Cryptocurrency Portfolio Selection Using Technical Analysis Indicators

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Abstract The study designed and recommended a portfolio selection framework that can outperform traditional investment benchmarks in the cryptocurrency market. The study utilized technical analysis indicators to choose the investment pool. The study considered the top 169 cryptocurrencies in Yahoo Finance with a market cap of at least $100M. The technical analysis indicators used were Simple Moving Average (SMA), Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), and On-Balance-Volume (OBV). The resulting safety-first and mean-variance portfolio outperformed the benchmark (S&P500 market index) in terms of descriptive statistics and pair-return difference T-test. Therefore, the portfolios generated could be viable investment alternatives for investors looking to build a portfolio in cryptocurrency markets.

Keywords: • simple moving average (SMA) • moving average convergence divergence (MACD) • relative strength index (RSI) • on-balance volume (OBV) • SP/A theory • cryptocurrency

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1 Introduction

For most investors, traditional stocks are the preferred option to build a portfolio. However, a new market utilizing digital currency recently emerged. The latest market is called cryptocurrency. Cryptocurrency is an emerging digital market with a virtual coinage system that functions much like a standard currency, enabling users to provide virtual payment for goods and services free from a central trusted authority (Farell, 2015). Cryptocurrency uses a decentralized ledger called a blockchain to record transactions and protect the information about transactions and exchanges made on the market (Chuen et al., 2017; Milutinović, 2018). Blockchain technology could act as a digital receipt that cannot be falsified. Cryptocurrencies and the blockchain were developed by a pseudonymous person named Satoshi Nakamoto in 2008 when Satoshi posted a paper to a cryptography forum entitled Bitcoin: A Peer-to-Peer Electronic Cash System (Arias-Oliva et al., 2019). The study recognizes that there are numerous risks involved in investing in cryptocurrencies. While cryptocurrencies are viable for an investment portfolio because of long-term profits, it is crucial to consider that the market is positively correlated. A portfolio's purpose is to limit market correlation, but most cryptocurrencies have a significant correlation. Hilmola (2021) discovered that nearly all privacy coins in Hilmola's study followed Bitcoin's price development. Thus, if Bitcoin, the mother coin of cryptocurrency, crashes, most cryptocurrencies are likely to follow. It is vital to have a long-term mindset when creating a portfolio in the cryptocurrency market as an investor.

The study's objectives are to (1) design and recommend a portfolio selection framework for the cryptocurrency market using technical analysis indicators and (2) determine whether the generated portfolio selection framework can outperform traditional investment benchmarks. The study's findings benefit investors who are not knowledgeable in creating a diversified portfolio or are exploring their portfolio selection techniques. Investors can utilize the portfolio framework design to maximize their gains more than traditional methods. Investors who believe in the effectiveness of technical analysis indicators in the cryptocurrency market can use the study to create their portfolio because the suggested portfolio selection techniques in choosing the investment pool may outperform traditional benchmarks. The methods can also be used or modified by beginner and advanced traders in the traditional or cryptocurrency markets. The technique and strategies can also be utilized by future researchers as reference data in the further development of the research topic.

2 Literature overview

Technical analysis indicators were used as a filter in the portfolio selection. Technical analysis is performed by using historical patterns of transaction data to assist traders in assessing and projecting possible market conditions. Technical analysis usually involves an examination of price and volume charts. The reason is that price and volume charts summarize all trading activity made by market participants, and these charts affect their decisions (Fang et al., 2020). According to Abboud (2017), technical analysis attempts to evaluate a financial instrument by primarily focusing on market price movement. Price and volume could reveal current and possible future market conditions. While Kamrat et al. (2018) believe that technical analysis aims to profit from trading stocks at the right time rather than from long-term saving, the study aims to use technical analysis to create long-term profits in investors' portfolios.

There are some researchers, such as Puzyrev (2019) and Siswantoro et al. (2020), who believe that technical analysis cannot be applied to cryptocurrency trading because of the market's price volatility and the existence of "market whales." Hudson & Urquhart (2019) add that technical analysis provides evidence against one of the most respected theories in finance, the efficient market hypothesis. Market efficiency states that all available information must be reflected in security prices, so technical analysis is thought to be unsuccessful.

However, many researchers still believe that technical analysis is practical and can be heavily applied to cryptocurrency trading. Fang et al. (2020) claim that many researchers have focused on technical indicators analysis for trading on cryptocurrency markets, while Phillips & Gorse (2018) argue that it is common for intraday traders to follow technical analysis pattern-based trading strategies. The reason for this could be that despite cryptocurrency volatility, the market still has graphs on its past market activity where the movement of the price can be exploited (Van der Avoird, 2020). Traders can receive more insight into the possible direction of prices in the future because of past data. Furthermore, a study by Huang et al. (2019) provided evidence that technical analysis strategies have strong predictive power and thus can be helpful in cryptocurrency markets like Bitcoin.

Related studies proved that technical analysis of cryptocurrency markets yielded significant profits. Corbet et al. (2019) stated that technical trading could generate 100 to 10,000 times of returns obtained from the buy-and-hold strategy in the cryptocurrency markets. Furthermore, Anghel (2021) concluded that economically significant profits seemed attainable by trading using prediction models inspired by Technical Analysis. Another study by Fousekis & Tzaferi (2021) stated that technical analysis utilizing information on past volume may attain abnormal profits and that past returns may be employed to forecast trading activity and liquidity in cryptocurrency markets.

Numerous researchers have applied technical analysis to the cryptocurrency market. Vo et al. (2019) applied traditional technical analysis to foresee what other investors are thinking based on the price and volume of the cryptocurrency. Shukla & Gupta (2019) have applied the principles of technical analysis to look for Bitcoin (BTC) and Ethereum (ETH) patterns and signals to conciliate the portfolio choice based on the Markowitz model with market strategies. Technical analysis of ETH and BTC let them identify the signals to set up long and short strategies. Danylchuk et al. (2020) and Anghel (2021) combined technical analysis with other complex techniques for their studies. Alonso-Monsalve et al. (2020), Kristjanpoller & Minutolo (2018), and Shukla, S & Gupta, K (2019) also used technical analysis along with other techniques in the cryptocurrency market.

3 Research Methodology

Figure 1: Conceptual Framework of the Study

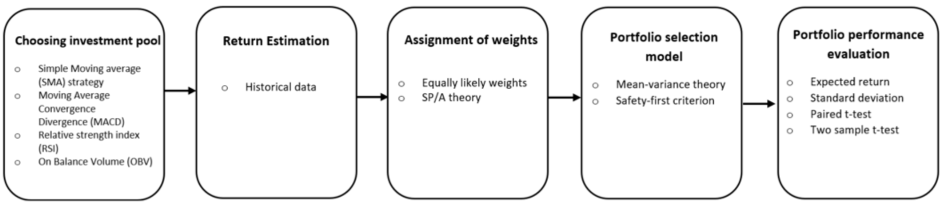

Figure 1 shows the conceptual framework of the study. The framework starts with choosing and screening an investment pool, determining the return estimation, and assigning weights. The subsequent procedures would be selecting models and evaluating the performance of the generated portfolio. Choosing investment pool determined the investment pool that will be used for the study. Return estimation determined the estimated returns when the investment pool is applied. The assignment of weights portion was used to determine the weights assigned to the probability of outcomes of the scenarios. The portfolio selection portion assigned portfolio weights of each asset considered, and the portfolio performance evaluation portion evaluated the performance of each portfolio generated.

The conceptual framework follows a standard portfolio performance evaluation procedure used by Chang et al. (2015) and Young (2020) in multiple studies. Additionally, the study adds another section from the initial framework entitled "choosing investment pool." This section proposes criteria for choosing the investment pool using the technical analysis indicators mentioned. The study aims to fill a research gap in the "choosing investment pool" portion of the portfolio selection model.

3.1 Choosing Investment Pool

In choosing the initial investment pool, the cryptocurrencies were screened through different criteria using technical analysis indicators to trim down the portfolio size and theoretically assign the cryptocurrencies with the highest likelihood of profitability and portfolio stability. Technical analysis was performed on the cryptocurrencies to determine the trend of the currency using technical indicators. The study utilized different technical analysis indicators in building the portfolio. The technical analysis indicators that were used were: Moving Average (MA), Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), and On Balance Volume indicator (OBV). The researchers believe that these technical indicators are the most appropriate for the study, considering the time frame of the research and the available historical data on price and volume. Other well-known technical analysis indicators usually require more than just price and volume. The cryptocurrencies were filtered out through various conditions of technical indicators. Once the cryptocurrencies are screened out, and an optimal number of investment pools is not achieved (e.g., n>5 or n<50), the condition rate will be adjusted accordingly. The proposed technical analysis indicators were used to determine favorable entry and exit points in the cryptocurrency market and, if applicable, determine the stability of the selected market for portfolios. The open-high-low-close (OHLC) and volume data for the cryptocurrencies were taken from Yahoo Finance. The study utilized Microsoft Excel to apply the technical indicators to the OHLC and volume data with an evaluation period of 2020 to 2021. The study considered the top 169 cryptocurrencies in Yahoo Finance with a market cap of at least $100M. Yahoo Finance is a website with free accessible stock quotes, portfolio management resources, and international market data. In Yahoo Finance, the top cryptocurrencies can be sorted, and the OHLC of cryptocurrencies and other stock markets can be downloaded into comma-separated values (CSV) files. Previous researchers have used Yahoo Finance to extract cryptocurrency data in their respective studies (Bashkeeva, 2021; Caferra, 2020; Chatterjee et al., 2020; Ferdiansyah et al., 2019; Mazanec, 2021; Pineault, 2022; Uras & Ortu, 2021).

3.1.1 Simple Moving Average (SMA) strategy

According to Wei et al. (2014) & Corbet et al. (2019), buy signals are generated when the short-period MA rises above the long period $(S > L)$, while sell signals are generated when short-period MA falls below the long-period $(S < L)$. A Simple Moving Average is calculated by adding the security prices for the most recent n periods and dividing by n. Rozario et al. (2020) defines the formula for SMA as:

$$SMA_n = \frac{1}{N} \sum_{i=n-N+1}^{n} x_i \tag{1}$$

Where N is a fixed window size of data points $(x_1, x_2 \ldots)$ where $n \geq N$. The study utilized two values for the Simple Moving Average. The study used a period of 10 days and 20 days. Brock et al. (1992), Han et al. (2013), and Chen et al. (2016) adopted 10 days SMA for their research which yielded significant gains that surpassed traditional benchmarks, while Grobys et al. (2020) gained significant gains using 20 days SMA. Ahmed et al. (2020) generated a return of 8.76% per annum (p.a.) over the average market return using a simple 20 days moving average trading, while Papailias & Thomakos (2015) generated a gain of 1000% using a modified 20-day weighted moving average. Costanza (2018) interpreted the values of SMA by determining that there is an entry signal for when the stock price crosses above the 20-day SMA while an exit signal if the price went below the 20-day SMA.

3.1.2 MACD

The technical indicator MACD is given by:

$$MACD = EMA_a(P) - EMA_b(P) \tag{2}$$

Where EMA_a and EMA_b are the exponential moving averages (EMA) over two periods where $a < b$. P is the current price at time T . Previous literature (Tajiri & Kumano, 2012; Awheda & Schwartz, 2013; Hansun, 2013; Grebenkov & Serror, 2014; Huang & Zhou, 2019; Vergura, 2020; Cai et al., 2021) define EMA as:

$$S_t = S_{t-1} + \alpha(P_t - S_{t-1}) \tag{3}$$

Where:
S_t = Exponential moving average at time t
P_t = instantaneous value at time t
α = degree of weighing decrease or smoothing constant

Smoothing constant α implies the degree of weighting factor reduction. α is set between 0 and 1. It is advised to buy when $MACD > 0$ and sell when $MACD < 0$ (Gerritsen, 2020; Schatzmann, 2020). Baisa et al. (2020) indicated a bullish signal when $MACD > signal\ line$ while a bearish signal when $MACD < signal\ line$. The study used the standard periods in $MACD$, which are 12, 26, and 9 (Baisa et al., 2020).

3.1.3 Relative Strength Index

The technical indicator Relative Strength Index utilizes average gains and average losses. The formula is given by:

$$RSI = 100 - \left[\frac{100}{1+\frac{Average\ gain}{Average\ loss}}\right] \tag{4}$$

The RSI can be interpreted using failure swings. Failure swings occur when the RSI goes below 30 or above 70 (Baisa et al., 2020). Alexandros (2021) explains that when the $RSI > 70$, an asset is labeled as overbought or overvalued. If RSI crosses back below 70, it indicates an exit signal. When the $RSI < 30$, an asset is marked oversold or undervalued. If RSI crosses back above 30, it suggests an entry signal. The study used the standard period for RSI, which is 14 periods.

3.1.4 On-Balance Volume Indicator

The On Balance Volume equation is given by:

$$OBV_t = OBV_{t-1} + \begin{cases} volume_t & if\ close > close_{prev} \\ 0 & if\ close = close_{prev} \\ -volume_t & if\ close < close_{prev} \end{cases} \quad (5)$$

Interpreting the use of OBV, the study assumed that a rise in OBV indicates an increase in price while a drop in OBV suggests otherwise, as illustrated in equation 9 (Vo et al., 2020, Singpurwala 2021).

$$\begin{aligned} &OBV\ \uparrow,\ price\ \uparrow \\ &OBV\ \downarrow,\ price\ \downarrow \end{aligned} \quad (6)$$

3.1.5 Condition and Decision of Technical Analysis Indicators

Table 1: Condition and Decision of Technical Analysis Indicators

Decision	**Condition**
SMA	
Accept coin	$SMA_{10} > SMA_{20}$
Reject coin	$SMA_{10} < SMA_{20}$
$MACD$	
Accept coin	$MACD > 0$
Reject coin	$MACD < 0$
RSI	
Accept coin	$0 < RSI < 30$
Reject coin	$30 \geq RSI \geq 100$
OBV	
Accept coin	$OBV_t > OBV_{t-1}$
Reject coin	$OBV_t \leq OBV_{t-1}$

Once the values of $SMA, MACD, RSI, and\ OBV$ were obtained, they were filtered out. Table 1 shows the conditions and decisions of technical analysis indicators in choosing the investment pool. According to Wei et al. (2014) & Corbet et al. (2019), buy signals are generated when the short-period moving average rises above the long period ($S > L$) and vice versa. The idea behind the SMA criteria is when the moving average during a short period rises above a long period, a price breakout will occur because there is a rising trend in the short period. Baisa et al. (2020), Gerritsen (2020), and Schatzmann (2020) advise to buy when $MACD > 0$ and sell when $MACD < 0$. The idea behind the $MACD$

criteria is when the $MACD > 0$, $EMA_a(P) > EMA_b(P)$, the short-term EMA is greater than long-term EMA and a price breakout is expected to occur because there is a rising trend in the short period EMA. Alexandros (2021) suggests buying when $RSI < 30$ and the market is oversold while selling when $RSI > 70$ and the market is overbought. When the market is oversold, it indicates a bearish momentum where it is ideal to enter the market because the price is assumed to go up and vice versa. Vo et al. (2020) and Singpurwala (2021) discovered that a rise in OBV indicates an increase in price, while a drop in OBV suggests otherwise. The idea behind the OBV criteria demonstrates that if the majority of the current OBV is greater than yesterday's OBV, it would indicate that there are greater uptrends than downtrends during the historical data considered. The OBV precedes price. Thus, the condition justifies the overall health of the coin. Ideally, the coins pass or satisfy 3 out of 4 technical indicators to be chosen as part of the investment pool.

3.2 Return Estimation

After determining the investment pool using the technical analysis indicators, the study determined and estimated the performance of the assets in the pool. The study then utilized historical data. The study used the OHLC and volume data of the top 169 cryptocurrencies in Yahoo Finance with a market cap of at least $100M.

3.3 Assignment of Weights

The assignment of weights portion was used to determine the weights assigned to the probability of outcomes of the scenarios. The study used equally likely weights and SP/A theory to assign weights in identifying the optimal portfolio.

3.3.1 Equally Likely scenarios and SP/A Theory

The study used historical data to forecast the outcomes of the scenarios. Each day in the back-test period was assigned equal probabilities where the probability (Pj) of each scenario is equal to $1/n$, where $\sum_i^n = 1, i = \{1, 2, 3 \ldots, n\}$. The SP/A theory provided probability weights based on fear and hope levels. SP/A theory was used in the assignment of weights of portfolios. SP/A theory is a dual criterion model that integrates two logically and psychologically separate criteria (Lopes & Oden, 1999). The criteria assume that investors base their decisions on fear and hope. Chang et al. (2018) observed that investors would likely put more weight on the worst outcomes when fearful while putting weight on the best outcomes when hopeful. The S in SP/A theory stands for security, the P stands for potential, and the A stands for aspiration (Shefrin & Statman, 2000). Investors would likely put more weight on the worst outcomes when they are fearful while putting weight on the best outcomes when hopeful (Chang et al., 2018). The study utilized $q_s = 3$ and $q_p = 1$. Chang et al. (2018, 2019) define SP/A theory as:

$$H_s(D) = D^{1+q_s} \tag{7}$$
$$H_p(D) = 1 - (1 - D)^{1+q_p} \tag{8}$$
$$H(D) = (1 - \theta)H_s(D) + \theta H_p(D) \tag{9}$$
$$P_j = H\left(D_{j-1}\right) - H(D_j) \tag{10}$$

where:
$H_s(D)$ = decumulative weights for fear
$H_p(D)$ = decumulative weights for hope
q_s = fear level of investor
q_p = hope level of investor
$H(D)$ = combined decumulative weight
P_j = probability of j^{th} scenarios

3.4 Portfolio selection model

The study used the mean-variance and safety-first models to assign the portfolio weights of each asset considered. The study used Python programming to identify the mean-variance and safety-first model optimal portfolios.

3.4.1 Mean-Variance Model

In the mean-variance model, the investor would base their decision on where to invest using the returns and risk of the portfolio. The model will determine the optimal portfolio with a beneficial trade-off of return and risk. Young et al. (2019, 2020) define the generic model of mean-variance as:

$$Max\ \lambda \bar{R}_x - (1 - \lambda)\sigma_{x^2} \tag{11}$$
$$\sigma_{x^2} = \ {w^2}_i {\sigma_i}^2 + \ \sum_i \sum_j w_i w_j \sigma_i \sigma_j \rho_{ij} \tag{12}$$

Additionally, Hanink (1985), Kroll et al. (1988) and Young et al. (2019, 2020) define the mean return $\bar{R}_x$ as:

$$\bar{R}_x = \ \sum_{i=1}^{n} w_i E_i \tag{13}$$

Where:
$\bar{R}_x$ = expected mean return on portfolio X
σ_{x^2} = variance of portfolio X
w_i = weight on asset i
E_i = expected return on the asset i
λ = modulator between the portfolio’s return and the portfolio’s variance
σ_i = standard deviation of asset i
ρ_{ij} = correlation between asset i and j

3.4.2 Safety-first Model

In the safety-first model, an investor minimizes the probability of a portfolio return falling below a certain threshold. Rachev (2001), Ding & Liu (2011), Chang & Young (2018, 2019a, 2019b), and Young et al. (2019, 2020) define the generic model of safety-first as:

$$Max\ \bar{R}_x \tag{14}$$
$$s.t.\ P(R_x \leq R_L) < \alpha \tag{15}$$
$$R_x = \sum_{i=1}^{n} w_i\, E_{ij} \tag{16}$$
$$\bar{R}_x = \sum_{i=1}^{n} w_i E_i \tag{17}$$

Where:
R_x= return of the portfolio
$\bar{R}_x$ = expected mean return on portfolio X
R_L = loss tolerance
w_i = weight on asset i
E_{ij} = return on the asset i
E_i = expected return on the asset i
α = acceptable probability of reaching the loss tolerance

3.5 Portfolio Performance Evaluation

Once return estimation, assignment probability weights, and portfolio selection models were completed, the performance of each portfolio was evaluated. The study utilized expected return, standard deviation, Paired t-test, and two-sample t-test for portfolio performance evaluation. The study applied these techniques to the actual market performance through a benchmark and the generated portfolios.

3.5.1 Expected return

The study used the Microsoft Excel application to obtain the expected mean return of the portfolios. The expected mean return is given by:

$$\bar{R}_x = \frac{R_{x1}+R_{x2}+R_{x3}+\ldots+R_{xt}}{t} \tag{18}$$

Where:
$\bar{R}_x$ = mean return of portfolio X during the back-test period
R_{xt} = return of portfolio X during test day t.
t = $\{1,2 \ldots n\}$

3.5.2 Standard Deviation

The study used the Microsoft Excel application to obtain the standard deviation of the portfolios. The standard of deviation is formulated as:

$$\sigma = \sqrt{\frac{\sum_{t=1}^{n}(R_{xt} - \bar{R}_x)^2}{n-1}} \tag{19}$$

Where:
σ = standard deviation of the portfolio
R_{xt} = return of portfolio x on test day t
$\bar{R}_x$ = mean return of portfolio x during the back-test period
n = number of data points

3.5.3 Paired t-tests

Due to the inadequate data that descriptive statistics show, paired t-tests and two sample t-tests were utilized. The generated portfolios and corresponding returns were compared using t-tests. The study used the Microsoft Excel application to obtain the paired t-test. The null and alternative hypothesis is given by:
H_o: The return difference is less than or equal to 0.
H_a: The return difference is greater than 0.

4 Discussion

4.1 Portfolio Details

The proposed investment pool was back-tested against benchmarks and other portfolios using the Python programming language. The Python code utilized the OS module, xlrd library, and the gurobipy or the Gurobi Python Application Programming Interface (API). The OS module was used for interacting with the operating system. In contrast, the xlrd library was used to read and format information from Excel files, and the Gurobi API was used to perform mathematical optimization modeling.

The study utilized the top 169 cryptocurrencies according to Market Capitalization. The historical data used were two years, from January 2018 to December 2020. The S&P 500 index was chosen as the benchmark as previous researchers observed a connection between the S&P 500 index and cryptocurrencies. Corbet et al. (2018) discovered volatility spillovers from the S&P 500 to cryptocurrencies, while Liu and Serletis (2019) found that the returns of the S&P 500 positively influence cryptocurrency market returns. Zeng et al. (2020) also showed that Bitcoin is the net recipient of spillover from the S&P 500. Related literature suggests that the price of Bitcoin is heavily affected by the S&P500

index (Conrad et al., 2018; Fang et al., 2020; Kim et al., 2020; Yousaf & Ali, 2021; Hung, 2022).

Table 2: Pricing for cryptocurrency trades in Coinbase

Pricing Tier	**Transaction Fee**
\$10,000 – \$50,000	0.35%
\$50,000 – \$100,000	0.15%
\$100,000 - \$1 Million	0.10%

Table 2 shows the transaction fees applied in the portfolios. The costs used in the portfolios are based on Coinbase's pricing tiers (Reiff, 2022). The fees are dependent on a budget of the model.

Table 3: Portfolio Details

Portfolio code	**RL/RRF**	**Budget**	**Transaction fee**	**Equally likely or SP/A**
SF	0.03	10,000	0.35%	Equally Likely
MV	0.5	100,000	0.10%	SP/A Theory

The evaluation compares eleven cryptocurrency portfolios, as shown in Table 3. The parameters examined were Loss Tolerance (R_L), Return and Risk Factor modulator (RRF), Budget, Transaction Fees, and Equally Likely scenarios or SP/A Theory. While multiple portfolios were tested, only the best SF and MV portfolios were presented in the study.

There were instances where the optimal solutions for some problems had an iteration time of more than 2 hours. The solution was to set a time limit as a stopping criterion. Puschner & Koza (1989) used loops that are bounded by a time limit to make the computation of the maximum execution time possible. Lin (2007) identified that some iterations have an infinite or close to an infinite loop, which must be interrupted by users using a time or iteration limit. Jones et al. (1993) also used an iteration limit in their optimization model. The study utilizes the 1000 seconds time limit constraint of Lin (2007) to make the solutions for all optimization problems calculable.

4.2 Portfolio Performance

Table 4: Descriptive Statistics of SF, MV, and Benchmark for the test period 2020 to 2021

	Bench	$\boldsymbol{SF}$	$\boldsymbol{MV}$	**Superior**
Mean Return	0.0009	0.0051	0.0066	$\boldsymbol{MV}$
St. Dev	0.0165	0.1085	0.0825	**Bench**
Max Return	0.0938	2.0161	0.6952	$\boldsymbol{SF}$
Min Return	-0.1198	-0.3053	-0.374	**Bench**
% with Positive return	0.5706	0.4575	0.4881	**Bench**
% with Negative return	0.4294	0.5425	0.5119	**Bench**
Cumulative return	0.4302	1.1808	10.2373	$\boldsymbol{MV}$
Max Cumulative return	0.4585	13.7945	29.266	$\boldsymbol{MV}$
Min Cumulative return	-0.3075	-0.7436	-0.2697	$\boldsymbol{MV}$
% with Positive cumulative return	0.7866	0.8647	0.9596	$\boldsymbol{MV}$
% with Negative cumulative return	0.2134	0.1353	0.0404	$\boldsymbol{MV}$
Total				$\boldsymbol{MV}$**: 6/11**

Table 4 shows the descriptive statistics of the dominant portfolios for the years 2020 and 2021. If the values of mean return, max return, min return, % with positive return, cumulative return, max cumulative return, min cumulative return, and % with positive cumulative return have a higher value, it is chosen as the superior portfolio. In contrast, if standard deviation, % with a negative return, and % with negative cumulative return have lower value, it is chosen as the superior portfolio. MV outperformed the portfolios in 6 out of 11 criteria. SF had a cumulative return of 118.08%, and MV had a cumulative return of 1024.73%, while the benchmark only had a cumulative return of 43.02%.

Table 5 shows the T-test results of the portfolios for the test period form 2020 to 2021. SF and MV were compared using paired T-test while comparison with benchmark utilized 2 sample t-test. From the P-values, the average return of MV is greater than the average return of SF, while the average return of MV is greater than the average return of the benchmark.

Table 5: T-test results of SF, MV, and benchmark for the test period 2020 to 2021

	SF	MV	Bench
SF	-	0.999	0.149
MV	0.001	-	0.035
Bench	0.851	0.965	-

The results suggest that SF with a cumulative return of 118% under Equally Likely weights, R_L = 0.03 and budget = 10,000 was profitable along with MV with a cumulative return of 1023% under SP/A theory, RRF = 0.5, budget = 100, 000. SF and MV outperformed the Benchmark S&P500 market index in terms of descriptive statistics. The paired t-test and 2-sample t-test of the p-value against the benchmark was also significant. The results support the superiority of the chosen portfolios. Therefore, the portfolios generated could be viable investment alternatives for investors looking to build a portfolio in cryptocurrency markets.

5 Conclusions

The study designed and recommended a portfolio selection framework that can outperform traditional investment benchmarks in the cryptocurrency market by utilizing technical analysis indicators to choose the investment pool. The study considered the top 169 cryptocurrencies in Yahoo Finance with a market cap of at least $100M. The technical analysis indicators used are Simple Moving Average (SMA), Moving Average Convergence Divergence ($MACD$), Relative Strength Index (RSI), and On-Balance-Volume (OBV). Historical returns were used for return estimation. Equally likely weights and SP/A theory were used for the assignment of weights. The Mean-variance and Safety-First models were used for the portfolio selection. Lastly, expected return, standard deviation, paired t-test, and 2-sample t-test were utilized for portfolio performance evaluation.

The results suggest that SF with a cumulative return of 118% under Equally Likely weights, R_L = 0.03 and budget = 10,000 was profitable along with MV with a cumulative return of 1023% under SP/A theory, RRF = 0.5, budget = 100, 000. While Chang et al. (2015) and Erfe et al. (2021) used a loss tolerance (R_L) = of -5%, the study saw effectiveness in a R_L of -3%. SF and MV outperformed the Benchmark S&P500 market index in terms of descriptive statistics. The paired t-test and 2-sample t-test of the p-value against the benchmark was also significant. Therefore, the portfolios generated could be viable investment alternatives for investors looking to build a portfolio in cryptocurrency markets.

Investors who believe in the effectiveness of technical analysis indicators in the cryptocurrency market can use the study to create their portfolio because the suggested portfolio selection techniques in choosing the investment pool outperformed traditional benchmarks. The study may contribute to future research on cryptocurrency portfolio selection by using technical analysis indicators in selecting an investment pool. As of 2022, more than 19,000 cryptocurrencies exist (Kharpal, 2022). Only 169 cryptocurrencies were considered in the study. Future research could consider more cryptocurrencies, especially undervalued currencies. Future research could also utilize more technical analysis indicators besides those used in the study. Determining how to quantify a technical analysis indicator into creating criteria is one of the challenges faced in the study.

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