU sRET | 01-Jun-2012 | – | 01-Apr-2018 | – | 71 | 2.5272 | 22.8268 | $-9.6014^{***}$ |
| CEPU sRET | 01-Jun-2012 | – | 01-Apr-2018 | – | 71 | 11.1213 | 50.5133 | $-10.5964^{***}$ |
| GREA | 01-Jun-2012 | – | 01-Apr-2018 | – | 71 | $-21.6210$ | 26.6461 | $-1.8532^{*}$ |
| USD logRET | 01-Jun-2012 | – | 01-Apr-2018 | – | 71 | 0.0298 | 0.2261 | $-8.6810^{***}$ |

Table 1: Descriptive statistics of the daily return series of Cryptocurrencies and the monthly explanatory variables. OoS refers to the Out-of-Sample, Obs. are the number of observations, St.Dev. is the Standard Deviation and ADF is the Augmented-Dickey-Fuller-test for unit roots. The asterisks *** and * correspond to the level of significance of 1% and 10%.

In particular, we use the monthly returns and realized volatility of the S&P 500, the MSCI Emerging Markets 50 (MSCI EM), and the Dow Jones Precious Metals (DJPM) index in order to investigate the impact of the U.S. and Emerging Markets, especially Chinese, equity markets as well as the influence of commodities. In terms of economic variables, we include the Global and the Chinese Economic Policy Uncertainty index (GEPU and CEPU, `www.policyuncertainty.com`) as well as the Global Real Economic Activity (GREA)[1], and the trade weighted USD index (`fred.stlouisfed.org/series/DTWEXM`). For the financial variables we use the logarithmic returns (logRet) and the monthly realized volatility $RV_m = \sum_{t=1}^{M} r_{t,m}^2$. We keep the volatility index VIX and GREA at levels. The two Economic Policy Uncertainty indices are used as simple returns (sRet).

## 4. Results

We use the presented exogenous drivers of the long-term volatility to forecast the conditional volatility of Bitcoin, Etherium, Litecoin, Ripple, and CRIX. The forecast horizon is set to one day, one week, and one month, i.e. 1-day, 7-days, and 30-days ahead forecasts since Cryptocurrencies are traded continuously. Tables 2, 3, and 4 present the results for

[1] We are thankful to Lutz Kilian for providing the updated data on his website (`http://www-personal.umich.edu/~lkilian/paperlinks.html`). The construction is described in detail in Kilian (2009).

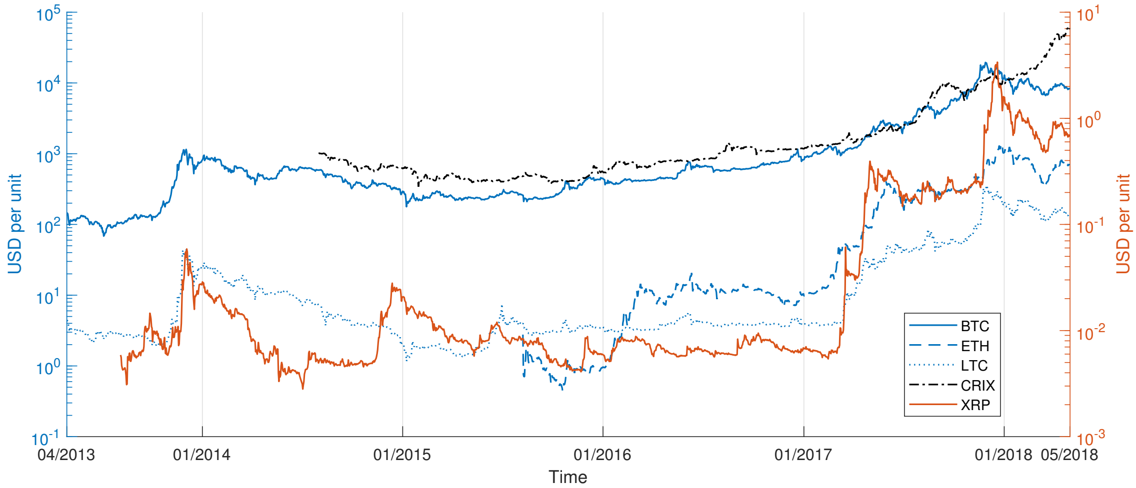


Figure 1: Prices of Bitcoin (BTC), Etherium (ETH), Litecoin (LTC), CRIX index points (CRIX), and Ripple (XRP) in log-scale with their respective sampling range ending April 30, 2018.

| | Bitcoin | | Etherium | | Litecoin | | Ripple | | CRIX | |
|---|---|---|---|---|---|---|---|---|---|---|
| | HMSE | HMAE | HMSE | HMAE | HMSE | HMAE | HMSE | HMAE | HMSE | HMAE |
| GARCH | 0.9617 | 0.8370 | 0.6178 | 0.7154 | 1.3595 | 0.9016 | 0.7450 | 0.7410 | 0.9415 | 0.8235 |
| SP500 logRet | 0.9144 | 0.8248 | 0.5993 | 0.7040 | 1.5138 | 0.9034 | 0.7280 | 0.7229* | 0.9227 | 0.7873 |
| SP500 RV | 0.9108 | 0.8284 | 0.5722* | 0.6822* | 1.3049 | 0.8917 | 0.7194* | 0.7275* | 0.8551 | 0.8004 |
| VIX | 0.9028 | 0.8216 | **0.5687*** | **0.6816*** | 1.4712 | 0.9013 | 0.7959 | 0.7465 | 0.9481 | 0.8232 |
| EM logRet | 0.8584 | 0.8138* | 0.5880* | 0.7007* | 1.4018 | 0.9053 | 0.7807 | 0.7380* | **0.7830*** | **0.7589*** |
| EM RV | 0.9055 | 0.8282 | 0.5841* | 0.6873* | 1.2381 | 0.8728 | 0.7337 | 0.7353* | 0.8438 | 0.7990 |
| GSCI logRet | 0.9112 | 0.8245 | 0.5903* | 0.6832* | 1.3967 | 0.8929 | 0.7921 | 0.7439* | 0.7943* | 0.7754 |
| GSCI RV | 0.8880 | 0.8098* | 0.6030 | 0.6953* | 1.2879 | 0.8953 | 0.7246 | 0.7408 | 0.8692 | 0.8031 |
| DJPM logRet | 1.4893 | 0.8348* | 0.5904* | 0.6972* | **1.0585*** | **0.8549*** | 1.1331 | 0.7788 | 0.9633 | 0.8118 |
| DJPM RV | 0.8476 | 0.8108* | 0.5699* | 0.6825* | 1.2800 | 0.8697* | 0.7205 | 0.7493 | 0.8364* | 0.7878 |
| GEPU sRet | 0.8287 | 0.8088* | 0.6662 | 0.7203 | 1.1558 | 0.8642* | **0.6783*** | **0.7210*** | 0.8473 | 0.7915 |
| CEPU sRet | 0.8260* | 0.7980* | 0.6243 | 0.7101 | 1.2747 | 0.8773 | 0.9661 | 0.7535 | 0.8476* | 0.7884 |
| GREA | **0.7916*** | **0.7965*** | 0.5743* | 0.6842* | 1.2679 | 0.8714* | 0.7236* | 0.7268* | 0.8194* | 0.7978 |
| USD logRet | 0.8348* | 0.8044* | 0.6010 | 0.7032 | 1.2953 | 0.8834 | 0.7829 | 0.7353* | 0.8116* | 0.7888 |
| 1/n | 0.8017* | 0.8027* | 0.5775* | 0.6893* | 1.0694* | 0.8553* | 0.6859* | 0.7324* | 0.7940* | 0.7838 |

Table 2: Forecasting results with GARCH-MIDAS and exogenous variables for 1-day ahead. Asterisks indicate the inclusion in the MCS ($T_R$ statistic, 70% confidence level, 50 000 bootstraps). The bold font in each column represents the lowest loss function.

the two loss functions. We do not find a single driver which is consistently outperforming its peers over the cross section of Cryptocurrencies and forecasting horizons. Hence, each Cryptocurrency tends to have a specific exogenous variable which results in the lowest corresponding loss function. For 1-day ahead forecasts, we find GREA to best predict Bitcoin, VIX for Etherium, DJPM logRet for Litecoin, GEPU for Ripple, and EM logRet for CRIX. These drivers lead to both the lowest HMSE and HMAE. However, the choice of exogenous variable seems to vary over different forecast horizons.

From the set of exogenous variables, only GREA is included in at least one MCS of each Cryptocurrency for 1-day and 7-days ahead forecasts (except for Etherium for 7-days ahead). In total, GREA appears to be included eight, six, and five times out of ten possibilities in the MCS for 1-day to 30-days ahead forecasts, respectively. This is

| | Bitcoin | | Etherium | | Litecoin | | Ripple | | CRIX | |
|---|---|---|---|---|---|---|---|---|---|---|
| | HMSE | HMAE | HMSE | HMAE | HMSE | HMAE | HMSE | HMAE | HMSE | HMAE |
| GARCH | 8.1179 | 1.2631 | 3.3295 | 1.0964 | 37.1404* | 1.6421 | 26.2656* | 1.3527* | 8.2771 | 1.2430 |
| SP500 logRet | 9.0960 | 1.2157 | **2.6575*** | **1.0139*** | 35.8485* | 1.6478 | 3000.3237 | 3.0976 | 8.1421 | 1.2330 |
| SP500 RV | 5.4774 | 1.1481 | 5.3801 | 1.1737 | 38.3603* | 1.6812 | 46.7910 | 1.3846* | 7.7623 | 1.1928 |
| VIX | 7.5111 | 1.2468 | 6.2196 | 1.1867 | 52.5350* | 1.7631 | 786.3291 | 2.1223 | 8.6250 | 1.2306 |
| EM logRet | 6.1602 | 1.1794 | 3.5889 | 1.1190 | 36.4116* | 1.6286 | 276.8415 | 1.8129 | 6.5234 | 1.1511 |
| EM RV | 6.2301 | 1.1757 | 7.5513 | 1.2162 | 41.1884* | 1.6293 | 26591.6654 | 5.7598 | 7.9635 | 1.1499 |
| GSCI logRet | 7.2096 | 1.2266 | 3.5245 | 1.1157 | 57.1778* | 1.8448 | 54.7719 | 1.5588 | 6.0336 | 1.1595 |
| GSCI RV | 8.3424 | 1.2031 | 6.8214 | 1.1288 | 32.9354* | 1.5391 | 69.5430 | 1.4254 | 5.6895 | 1.1525 |
| DJPM logRet | 6.1031 | 1.1999 | 3.6145 | 1.0998 | **19.1987*** | 1.4563* | 195.8936 | 1.7228 | 7.8160 | 1.2145 |
| DJPM RV | 4.6663 | 1.1290 | 10.0558 | 1.2479 | 68.4709* | 1.7620 | 481.1845 | 1.8688 | 3.5572 | 1.0676* |
| GEPU sRet | 4.4423 | 1.1025 | 4.9343 | 1.1805 | 29.4533* | 1.5263 | 606.1552 | 1.9654 | 5.1119 | 1.1421 |
| CEPU sRet | 5.8531 | 1.1522 | 3.7277 | 1.1337 | 26.5321* | 1.5430 | 57.7435 | 1.6252 | 10.7019 | 1.2580 |
| GREA | 3.7043* | 1.0795 | 3.8840 | 1.0841 | 48.3778* | 1.7340 | **17.1473*** | **1.3250*** | **2.9262*** | **1.0319*** |
| USD logRet | 6.6134 | 1.1409 | 3.2995 | 1.0879 | 22.4776* | 1.5228 | 40.8356* | 1.3867* | 5.9842 | 1.1664 |
| 1/n | **3.6326*** | **1.0542*** | 2.6706* | 1.0315* | 20.1888* | **1.4344*** | 59.9854* | 1.3605* | 3.9512 | 1.0609* |

Table 3: Forecasting results with GARCH-MIDAS and exogenous variables for 7-days ahead. Asterisks indicate the inclusion in the MCS ($T_R$ statistic, 70% confidence level, 50 000 bootstraps). The bold font in each column represents the lowest loss function.

| | Bitcoin | | Etherium | | Litecoin | | Ripple | | CRIX | |
|---|---|---|---|---|---|---|---|---|---|---|
| | HMSE | HMAE | HMSE | HMAE | HMSE | HMAE | HMSE | HMAE | HMSE | HMAE |
| GARCH | 4.2120 | 1.1111 | **1.6939*** | **0.9724*** | 28.5555* | 1.5447 | 121.5752* | 1.5553* | 6.2424 | 1.1921 |
| SP500 logRet | 7.1176 | 1.2094 | 1.8466* | 0.9738* | 44.5350* | 1.7069 | 163.1953* | 1.7635 | 20.8696 | 1.4830 |
| SP500 RV | 4.5624 | 1.1124 | 11.0322 | 1.3079 | 42.4614 | 1.6287 | 119.8807* | 1.5360* | 44.6636 | 1.5870 |
| VIX | 5.4433 | 1.1419 | 12.6446 | 1.3441 | 65.3888 | 1.8008 | 251.1899* | 1.9090* | 9.6614 | 1.2389 |
| EM logRet | 4.0489 | 1.1062 | 10.8188 | 1.3292 | 25.9422* | 1.4919 | 241.6400* | 1.8357* | 10.2282 | 1.2689 |
| EM RV | 5.6618 | 1.1334 | 13.9222 | 1.3459 | 38.8996 | 1.6561 | **36.0425*** | 1.3972* | 16.6892 | 1.3901 |
| GSCI logRet | 3.8287 | 1.1084 | 6.1791 | 1.1783 | 47.9303 | 1.7803 | 155.2389* | 1.6200* | 4.5275* | 1.1162* |
| GSCI RV | 5.4165 | 1.1447 | 5.5677 | 1.1230 | 29.2407* | 1.5298 | 60.9905* | **1.3528*** | 15.0729 | 1.2750 |
| DJPM logRet | 6.4314 | 1.1496 | 1.8044* | 0.9893* | 36.9077* | 1.3789* | 152.2339* | 1.6807* | 7.8236 | 1.1910 |
| DJPM RV | 4.3782 | 1.0913 | 78.9157 | 1.9047 | 40.3778* | 1.6326 | 93.2335* | 1.5619* | 3.9212* | 1.0687* |
| GEPU sRet | 2.8203 | 1.0716 | 21.2360 | 1.3683 | 171.5498 | 1.8191 | 36.6257* | 1.3978* | 4.8868 | 1.1228 |
| CEPU sRet | 3.5675 | 1.0645 | 2.8807 | 1.0734 | 24.2919* | 1.4645 | 650.5206* | 2.2817* | 3.7997* | 1.1273 |
| GREA | 3.2395 | 1.0580 | 5.5656 | 1.1331 | 26.3396* | 1.5282 | 54.2038* | 1.3814* | **3.0241*** | **1.0586*** |
| USD logRet | 3.6855 | 1.0911 | 1.7836* | 0.9834* | 43.4598* | 1.6436 | 724.1368* | 2.2690* | 6.9914 | 1.2301 |
| 1/n | **2.3490*** | **1.0037*** | 2.8977* | 1.0295* | **19.5149*** | **1.3423*** | 80.4794* | 1.4315* | 3.3220* | 1.0592* |

Table 4: Forecasting results with GARCH-MIDAS and exogenous variables for 30-days ahead. Asterisks indicate the inclusion in the MCS ($T_R$ statistic, 70% confidence level, 50 000 bootstraps). The bold font in each column represents the lowest loss function.

interesting, since the second best choices only result in six, three, and six appearances. This finding indicates that GREA—a proxy for the world's business cycles—is a very good predictor of Cryptocurrencies' volatility over their cross section. Figure 2 illustrates the fitted long-term component including GREA for the Bitcoin time series. We note that our benchmark model, the basic GARCH(1,1) does a very poor job and is only included eight times over all 30 possibilities. Even more astonishing is the finding that common choices of volatility drivers of other asset classes, in particular VIX (5) or the S&P 500 logRet (8), do not predict the volatility of Cryptocurrencies sufficiently, especially not for longer horizons. Comparing our forecasting results with the in-sample results of Conrad et al. (2018) for Bitcoin, we confirm that macroeconomic business cycle indicator contain important information for Cryptocurrency volatility. The authors employ the Baltic Dry index which is somewhat similar to Kilian's (2009) GREA. However, we cannot support the findings that variables as S&P 500 RV or the VIX are important for the volatility of Bitcoin. Interestingly, GREA also turns out to be of explanatory value for other

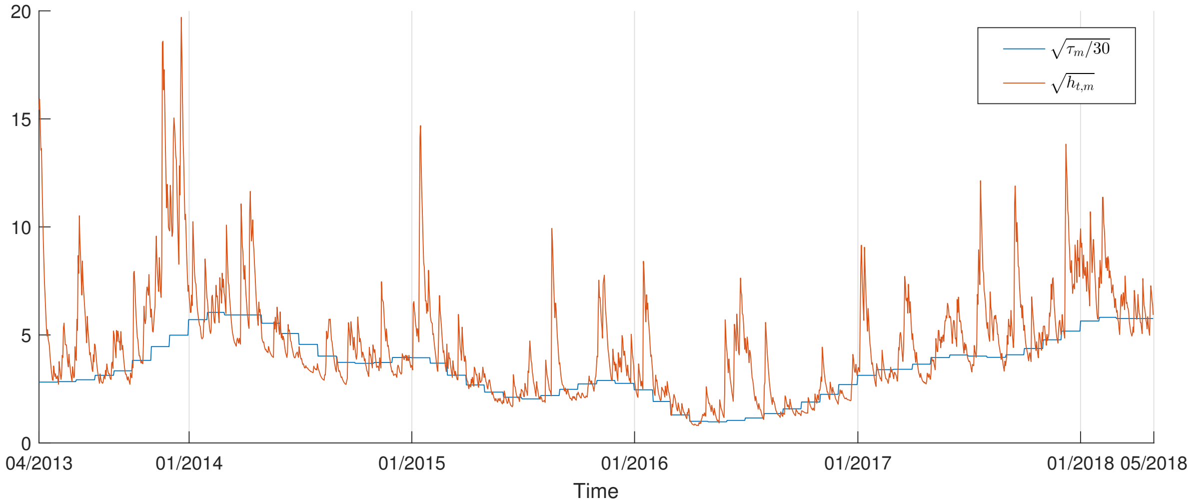


Figure 2: Daily volatility (red) and daily long-term volatility component with GREA (blue) for Bitcoin from May 1, 2013 to April 30, 2018.

commodities (Nguyen & Walther, 2018). Following GREA in appearances in the MCS are DJPM logRet (13), DJPM RV (12), and USD logRet (12).

The GARCH-MIDAS model with GREA as exogenous driver is only outperformed by one other configuration, i.e. the average forecast combination of all models under investigation. It is included in 28 out of 30 different MCS and appears to be the best choice seven times. We conclude that the model averaging is an even better predictor than just GREA by itself, since it somewhat diversifies the forecasts at each point in time. This becomes obvious if one compares the results for Ripple's HMSE. Here, some models really underestimate the variance at certain points in time, leading to a big deviance and high loss function. However, the forecast combination pools all information and lowers the impact of such outliers.[2]

## 5. Conclusions

In this article, we investigate the use-fullness of exogenous drivers to predict the 1-day, 7-days (one week), and 30-days (one month) ahead volatility. Out of a set of 14 different economic and financial drivers, we conclude that the Global Real Economic Activity

[2]Based on several robustness checks, this result hold. We changed the lags of the MIDAS model to 36 months, use a GJR-GARCH to account for the well-known leverage effect in the short-term dynamics as well change the underlying return distribution to Normal.

proxy outperforms its peers. Only the average forecast combination of all models under investigation is even better. This is interesting for several reasons: Firstly, the volatility of Cryptocurrencies appears to be driven by the global business cycle rather than country-specific economic or financial variables. Secondly, the superiority of the average forecasting combination suggests that even though GREA is the best predictor on average, other exogenous variables contain useful information and diversify the impact.

Future research could extend our work by re-investigating the issue with a different methodology, e.g. using intra-day data to construct daily realized volatility measures and adopt HAR-MIDAS as in Santos & Ziegelmann (2014). Since we only use economic and financial variables, one could investigate whether the long-term volatility is driven by Cryptocurrency-specific drivers.[3] Moreover, it would be interesting to scrutinize the value-added of exogenous drivers for trading strategies, risk management, and portfolio allocation. Lastly, we only investigate the average forecast combination. Thus, an in-depth analysis of loss function minimizing forecast pooling would extend the literature.

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[3]We intended to use the RV of the Cryptocurrencies to model the long-term volatility with GARCH-MIDAS, but dropped the idea, since it shortened our sample and the available observations significantly.

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