Int. J. Nonlinear Anal. Appl. 16 (2025) 7, 27–36
ISSN: 2008-6822 (electronic)
http://dx.doi.org/10.22075/ijnaa.2024.32895.4890

Predicting the expected returns of cryptocurrencies using CAPM and D-CAPM approaches

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(Communicated by Seyyed Mohammad Reza Hashemi)

Abstract

In the present study, the expected returns of cryptocurrencies were compared capital asset pricing model (CAPM) and downside capital asset pricing model (D-CAPM) approaches. For this purpose, fifty cryptocurrencies were studied as representative of risky assets in a five-year period from 2018 to 2022 with daily frequency. First, the panel was investigated using Levin-Lin-Chu, Im-Pesaran, and Shin and Dickey-Fuller's tests. Then, using paired t-statistics, the difference between the return estimates of the two models was investigated. Finally, using R2 and the generalized linear test model, the better model was selected to justify the changes in asset returns in these cryptocurrencies and portfolios. Based on the results, in almost 90% of the analyzed portfolios, the D-CAPM model was better than the CAPM model and had more justification power than the old CAPM model. In less than 1% of the models, the degree of justification and the appropriateness of the models were the same.

Keywords: cryptocurrency, capital asset pricing model (CAPM), downside capital asset pricing model (D-CAPM)
2020 MSC: 91B24, 91G30

1 Introduction

Currently, 5,609 different cryptocurrencies are traded with a market value of $260 billion [5]. As their numbers are increasing, their value is decreasing [21]. The cryptocurrency market has attracted an increasing number of new participants. However, factors affecting the price have not yet been explored. More studies have been conducted on more reliable markets such as the stock market and the bond market. The existing literature indicates that the stock market is guided by fundamental economic factors to which investors react differently [7]. However, evidence suggests that fundamental economic variables do not affect the price of Bitcoin [3].

The well-known factors of the investment literature have also made their way into the cryptocurrency market. Factors in the stock and bond markets are known as the market, size, value, or motion [9, 14, 23]. Researchers showed that the motion factor has the highest effect in this regard. The motion factor has different effects on cryptocurrencies [13]. Others record significant effects for motion [22, 27]. However, they find no evidence for a significant effect of motion [11]. Researchers examine a three-factor model that includes market, size, and motion factors [24]. They

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Received: December 2023 *Accepted:* February 2024

conclude that the model significantly improves compared to the CAPM. Investors select their optimal portfolio from the set of risky assets available in the capital market. William Sharpe presented the CAPM model or capital asset pricing model in 1964. Four decades since the life of the CAPM model, it is the most widely used model in various fields of financial management and investment, such as estimating the cost of capital of companies' shares, evaluating the performance of managed portfolios, etc. It is also taught in financial management and investment books [4]. However, experimental studies indicated that this model, in which the expected return is affected by beta, has low potential to explain and interpret stock returns. This doubt led to efforts to develop a more efficient model.

Estrada invented a model called the downside capital asset pricing model or the D-CAPM model in 2002. It can be an appropriate estimate of the expected return in asymmetric market conditions. He stated that capital assets up to 38% and adjusted capital asset pricing up to 55% provide a suitable estimate of the expected return in asymmetric market pricing conditions [16]. Now, the following questions are raised for the researcher: Is there a healthy and acceptable standard for estimating the expected return of mutual investment funds?

Considering the presentation of the new pricing and performance evaluation model, if correct criteria have been presented for pricing, return, and performance evaluation in investment companies? To what extent are these criteria different from the previous criteria and which one has a better evaluation? The basic question of this study is what is the relationship between risk and return in joint venture companies? And which model best expresses the relationship between risk and return? Therefore, this study seeks to compare and investigate the implementation mechanisms of CAPM and D-CAPM models in cryptocurrencies. Due to many events that happened over the last few years, the overall market value and long downside market in the cryptocurrency space have increased greatly. The cryptocurrency market has matured somewhat. Thus, using new data can shed new light on it. This study uses data from 2018 to 2022. It includes 50 highly traded cryptocurrencies. This selection is done using the historical data of cryptocurrencies ranked by Capital Market (www.CoinMarketCap.com).

2 Theoretical literature and a review of research background

2.1 Theoretical literature

2.1.1 Capital asset pricing model

Harry Markowitz tried to help investors select their optimal portfolio from the set of risky assets available in the capital market. William Sharpe presented the capital asset pricing model in 1964. Four decades since the life of the CAPM model, it is the most widely used model in various fields of financial management and investment, such as estimating the cost of capital of companies' shares, evaluating the performance of managed portfolios, etc. It is also taught in financial management and investment books [4].

The CAPM model includes 4 assumptions:

1. Taxes and transaction fees are not considered
2. Investors can borrow or lend money without interest rate risk
3. There is no perfect capital market
4. Investors are only worried about expected returns.

Traditional CAPM is a static model of portfolio allocation under conditions of uncertainty and risk aversion. As Brealey and Myers, Fama , and other existing literature show, this model relates the return R_i of asset i to the risk-free asset return R_f and the market return R_m [10, 15]. It can be shown mathematically as follows:

$$E\left[R_i\right] = R_f + \beta_{m\,i}\left(E\left[R_m\right] - R_f\right) + e,$$

here, E is the expected indicator or mathematical expectation, and the market beta is:

$$\beta_{m_i} = \frac{\mathrm{COV}(R_i, R_m)}{\mathrm{VAR}(R_m)}$$

where the term β_{m_i} is the systematic risk measure of asset i.

2.1.2 Downside Capital Pricing Model (D-CAPM)

It is the generalization of the capital asset pricing model that uses βd instead of β [8]:

$$\beta_i^D = \frac{\sum_{im}}{\sum_m^2} = \frac{E\left\{\min\left[\left(R_i - \mu_i\right), 0\right] \times \min\left[\left(R_m - \mu_m\right), 0\right]\right\}}{E\left\{\min\left[\left(R_m - \mu_m\right), 0\right]^2\right\}}$$

2.2 Literature review

2.2.1 Foreign literature review

Harry Markowitz tried to help investors select their optimal portfolio from the set of risky assets available in the capital market. William Sharpe presented the CAPM model or capital asset pricing model in 1964. After four decades since the life of the CAPM model, it is the most widely used model in various fields of financial management and investment. However, experimental studies indicated that this model, in which the expected return is affected by beta, has low potential to explain and interpret stock returns. This doubt led to efforts to develop a more efficient model. Estrada invented a model called the downside capital asset pricing model or the D-CAPM model in 2002 that can be an appropriate estimate of the expected return in asymmetric market conditions. He stated that capital assets up to 38% and adjusted capital asset pricing up to 55% provide a suitable estimate of the expected return in asymmetric market pricing conditions [16]. Due to the lack of approval of the law related to cryptocurrency transactions in financial institutions, no research has been conducted so far in the area of calculations related to comparing the efficiency of CAPM and D-CAPM models in measuring the expected returns of cryptocurrencies. In foreign studies, the challenges facing Bitcoin include the challenges of banking system legislation, creating confidence for people, changing people's habits to use Bitcoin, and the costly nature of Bitcoin mining.

Bitcoin transactions have no boundaries and they are not subject to sanctions and can increase the national gross domestic product, especially in the export sector. Also, Bitcoin can account for a significant share of liquidity in the future. Due to the shortcomings in CAPM, in the second half of the 20th century, many tests were conducted on the reliability and stability of systematic risk under different market conditions, which was the most significant factor in the development of the D-CAPM model. However, some criticisms were reported on this method of measurement, especially in asymmetric market conditions since there was an inability to show upward and downward changes in return and poor performance of beta coefficient and CAPM in some economic conditions of the market. The concept of negative risk (the most significant factor in the development of the D-CAPM model) was proposed after the 1950s. However, in the 1970s when balanced asset pricing models along with risk negative was proposed, the concept of negative risk was considered by financial and management experts. The first work in this regard was done. Then, researchers proposed pseudo-CAPM models based on negative risk criteria. Also proposed a method to respond to upward and downward changes in returns in asymmetric market conditions.

Then, researchers examined gradual downward changes in the asymmetric conditions of the market and concluded that independent asset risk can be better achieved using gradual downward changes. In the same year, Other researchers tested beta stability in five upward and downward markets. With the development of negative risk, Huang and Satchell and Hervey and Sidku showed that if the pricing model was used together with negative risk, the new model showed a much better performance compared to the previous models in the American financial markets [12].

Also, researchers extended downward gradual changes and obtained a stock risk-reducing factor in the US financial market that could estimate a cross-sectional rate of return. Estrada invented a model called the "Downside Capital Asset Pricing Model" from 2000 to 2002 [2]. It could provide an appropriate estimate of the expected return in asymmetric market conditions. He believed that in asymmetric market conditions, CAPM provides an estimate of up to thirty-eight percent and D-CAPM up to fifty-five percent of the expected return. Also, concluded that βD provides a more appropriate estimate of the expected rate of return in the asymmetric market compared to β [18]. A study conducted in British companies revealed that βD is 15 to 25% higher than β and D-CAPM has more capability compared to CAPM to estimate the expected rate of return [28].

Researchers conducted a study entitled Simulating Stock Prices using the geometric Brownian motion model in Australian companies [20]. They simulated the path of stock prices using the geometric Brownian motion model. In this study, they examined the Australian companies listed on the S&P and the 50 ASX companies. Using the CAPM model, they first predicted the annual expected return of each stock. Then, geometric Brownian motion was used once for individual stocks and once for composite portfolios in different states. Three methods of correlation coefficient, MAPE, and percentage of predictions in the correct direction were used to examine the prediction accuracy. The results revealed that although based on the MAPE criterion, the prediction of periods of 1 week, 2 weeks, 1 month, 2 months, and one year is done optimally, the lowest prediction error was obtained in the periods of 1 week, 2 weeks, and 1 month. After that, as the prediction time horizon increases, the error values increase.

Researchers conducted a study entitled "Stock price predicting using geometric Brownian motion" [1]. Based on the geometric Brownian motion model, they predicted the stock prices of 7 companies in the combined index of the Jakarta Stock Exchange. Using the MAPE criterion to examine the accuracy of the predicted values, they showed that the geometric Brownian motion model has a high rank in the prediction with high accuracy so the MAPE value for the smaller predicted values was 20%. The exponential growth of Bitcoin and other cryptocurrencies in recent years has attracted people's attention. The cryptocurrency market is relatively young (Bitcoin was developed in 2009, but its active trading began in 2013), so it is still highly unknown [6]. As stated earlier, the cryptocurrency market has only been developed in recent years and a few studies have been conducted about them. Researchers provide a comprehensive analysis of 1469 cryptocurrencies considering various issues such as market share and turnover. Others showed that this market is much more volatile than others. Also, they analyzed the degree of its competitiveness. As a result focused on finding the efficacy of agree and disagree evidence, respectively. Other researchers have examined anomalies in the cryptocurrency market. they examined the efficiency of the cryptocurrency market. This study revealed that the level of market returns in the five major cryptocurrencies is highly variable. Before 2017, cryptocurrency markets were mostly inefficient. However, the cryptocurrency market became more efficient during 2017-2019. The results also showed that Litecoin is the most efficient cryptocurrency, while Ripple is the least efficient. Researchers obtained negative, positive, and statistically significant premiums using stock and portfolio data from the UK as data. The results revealed that D-CPM (downside beta coefficients) is not useful in asset pricing less than CAPM (normal beta coefficients). Investors in downside risk are rewarded with higher premiums than those investing in normal beta risk.

2.2.2 Review of domestic literature

Using the data collected from the Tehran Stock Exchange, the research investigated the impact of negative systematic risk in the multi-factor model of capital asset pricing [28]. By explaining the D-CAPM multi-factor model, they compared this model with the multi-factor model A CAPM. In the mentioned study, after calculating the D-CAPM model in comparison with the CAPM model, a relationship between risk and return was shown. Also, the portfolio resulting from the mentioned model was more efficient compared to the portfolio resulting from the CAPM model.

Researchers reviewed the information related to the price and return of the mentioned currencies from 2018 to 2021 on a daily basis [26]. In the stock market, stock returns are predicted using both models and compared with real returns. Results showed that the D-CAPM model has worked much more efficiently regarding the match of the predicted values with the actual values with a better expression of the relationship between risk and return compared to the traditional CAPM model. Researchers that the historical beta model has a very low estimate of Bitcoin returns in all periods [17]. The adjusted beta model showed very different results with the most accurate estimate in a year period. The reason why the adjusted beta shows more promising results is probably due to the shorter period and Bitcoin's volatility, making CAPM show better results.

With increasing development in all countries, cryptocurrencies have attracted the attention of many investors. Also, the possibility of exchanging and trading these currencies is improving every day compared to other risky assets. All these factors have led to the high liquidity of these currencies in the capital market, and the large volume of supply and demand for them, making the changes in the price and return of these assets to be affected by supply and demand more than anything. Thus, it can be expected that the value of these assets will be less affected by global tensions, economic crises, and financial policies of countries compared to other risky assets [25].

3 Research methodology

3.1 Statistical population and sample

The method of this study is descriptive and based on library documents, followed by statistical tests. In this study, to review the literature, the available documents including articles, scientific books, and official statistical data published are first used. Then, to infer and test the hypotheses and answer the research questions, the desired statistical information is collected and processed from the published documents by the statistics and information-generating devices. The R software will be used in this study. In this regard, the most traded cryptocurrencies in 2018-2022 will be reviewed based on daily data. Finally, we will examine the accuracy of the expected return compared to the actual return in the capital asset pricing model (CAPM) and the downside capital asset pricing model (D-CAPM). In this article, valid data (from coinmarketcap.com and tradingview.com sites) is used.

3.2 Research hypotheses

Hypothesis 1: Cryptocurrency indices of the D-CAPM model explain the relationship between risk and return more efficiently than the conditional CAPM model.

3.3 Model and method of measuring research variables

In this article, the calculated index was assumed to be of equal weight, so the analyzed data were considered in the form of portfolios of equal weight (including one, two, ..., or all 50 cryptocurrencies with equal weight). The market capacity is daily and based on the trading made on that day. Several portfolios, selected alternately by investors, were investigated. In the capital asset pricing model (CAPM), Rm is the return of the market portfolio, which is the market average of 50 cryptocurrencies, Rf is the return on the risk-free asset, which is considered at the SOFER rate, Ri is the expected return (i) which is equal to the ratio of $\frac{P_t}{P_{t-1}}s, \beta_{m_i}$ is the sensitivity coefficient (regression coefficient in symmetrical mode), and $E[R_m] - R_f$ is the risk premium.

Beta is the systematic risk index. The above equation gives credibility to the conclusion that systematic risk is the only significant factor in determining the expected return and unsystematic risk does not play a role in this regard.

The downside capital asset pricing model (D-CAPM) can provide a suitable estimate of the expected return in asymmetric market conditions. According to this model, risk is calculated through the pseudo-variance. Thus, it is possible to divide the pseudo-covariance by the return of the pseudo-variance of the market and obtain the negative beta [8]. In the downside risk pricing method, Markowitz proposed two methods to calculate the downside risk. The first method is the semi-variance method which is obtained from the sum of the squares of the deviations from the mean rate of return (semi-variance below the mean rate) and the second method is the use of the semi-variance which is obtained from the sum of the squares of the deviations from the target return rate of semi-variance below target rate [19].

$$\mathrm{SV}_m = \frac{1}{k}\sum_{t=0}^{k} \max\left[., (E - r_t)\right]^2$$

$$\mathrm{SV}_t = \frac{1}{k}\sum_{t=0}^{k} \left[0, (t - r_t)\right]^2$$

r_t: Asset return during T

t: Target rate of return

K: The number of observations

E: Mathematical expectation of rate of return

Thus, in this article, μ and 6, respectively, represent the mean and standard deviation of the one-day returns of the desired cryptocurrencies, estimated using the historical data of the price of cryptocurrencies. After estimating the return values in future periods, the predicted values are compared with the actual return values on the corresponding days, and the prediction error (accuracy) is calculated using the RMSE and MAE criteria in this way:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{R}_{t_i} - R_{t_0}\right)^2}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|\left(\hat{R}_{t_i} - R_{t_0}\right)\right|.$$

Also, n is the number of days that the model predicts. Using the general linear model test (GLMT), the error difference between the CAPM and D-CAPM models is significant, and the D-CAPM model error is less.

3.4 The research significance

Given the shortcomings of the single-index model of CAPM in expressing the relationship between risk and return, the present study seeks to compare the error rates of the two models by using the downside capital asset pricing model (D-CAPM).

4 Testing hypotheses and research results

In this study, different cryptocurrencies were investigated based on different methods, and 50 cryptocurrencies were investigated and evaluated differently. Table 1 presents the names of these cryptocurrencies.

For this purpose, the panel was first investigated using three tests including Levin-Lin-Chu, Im-Pesaran-Shin, and Dickey-Fuller. Then, using different statistics, the difference between the return estimates of the two models was examined. Then, we examined to know which model can better justify the changes in return on assets in these cryptocurrencies and different portfolios. It was observed that the CAPM model was better than the D-CAPM in some portfolios. However, in almost 90% of the analyzed portfolios, the DCAPM model was better than the CAPM model and had more justification power than the CAPM model. In less than 1% of the models, both models were the same regarding the degree of justification and appropriateness of the model. To obtain these results, all possible portfolios are considered for construction. Figure 1 shows the summary of the results of this section.

Table 1: Cryptocurrencies investigated in this study based on an alphabetical order.

Row	Name	Abbreviation	Row	Name	Abbreviation	Row	Name	Abbreviation
1	Aelf	ELF	18	File coin	FIL	35	Solana	SOL
2	Avalanche	AVAX	19	Gemini Dollar	GUSD	36	Stellar	XLM
3	Binance USD	BUSD	20	Golem	GLM	37	Storj	STORJ
4	Bitcoin	BTC	21	Holo	HOT	38	SwissBorg	CHSB
5	Bitcoin Cash	BCH	22	Huobi Token	HT	39	Tether	USDT
6	Bitcoin SV	BSV	23	KuCoin Token	KCS	40	Tezos	XTZ
7	BNB	BNB	24	Litecoin	LTC	41	Theta Network	THETA
8	Cardano	ADA	25	Maker	MKR	42	TRON	TRX
9	Chainlink	LINK	26	MediBloc	MED	43	True USD	TUSD
10	Dai	DAI	27	Monero	XMR	44	UNUS SED LEO	LEO
11	Dash	DASH	28	NEM	XEM	45	USD Coin	USDC
12	Decentraland	MANA	29	OMG Network	OMG	46	Ve Chain	VET
13	Decred	DCR	30	Pax Dollar	USDP	47	Wrapped Bitcoin	WBTC
14	Dogecoin	DOGE	31	Polkadot	DOT	48	XRP	XRP
15	Enjin Coin	ENJ	32	Polygon	MATIC	49	Zcash	ZEC
16	EOS	EOS	33	Quant	QNT	50	Zilliqa	ZIL
17	Ethereum	ETH	34	Shiba Inu	SHIB			

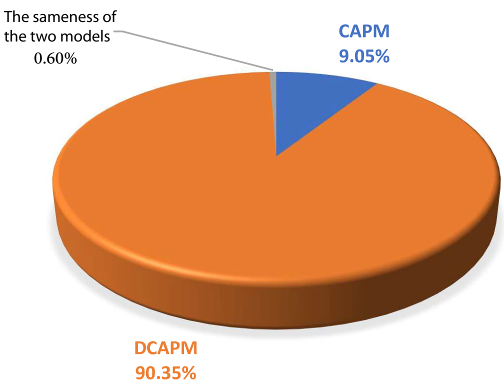

Figure 1: Comparison of two CAPM and DCAPM models to justify the volatilities in the studied cryptocurrencies.

Due to the large volume of the investigation process, the identification of factors affecting the observed conditions was left to future studies. Some portfolios selected frequently and alternately by investors were examined (Table 2). One of these portfolios is made of all these cryptocurrencies, which is called the portfolio with equal weights due to the use of 50 powerful cryptocurrencies in this study. In another portfolio, the lowest value at risk and the highest return are obtained. In all these portfolios, we first examined whether the panel model or pooled model is suitable for the data. Then, two models were examined based on the results obtained. A generalized linear test was used to decide on the better model. If we consider cryptocurrency markets mixed, different portfolios can be made with it. In this case, one of the possible portfolios will be the portfolio made of all the best-selling and frequent cryptocurrencies. In this case, the balanced portfolio made of these cryptocurrencies is shown in Figure 2. There are strong and unexpected volatilities in the market consisting of these cryptocurrencies and the necessity of risk control is strongly felt. This issue is carefully explained in Error! Reference source not found, which represents the level at risk of this portfolio (Figure 3).

Table 2: The number of examined portfolios and investigating the appropriateness of the model.

Superior model	**The number of identified portfolios**	%
CAPM	101,893,941,569,257	9.05%
DCAPM	1,017,250,565,832,310	90.35%
Equality of two models	6,755,399,441,056	0.60%
Total	1,125,899,906,842,620	100%

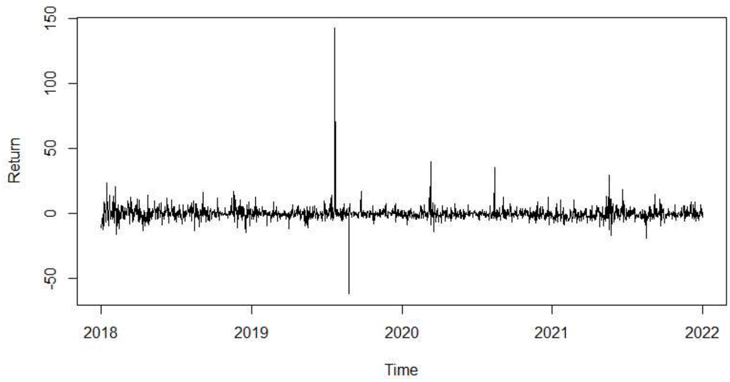

Figure 2: Error! No text of specified style in document. - Stock market volatilities in the portfolio of 50 popular cryptocurrencies investigated in this study.

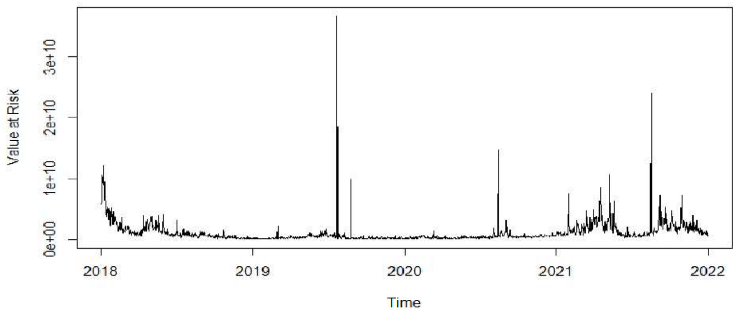

Figure 3: Error! No text of specified style in document. Values at risk for equal weight portfolio.

4.1 Equal weight of cryptocurrency markets

First, using Levin-Lin, Chu, Im-Pesaran-Shin, and Dickey-Fuller tests, the results showed that the panel model was suitable for these data. This result was expected due to the lack of homogeneity of cryptocurrencies at the time of selecting cryptocurrencies (Table 3).

Table 3: Examining the appropriateness of the panel model.

Test	**Test statistic value**	**Test significance**	**Conclusion**
LLC	-214.28	¡0.001	Panel model is appropriate
IPS	-201.37	¡0.001	Panel model is appropriate
ADF	11280	¡0.001	Panel model is appropriate

Now, using the relationships stated before, we examine the CAPM and DCAPM models. For this purpose, we first examined whether the volatilities detected in the general state are significantly different from the unfavorable state or not. For this purpose, the paired t-test was used (Table 4).

Table 4: Investigating the appropriateness of the research subject for the selected portfolio.

Examined pair	**Test statistic value**	**df**	**Sig.**	**Conclusion**
difference of efficiency in CAPM and DCAPM models	59.548	77082	¡0.001	Significant difference

Then, two CAPM and DCAPM models were fitted using the stated relationships. In this regard, since the objective of the study is to identify the appropriateness of the model, the R2 criterion and the GLT test were used. Table 5 presents the results of this study. As shown, the D-CAPM model can justify the behavior of cryptocurrencies significantly better than the CAPM model (Figure 4).

Table 5: Examining the significant difference between two the models.

Model	R2 value	Model error level	Model appropriates	GLT test statistic	Df1	Df2	Sig	Conclusion
CAPM	0.96	2.54	Appropriate	28.06	1	49	¡0.001	DCAPM model is significantly better than CAPM.
DCAPM	0.97	0.03569	Appropriate					

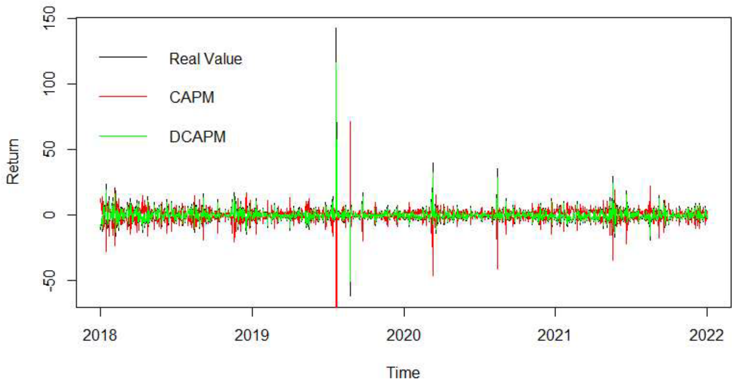

Figure 4: Investigating the appropriateness of CAPM and DCAPM models for estimating the value of cryptocurrency stocks in an equal-weight portfolio.

4.2 Weighting based on the reduction in value at risk

For this purpose, weights were considered. They should meet two criteria simultaneously.

- They should minimize the total weighted variance covariance matrix of the portfolio
- They should maximize the expected return for the portfolio.

For this purpose, the conventional optimization method has been used, and other methods such as SSD, mean-variance, etc. were left to future studies.

It is not always possible to keep the cryptocurrency markets in a stable behavior with each other and a different plan and tool is needed for each market.

Table 3 shows the 50 markets that cannot be used by the mixed method for market analysis), the weights were identified on a monthly basis and used for the weight of the investigated models. Then, the modified weights were estimated based on the level of participation of each cryptocurrency in different periods (random sample with a probability of 1.60 in each month).

5 Conclusions

Since no difference was observed in the performance of the markets and no cryptocurrency was completely removed in this state, there is no need to examine the possibility of mixing and the difference in the expected return of the two models, and only the appropriateness of the model should be examined.

Now, using the stated relationships, since the objective of the study is to identify the appropriateness of the model, the R2 criterion for description and the GLT test were used. The results of this investigation are shown in Table 6. As shown, the DCAPM model is significantly better than the CAPM model in justifying the behavior of cryptocurrencies. See Figure 5 for a better display of the appropriateness of the DCAPM model in this portfolio.

Table 6: Investigating the significant difference between two models.

Model	R2 value	Model error level	Model appropriates	GLT test statistic	Df1	Df2	Sig	Conclusion
CAPM	0.89	2.638	Inappropriate	33.43	1	49	¡0.001	D-CAPM model is significantly better than CAPM.
DCAPM	0.98	0.789	Appropriate					

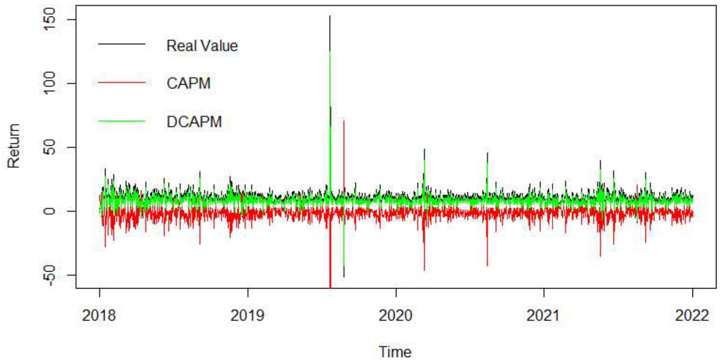

Figure 5: Investigating the appropriateness of CAPM and DCAPM models for estimating the value of cryptocurrency stocks in the balanced portfolio based on the reduction in value at risk.

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