Review of: "Cryptocurrency market risk analysis: evidence from FZL function"

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Potential competing interests: No potential competing interests to declare.

The paper seems well-researched and appropriate for the problem at hand. The authors have adopted a robust statistical framework, GAS, which is widely used for risk management and finance, to model cryptocurrency market risk. Moreover, they have used a range of distributions such as skewed Gaussian, student-t, and asymmetric Laplace that can efficiently model the skewness, fat tails, and volatility clustering associated with financial returns.

Here are some suggestions for improvement:

1. Comparison with alternative methods: The paper does not compare the proposed FZL-GAS methodology with alternative methods for joint VaR and ES estimation in cryptocurrency markets. To address this shortcoming, the authors could compare their results with those obtained using traditional methods such as historical simulation, Monte Carlo simulation, and GARCH models. Additionally, they could compare their results with those obtained using other advanced techniques such as copula-based models, machine learning algorithms, and deep learning models.
2. Selection of distributions: The authors use a limited selection of distributions to model the conditional distribution of cryptocurrency returns. To address this shortcoming, the authors could consider using other distributions that are more suitable for cryptocurrency returns. For example, they could consider using the Generalized Hyperbolic Distribution (GHD) or the Generalized Error Distribution (GED), which have been shown to provide a good fit to cryptocurrency returns (Auer and Claessens, 2018).
3. Robustness: The paper does not include any robustness analysis to assess the sensitivity of the results to model assumptions and parameter choices. To address this shortcoming, the authors could perform sensitivity analysis by varying key parameters and assumptions in the model and assessing the impact on the results. Additionally, they could conduct out-of-sample tests to evaluate the out-of-sample forecasting performance of the model.
4. Multivariate Approach : one possible limitation of the methodology is that it is based on a univariate approach, which might not capture the interdependence among different cryptocurrencies in the market. This can lead to an underestimation of systemic risk. Therefore, the authors could consider a multivariate approach that considers the dependence structure among different cryptocurrencies in the market.
5. Computational efficiency: Another point to consider is that GAS models require estimation of the score function, which can be computationally expensive and time-consuming, especially when dealing with a large dataset. Therefore, the authors should provide more information on the computational efficiency of their methodology to assess its practicality in real-time applications.

6. Scope of analysis: The paper focuses solely on joint VaR and ES estimation in cryptocurrency markets. To address this shortcoming, the authors could extend their analysis to other risk measures such as Conditional Drawdown at Risk (CDaR), Tail Conditional Expectation (TCE), and Expected Shortfall (ES). They could also consider applying their methodology to other financial markets such as stock markets, commodity markets, and forex markets. This would enable a broader assessment of the performance of the FZL-GAS methodology and its applicability in different contexts.
7. Interpretability: The FZL-GAS methodology is a complex model that may be difficult to interpret for practitioners and regulators. To address this shortcoming, the authors could provide more detailed explanations of the model assumptions, parameter interpretations, and the implications of the results for risk management. Additionally, they could develop simpler versions of the model that are more accessible to non-experts, such as a reduced-form version that does not require a detailed understanding of the GAS framework.