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Abstract Cryptocurrencies have recently gained a lot of interest from investors, central banks and governments worldwide. The lack of any form of political regulation and their market far from being “efficient”, require new forms of regulation in the near future. From an econometric viewpoint, the process underlying the evolution of the cryptocurrencies’ volatility has been found to exhibit at the same time differences and similarities with other financial time-series, e.g. foreign exchanges returns. This short note focuses on predicting the conditional volatility of the four most traded cryptocurrencies: Bitcoin, Ethereum, Litecoin and Ripple. We investigate the effect of accounting for long memory in the volatility process as well as its asymmetric reaction to past values of the series to predict: one day, one and two weeks volatility levels.

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1 The volatility of Cryptocurrencies

Many of the stylized facts that characterize usual financial time-series also apply to cryptocurrencies. For instance, similar to equity prices, cryptocurrencies exhibit: i) time-varying volatility, ii) extreme observations, and iii) an asymmetric reaction of the volatility process to the sign of past observations (*i.e.*, leverage effect). However, standard dynamic volatility models like the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model of Bollerslev (1986) do not perform accurately and Catania and Grassi (2017) show that they are outperformed by more refined alternatives like the Score Driven model with conditional Generalized Hyperbolic Skew Student's t (GHSKT) innovations. The specification of the conditional distribution of the aforementioned Score Driven volatility model, GHSKT, is important since it characterises the filter for the conditional volatility, see Creal et al. (2013) and Harvey (2013). For instance, Catania and Grassi (2017) find that the robust volatility filter implied by the Score Driven-GHSKT model is of primary importance in describing the stochastic evolution of cryptocurrencies. Indeed, in their analysis involving 289 cryptocurrencies, GARCH is never preferred according to likelihood criteria.

The aim of this short note is to extend results of Catania and Grassi (2017) to the important tasks of predicting future volatility levels of the four most representative cryptocurrencies: Bitcoin, Ethereum, Litecoin and Ripple. Those cryptocurrencies are the most important in terms of diffusion and market capitalization. At the time of writing market capitalization in USD dollars is 185.5 billion for Bitcoin, 44.3 billion dollars for Ethereum, 9.7 billion dollars for Ripple and 5.5 billion dollars for Litecoin. All together, these cryptocurrencies represent the 73% of the total cryptocurrency market value. See Catania and Grassi (2017) for a detailed description of those cryptocurrencies.

Since volatility is unobserved and realized volatility measures are not available, in our forecasting analysis we proxy future volatility levels with the square of the realized log-returns. Squared returns are known to be a poor volatility proxy, and poor volatility proxies are known to affect forecast comparison, see Andersen and Bollerslev (1998). To lower the influence of a volatility proxy on our results, model comparison is performed using the Quasi-Like (QLIKE) loss function which, as discussed by Patton (2011), is robust to this choice of volatility proxy. Specifically, let $\widehat{\sigma}_{j,t+h|t}$ be the h -step ahead volatility prediction made by model j at time t , and let r_{t+h} the log returns at time $t+h$, the QLIKE loss is defined as:

$$QLIKE(\widehat{\sigma}_{j,t+h|t}^2, \sigma_{j,t+h|t}^{2*}) = \log\left(\widehat{\sigma}_{j,t+h|t}^2\right) + \frac{\widehat{\sigma}_{j,t+h|t}^2}{\sigma_{j,t+h|t}^{2*}} \quad (1)$$

where $\sigma_{j,t+h|t}^{2*} = r_{t+h}^2$ is the volatility proxy. QLIKE values associated to each model are computed recursively over a forecast horizon of length H . Values are then averaged and models with lower average values are preferred. In order to statistically assess the differences among alternative models, we employ the Model Confidence

Set procedure of Hansen et al. (2011) using the R package MCS detailed in Bernardi and Catania (2016).

2 Forecast Analysis and Model Comparison

The set of models we consider includes the GARCH model of Bollerslev (1986) (\mathcal{M}_1), the Score Driven-GHSKT model (\mathcal{M}_2) along with three extensions with: i) leverage (\mathcal{M}_3), ii) time-varying skewness (\mathcal{M}_4), and iii) fractional integration in the volatility process (\mathcal{M}_5), see Catania and Grassi (2017) for a detailed specification of these models. It is worth noting that, the volatility filter of the Score Driven-GHSKT model also depends from the shape and skewness parameters of the GHSKT conditional distribution. This way, volatility predictions delivered by model \mathcal{M}_4 will be affected by the specification of time-varying skewness coefficients.

The data we consider are percentage log differences of the daily cryptocurrencies closing values. The Bitcoin and Litecoin series start the 29th of April, 2013, while Ethereum and Ripple series start the 8th and the 5th August, 2013, respectively. All series end the 1st of December, 2017.¹ Bitcoin and Litecoin have 1'678 observations while Ethereum and Ripple have 847 and 1'580, respectively.² The full sample is equally divided in two parts: i) the in-sample period where models' parameters are estimated the first time and, ii) the out-of-sample period where predictions are made. The length of the out-of-sample period is 839 for Bitcoin and Litecoin, and 424 and 790 for Ethereum and Ripple, respectively. Models' parameters are updated each time a new observation becomes available using an expanding window until the end of the sample. We select three forecast horizons: i) one day ($h = 1$), ii) one week ($h = 7$) and, two weeks ($h = 14$).

Table 1 reports the average QLIKE values for all cryptocurrencies and forecast horizons. Results are reported relative to the GARCH model, \mathcal{M}_1 , acting as a benchmark. That is, values lower than one indicate outperformance with respect to \mathcal{M}_1 and viceversa. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure with confidence level 10%.

Results indicate that \mathcal{M}_1 is generally outperformed by the more refined Score Driven-GHSKT model, \mathcal{M}_2 . Gains increase when the forecast horizon grows. We find that for Bitcoin, \mathcal{M}_2 reports better results than its extensions \mathcal{M}_3 , \mathcal{M}_4 and \mathcal{M}_5 . This result confirms the findings of Catania and Grassi (2017) in their in-sample models comparison. Results for Ethereum show that many models belong to SSM indicating that all models perform similar in predicting future volatility levels. This result might be influenced by the low number of observations available for Ethereum. Results for Ripple and Litecoin are very clear: \mathcal{M}_5 is preferred for Ripple and \mathcal{M}_3 for Litecoin. That is, long memory is an important feature for the

¹ Note that the cryptocurrency market trades 24 hours a day, all days. Here with closing value we mean the price at (UTC) midnight.

² All series are available from <https://coinmarketcap.com>.

	\mathcal{M}_1	\mathcal{M}_2	\mathcal{M}_3	\mathcal{M}_4	\mathcal{M}_5	\mathcal{M}_1	\mathcal{M}_2	\mathcal{M}_3	\mathcal{M}_4	\mathcal{M}_5
	Bitcoin					Ethereum				
$h = 1$	1.00	0.99	0.99	1.00	0.99	1.00	1.00	1.00	1.00	1.00
$h = 7$	1.00	0.97	0.97	0.99	0.98	1.00	0.97	0.98	0.98	1.00
$h = 14$	1.00	0.97	0.97	0.99	1.02	1.00	1.00	1.00	1.00	1.04
	Ripple					Litecoin				
$h = 1$	1.00	0.97	0.97	0.99	0.96	1.00	1.00	1.00	1.02	1.02
$h = 7$	1.00	0.98	0.98	1.01	0.97	1.00	0.98	0.97	0.99	0.98
$h = 14$	1.00	0.99	0.99	1.02	0.98	1.00	0.94	0.94	0.97	0.94

Table 1 Average QLIKE values for all cryptocurrencies and forecast horizons $h = 1, 7, 14$. Results are reported for the five models the GARCH model of Bollerslev (1986), \mathcal{M}_1 , the Score Driven–GHSKT model detailed in Catania and Grassi (2017), \mathcal{M}_2 , and its three extensions including: i) leverage (\mathcal{M}_3), ii) time–varying skewness (\mathcal{M}_4), and iii) fractional integration in the volatility process (\mathcal{M}_5), see Catania and Grassi (2017). Results are reported relative to \mathcal{M}_1 . Values lower than one indicate outperformance with respect to \mathcal{M}_1 and viceversa. Gray cells indicate those models that belong to the Superior Set of Models delivered by the Model Confidence Set procedure with confidence level 10%.

prediction of the Ripple’s volatility, and the inclusion of an asymmetric reaction of the volatility process is of primary importance for Litecoin.

3 Conclusion

This short paper focuses on predicting the conditional volatility of the four most traded cryptocurrencies: Bitcoin, Ethereum, Litecoin and Ripple. We investigate the effect of accounting for long memory in the volatility process as well as its asymmetric reaction to past values of the series to predict volatility levels. Our findings indicate that more sophisticated volatility models that include leverage and time-varying skewness can improve volatility predictions at different forecast horizons from 1% to 6% compared to more standard alternatives. Applications in portfolio optimizations, hedging and pricing of derivative securities, where volatility modelling is of primary importance, can benefit from these findings.

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