

## **White Paper**

### **EVAI GENERAL CRYPTOCURRENCY RATING FRAMEWORK**

#### **Abstract**

Evai are pioneering a world-class decentralised rating system for Crypto, DeFi and NFTs that can be used by anyone to evaluate these new asset classes. Through a combination of peer-reviewed financial research and economic modelling, Evai provides decentralised and impartial ratings based on a multi-factor AI & ML model without human intervention.

#### **Introduction**

Evai was created as a response to the financial crisis of 2008 which initiated the phenomenon of ‘Quantitative Easing’ (QE). QE has expanded money supply at the fastest rate since records began and has become a policy response to all economic headwinds that we face, including the economic downturn brought about by the Covid pandemic.

When we look back at the 2008 financial crisis, we can see that one of the major causes was the misallocation of assets resulting from incorrect ratings being attached to high-risk assets. It is therefore apparent that accurate ratings play a key role in fostering stability within our financial system.

With the advancement of technology, we are now able to harness the power of Artificial intelligence and Machine Learning to deliver truly decentralised ratings, free from human bias, based upon a solid foundation of universally accepted academic theory.

Evai are delivering an unbiased financial ratings system that can theoretically be applied to all liquid asset classes. When accurate ratings are applied to the current, approximately 12,000 digital assets that make up the crypto ecosystem, the resultant ratings can be used to reliably inform asset allocation and furthermore, Evai Ratings have been empirically tested and proven to offer predictive value, with the implication that investors may be able to exploit exceptions to the widely accepted “Efficient Market Hypothesis”.

Such an advancement in ratings technology adds value at every level from educational and regulatory through to market efficiency and profitability.

## **Problems Identified**

- The absence of an impartial rating system
- Ratings often determined by human analysts
- There is no universally accepted source of reliable data

## **Evai Solution**

Evai provides an unbiased cryptoasset rating platform to identify the true underlying value of assets in an emerging marketplace through AI and ML. Evai are further using these ratings to exploit potential exceptions to the Efficient Market Hypothesis to deliver abnormal market returns.

### **1. OVERVIEW OF THE RATINGS PROCESS**

The first level of financial ratings is univariate, where the rating will be based on a single factor.

The second level of financial ratings is more complicated, represented by the multi factor model, developed in Gregoriou (2011) and Gregoriou (2019) on asset pricing. In the multifactor model, the cryptocurrencies are rated on excess returns, after accounting for multiple factors. Evai will use both rating levels for comparison purposes in constructing a unique, comprehensive digital asset rating model.

In terms of data, we will use multiple data sources which will be in tandem with our own proprietary data gathering techniques. The resultant ‘clean’ data is then used to update the ratings model frequently. In instances where we do not have a full information set, we will provide a shadow rating, which will be based on incomplete data and make this clear to the market. In instances where the data is not rich enough or we deem it to be unreliable, we will not rate and will explain the reasons for this.

## 2. UNIVARIATE (SINGLE FACTOR) RATINGS

We will have a univariate set of models that we use for individual ratings, these are single factor models which are the following thus far:

- **Liquidity:** Composed by the following indicators: Turnover Ratio, Adjusted Turnover Ratio, Amihud Ratio, FKG ratio (Gregoriuet al. ,2011), Roll Spread, Effective spreads, Quoted Spreads, overall 7 indicators.
- **Sentiment:** Composed by Fear & Greed index, social development History Index, overall 2 factors.
- **Risk:** Sharpe Ratio, Sortino Ratio, overall 2 indicators.
- **Momentum:** Moving Average, Rate of Change, overall 2 indicators.
- **Utility:** Firm Profitability- Proxy ROI, overall 1 indicator.
- **Bias:** Peak End Value Demand, overall 1 indicator.
- **Overextension:** Fibonacci retracements, Ichimoku Cloud, Bollinhger Band, Stochastic Oscillator, overall 4 indicators.
- **Market Risk:** Market Factor, overall 1 indicator.
- **Capitalisation:** Size, overall 1 indicator.

We will have 9 main factors in the univariate framework, multivariate framework, so overall we will have 21 factors.

During the ratings analysis, each of these criteria is rated on the A to D scale.

<b>Univariate Cryptocurrency Rating</b>	
SECURE	
A1	Exceptionally Strong
A2	Very Strong
A3	Strong
B1	Good
VULNERABLE	
B2	Moderately weak
B3	Weak
C1, C2, C3	Very weak
D	Distressed

The following table gives the details of deciding the rating scale of cryptocurrencies according to the value of each rating criteria.

<b>Indicator</b>	<b>Variable Description</b>
<b>LIQUIDITY MEASURES</b>	
Turnover Ratio	Turnover ratio is the volume of cryptocurrency traded relative to the outstanding currency. The higher the turnover ratio, the more frequently the cryptocurrency is being exchange. The easier it is to exchange, the more liquidity and consequently the higher the value of the asset.  The Turnover Ratio is compared to a moving average of past performance to assess the rating. The periods to be considered are to be optimised using machine learning.
Adjusted Turnover Ratio	This measure is defined as the standardized turnover-adjusted number of zero-trading volume days over one month. A cryptocurrency with higher number of zero daily volume is less likely to be traded and thus less liquid. (Liu, 2006).

	<p>The Adjusted Turnover Ratio is compared to a moving average of past performance to assess the rating. The periods to be considered are to be optimised using machine learning.</p>
Amihud Ratio	<p>Amihud Illiquidity Ratio (Amihud, 2002) represents liquidity premium that compensates for price impact. It is measured as Cryptocurrency returns relative to volume. Cryptocurrencies with high Amihud ratio have a large price impact as buying and selling will move the price by a relatively large amount. These cryptocurrencies are considered relatively less liquid than cryptocurrencies with low Amihud ratio.</p> <p>The Amihud Ratio is compared to a moving average of past performance to assess the rating. The periods to be considered are to be optimised using machine learning.</p>
FGK Ratio	<p>Evai's exclusive illiquidity measure based on the 2011 research of Professor Andros Gregoriou.</p> <p>The FGK Ratio is a modification of the Amihud ratio that compares price impact against turnover rather than volume. It therefore overcomes some of the disadvantages of the Amihud Ratio like size bias. The lower the ratio, the smaller the price impact of orders and the more valuable the cryptocurrency.</p> <p>The FGK Ratio is compared to a moving average of past performance to assess the rating. The periods to be considered are to be optimised using machine learning.</p>
Roll Spread	<p>Roll (1984) measures the extent to which market-making will cause cryptocurrency prices to move in response to the bid-ask spread. The larger this zig-zag movement, the lower the liquidity and the more difficult to exchange cryptocurrencies at a stable price. This measure is usually used over high frequencies (intraday).</p> <p>The Roll Spread is compared to a moving average of past performance to assess the rating. The periods to be considered are to be optimised using machine learning.</p>
Effective Spread	<p>This will measure the actual cost of trading as two times the spread between the bid-ask midpoint and the actual price traded. It will require information about the price at which transactions are executed as well as the bid-ask spread. The difference between the quoted and effective spread can be positive or negative, providing information about the true cost of trading.</p>

	The Effective Spread is compared to a moving average of past performance to assess the rating. The periods to be considered are to be optimised using machine learning.
Quoted Spread	<p>Quoted bid-ask spread is the difference between the best bid and best ask price. A narrow spread implies lower trading costs and more liquidity.</p> <p>The Bid-Ask Spread is compared to a moving average of past performance to assess the rating. The periods to be considered are to be optimised using machine learning.</p>
<b>SENTIMENT ANALYSIS</b>	
<b>Indicator</b>	<b>Variable Description</b>
Fear and Greed Index	<p>The Crypto Fear &amp; Greed Index is evaluated as an equally weighted index of five indicators, i.e., Volatility, Market Momentum, Volume, cap factor and crypto Social Media history.</p> <p>The indicator quantifies the simple yet important element of investing psychology, i.e., most investments happen mainly due to greed or fear, and most sell-offs similarly happen mainly due to either greed or fear.</p> <p>The Fear and Green Index is constructed to run from 0 to 100. A score of 100 is a top rating and a score of 0 equates to the lowest rating.</p>
Social Development History Index	<p>Evai.io understands the importance of social media ranking. The Evai.io cross-platform cryptocurrency online performance Index represents a holistic view of crypto coin performance in Facebook, Twitter, Reddit and GitHub.</p> <p>This index allows investors to track the specific information they need to drive their unique investing strategies.</p> <p>The Social Development Index is constructed to run from 0 to 100. A score of 100 is a top rating and a score of 0 equates to the lowest rating.</p>
<b>RISK INDICATORS</b>	
<b>Indicator</b>	<b>Variable Description</b>
Sharpe Ratio	<p>The Sharpe Ratio measures the return on the Cryptocurrency above that of the risk-free rate, relative to the standard deviation of those returns. It is the return per unit of risk and the higher the measure the better the investment. Sharpe (1966).</p> <p>The Sharpe Ratio is compared to a moving average of past performance to assess the rating. The periods to be considered are to be optimised using machine learning.</p>

Sortino Ratio	<p>The Sortino Ratio also measures risk per unit of risk but now risk is measured as downside deviation. This is the deviation below the minimum accepted rate rate of return (MAR). Therefore it only combines worse-than-expected outcomes in the measure of risk. Sortino (1991, 1994).</p> <p>The Sortino Ratio is compared to a moving average of past performance to assess the rating. The periods to be considered are to be optimised using machine learning.</p>
<b>MOMENTUM</b>	
Moving Average-	<p>A Moving Average will capture the underlying trend for the Cryptocurrency. It is calculated as either the simple moving average of closing prices or an exponentially weighted moving average. These can be of evaluated over varying timeframes.</p> <p>The Closing Price relative to the Moving Average is used to evaluate ratings. Strong uptrends tend towards strong ratings and strong downtrends tend towards low ratings. Signals are to be optimised using machine learning.</p>
Rate of Change	<p>The Rate of Change is one of very many indicators that try to capture momentum. It is calculated as the percentage change over a specific period of time. The rate of change over a period of (say) 10 days would be monitored for evidence that momentum is increasing or decreasing. It would also be compared against the price to identify divergence of price and momentum.</p> <p>The price relative to the Rate of Change index are used to identify the momentum. A higher price with more momentum relates to a positive rating while a higher price with momentum that is not moving higher is a sign that the trend may be vulnerable to reversal and attracts a lower rating. Specific levels are to be optimised using machine learning.</p>
<b>UTILITY</b>	
Firm Profitability- Proxy- ROI	<p>Return on Investment (ROI) relates net income to investments made in a cryptocurrency, giving a better measure of cryptocurrency profitability.</p> <p>Measuring ROI helps in making comparison between different cryptocurrencies in terms of profitability and asset utilisation. The level of profitability over the past year is used to assess the rating. The period to be assessed is to be optimised using machine learning.</p>

<b>BIAS</b>	
Peak End Value Demand	<p>This is the peak return that has been achieved over the last month and the final return for the month or preceding months for the lagged version.</p> <p>It is a variable that seeks to capture well-known behavioural biases in decision-making related to the importance attached to peak and end experience by investors.</p> <p>Positive peak and end readings provide a high rating. Negative peak and end readings provide a low rating. Machine learning will be used to fine tune intermediate indications.</p> <p>A simple two factor Peak-End model can more comprehensively explain the variations in returns between portfolios sorted by firm size and momentum than popular factor models (the single-factor CAPM, the Fama-French Three-Factor Model, the Carhart Four-Factor Model, and the Fama-French Five-Factor Model). This is groundbreaking with respect to crypto currencies.</p>
<b>OVEREXTENSION</b>	
Fibonacci retracements	<p>Fibonacci retracement levels can help to quantify levels of retracement risk. They are based on the Golden Ratio (0.618) and are considered to be levels where profit-taking or re-evaluation may naturally have taken place. The greater the retracement risk, the more vulnerable the Cryptocurrency.</p> <p>Retrenchments across currencies are ranked and used to assess the level or retracement risk. Where the potential retracement is small, the rating will be high; where the potential retracement is high, the rating will be low.</p>
Ichimoku Cloud	<p>Ichimoku cloud is part of the Japanese collection of technical tools. It is based on a combination of multiple moving averages and trading ranges. It provides information about trend as well as support and resistance levels.</p> <p>Ichimoku cloud produces numerous indicators that feed into the rating process. These indicators are optimised for particular Cryptocurrencies and market conditions.</p>
Bollinger Band	<p>The Bollinger Band is one method of identifying extreme price movements. It is a trademarked property of John A. Bollinger. The Bollinger Band consists of a moving average of the price combined with upper and lower bands that are based on multiples of the standard deviation of the moving average. The bands identify price extremes and the relative performance of the bands (converging or diverging) will help to</p>



	<p>determine market conditions: consolidation or trending. They can be used to identify risk, reversal potential or the relative weight to apply to consolidation-trending tools. Bollinger Bands can identify initiation of a trend (a positive rating if positive and a negative rating if negative). They can also show risk of a pull back if the extreme is reached and not sustained (negative rating for a negative pullback and a positive rating for a positive pull back). Extremes and parameters are to be identified and optimised with machine learning.</p>
Stochastic Oscillator	<p>The Stochastic Oscillator is another momentum indicator. This indicator compares the current price to the price range over a given period. High readings show strong upward momentum and low reading strong downward momentum. Divergence between the Cryptocurrency price and the momentum indicator are also used.</p> <p>The price relative to the Stochastic Oscillator is used to identify the momentum. A higher price with more momentum relates to a positive rating while a higher price with momentum that is not moving higher is a sign that the trend may be vulnerable to reversal and attracts a lower rating. Specific levels are to be optimised using machine learning.</p>
<b>MARKET RISK</b>	
Market Factor	<p>The Market Factor shows the relationship between the return on a Cryptocurrency and the return on a basket of Cryptocurrencies. It is a measure of Systematic Risk, and it shows how much this Cryptocurrency would be affected by shocks that affect the whole Crypto currency market. This is sometimes called the beta. A beta of 1 indicates that the return on this Cryptocurrency is very similar to the overall market; a beta above 1 means that the Cryptocurrency is very sensitive and will react more in both positive and negative way to changes in the Cryptocurrency market; a beta below 1 shows that the reaction to the market is muted. A higher beta is considered to be higher risk.</p> <p>The Market factor is compared to a moving average of past performance to assess the rating. The periods to be considered are optimised using machine learning.</p>
<b>CAPITALISATION</b>	

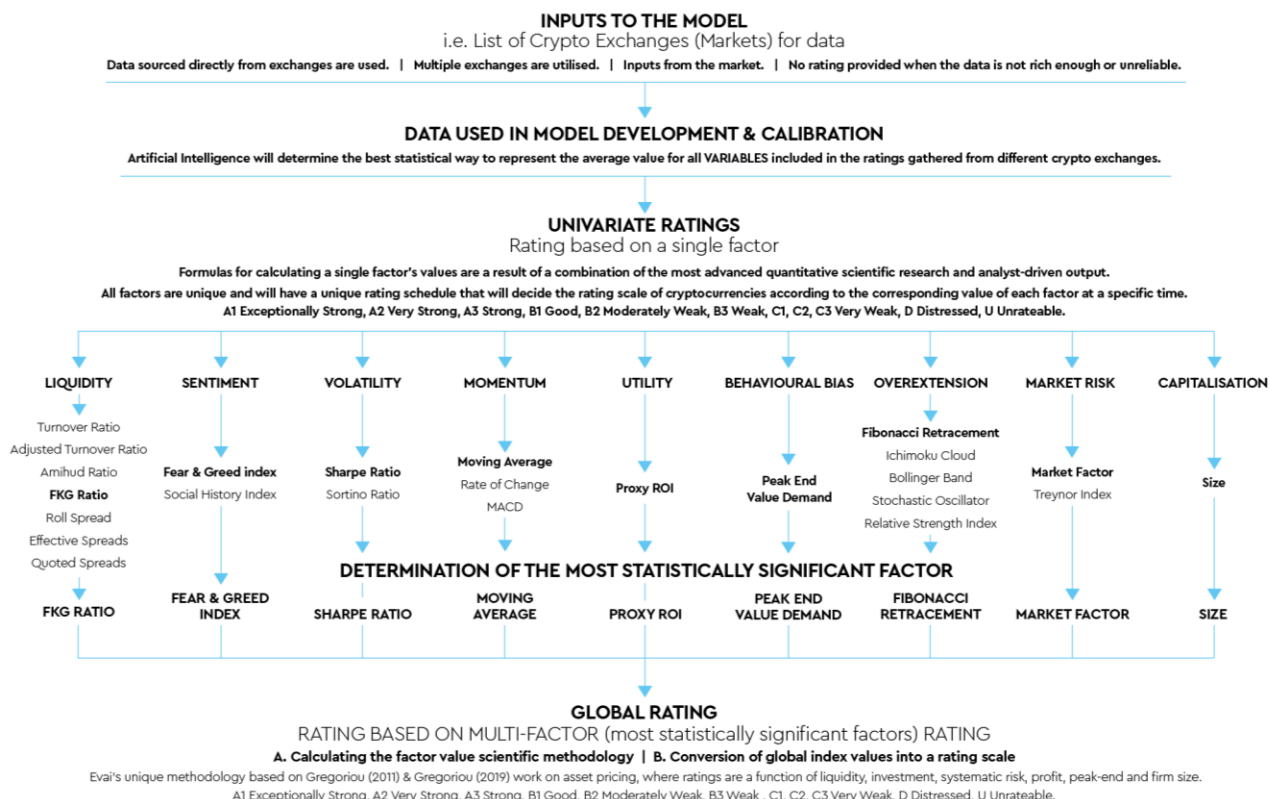
Size	<p>Size is a measure of capitalisation. There is a size factor for equities with strong evidence that firms with lower capitalisation have a relatively high return even when risk has been accounted for. Our research suggests that for Cryptocurrencies, there is a positive size effect with the Cryptocurrencies with a larger capitalisation making higher returns, even when other risks have been accounted for.</p> <p>The rating is assessed by comparing Market Capitalisation across Cryptocurrencies. Those with the highest Capitalisation have the highest rating and those with the lowest have the lowest rating.</p>
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### 3. MULTIFACTOR RATINGS

The multi variate financial rating models will be the unique contribution of Evai.io, aiming to design a multifactor model for Cryptocurrencies. The model will be based on Gregoriou et al (2019), where financial ratings are a function of systematic risk, firm size, profit, investment, sentiment, peak, end and liquidity. This 7-Factor model has been developed for the equity market (Gregoriou A., J.V. Healy, H. Le, 2019).

Initially, the rating model will include only the following indicators: Amihud Ratio, (Liquidity), Fear & Greed Index (Sentiment), Sharpe Ratio (Risk), Moving Average (Momentum), Firm Profitability-Proxy - ROI<sub>i</sub> ,(Utility), Peak End (Bias). The rating model will be constantly improving, more factors will be added, and the methodology will be tested across different digital assets and portfolios. Our model will optimise against the daily return on investment.

## Evai Ratings Model Flow Chart



## 4. MACHINE LEARNING AND AUTO-ML

The reason for applying Machine Learning (ML) techniques to financial data is that ML methods model non-linear relationships in the data. Non-linear techniques are required when outputs are not directly proportional to the inputs. Traditional analytical methods (e.g. OLS) assume a linear relationship, exists, or utilises non-linear functions that can be simplified to a linear model. Machine Learning is a sub field of Artificial Intelligence (AI), and encompasses a large and varied set of algorithms, suited to different tasks.

Here, we are concerned only with one of these categories, Supervised Learning, and the task is regression. Even so, there are many algorithms suitable for this task, and even more variants of each of these algorithms. Typically, ML algorithms have numerous hyper-parameters that require tuning.

This is especially true of Deep Learning (Deep Neural Networks), which require considerable expertise to implement effectively. In order to make ML more accessible to non-expert users, speed up model development and deployment, automate data pre-processing and hyper-parameter tuning, and provide a performance ranking of different algorithms, Automated Machine Learning (AutoML) has been developed. AutoML is a set of algorithms that provide a unified interface to diverse ML algorithms as well as performing some or all of the aforementioned tasks, and more. AutoML is state-of-the-art technology still in its early evolution. There are several rival AutoML systems offered by various vendors. Commercial examples are; AutoAI in IBM Watson Studio, Google Cloud AutoML, and AutoML Microsoft Azure cloud service. There also exist several open-source versions of AutoML, such as: Neural Network Intelligence, Microsoft's open-source AutoML toolkit, TransmogriAI, end-to-end AutoML toolkit for structured data, and H2O AutoML.

For our work it was necessary to select a specific instantiation of AutoML, and we elected to use the latter of the above, H2O Automl. We chose this because it is open source, meaning that the source code for all of the algorithms used is in the public domain. Thus, we avoid problems inherent in using proprietary "black-box" systems. Also, it offers a selection of up-to-date ML algorithms, and is among the industry leaders in the field.

#### **4.1 H2O AutoML**

H2O AutoML (LeDell and Poirier 2020) provides an interface that automates the process of training a large selection of candidate models, by providing a simple wrapper function that performs a number of modelling-related tasks. These include; Automatic training and tuning of many models within a user-specified number or time-limit. Production of Stacked Ensembles – one based on all previously trained models, another one on the best model of each family – are automatically trained on collections of individual models to produce highly predictive ensemble models which, in most cases, will be the top performing models in the AutoML Leaderboard. Several model explainer methods are provided. These apply to AutoML objects (groups of models), as well as individual models (e.g. leader model). Explanations can be generated automatically with a single function call, providing a simple interface to explore and explain the AutoML models. The H2O AutoML interface is designed to have as few parameters as possible so that all the user needs to do is point to their dataset, identify

the response column and optionally specify a time constraint or limit on the number of total models trained.

The following algorithms are currently supported by AutoML; Distributed Random Forest (DRF), Extremely Randomised Trees (XRT), General Linearised Models (GLM), Gradient Boosting Machine (GBM), Deep Learning (Neural Networks), Stacked Ensembles. There follows a brief description of each algorithm.

## **4.2 How we Use Machine Learning**

We will use the AutoML machine learning algorithm to better learn the true data generating process linking the individual predictive factors included in our models. The AutoML algorithm will train (fits) the ML algorithms we select as being most appropriate for the learning task at hand. It will also train two ensemble models, optimally combining the best performing individual ML algorithms. The trained models will be presented in a "Leaderboard", ranked in order of performance, as determined by different statistical performance indicators. This will allow identification of the best performing model. Also provided will be tables that allow identification of the relative importance and percentage contribution of each individual factor (independent variable) in explaining the variance of the dependent variable in the model. The Out-Comparison of model Predicted v. Actual values, also will allow us to determine whether the models we train provide a statistically significant economic advantage compared to reference linear models. Real-time adjustments are implemented to optimise weightings with the objective of maximising the accuracy of the model.

## **5. RATING ASSESSMENT**

### **5.1 Introduction**

The evai ratings are used to create a portfolio of digital assets. This portfolio is compared to a variety of benchmarks. The ratings improve the performance of the portfolio relative to the benchmarks outside of specific cases. The results are robust to alternative benchmark specifications, alternative time periods and alternative risk measurements. There is strong evidence that evai ratings can improve

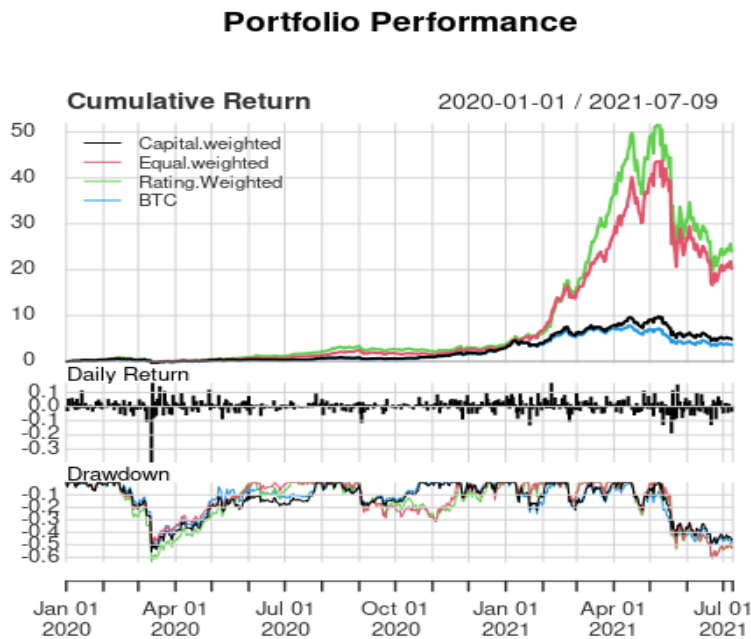
investment performance.

## 5.2 Results

Table 1 shows annualised returns, annualised volatility and the Sharpe Ratio, return per unit of risk, for the Rating-based portfolio and a number of benchmarks.

The rating-based portfolio has the highest return of the benchmarks against which it is tested. This provides a compensation for the increased risk. The return per unit of risk, as measured by the Sharpe-Ratio, is more-or-less the same as that for the equally-weighted portfolio.

Table 2 reports a number of daily performance metrics for the four portfolios over the period from the beginning of 2020 to mid-July. The advantage of the diversified portfolio of Crypto assets is clear from the performance of rating-weighted and equally-weighted portfolios. BTC has a weight of 60% in the capitalisation weighted portfolio.



The worst day for the rating-weighted portfolio is 12 March 2020 when the fund loses 43% of its value. There is a lot of risk in Crypto and the rating-based portfolio does not seem to avoid this. The portfolio suffers the maximum drawdown, the greatest 5% VaR and some negative skew. These metrics would be improved if the SAND coin were incorporated into the portfolio. SAND was removed as an outlier as a consequence of the 4000 percent increase that was experienced on 14

August 2020.

### 5.3 The portfolios

- **The rating-based portfolio** is based on weights calculated according to the ratings at the beginning of 2020. The weight for each coin is determined by:

$$weight_i = \frac{RT_i}{\sum_{i=1}^{i=N} RT_i}$$

,

where  $RT_i$  is the ten scale rating for the nth currency where A3 = 1 and U = 10.

- **The equally weighted portfolio** weights all coins equally.
- **The capitalisation-weighted portfolio** weights coins according to the capitalisation at the beginning of 2020. The weight for each coin is determined by:

$$weight_i = \frac{CP_i}{\sum_{i=1}^{i=N} CP_i}$$

,

where  $CP_i$  is the capitalisation of the nth currency. Coins without capitalisation data at the beginning of 2020 are excluded.

- **BTC** is also used as a benchmark of performance.

### Extensions

Additional testing needs to be done with alternative specifications. These will include:

- a more dynamic weighting process that will assess performance when portfolios are rebalanced once per year.
- An adjustment of the weighting mechanism that will increase the importance of the rating system, boosting the highly rated currencies and reducing the weight of the low rated currencies.
- At the moment there are 39 currencies being assessed over a two year period. The results do not change significantly when the portfolios are assessed over the period 2017 to the present day. They do not change significantly when SAND is included. For the current study SAND was excluded as it had a near 4000 percent increase in value on 14 August 2020 when it began trading

on Binance. With SAND, the rating-based portfolio has a more positive risk profile with a positive skew to the distribution of returns.

- Creation of **smart beta** portfolios. A momentum portfolio, based on those coins with the best performance over the last 6 to 12 months; a minimum-variance portfolio, based on those portfolios with the lowest variance over the last 6 to 12 months. If some validation metrics can be discovered, growth and value portfolios can be created.
- **Long-short portfolios** can be created. For example, the portfolio could be long 50% based highest rating and short 50% based on the lowest rating. It is also possible to have a 130% long, 30% short strategy to maintain market neutrality. These will depend on the cost of shorting.
- It is also possible to examine a **correlation matrix** of the returns of these 38 coins for the period since the beginning of 2020. Doing that reveals the following:

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