Zero Theorem Literature Review

"Using High-Frequency Entropy to Forecast Bitcoin's Daily Value at Risk, D. T. Pele, M. Mazurencu-Marinescu-Pele, 2019"

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Highlights

- Suggesting an effective model that uses Entropy to Forecast Bitcoin Daily value.

Background

The cryptocurrency was introduced in 2008 and now it's the most important market asset with a capitalization of approx. 180 billion USD. A major concern regarding cryptocurrency is the risk analysis in contrast with other market assets. Hence, the primary risk is bitcoin which is profoundly associated with alternative coins. However, different researchers used different techniques for back testing and estimating bitcoins' prices. GARCH was the first model to evaluate value at risk but it's optimal for known and largest cryptocurrencies. It has a limitation on the performance of time-series. Several other models such as parametric normal, historical simulation, Gaussian, and GARCH evaluates one-day value at risk. Parametric normal and historical simulation has limitations in value at the time of risk estimation. To avoid all restrictions there is a need for a model that better forecasts bitcoins value-at-risk and works effectively on a time-series frame.

Introduction

In this context, Pele and Mazurencu-Marinescu-Pele (2019) estimated the entropy intraday distribution of log returns through the symbolic time series analysis (STSA) which is the significant concern that has strong logical force for the quantiles of the intraday Value at Risk and the quantiles of the day-by-day returns. It performs better for a period series of EUR/JPY trade rates and anticipating capacity for the Bitcoin one-day value at risk than the old-style GARCH models. It's the lifesaver in times of bitcoin exchange rate which applies permutation entropy to analyze complexities.

Methodology

The working methodology uses Shannon entropy of Bitcoin's return to identify how probability loss is interlinked with entropy and then evaluates day value at risk using entropy with back testing techniques.

Entropy computes variability and complexity of a system in different domains where high entropy means more uncertainty and vice versa. Symbolic time-series analysis was performed to produce low-resolution data. Let's assume $P_{t,v}$ is the day trading price of bitcoin in t day with $t \in [1, T]$ and v corresponds to the trading time $v \in [1, N_t]$, N_t refers to the trading moments in one day. It uses a binary sequence where 0 refers to the price going up and 1 to the price going downward respectively. The regression model is applied to compute the hypothesis where negative bitcoins of daily returns can be explained by a lower value of entropy.

$$P\left(Y_t^* = 1\right) = \frac{\exp\left(b_0 + b_1 S_t\right)}{1 + \exp\left(b_0 + b_1 S_t\right)}$$

In above equation,S_t refers to the Shannon information entropy at day t, Y_t^* specifies lower tails where:

$$Y_t^* = \begin{cases} 1, & \text{if } r_t < -VaR_\alpha \\ 0, & \text{if } r_t \geq -VaR_\alpha \end{cases}$$

and VaR at significance level α is defined as:

$$\Pr\left(r_t < -VaR_\alpha\right) = \alpha$$

Results and Discussion

In order to evaluate the performance of forecasting ability with back testing technique different models were applied such as Historical VaR forecast, Normal GARCH, Student's GARCH model, Entropy VaR, and Entropy Auto regression VaR. When using 1% significance the Auto regression entropy model performs outclass with contrast to Historical VaR and Gaussian Model.The student GARCH model produces unrealistic results in the real-time frame.The same problem arises when the significance level is set to 5%. Below Table 1 and Table 2 shows representation of forecasting models with probabilities.

Table 1: 1% VaR forecast back-test results

Model	$\Pr(\boldsymbol{R}_t < -V\hat{a}\boldsymbol{R}_t)$	LR_{uc} Test	$\boldsymbol{LR_i}$ Test	LR_{full} Test
Historical VaR	0.014	0.014	6.766	8.142
n.GARCH(1,1) VaR	0.025	**13.476**	0.272	13.748
t-GARCH(1,1) VaR	0.003	**4.657**	**6.489**	**11.147**
Entropy VaR	0.003	**4.657**	**6.489**	**11.147**
Entropy AR VaR	0.002	**7.108**	**7.837**	**14.945**

Table 2: 5% VaR forecast back-test results

Model	$\Pr(\boldsymbol{R}_t < -V\hat{a}\boldsymbol{R}_t)$	LR_{uc} Test	$\boldsymbol{LR_i}$ Test	LR_{full} Test
Historical VaR	0.061	2.337	**3.924**	**6.262**
n.GARCH(1,1) VaR	0.060	1.905	**4.276**	**6.182**
t-GARCH(1,1) VaR	0.017	**24.014**	1.049	**25.063**
Entropy VaR	0.020	**20.023**	0.720	**20.744**
Entropy AR VaR	0.019	**21.955**	0.874	**22.830**

Hence, data depicts that the AR-VAR forecast gives a negative of the Value at Risk. Christoffersen's unconditional, independence and the full test shows that the entropy-based AR-VAR forecast model performs 99% with a confidence level.

Conclusion

This led to the conclusion that suggested study is about the relation between entropy and Value-at-Risk for Bitcoin. From the results it is clear that suggested methodology evaluated the entropy of intraday dissemination through the representation of time series investigation (STSA)and obtaining low-resolution information from high-resolution data of Bitcoins. Moreover, it produces promising results that showed entropy has a powerful logical force at the cost and return value of Bitcoin.

References

Pele, D. T. and Mazurencu-Marinescu-Pele, M. (2019). Using high-frequency entropy to forecast bitcoin's daily value at risk. *Entropy*, 21(2):102.