Overview of Risk Estimation Methods for Cryptocurrency

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Abstract— In the current climate, cryptocurrency trading is becoming increasingly more accessible through smartphones. Coupled with a high market value of cryptocurrency, it is essential to strategize trading and investment to make the most of the cryptocurrency boom. This paper provides a systematic survey on risk estimation methods for cryptocurrencies based on the empirical results of relevant academic literature. Volatility analysis revealed that cryptocurrency markets are highly volatile in comparison to stock and gold. Value-at-Risk (VaR) measures showed varied distributions. Tail risk analysis was commonly measured through VaR using quantile regression. Ratio-based estimations were part of the larger goal of portfolio optimization techniques. Single-objective and multi-objective optimizations relied on Omega and Sharpe ratio respectively. This survey provides useful guidance in assessing various empirical, statistical and advanced risk estimation for cryptocurrency markets. It also provides an insight into quantitative analysis for risk estimation and the utility of risk estimation in portfolio optimization.

Keywords— Bitcoin, Cryptocurrency, Regression, Risk, Sharpe Ratio, Volatility.

I. INTRODUCTION

Cryptocurrency is a form of digital currency that can verify transactions without involving banks as an intermediary. It gets its name from the fact that transactions are verified through encryption. They are built using blockchain technology and form a peer-to-peer system allowing any two parties to send and receive currency. These transactions occur in the form of blocks recorded in a public digital distributed ledger.

Cryptocurrency is becoming increasingly accessible through mobile applications. Through smartphones and computers, cryptocurrency is available to populations that don't have access to traditional banking systems, credit cards and other modes of payment. A decentralized secure mode of payment thrives in the current cashless digital economy.

Cryptocurrency is scarce in comparison to its demand. These highly secure blocks of transactions are durable and transportable. Their traceability, immutability and public trust lend to themselves a high market value.

The combined accessibility of cryptocurrency and their high market value have fueled the growth of cryptocurrency trading. This calls for strategies that maximize profits in the cryptocurrency arena. Risk associated with exchanges must be controlled to mitigate the probability of huge losses in investment and trading.

Common measures of risk are used in the assessment of all types of risks, including credit risk, investment risk and market risk. Discussed below in this study are Volatility measures, Value-at-Risk (VaR), Tail Risk, Sharpe ratio and Omega ratio.

Volatility can be measured using mean, variance, skewness and kurtosis. In statistics, mean is another term for average. Standard deviation measures the dispersion or spread of data from its expected value or mean. The variance is the square of standard deviation. Skewness quantifies the deviation from a normal distribution, a characteristic bell-shaped symmetric curve. Kurtosis quantifies the deviation from the tails of a normal distribution. VaR estimates the loss of an investment probabilistically in normal market conditions, given a predefined time period and a degree of confidence on an assumed, calculated or derived profit-loss distribution. Tail risk is the probabilistic measure of an investment moving more than three standard deviations from the expectation, exceeding the risk in the normal distribution. Tail risk is commonly measured through VaR. A variant of VaR is Conditional-Value-at-Risk (CoVaR). CoVaR is the expectation of returns or prices beyond VaR at a given confidence level. Sharpe ratio is the ratio of the difference between expected return and risk-free return to the standard deviation of the investment. This difference is known as excess return. Omega ratio, commonly referred to as Omega, is yet another risk-return measure but unlike the Sharpe ratio it also considers higher moments of distribution.

II. VOLATILITY ANALYSIS

The volatility of market prices affects the variations a portfolio sees. These changes in prices directly affect the risk associated with investing in these markets.

Dempere [1] studied the explanatory or predictive power of several independent variables (daily log-returns of

Bitcoins, Ethereum and Ripple) over selected independent variables (Google trends for words such as “cryptocurrency”). The explanatory power of these selected variables in Bitcoin, Ethereum and Ripple were studied using GARCH modelling and its variants. GARCH is a statistical modelling technique used to help predict the volatility of returns on financial assets.
ADF and PP tests were applied to all the selected variables to make sure that all variables used in this study were stationary time series. Cryptocurrency names were used as search terms to derive Google trends. Along with this, daily log-returns of exchange rate of major currencies, S&P 500 index, gold, and oil prices were included in the studied variables.

The results in this study provides evidence about the statistical predictive power of Google trends over the return of financial assets like cryptocurrencies. Cryptocurrencies are relatively new financial assets with short historical time series data available.

The significance of relationships identified in this study may become obsolete with changing data in coming years. Drastic changes could be seen in the relationships discovered in this study owing to government regulations such as restrictions and bans that could impact the trading of cryptocurrency.

Liang et. al. [2] analyzed the temporal volatility, centrality structure and systemic risk in cryptocurrency markets. The study was conducted on the price history available. Their dynamic changes were studied as a relation to known financial events by constructing correlation matrices and asset trees.

Temporal volatility was described by mean, variance, skewness and kurtosis. Quantitative analysis revealed that correlation coefficients were impacted by financial events. The central node of the asset tree was chosen to be the node with the highest sum of correlation coefficients of edges. The topology of the asset tree was characterized by the mean occupation layers of the central nodes. Although the central node was varying, it was found that Bitcoin was the dominant node. The mean occupation layer was found to be highly fluctuating.

Minimum portfolio risk was used as an estimate to measure systemic risk. High similarity between risk and normalized tree length was demonstrated. The weighted portfolio layer, like the mean occupation layer, was highly volatile. This study revealed that the cryptocurrency market was relatively unstable and fragile in comparison to traditional financial markets.

A comprehensive volatility comparison was performed against foreign exchanges and stock by Liang et. al. [3]. Correlation matrices and asset trees were constructed from the daily close prices of cryptocurrency, foreign exchange and stock. Dynamic properties such as volatility, centrality, clustering structure, robustness, and portfolio risk were compared.

The distribution of the correlation matrix was described by mean, variance, skewness and kurtosis. Volatility comparison revealed that the correlation between variance and kurtosis was positive, while the correlation between mean and skewness was negative when comparing cryptocurrency markets against foreign exchange and stock. Variations in the central node of the asset tree were similar to the stock market, indicating that these markets were continuously changing.

The robustness was measured in terms of the behavior of the asset tree using a survival ratio. It was concluded that the survival ratio of foreign exchange was the highest, followed by the stock market and cryptocurrency market.

Clusters in the cryptocurrency markets did not obey any evident rule and changed rapidly. In comparison, the clustering structure in foreign exchange and stock showed consistency with the geography and the business sector respectively.

It was found that the cryptocurrency was more similar to the stock in terms of portfolio risk. The three markets had consistent behavior in the weighted portfolio layer. The behavior of the three markets were similar with respect to the temporal volatility.

Vo et. al. [4] modelled and forecasted volatility of Bitcoin returns by fitting a parametric distribution and choosing a time series model.

USD/BTC hourly log returns that were considered in this study were characterized by leptokurtosis. It was found that Generalized Hyperbolic distribution best fit the time series.

Using Residual Sum of Squares (RSS) and Normalized Residual Mean Square Error (NRMSE) as the evaluation criteria, the ARMA (1,2)- fGARCH (2,2)/TGARCH was found to be the best time series model under the GHYP distribution in comparison to SVM (support vector machine) and NN (neural network). The fitted model of the USD/BTC hourly log returns was also an accurate model for VaR forecast. The correlation analysis between Bitcoin returns and financial indices

(DJIA, ASX) showed that the Bitcoin prices did not follow these instruments.

III. VaR ESTIMATION

Value-at-Risk (VaR) is a statistic that estimates and quantifies the level of financial risk over a specified time period.

Silhali et. al. [5] used a two-sided HS-GARCH-Weibull model for portfolio VaR estimation of Bitcoin, Litecoin, Ripple and Dash. The study used data from Analytical Service CoinMarketCap. The distribution was assumed to be a shifted standardized two-sided Weibull distribution. Extreme volatility, volatility clustering, heavy tails, and skewness were captured in this model.
The predictive power of this model outperformed other more widely used VaR estimation methods (HS-empirical, HS-normal quantile, HS-t quantile, HS-EWMA, HS-GARCH-normal, HSGARCH-t, VC-normal, VC-t, DCC-MGARCH-normal, and DCC-MGARCH-t). This predictive power was evaluated using backtesting. Actual over expected exceedance ratio (AE), unconditional coverage, conditional coverage, and dynamic quantile tests were the methods used for backtesting.

Hrytsuik et. al. [6] fit a Cauchy distribution for portfolio VaR estimation of Bitcoin, Bitcoin Cash, Litecoin, XRP, Ethereum and NEM. This study used data from CoinMarketCap to fit the Cauchy distribution. Pearson, Kolmogorov-Smirnov, and Shapiro-Wilk tests rejected the hypothesis of a normal distribution. VaR was measured analytically using a least squares method based on the functional form of the distribution.

IV. TAIL RISK ANALYSIS

Financial events impact the tails of the distribution to which prices are fit. A fatter tail would suggest that there are significant fluctuations in the market price.
Nguyen et. al. [7] investigated this tail risk dependency among 21 different cryptocurrency markets. Data was collected from CoinMarketCap. The tail risk spillover effect among cryptocurrency markets was estimated by using the Least Absolute Shrinkage and Selection Operator (LASSO) quantile regression model with VaR as the risk measure. The VaR was modelled for various tail thresholds as a function of loss exceedance. The returns lower than a tail threshold defined beforehand were used to compute the loss exceedance.

The study found that the right tail dependence was less prominent than the left. It was also observed that even while the return distributions became less skewed over the considered period, the left-tail spillovers were overshadowed by the right tail counterparts. This observation strongly proved against the hypothesis that right tail spillovers were caused due to positively skewed return distributions coupled with potential peso problems. In addition, the study noted that Bitcoin and Litecoin were major drivers of tail risk when markets were bullish while the major drivers when markets were bearish were Ethereum and Ethereum Classic.

Conditional tail risk was estimated using Conditional-Value-at-Risk(CoVaR) by Borri [8]. The website cryptocompare.com was used for the collection of cryptocurrency prices of Bitcoin, Ethereum, Ripple, and Litecoin. CoVaR was estimated by quantile regression. The difference between the CoVaR of an asset conditional on a state of distress in another asset and the median state was measured by ΔCoVaR. ΔCoVaR indicated the fragility of individual assets.

CoVaR and ΔCoVaR were estimated for four cryptocurrencies (Bitcoin, Ethereum, Ripple, and Litecoin), gold, VIX volatility index, a commodity index, and a U.S. equity market index. A forward-looking systemic risk measure was formulated by regressing CoVaR and ΔCoVaR over macro variables common to all cryptocurrencies in different forecast horizons.

It was found that cryptocurrencies were highly correlated with each other conditionally and unconditionally. However, they were poorly correlated with other assets like gold. The study showed that cryptocurrency specific macro variables were useful in predicting future conditional tail-risk. A combination of high currency specific value-at-risk, high volatility and volume, and low returns was demonstrated to forecast large negative values for CoVaR and ΔCoVaR.

V. RATIO BASED ESTIMATION

Sharpe ratio is a well-known measure for calculating the average returns that are earned per unit of volatility or total risk.

This measure has been proposed to quantify the portfolio risk by Estalayo et. al. [9]. In this study, the historical selling and buying prices of seven well known cryptocurrencies were used. The prices from their release date up until the 30th of December 2019 were used. A stacked dual-layer Gated Recurrent Unit neural network architecture was used for selling price prediction which was consequently used to calculate the rate of return and risk. Six different multi-objective evolutionary algorithms were compared. The best results were obtained for Speed-constrained Multi-objective Particle Swarm Optimization (SMPSO) and Multi-objective Evolutionary Algorithm based on Decomposition (MOEAD).

The study performed by Castro, Javier Gutiérrez, et al. [10] involved the application of Omega, a universal performance measure. Omega not only accounts for the mean and the variance but all the higher-order moments. It proved to be a better measure since it reflected all the statistical properties of the distribution of returns. Instead of defining risk as the standard deviation of portfolio returns distribution, this study defined it by a put option, the discounted expected loss.

VI. PORTFOLIO OPTIMIZATION

Portfolio optimization is the process of allocating investments over a group of financial assets based on predetermined optimality criteria. Unlike when dealing with traditional economic trading markets, cryptocurrencies are dealt with in a much more dynamic manner. Portfolio optimization is one form of mitigating risk. The methods used to perform optimization may inherently estimate risk. Hence, portfolio optimization methods are investigated.

[9] highlighted the interrelationship between returns, diversity and the risk when dealing with optimization of portfolios. It laid emphasis on the popular Pareto trade-off between the risk estimated while investing and the earnings received from a portfolio. This trade-off results in a Pareto relationship defined in the theory of modern portfolio management proposed by Markowitz. The proposed framework further augmented this twofold criterion by introducing a third objective, which quantified both exclusively as well as explicitly the investment's diversity. This was then utilized as an intuitive measure for any generic user of the system. Multi-layered deep recurrent neural network regression models were applied in this proposed framework for the estimation of selling price of each of the assets in the portfolio. When compared with other regression techniques, this model proved to perform significantly better. The performance of six multi-objective evolution algorithms were compared to settle on a solver. The solver was required to maintain a balance amongst the previously mentioned objectives. Out of these, MOEAD and SMPSP outperformed the remaining algorithms and also ensured to provide Pareto fronts with diverse spacing characteristics amongst the portfolios produced. The study performed in [10] aimed to optimize portfolios by using Omega as a measure. It found the weights of each of the assets such that the portfolio's Omega performance measure was maximized. In addition to this, the study computed the expected loss which maximized Omega to assist in decisions related to capital allocation

VII. CONCLUSION

The survey conducted explores various empirical, statistical and advanced risk estimation methods for cryptocurrency markets. The survey is categorized into volatility analysis, VaR estimation, tail risk analysis, ratio-based estimation and portfolio optimization. Each category investigates risk estimation for the specific risk measure.

Volatility analysis revealed that cryptocurrency markets are highly volatile with respect to financial events and other financial markets such as gold and stocks. A common method that was used to measure volatility was the construction of correlation matrices.

A review of methods that estimate VaR revealed that the distribution chosen was different for different data.

The survey conducted for tail risk estimation showed that all practices modelled tail risk after VaR or a variant. The estimation itself was done through quantile regression.

A survey of ratio-based estimation methods showed that Omega ratio proved to be a better predictor than Sharpe ratio, accounting for higher moments.

A review of methods for risk control through portfolio optimization was additionally investigated. While a single objective optimizer relied on Omega, multi-objective optimizers relied on Sharpe ratio.

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