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An Examination of Negative Correlations Using Pearson Correlation Analysis to Optimize the Diversification of Cryptocurrency Portfolios

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ABSTRACT

The study aims to analyze correlations among various cryptocurrencies using the Pearson correlation method. It examines daily peak price data of 10 major cryptocurrency categories from October 1, 2017, to December 31, 2022, sourced from www.coinmarketcap.com. The primary goal is to compute correlations between cryptocurrency pairs using the Pearson coefficient. Notably, stablecoin and crypto coin pairs exhibit the most negative correlation compared to crypto currency pairs. Among the pairs, ETH-BNB displays the strongest positive correlation (0.948), while LTC-USDT shows the highest negative correlation (-0.347). An exchange simulation involving LTC-USDT reveals a 12.09% asset rise from January 1 to December 31, 2022, contrasting a potential -48.69% decline if holding LTC during that period. Extending the analysis from October 1, 2017, to December 31, 2022, indicates a substantial asset gain of 251,047.85% through LTC-USDT exchanges. These findings are relevant for investors seeking risk reduction and portfolio diversification in cryptocurrency investments, contributing significantly to existing literature on bitcoin investment strategies.

INTRODUCTION

The cryptocurrency market has experienced significant growth in recent years, attracting investors who are interested in this emerging market due to its high returns and potential for diversification benefits. One of the main problems in cryptocurrency portfolio investment is the high volatility and risk associated with the market. Cryptocurrencies are known for their high price fluctuations, which can result in significant gains or losses in a short period [1]. This can make it difficult for investors to determine the optimal allocation of assets in their portfolios and to manage risk effectively [2][3][4].

Research has shown that the high volatility of cryptocurrencies is a major concern for investors, as it can lead to significant losses in short periods[1]. The high volatility of Bitcoin has led to significant price fluctuations, making it difficult for investors to determine the optimal allocation of assets in their portfolios [5] Another issue in cryptocurrency portfolio investment is the lack of regulation and inconsistent regulations across different countries [6][7].

The lack of clear regulations has made it difficult for investors to make informed decisions about investing in cryptocurrencies, as there are no standardized guidelines for investor protection or security measures. The lack of regulation in the cryptocurrency market has made it difficult for investors to access traditional financial services and protect their investments[8]. In addition to the above problems, security breaches in cryptocurrency exchanges and wallets have also been a major concern for investors [9][10].

Research has shown that these breaches have resulted in the theft of millions of dollars' worth of cryptocurrencies, raising concerns about the security of investing in cryptocurrencies. This issue was discussed and highlighted the need for improved security measures in the cryptocurrency market to protect investors [11].

Overall, these problems highlight the challenges and risks associated with cryptocurrency portfolio investment [12]. While the market has the potential for significant gains, investors need to carefully consider the high volatility, lack of regulation, and security risks associated with the market to make informed decisions about their investments [1][6].

To make informed investment decisions, it is crucial to understand the correlation between different cryptocurrencies [13][6,14][15]. This study aims to identify a set of cryptocurrencies with negative correlations, which can provide diversification benefits for investors[16]. The Pearson Correlation Coefficient will be used to measure the linear relationship between each pair of cryptocurrencies in the set.

The Pearson Correlation Coefficient has been widely used to measure the linear relationship between two variables [17][18][19][20][21]. A negative correlation between two cryptocurrencies means that they tend to move in opposite directions, which can reduce risk and provide diversification benefits for investors. Several studies have investigated the correlation between cryptocurrencies, but few have focused on identifying a set of cryptocurrencies with negative correlations.

Studies have shown that the Pearson Correlation Coefficient is an effective tool for measuring the linear relationship between cryptocurrencies and that it can be used to identify positive and negative correlations between different cryptocurrencies [14]. Other research has explored the use of the Pearson Correlation Coefficient in analyzing the volatility of cryptocurrencies and the potential for spillovers between cryptocurrencies and traditional financial assets [22].

The use of the Pearson Correlation Coefficient in cryptocurrency analysis has been shown to provide valuable insights into the behavior of cryptocurrency markets and can be used to inform investment strategies. However, it is important to note that the Pearson Correlation Coefficient only measures linear relationships and may not capture other important relationships between cryptocurrencies[23].

Minimizing the risk of a decline in the exchange rate of cryptocurrencies against fiat currencies is an essential aspect of successful cryptocurrency trading. One strategy to minimize this risk is to trade between cryptocurrency pairs, instead of fiat currencies. This allows traders to mitigate the volatility of fiat currencies and reduce the risk of losing value. According to a study by the University of Basel, a portfolio composed of cryptocurrencies with low correlation, i.e., those with dissimilar price movements, can yield higher returns and lower volatility than a portfolio of cryptocurrencies with high correlation [24]. This highlights the importance of analyzing the correlation between different cryptocurrencies when constructing a portfolio. Furthermore, trading between cryptocurrencies can be beneficial for short-term gains. This indicates that short-term trading between cryptocurrency pairs can be a viable strategy for traders seeking to make quick profits.

RESEARCH METHODS

Theoretical Framework

The method employed in this research is the Pearson Correlation method, which is used to analyze the negative correlations among ten different cryptocurrency pairs. Pearson Correlation is a powerful statistical technique that allows us to measure the linear relationship between two variables[25][26]. In the context of this study, the Pearson Correlation method is used to identify potential negative relationships among the values of different crypto assets. By calculating the Pearson correlation coefficients for each cryptocurrency pair, we can uncover whether there are significant negative correlations among them. This approach provides valuable insights into how specific cryptocurrency pairs may move in opposite directions, which can be essential information for investors seeking portfolio diversification and risk reduction. The Pearson Correlation method applied in this research is a reliable and relevant analytical tool for understanding the relationships between crypto assets in this dynamic market [27].

For our research, we gathered data from coinmarketcap.com, specifically collecting the daily highest price time series data of ten selected cryptocurrency assets. These assets represent pairs that are actively traded on various cryptocurrency exchanges. This dataset, spanning from November 1, 2017, to December 31, 2022, serves as the fundamental basis of our study, enabling us to utilize the Pearson Correlation method to investigate potential negative correlations among these cryptocurrency pairs. The use of this dataset ensures that our analysis is firmly rooted in real-world trading data, bolstering the significance and trustworthiness of our findings.

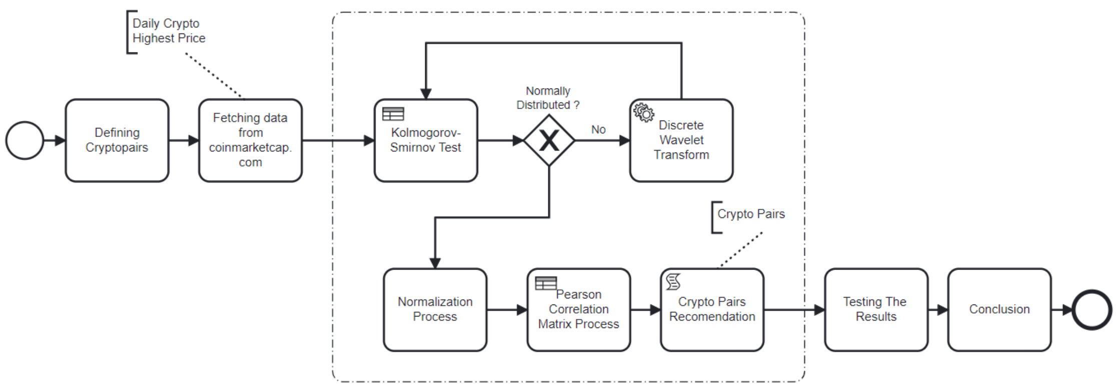

Figure 1. Research Map

The first phase of the research involved the data collection process, encompassing the fetching of time series data from daily highest prices within the timeframe spanning from October 1, 2017, to December 31, 2022. This data was sourced from the website coinmarketcap.com. The selection of daily highest price data provides a comprehensive representation of the cryptocurrency market's fluctuating dynamics over this substantial period. The decision to initiate data collection on October 1, 2017, was driven by the fact that complete data for the ten selected cryptocurrencies became available starting from that date. This data collection stage forms the bedrock of the analysis, ensuring that the subsequent methodologies are grounded in real-world trading information, thus enhancing the accuracy and credibility of the study's findings.

Table 1. Cryptocurrency daily high price in rupiah

DATE	BTC	ETH	XRP	LTC	XMR
31/12/22	258,389,514	18,725,270	5,361	1,101,480	2,306,043
30/12/22	260,161,736	18,789,605	5,361	1,060,879	2,274,338
29/12/22	260,512,570	18,839,716	5,642	1,050,256	2,319,018
28/12/22	264,510,564	18,987,561	5,758	1,085,915	2,318,316
27/12/22	264,963,681	19,222,821	5,824	1,108,029	2,304,904
26/12/22	264,309,251	19,166,566	5,767	1,107,689	2,299,795
…	…	…	…	…	…
01/10/17	59,318,381	4,084,010	2,791	743,027	1,289,684

DATE	ETC	DOGE	ADA	BNB	USDT
31/12/22	247,399	1,105	3,911	3,847,078	15,535
30/12/22	247,693	1,115	3,819	3,853,122	15,488
29/12/22	250,508	1,115	3,924	3,854,820	15,642
28/12/22	247,855	1,153	4,076	3,855,641	15,716
27/12/22	254,674	1,188	4,155	3,875,736	15,660
26/12/22	254,531	1,192	4,144	3,822,146	15,623
…	…	…	…	…	…
01/10/17	175,308	16	434	20,595	13,499

Source: coinmarketcap.com

RESULTS

In this section, we will discuss the study's discoveries, providing insights into the identified correlations, their relevance to trading tactics, and the potential advantages they offer to individuals involved in cryptocurrency trading and investment. The outcome of the procedure is as follows:

1. Data Distribution Test

We conducted a normality test on the data distribution using the SPSS software as a tool to implement the Kolmogorov-Smirnov algorithm. This test was performed to assess whether the data follows a normal distribution, a crucial step in determining the appropriateness of certain statistical analyses and assumptions [28].

The Kolmogorov-Smirnov test takes the form of the following equation:

$$D_n = \max_x \mid F_x - S_n(x)$$

If x_1, ..., x_n are sorted examples with $x_1 \leq \dots \leq x_n$, then determine $S_n(x)$ as follows.

$$S_n(x) = \begin{cases} 0, & x < x_1 \\ k/n, x_n \leq x < x_{k+1} \\ 1, & x \geq x_n \end{cases}$$

If $D_{n,\alpha}$ is the critical value from the table, then $P(D_n \leq D_{n,\alpha}) = 1 - \alpha$. D_n can be used to test the hypothesis that a random sample comes from a population with the distribution function $F(x)$.

If $\max_x |F_x - S_n(x)| \leq D_{n,\alpha}$ then, the data sample satisfied the function $F(x)$.

The outcomes of the examination for all crypto assets can be observed in Figure 2. The test results for the chosen crypto assets demonstrates a normal distribution.

One-Sample Kolmogorov-Smirnov Test

			BTC	ETH	XRP	LTC	USDT	XMR	ETC	DOGE	ADA	BNB
N			1199	1199	1199	1199	1199	1199	1199	1199	1199	1199
Normal Parameters[a,b]	Mean		401157503.049	23253918.075	7831.791	1536641.139	14581.361	2199795.452	295161.622	910.247	7197.294	2156659.082
	Std. Deviation		254089878.669	18995555.016	5111.881	972953.007	502.375	1281873.420	274882.393	1509.730	9265.940	2720614.362
Most Extreme Differences	Absolute		0.138	0.161	0.154	0.201	0.147	0.102	0.189	0.318	0.228	0.346
	Positive		0.138	0.161	0.154	0.201	0.147	0.097	0.164	0.318	0.225	0.346
	Negative		-0.111	-0.129	-0.144	-0.154	-0.084	-0.102	-0.189	-0.276	-0.228	-0.216
Test Statistic			0.138	0.161	0.154	0.201	0.147	0.102	0.189	0.318	0.228	0.346
Asymp. Sig. (2-tailed)[c]			0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Monte Carlo Sig. (2-tailed)[d]	Sig.		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	99% Confidence Interval	Lower Bound	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		Upper Bound	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

a. Test distribution is Normal.
b. Calculated from data.
c. Lilliefors Significance Correction.
d. Lilliefors' method based on 10000 Monte Carlo samples with starting seed 2000000.

Figure 2. The KS-Test results with IBM SPSS

2. Data Normalization

To ensure that variables share a consistent scale and adhere to a standard distribution, we employ a normalization procedure using Z-Transformation. This technique finds extensive application in domains like finance, machine learning, and research, where precise and standardized data are crucial for conducting meaningful analyses and making informed decisions. The outcomes of this process are detailed in Table 2.

Table 2. Normalized cryptocurrency data

DATE	BTC	ETH	XRP	LTC	USDT	XMR	ETC	DOGE	ADA	BNB
31/12/22	-0.137	0.125	-0.433	-0.413	2.139	0.083	-0.174	0.129	-0.355	0.621
30/12/22	-0.130	0.129	-0.433	-0.456	2.044	0.058	-0.173	0.136	-0.365	0.624
29/12/22	-0.128	0.132	-0.382	-0.468	2.355	0.093	-0.162	0.136	-0.353	0.624
28/12/22	-0.112	0.140	-0.360	-0.430	2.504	0.093	-0.172	0.161	-0.337	0.625
27/12/22	-0.110	0.154	-0.349	-0.406	2.391	0.082	-0.147	0.184	-0.328	0.632
26/12/22	-0.113	0.150	-0.359	-0.406	2.317	0.078	-0.148	0.187	-0.330	0.612
	…	…	…	…	…	…	…	…	…	…
01/10/17	-0.944	-0.712	-0.905	-0.796	-1.967	-0.710	-0.436	-0.593	-0.730	-0.785

3. Pearson Correlation Matrix

In the context of investment and finance, the Pearson Correlation is frequently used to study the relationships between different assets in a portfolio. By analyzing the correlations between assets, investors can make more informed decisions about diversifying their portfolios to

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manage risk effectively. Pearson Correlation is calculated for each possible pair of selected cryptocurrencies, allowing investors to assess the degree to which these digital assets move in tandem or exhibit contrasting behaviors. This analysis aids in identifying potential diversification opportunities, as investors seek to construct portfolios that are less vulnerable to market fluctuations.

We utilized the RapidMiner tool to compute Pearson correlations, and the results are presented in Figure 3.

Attribut...	BTC	ETH	XRP	LTC	XMR	ETC	DOGE	ADA	BNB	USDT
BTC	1	0.904	0.849	0.893	0.892	0.688	0.731	0.873	0.853	-0.299
ETH	0.904	1	0.859	0.755	0.842	0.823	0.813	0.894	0.949	-0.201
XRP	0.849	0.859	1	0.868	0.904	0.830	0.888	0.883	0.859	-0.234
LTC	0.893	0.755	0.868	1	0.887	0.700	0.793	0.808	0.720	-0.346
XMR	0.892	0.842	0.904	0.887	1	0.825	0.872	0.854	0.862	-0.190
ETC	0.688	0.823	0.830	0.700	0.825	1	0.938	0.840	0.822	-0.124
DOGE	0.731	0.813	0.888	0.793	0.872	0.938	1	0.847	0.825	-0.153
ADA	0.873	0.894	0.883	0.808	0.854	0.840	0.847	1	0.835	-0.255
BNB	0.853	0.949	0.859	0.720	0.862	0.822	0.825	0.835	1	-0.048
USDT	-0.299	-0.201	-0.234	-0.346	-0.190	-0.124	-0.153	-0.255	-0.048	1

Figure 3. Pearson Correlation Matrix

In Table 3, we present the cryptocurrency pairs ranked by their highest negative correlations. It is worth noting that as the magnitude of the negative correlation increases, the potential for significant price divergences resulting from their price movements also rises. Notably, our findings reveal that LTC paired with USDT exhibits the most pronounced negative correlation among the selected cryptocurrency pairs. This discovery holds significance for investors and traders seeking opportunities to leverage such correlations for profit within the cryptocurrency market.

Of particular interest is the observation that the most negative Pearson Correlation values denote the strongest negative correlations. This intriguing finding signifies the contrasting behavior in the price movements among crypto pairs. When one asset experiences an increase in value, its counterpart in the pair demonstrates a price decrease. This behavior serves as a valuable reference for selecting crypto pairs to exchange, thus potentially capitalizing on short-term financial gains.

Table 3. Pearson correlation of the crypto pairs

No	First	Second	Value
1	LTC	USDT	-0.347
2	BTC	USDT	-0.303
3	ADA	USDT	-0.261
4	XRP	USDT	-0.237
5	ETH	USDT	-0.203
6	XMR	USDT	-0.190
7	DOGE	USDT	-0.151
8	ETC	USDT	-0.126

No	First	Second	Value
16	LTC	ADA	0.810
17	ETH	DOGE	0.813
18	ETC	BNB	0.820
19	DOGE	BNB	0.824
20	XMR	ETC	0.824
21	ETH	ETC	0.825
22	XRP	ETC	0.828
23	ADA	BNB	0.833

No	First	Second	Value
31	ETH	XRP	0.860
32	XMR	BNB	0.863
33	XRP	LTC	0.868
34	XMR	DOGE	0.870
35	BTC	ADA	0.875
36	XRP	ADA	0.884
37	LTC	XMR	0.886
38	XRP	DOGE	0.887

9	BNB	USDT	-0.046
10	BTC	ETC	0.690
11	LTC	ETC	0.698
12	LTC	BNB	0.720
13	BTC	DOGE	0.732
14	ETH	LTC	0.755
15	LTC	DOGE	0.791
24	ETC	ADA	0.841
25	ETH	XMR	0.843
26	DOGE	ADA	0.847
27	BTC	XRP	0.852
28	BTC	BNB	0.853
29	XMR	ADA	0.854
30	XRP	BNB	0.859
39	BTC	XMR	0.893
40	BTC	LTC	0.894
41	ETH	ADA	0.895
42	XRP	XMR	0.904
43	BTC	ETH	0.905
44	ETC	DOGE	0.936
45	ETH	BNB	0.948

4. Result Testing

To substantiate the recommendations for these cryptocurrencies, we implemented a z-score calculation approach for cryptocurrency pairs. Under this method, should the z-score of one cryptocurrency fall lower, it implies that the cryptocurrency should be traded (sold) with its counterpart, and conversely. Conversely, if the z-score is higher, it is advisable to retain (hold) the cryptocurrency. The chart depicting the normalized cryptocurrency prices of LTC and USDT during the period from January 1, 2022, to December 31, 2022, is presented in Figure 4, while Figure 5 illustrates the graph showcasing the z-score values.

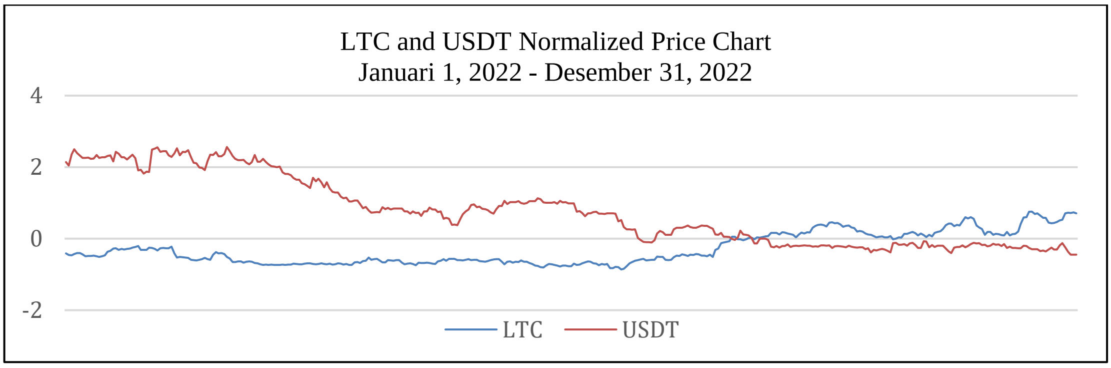

Figure 4. LTC and USDT normal price chart

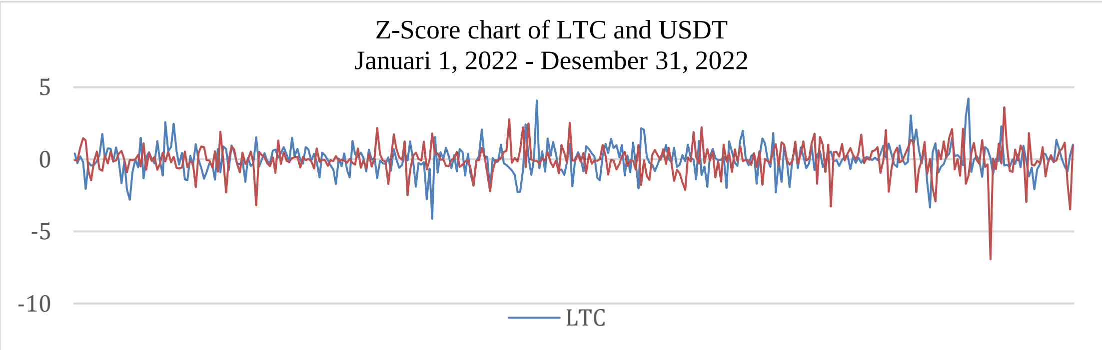

Figure 5. Z-Score of LTC and USDT

Our examination of cryptocurrency pairs involved a year-long dataset spanning from January 1, 2022, to December 31, 2022, with a specific focus on the LTC and USDT pair. The objective was to provide evidence that engaging in exchanges within both pairs would yield more favorable outcomes compared to simply holding a cryptocurrency without conducting any trades.

The test results are depicted in Figure 6, illustrating the outcome of our analysis conducted during the period from January 1, 2022, to December 31, 2022. When LTC is exchanged for USDT within this time frame, the total value of the invested assets at the end of the period exhibits an impressive increase of 12.09%. In contrast, holding LTC without engaging in any exchange with USDT results in a significant decrease of -48.69% in the total asset value at the end of the same period.

Employing the same analytical method, we conducted tests over a more extended period, covering the period from October 1, 2017, to December 31, 2022. Within this extended timeframe, holding LTC without exchange led to an impressive growth of 1,382.42% in the total value of the invested assets. However, when LTC was exchanged for USDT during the same period, the final asset value of LTC at the end of the period experienced a remarkable surge of 251,047.85%, as vividly portrayed in Figure 7.

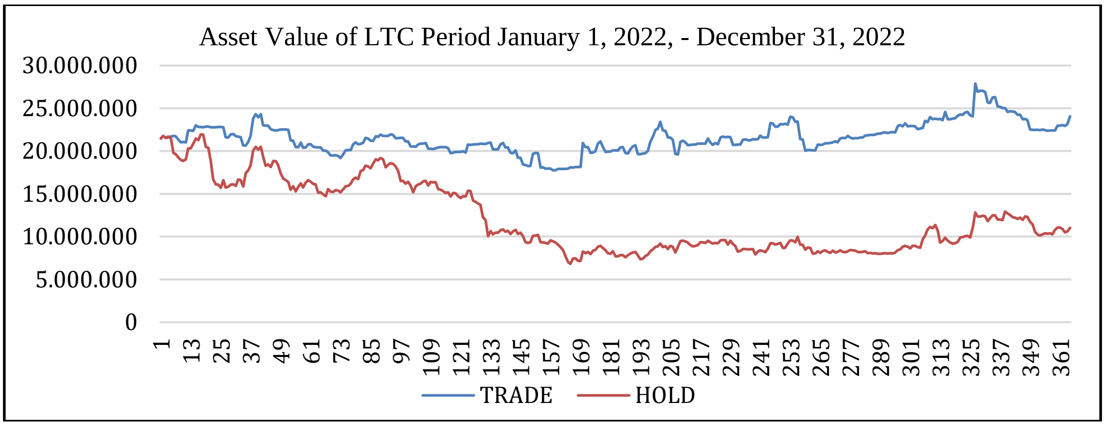

Figure 6. LTC asset value trading and hold on January 1, 2022 – December 31, 2022

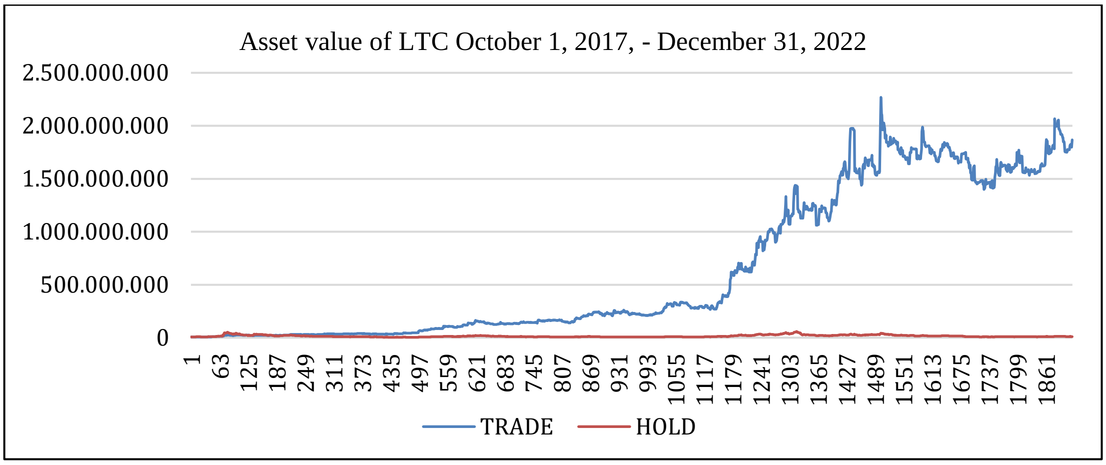

Figure 7. LTC asset value trading and hold on October 1, 2017 – December 31, 2022

The resulting comparison of asset prices when interchanging LTC with USDT is depicted in Figure 7. This visualization delineates the contrasts in asset values achieved through these exchanges, providing insights into the potential benefits of utilizing the z-score-based trading strategy.

DISCUSSION

Additional discourse regarding the application of this methodology within the realm of cryptocurrencies may encompass comparisons with alternative correlation techniques, modifications to account for market volatility, and the potential utilization of this data to enhance investing strategies. Additionally, for more informed cryptocurrency investment decisions, it is critical to examine the difficulties and constraints associated with cross-correlation analysis, such as its susceptibility to outlier data and the need for precise result interpretation.

CONCLUSIONS AND RECOMMENDATIONS

This study demonstrates that despite the potential for cryptocurrency exchange rates to decrease, engaging in asset exchanges within crypto pairs exhibiting strong negative correlations can help sustain and potentially increase investment value, offering prospects for long-term returns. Nevertheless, it is imperative to acknowledge the inherent unpredictability of the cryptocurrency market, which is susceptible to rapid shifts. Consequently, investors must exercise prudence, thoroughly evaluate risks, and align their investment objectives before reaching decisions. Moreover, ongoing research and development endeavors are indispensable for refining and enhancing algorithmic trading strategies within the cryptocurrency domain.

Despite the fluctuations in exchange rates experienced by numerous cryptocurrencies over specific periods, their overarching trends underscore a notable uptrend in value since their inception on asset exchanges. Considering this market volatility, investors can implement strategies that involve the exchange of cryptocurrency pairs with negative correlations.

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