ANALYSING DIFFERENT FREQUENCIES OF BITCOIN TIMESERIES

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ABSTRACT

At least since the first Bitcoin futures were launched in December 2017, quantitative risk management on Bitcoin is no longer indispensable. This paper provides methodology and fundamental findings on approximations of intraday bitcoin returns through both symmetric and non-symmetric probability distributions. Different time frequencies of Bitcoin returns were analysed, and their non-Normal behaviour is shown. Their exchange rates versus the US Dollar, between April 14, 2017 until August 7, 2017, were considered by fitting parametric distributions to them. The non-normality changes with the size of the timesteps, where standard heavy-tailed distributions give good fits of the data. These results are a first attempt to characterize intraday risk of the Bitcoin.

KEYWORDS

Bitcoin, Quantitative Risk Management, Probability Distributions.

1. INTRODUCTION

Since Bitcoin multiplied its value in 2017, it gained a lot of attention also from institutional investors. Nonetheless there is less information about the characteristics of Bitcoin returns, especially for intraday timeseries. Therefore, analysing the Bitcoin, in favour of characterizing its behaviour will be done in this paper. This analysis is focused on data of different time frequencies and of different exchanges. Daily returns of the Bitcoin were already analysed [1]. This paper tries to extend their analysis by characterizing the statistical properties of intraday returns. This paper is organized in four sections. The first section is an introduction, the second section describes the data used for the analysis. The third section handles the analysis and includes fits of the most common parametric distributions to the data. The fourth and last section presents the results and conclusions.

2. DATA

The data used in this paper are exchange rates of the Bitcoin to the US Dollar. The data was collected through requesting certain exchanges APIs. The requested exchanges were: Bitfinex, Bithump and Kraken [2-4]. The data was collected from April 14, 2017 until August 7, 2017. Requests

where made about every 10 seconds. Then log-returns were calculated and used for further analyses. Out of this data other time frequencies were built and analysed, e.g. minutely or hourly returns. It must be said that the limitation of data prevents an over generalization of these results on other market situations. If there was missing data, due to technical issues, returns with too big timespans were excluded.

3. STATISTICS OF CRYPTOCURRENCIES

The market situation during the observed timespan could be describes as a steady upward trend with a up and down movement. There were also noticeable spreads of the price between the different observed exchanges. However, over generalizations of this market situation on others should be avoided.

3.1 Normal distribution and qq-plots

The next charts see Figures 1, show the qq-plot of the empirical Bitcoin log-returns versus the quantiles of the standard normal distribution for the Bitfinex exchange. The same analysis was made for other exchanges, with similar findings.

Figure 1: QQ Plot of returns with a time span of 10 seconds from bitfinex exchange versus the normal distribution

Figure 2: QQ Plot of returns with a time span of 60 seconds from bitfinex exchange versus the normal distribution

Figure 3: QQ Plot of returns with a time span of 60 minutes from bitfinex exchange versus the normal distribution

We see a substantial deviation from the normal distribution in all nine plots. This finding substantiates the approach of fitting heavy-tailed distribution to the data in the next section. It also seems that the deviation from the normal distribution is getting smaller the bigger the timespan of the log returns gets. We can evaluate this hypothesis in the next section, where an attempt is made to approximate the returns through different distributions.

3.2 Heavy-tailed distributions

Due to the previous findings, heavy-tailed distributions will be used in the next section to approximate the data. Also, as shown, for Example see, for daily data, heavy-tailed distributions describe exchange rate returns more accurately [1]. Thus, following distributions were chosen for the analysis: Normal (as "default" case, even though it is light-tailed), Asym. Student's t (Asym. t), Sym. Student's t (Sym. t), Asym. generalized hyperbolic (Asym. GHYP), Sym. generalized hyperbolic (Sym. GHYP), Asym. hyperbolic (Asym. HYP), Sym. hyperbolic (Sym. HYP), Asym. normal inverse gaussian (Asym. NIG), Sym. normal inverse gaussian (Sym. NIG), Asym. variance gamma distribution (Asym. VG) and the Sym. variance gamma distribution (Sym. VG). For further information to the distributions [1]. All these distributions were fitted by the maximum likelihood principal to the data and regularized by the Akaike information criterion (AIC) [5]. The AIC values is shown in Tables 1,2,3.

Table 1: AIC values of the fits of Bitcoin returns with a time span of 10 seconds from different exchange

Distribution	Bitfinex	Bithump	Kraken
Asym. GHYP	-32'328'026	-12'102'313	-118'450'115'023
Asym. HYP	-21'950'372	-12'659'881	-7'357'501
Asym. NIG	-22'941'608	-13'152'694	-7'601'226
Asym. VG	-28'182'393	12'659'881	-7'604'861

Asym. t	-22'286'355	-12'710'464	-8'165'348
Sym. GHYP	-27'838'478	-21'866'283	-18'213'666
Sym. HYP	-21'950'422	-12'660'057	-8'316'350
Sym. NIG	-22'946'151	-13'502'202	-9'578'103
Sym. VG	-32'610'311	-21'088'928	-15'667'553
Sym. t	-22'286'356	-12'710'466	-8'454'581
Gauss	-20'097'855	-11'737'505	-7'513'258

Table 2: AIC values of the fits of Bitcoin returns with a time span of 60 seconds from different exchange

Distribution	Bitfinex	Bithump	Kraken
Asym. GHYP	- 1'547'669	- 1'575'366	- 1'722'831
Asym. HYP	- 1'541'419	- 1'434'834	-1'373'093
Asym. NIG	- 1'547'669	- 1'429'387	- 1'371'198
Asym. VG	- 1'779'399	- 1'685'076	- 1'702'592
Asym. t	- 1'542'468	- 1'542'468	- 1'360'310

Sym. GHYP	- 1'886'436	- 1'666'192	- 1'715'163
Sym. HYP	- 1'541'416	-1'434'833	- 1'373'092
Sym. NIG	- 1'547'668	- 1'429'381	- 1'371'200
Sym. VG	- 1'625'451	- 1'692'318	- 1'700'718
Sym. t	- 1'542'470	- 1'423'867	- 1'360'313
Gauss	- 1'463'692	- 1'379'026	- 1'307'348

Table 3: AIC values of the fits of Bitcoin returns with a time span of 60 minutes from different exchange

Distribution	Bitfinex	Bithump	Kraken
Asym. GHYP	- 15'677.9	- 16'464.5	- 16'498.9
Asym. HYP	- 15'637.1	- 16'428.5	- 16'439.7
Asym. NIG	- 15'677.4	- 16'466.6	- 16'499.6
Asym. VG	- 15'636.9	- 16'435.9	- 16'451.7
Asym. t	- 15'674.3	- 16'451.9	- 16'492.4
Sym. GHYP	- 15'674.7	- 16'464.6	- 16'498.1
Sym. HYP	- 15'630.9	- 16'430.2	- 16'439.3
Sym. NIG	- 15'673.7	- 16'466.6	- 16'498.3

Sym. VG	- 15'630.1	- 16'437.9	- 16'451.7
Sym. t	- 15'672.3	- 16'451.9	- 16'491.9
Gauss	- 14'989.1	- 15'731.8	- 15'639.3

4. CONCLUSION

Heavy-tailed distributions can model the Bitcoin returns better than the normal distribution. Especially extreme observations can be modelled more dynamically and accurately than in a normal distribution. This could be shown through comparison of the fits of the normal distribution fits and heavy tailed distributions to the data. It could also be shown, that the deviation from normality of the returns has changed with bigger timesteps. The heavy tails are getting smaller, and the data appears to be more normal distributed. Substantial differences between the exchanges in terms of the distribution of returns couldn't be observed in this analysis. Nonetheless there still is arbitrage in the crypto market, since there is a lot of variation in qualitative factors of exchanges. Implications for this are in risk management, where one needs to compute value-at-risk and expected shortfall as well as for investment purposes. To my knowledge, this is the first study looking at the different time frequencies of Bitcoin returns and exchanges.

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