Original Research Article

Crypto Price Prediction as an Investment Opportunity: An Empirical Study of Three Global Cryptocurrencies

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ABSTRACT

Aims: To determine the investment feasibility of evaluating cryptocurrency opportunities as an investment product under the possibility of crypto price valuation selection. The study analyzes three indicators: asset price returns in unrelated time, selection of cryptocurrency investment price weights, and crypto price forward contract opportunities on ARCH-GARCH probability forecasts in the selection of price valuations by individual cryptocurrency prices.
Study design: Quantitative research.
Place and Duration of Study: The period from 10 September 2021 to 4 September 2022 using sample data downloaded from the Yahoo Finance website database with metric data retrieval bound in amount, data quantity, or distance relative to writing opportunities to examine the distribution of the amount of research data.
Methodology: This study employed Bitcoin (BTC), Ethereum (ETH), and Tether (USDT) cryptocurrencies as the research objects with used panel and multiple regression analysis methodologies and using forecasting the appropriate ARCH and GARCH methods
Results: The results show that the prediction of future crypto price selection in BTC and ETH tokens has a probability of 78.6% and 59.6%, respectively. The study highlights that the prediction of future BTC and ETH price selection with 79.21% and 78.64% forecast results as found in the ARCH-GARCH(1, 0, 1) technique. Meanwhile, USDT token has no possibility to be forecasted in the future, leaving 7.3% possibility of crypto price selection under probability by investors in the form of high (or different) price fluctuation inequalities.
Conclusion: conclusions could state that the partial (combined) selection of crypto coin price assessments and individual crypto assets can reduce the expected return from the selection of the asset price so that this form of investment in crypto assets can reduce the level of observation of return on wealth from crypto assets for investors especially in expecting the chance on that investment

Keywords: Price selection, Cryptocurrency, Crypto coin investment, Investor, return level.

1. INTRODUCTION

Peer-to-peer cryptocurrency is a system that can eliminate third parties in the market. Peer-to-peer enables cryptocurrency payments to be sent quickly across networks worldwide without fees, regardless of the banking entities in a country (Carpenter, 2016). Cryptocurrency can function independently of the conventional financial system since it is now present in the financial market, which is part of a global financial system. Moreover, a system known as blockchain is responsible for the operation of cryptocurrency. Because this technology is based on cryptography, it enables users to send and receive payments directly with one another (Kozak & Gajdek, 2021). Furthermore, people who wish to invest in cryptocurrency and evaluate the price of crypto assets may find that blockchain technology presents them with an opportunity.

According to Ahelegbey et al. (2022), diversified crypto asset investment returns were achieved by gaining actions in the form of hedging investors from their valuation prices. This was described in terms of the probability of a diverse portfolio of crypto assets. In addition, the consolidation of crypto assets serves as an important component of a sound portfolio structure in the context of investment activities that aim to accomplish a particular level of optimal valuation (Inci & Lagasse, 2019).

However, fluctuations in the brief trading time circumstances associated with cryptocurrency make it possible to hedge risky bets. From the findings in the field, crypto assets are more similar to speculative investments rather than actual cash investments (Guesmi et al., 2019). Due to the fact that cryptocurrency investments typically do not have a track record, investors are therefore misinformed about the reasons and aims for investing in cryptocurrency. Because of these drawbacks, bitcoin is a risky investment (although it always tends to increase), particularly because it has not yet expanded throughout most of the world's financial market (Rahim et al., 2021).

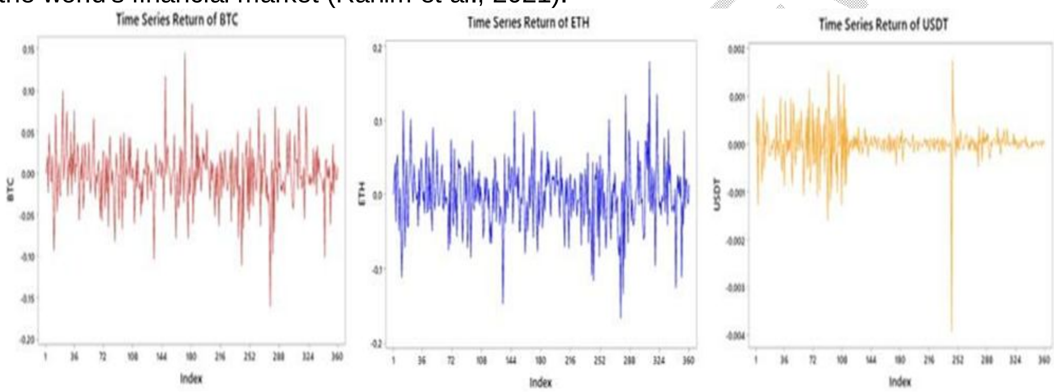

Figure 1. The returns in 1 year 2021-2022 (September) on three cryptocurrencies

Observations on a different crypto market revealed a return on investment for Ethereum (ETH) tokens of 72.02 percent, followed by Bitcoin (BTC) tokens at 38.98 percent and Tether tokens (THT) tokens at 0.23 percent. This percentage is the potential rate of return on top crypto investments based on the market return index by crypto throughout the trading period compared to studies of other markets, such as investing in silver by 42.16 percent, then copper by 20.75 percent, and gold by 8.54 percent (Abdelrhim, et al., 2020).

Several studies have reviewed that short-term cryptocurrency investments have a diversification risk by comparing investments from other currencies to a number of traditional investments and other alternatives so that in a smaller currency value, even though it does not affect crypto, it is still correlated with crypto (Inci A & Lagasse R, 2019). Given the reality of price fluctuations, however, the evidence of long-term support on the cryptocurrency market is unclear. Thus, future investments in cryptocurrency can be made by picking the probability of its price, so that every present crypto investor makes a profit.

Because the cryptocurrency market has such a long track record, investors can forecast future values accurately and make money in the market (Ankenbrand & Bieri, 2018; Kaya Soylu et al., 2020). Therefore, as a result of the fact that the objective of this research was to discover and evaluate the potential of cryptocurrency as a form of estimation in investing under the probability of price selection in crypto assets, this investigation was carried out. In addition, it was stated that the top tier of cryptocurrency assets could be exchanged at a generally acceptable price, albeit not as successfully as in traditional asset classes.

2. MATERIAL AND METHODS

2.1 Material

2.1.1 Price And Asset Return At Time Unaffected

In a nutshell, Mandlebrot's assumption states that constant volatility (price movement) is the price in a financial asset that does not apply to be calculated. Suppose this assumption is used to measure the model from the time of asset volatility that is not correlated and the same as the Brown Geometric modeling (spread of prices becomes random), which is linked to the volatility of asset returns. In that case, it can change "the price of the log asset equals the price of the return on the log asset" (Alexander Carol, 2008). The symbol denotes the notation P_t by the time t of the standard asset price.

$$\Delta \ln P_t = \alpha + \varepsilon_t \sim \varepsilon_t := N\,(0, \sigma^2)$$

With $\alpha = \mu - \frac{\sigma^2}{2}$ Part (1) can be linked to the cryptocurrency trading process, where the influence of variations from investors competing in receiving asset values in a short and undetermined time (unrelated to the time of volatility distribution) can produce diversification in the investment environment and a unique strategy in the form of optimal opportunity growth strategy (Drokin & Zhitlukhin, 2020).

2.1.2 The Selection of Investment Price in Time (t)

Generally, in the form of the variety of asset values that can be found on the market, determining the price of these assets involves taking into account a number of different factors, such as the proportion, number of portfolio units, and the amount of investment in specific assets (Fahim, 2019). In layman's terms, the factors to be considered when evaluating asset prices at time t (certain) can be assessed by self-financing portfolios as the valuation of asset investment prices that fluctuate in the returns on the underlying investment returns as investment opportunities in the market within a certain amount of time (Sheng & Shen, 2020).

In order to do the evaluation of price selection at time t by (2), a long-term or short-term time function that begins with the time sequence to zero is utilized.

$$\theta_t^{(i)} = \frac{W_t^{(i)}}{W_t}$$

Where $W_t^{(i)} = \Delta_t^{(i)} \cdot S_t^{(i)}$ is the value of investment assets that are in the I sequence where W_t being the total value of the investment weight of asset prices in the t-time sequence (Fahim, 2019).

2.1.2 Currency Contract Forward

The practice of optimal financial valuation is essential for anyone seeking to protect the value of their portfolio, as an optimal valuation of financial assets can bring benefits by prioritizing the precautionary principle of future price movements (Dietz et al., 2016). So, an investor protection movement occurs for their portfolio contracts where the obligation is for the future or T (maturity time) when the price is performed (K) (Junghenn, H., D., 2011). This assumption can be formulated by prioritizing investor purchase contracts.

$$F_t = S_t - e^{rt} S_0, \;\; 0 \le t \le T$$

Through (3), F_t is a forward contract where S_t is the price of the asset at time t, and r is the exchange rate of money, and S_0 is the initial price of the item. Bouri et al. (2020) discovered that adopting cryptocurrency affects the price investors pay to diversify their capital portfolios with other cryptocurrencies.

If the buyer rates at $F_t < S_t - e^{-r(T-t)}K$ or if a very small contract for a buy position with execution results in one taking a short decision position on the security and a long decision position from now on, or if each investor can deposit assets into a risk-free account at an annual rate of r (interest rate) then the buyer will take a short decision position on the security and a long decision position going forward.

2.1.3 <u>The Selection of Asset Price Assessment under Probability</u>

If the S_n asset price selection has been obtained in the return value of an asset, the asset's price value can be changed to an undeveloped price value. Thus, the expectation of return value R_i with price selection S_n is defined by $R_i \coloneqq E[R_i]$ (Fahim, 2019) or the expectation of $E[R_i]$ by R_i is shown to quantify the level of price return volatility in assets based on the assets' estimated risk (Stavroyiannis, 2018).

$$R_\theta \coloneqq \sum_{i=1}^{N} \theta_i R_i$$

Where the formula $\theta_p = \left(\frac{\sigma_j^2}{\sigma_i^2+\sigma_j^2}\right)$ with σ_j^2 is the variance of second asset of the return asset price $R_i = \frac{S_{n+1}-S_{n-1}}{S_{n-1}}$ and σ_i^2 is the variance of first return asset price R_i. The relationship of the selection of asset price valuation under the decision of an investor can make the probability of selection of funds distributed in the investment can be defined through the consideration of portfolio weights $\theta_1, \ldots, \theta_N$ which is straight on the formula θ_p.

Thus, there is a basic type of asset investment accompanied with expectation. This objective might boost the likelihood of observing varied asset returns when investing (Cornil et al., 2019).

2.2. Methots

2.2.1 Measurement

The development of the research concept is accomplished through predictive research in which the relationship between a phenomenon and its resulting cause is replaced by future prediction findings (Boncz Imre, 2015). The processing of the calculated data compilations the adjusted closing price derived from the formulation of the log price and return of crypto coins that are interpreted as investment goods with varying features and circumstances (Sun et al., 2020).

2.2.2 Analysis Method

Sample data processing was collected and calculated using Microsoft Excel 2019 as data management and material for calculating research variable parameters with the assistance of SPSS 25 and E-Views 12 statistical analysis software as a test process for parameter variables for measuring observations in the quantity of data (Judd et al., 2017). The research analysis results were presented in three stages, which included the presentation of statistical reviews of the research data, classical validation testing and parameter panels, panel data regression output and OLS, and the results of time series forecasting using the appropriate ARCH and GARCH methods (Sun et al., 2020).

$$CPR_t = \beta_0 + \beta_1 PRUT + \beta_2 IWPP + \beta_3 CRF + e_1$$

The description of the variable test on the equation (5).

CPR_t : *Cryptocurrency Price Rating until time-t*

$PRUT$: *Price Refunds At Unrelated Time*

$IWPP$: *Investment Weight Periode Price*

CRF : *Crypto Rate Forward*

e_1 : *Margin of error term*

In the meantime, the prediction model will compute the spread (variance) via ARCH with the General ARCH (GARCH) component based on the valuation of crypto prices in a certain period (CPR t). When the heteroscedasticity model and stationarity test in addition to the Lagrange ARCH are acceptable, the third stage of additional testing will be conducted (Gusti Ngurah Agung, 2009).

The combination of results from regression analysis and testing of time series forecasts has the potential to advance the goal of crypto assets as products that are able to present diversification of investor decisions through short-term time levels with variations in time series taking that can be reflected as a relationship between the economic and financial effects that are caused by cryptocurrencies (Corbet et al., 2018; Kim & In, 2010)

2.2.3 Research Hypothesis Line

Following the argumentation of Kabašinskas & Šutienė (2021), explaining the relationship between economics and finance in the fundamental principle of traditional financial markets that the determination of an asset price has a number of facts that have found opportunities in the form of profit-taking from several financial markets which cannot disappear in such a time fast. Therefore, crypto coin trading assets will have a good possibility of holding a cryptocurrency asset portfolio that continues to expand and adjusts from the rate of return by price selection constructed from the decisions of investor commitment (Quoc & Brisbane, 2020).

Figure 2 is the path of the hypothetical problem that has been emphasized in the literature through the preparation of writing variables. This path can be found by tracing backwards from the statements modified by multiple authors to see the relationship to the formulation of earlier research.

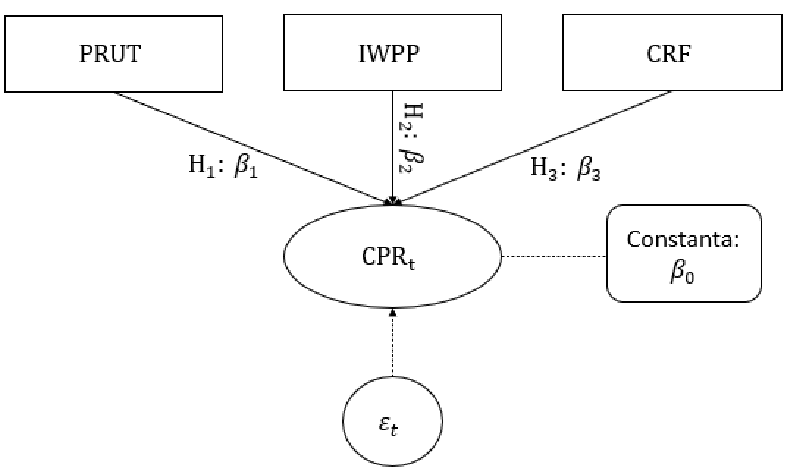

Figure 2. Hypothesis of Research Structure Writing Line

2.2.3.1. The Relationship of Returns at Time Unrelated to Crypto Price Valuation
according to Borri & Magistris (2022), returns on crypto assets such as BTC would disburse funds with a profit rate in the shape of a sloping curve and may signal a surge in price movements (volatility) to tail risk as assessed by kurtosis yields. Thus, the price-return classification is a premium cryptocurrency or a cryptocurrency coin with variability on the high degree of price. Kececi (2020) highlighted that high variability risk can necessitate investors' capital strategies at a larger threat to overcome losses, causing crypto coin prices to fluctuate upwards and investors to employ a unique monitoring approach when selecting insecure crypto coins.

H_1 : PRUT negatively affects the selection of crypto price valuation

2.2.3.2. The Relationship of Investment Weight Price Period to Crypto Price Valuation
According to Tenkam et al., (2022), the crypto market in 2009 spawned a diversification of digital financial portfolios that was efficiently spread across financial market classes. A diverse price distribution promotes investors' assessment of the risk management of their crypto portfolio in terms of calculating risk with a return on wealth proportional to the amount of assets invested.

Guinda & Bhattacharyya, (2021) unearthed that 80% of crypto coin asset selection is positive, beginning with ETH crypto assets with bearish periods that have been proven to fluctuate in an erratic positive and negative direction when used to protect their portfolio capital at diversification considerations of the portfolio
.
H_2: IWPP positively affects the selection of crypto price valuation

2.2.3.3. Crypto Forward Relationship to Crypto Price Valuation
Crypto assets have the potential to generate interest effects in the amount of 4% on an annual basis if smart contracts based on crypto assets are used in maximum time and historically (Tien et al., 2020). Therefore, the implementation of smart contracts in contract fees associated with transactions between traditional and digital currencies results in risks that investors must consider regardless of the oversight provided by the blockchain linking them to payment systems. Hu et al. (2019) discovered that in a cryptocurrency market that fluctuates based on the payment price that is set between traders and buyers, hedging actions on smart contracts can significantly reduce the level of decision risk or become a (new) solution in the process of negotiating cryptocurrency prices with the usability at the time of receiving the annual interest effect.

H_3: CRF positively affects the selection of crypto price valuation

3. RESULTS AND DISCUSSION
3.1 RESULTS
3.1.1 Descriptive Data Summary
Table 1 and 2 are the data on the distribution of output variables and research samples that have been processed as descriptive statistical data reviews.

Table 1. The Output of Descriptive Panel

	The Description Of Data Panel			
	PRUT	IWPP	CRF	CPR
Variance	1,137	1,364	2,194	18,252
σ	1,006	1,168	1,481	4,272

μ	1,490	-3,597	-2,047	-5,729
ε_{err}	.0324	.0355	.0450	.1299
N	1080			

σ : Standard deviation. ε_{err} : Standard error mean (S.E). μ : Rata-rata data

The output of table 1 displays two independent indicators in the form of crypto investment period weight (iwpp) and forward contracts of crypto assets (crf) in data proximity measured at standard deviation (σ) and measured price spread rate $\boldsymbol{\sigma^2}$ (through variance) and it can be concluded that the predictor of the crypto price indicator is biased away from its mean value. Conversely, the findings of the crypto price appraisal (cpr) selection in the market are significantly over the sample's mean level.

According to sheng & shen's research (2020), the problem of portfolio valuation in cryptocurrency asset investment prices has different swings compared to other traditional assets (iwpp). While crypto contracts have some security issues, investors (crf) are concerned about the influence that price diversification will have on the market (bouri et al., 2020).

Table 2. The Output of Descriptive Sample

	BTC				ETH				USDT			
	PRUT	IWPP	CRF	CPR	PRUT	IWPP	CRF	CPR	PRUT	IWPP	CRF	CPR
Variance	.000	.000	.025	.876	.000	1,48	.306	.870	1,789	160,2	.000	.000
σ	.0002	.0056	.1568	.9360	.0001	1,21	.5529	.9329	1,337	400,4	.0131	.0002
μ	-6,09	.0027	-.083	-2,88	.0729	-3,76	-1,04	-2,88	1.074	.0027	-.0001	-11,56
ε_{err}	.0001	.0002	.0082	.0493	.0001	.0642	.0291	.0491	.0704	21,10	.0006	.00001
N	360				360				360			

Descriptive output from Table 2 on three samples of cryptocurrency assets, individually the results of the crypto investment weight price selection indicator (IWPP) on ETH assets fluctuate negatively and positively and the crypto forward contract indicator (CRF) in BTC, ETH and USDT move far from the price selection average. Table 2 shows a negative difference in average unrelated crypto price returns (PRUT) on BTC moderator assets.

Fahim, (2019) demonstrates the investment weight of various assets over time affects the selection level of fluctuating cryptocurrency values (Bouri et al., 2020). In addition, crypto smart contracts at the security level stimulate digital contract price movements in diverse ways, as they can raise various returns and trigger future dangerous expectations (Cornil et al., 2019).

The valuation in the results of Table 2 in terms of the distribution of this study shows that crypto coins have become risky in diversification due to a number of selection influences from the crypto prices (Inci & Lagasse, 2019). Consequently, regardless of oversight, the acceleration in blockchain surveillance of the crypto market will become even more stringent (Carpenter, 2016). Accordingly, the crypto market offers investors an opportunity to accelerate their prediction rate to earn substantial rewards from speculative price options. (Kaya Soylu et al., 2020).

3.1.2 the interpretation of ols model

The testing of the modeling test results in panel and multiple regression (OLS) can be shown in Table 2 and Table 3

Table 3. The Model Regression Panel Statistics

	Panel OLS				Validation	χ^2
	Coeff.	PRUT	IWPP	CRF		
β	-5,750**	-.1298	.3656**	-.7473**	Chow-Test	.0000
ε	.1906	.1190	.0248	.0524	Hausman-Test	.0000
					Result	Fixed-Effect
R^*	.953					

β : Coefficients from variable. ε : Standard error regression. R^* : Adjusted square statistics

Consequently, the evaluation of crypto price selection (Coeff.) is negative, or the selection effect of crypto prices can reduce the expected rate of return from a crypto asset based on the price of a risky currency by -5.75 percentage points (Stavroyiannis, 2018). So, hypothetically, the unrelated time return indicator (PRUT) is negative but insignificant at -0.1298.

Table 3 is further challenged by the findings of Tien et al., (2020) on crypto forward contracts (CRF), which are significantly negative and conceptually significantly positive. That is to say, the risk of the payment system arises as a genuine sensitivity in the course of a sequence of events that unfold over time and include historical price trading data at annual intervals (Hu et al., 2019). In addition, the investment weight price selection indicator (IWPP) agrees with the significant positive hypothesis, which is a very important finding.

Tenkam et al., (2022) found that diversified digital financial distribution leads to growth results by investors in managerial portfolio risk, with a rate of return from investment weights that can produce 80% of each crypto coin asset selection.

Table 4. Sample Regression Statistics

	BTC				ETH				USDT			
	Coeff.	PRUT	IWPP	CRF	Coeff.	PRUT	IWPP	CRF	Coeff.	PRUT	IWPP	CRF
β	-1.812**	-296,53**	48,87**	1,48**	-2.117**	-2.900**	.152**	-.382**	-11,60**	.0001	18,41**	1.345**
ε	67,47	11,05	4,12	.156	136,6	187,4	.026	.067	.214	.0001	5,50	270,58
R^*	.786				.596				.073			

Sample regression as the results of the coefficient (CPR) for three cryptocurrencies is presented in table 4. These results show that investors' expectations of returns on the value of crypto assets can be reduced using these cryptocurrencies. Concurrently with the selection indicator for cryptocurrency coin investment price weights where (Tenkam et al., 2022) through the development of crypto assets up until now in investments that have the potential to be diversified by portfolio expectations can increase from cryptocurrency returns (IWPP +) to investor expectations which will decrease or make investors warier of investing in crypto assets (Guinda & Bhattacharyya, 2021).

In the ETH sample, it can reduce the level of risk on the consideration of the contract fee (CRF) in the ETH smart contract between the exchange of two traditional and digital currencies (ETH and USD for example) (Tien et al., 2020). USDT has disagreements with (Kececi, 2020) who found that the high level of crypto variability can cause investors to risk some of the capital that will be issued to cover their income. The USDT altcoin provides a timely return on assets unrelated to certain indicators or has a low risk in the variability of crypto-currencies, thereby reducing the risk of a large part of an investor's capital.

3.1.3 ARCH-GARCH Forecasting

The valuation of Table 5 is the form of predictive analysis data of squared residuals with residual variance in the ARCH-GARCH approach.

Table 5. The Output of Variance Prediction Period Results

	Variable						Sample	DF
	BTC	**Prob.**	ETH	**Prob.**	USDT	**Prob.**		
Coeff. Variance	.0393	.1566	.0263	.1937	.7028	.0000	BTC	0.01**
Residual $(-1)^2$	.1605	.0203	.1909	.0059	.5412	.0000	ETH	0.01**
GARCH (-1)	.7921	.0000**	.7864	.0000**			USDT	0.01**
LM-ARCH								
F-Statistics	1.831	.1768	.1255	.7233	.0981	.7543		

LM-ARCH: Heteroscedasticity test (lagrange ARCH). DF: Dickey Fuller-Test

In the level of the ARCH-GARCH (1, 0, 1) or ARCH (0, 0) levels with the GARCH (0, 1) being significantly positive by the BTC and ETH coin price selection (CPR) factors. While USDT's different results can be measured by the ARCH-GARCH (1, 0, 0) or ARCH (1, 0) and GARCH (0, 0) levels, both of which indicate that there is ARCH in the USDT sample model or that there is an unequal variance of crypto price selection (CPR).) USDT in salvage value, the ARCH-GARCH (1, 0) and GARCH (0, 0) levels indicate that there is ARCH in the USDT sample model The ARCH-GARCH model, as determined by the valuation stated in Table 5, has completed the process lag necessary for processing with the graphical testing results displayed in Figure 1.

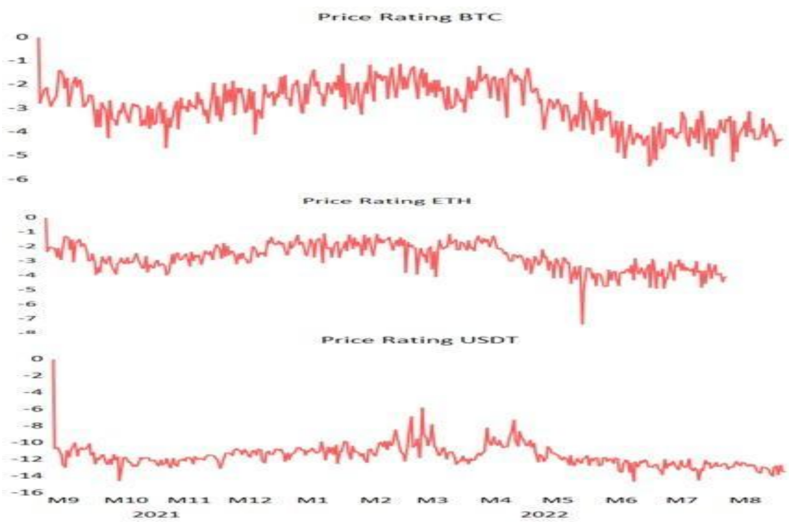

Figure 3. The Graphics of Stationerity of Selection of Crypto Price Valuation

A plot of the test findings between the crypto price selection factors determined by three separate crypto samples is displayed in Figure 1. This plot demonstrates that the data contains elements that are stationary. Figure 2 can be used to determine the objectivity of volatility in investors who select future crypto prices, so that the prediction of price selection variations (CPR) with three different cryptocurrencies can be determined.

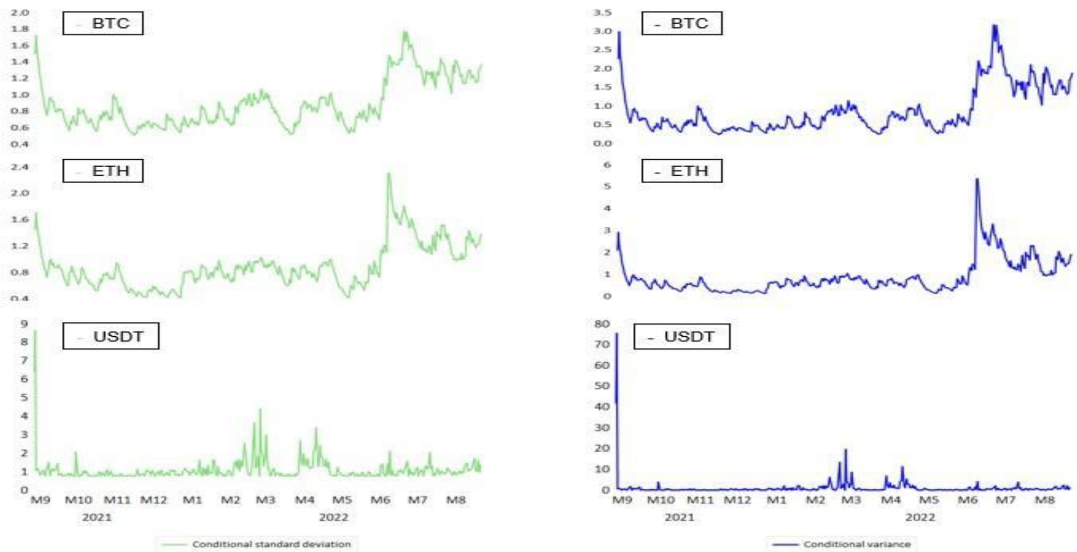

Figure 4. The Graphics of Volatility Prediction of ARCH-GARCH (Standard Deviation) (Left) with the Vlatility Prediction of ARCH-GARCH (Variance) (Right)

Alexander Carol, (2008) discovered that investors can utilize price distribution trends with a specific amount of data (right picture). Consequently, through a relationship that may be claimed to exist, the trend of the dispersion of cryptocurrency prices can shift away from the mean value. The USDT cryptocurrency is not an exception, as it has an unequal distribution of prices or is closer to the average price selection (other factors) than the distribution trend of these price selections.

According to the findings of Drokin & Zhitlukhin' study (2020), if the variability of price distribution disparities is allowed, this can interact with various altcoin assets. Moreover, BTC and ETH assets have a large price movement variability, hence raising the risk in crypto portfolio management for investors selecting future crypto price evaluations (Tenkam et al., 2022).

Incorporating to the findings of Borri & Magistris, (2022) that high returns for a type of crypto will cause the conditional price volatility of returns to be high, there will be a risk of variation in investor capital to cover losses of their capital from the level of crypto security that is beginning to spiral out of control (Kececi, 2020).

3.2 Discussion

3.2.1 Interpretation Of Regression

Through the results of Table 3, the CRF findings with the hypothesis from Tien et al., (2020) are contradictory in the findings, because there cannot be a new solution actually to reduce the level of risk in the environment, or this is contrary to the statement from Hu et al., (2019) that in a fluctuating crypto market it becomes a solution to hedge the level of risk in a real environment. Meanwhile, the PRUT indicator Table 3 is negative and not significant which can be stated due to differences in price variability and high risk of crypto coin volatility with differences in investor capital strategies that are high risk in overcoming losses that vary in certain crypto coin currencies (Bouri et al., 2020; Kececi, 2020).

Based on the distinctions between the three altcoins according to Table 4, the CRF variable in the ETH crypto asset is statistically negative -0.382, or according to findings (Hu et al., 2019; Tien et al., 2020) in studies, it can be concluded that ETH tokens can reduce the level of risk consideration by investors to the relationship of the payment system and by the function of the ETH crypto smart contract to be negative (bearish) fluctuations. Yields can also be determined by the combined influence of the three altcoins (Table 3), which has the ability to diminish investors' consideration of the blockchain monitoring system during the payment process or price selection transactions involving crypto coins.

Whereas the result in Table 3 of the PRUT variable panel output is appropriate or negative -0.1298 but is not significant, the result in Table 4 of the USDT crypto token by the PRUT variable or return on assets in time that is not related to the crypto price appraisal selection (CPR) is positive by 0.0001 and is not significant. This is in contrast to the different results in Table 3 of the PRUT variable panel output. As a result of these disparities, it is possible to draw the conclusion that the combined price movements of the three altcoins have spikes that are not the same as or inconsistent with (Borri & Magistris, 2022) where it is not typical for the majority of crypto coins to experience high price variability.

Nevertheless, such unpredictability might be a cautionary measure when the price of a cryptocurrency coin climbs, and one then wishes to upgrade from a suitable strategy of monitoring investment in cryptocurrency coins (Kececi, 2020). Therefore, the combined rate of cryptocurrencies by PRUT can potentially increase the risk of increasing the profit slope against the selection action of crypto price valuation. However, this does not apply to USDT assets because those assets can improve the selection of USDT crypto price valuation using different indicators.

3.2.2 The Interpretation of ARCH-GARCH Forecast Output

Estimation of the selection of crypto coin price valuations on price proximity to the average future crypto price valuation shown in Figure 3 as a result of GARCH (-1) predictions in BTC and ETH assets respectively of 79.21% and 78.64% predictions made with ARCH-GARCH levels (1, 0, 1) through variables (CPR) with contribution indicators (CPR) BTC and ETH consisting of price returns in unrelated times (PRUT), crypto period investment weight (IWPP) , with a crypto rate forward (CRF) it will have the opportunity to increase the selection assessment of BTC and ETH crypto prices by 78.6% and 59.6% with the proximity of various indicators (CPR) of BTC and ETH crypto prices which seem positive from the average value crypto price selection assessment indicator.

Meanwhile, the prediction level of the USDT altcoin with the ARCH-GARCH level (1, 0, 0) by the ARCH model (1, 0) does not indicate any future predictions, or there is an unequal distribution of volatility in the selection of USDT crypto price valuations. In the meantime, the prediction level of the USDT altcoin is with the ARCH-GARCH level (1, 0, 0). Because of this, the USDT crypto price selection (CPR) assessment indicator contribution form will only have a 7.3% chance of being selected on the indicator (CPR), and this can be emphasized through the findings (Borri & Magistris, 2022) that some altcoins mostly do not have a form of price variability tall one.

The predicted distribution of price selection for BTC and ETH cryptocurrencies in Figure 2 (right) has a fluctuating price volatility surface. However, certain distribution predictions for price selection for altcoin USDT do not vary with a sloping graphic surface pattern. According to Table 2 (CPR), the statistical distribution of the price selection for the 3 cryptocurrencies for BTC and ETH is 87.6% and 87.0%, respectively, whereas USDT has an unpredictable price selection of 0%.

The results of Figure 2 (right) can be reiterated through Table 4 to show that three altcoins have the potential to reduce investor expectations of returns with the difference in the CPR indicator by the ETH sample, which reduces the level of assessment of crypto price selection on CRF and USDT crypto assets that are not related by certain indicators and reduces the risk of the majority of investor capital (Kececi, 2020; Tien et al., 2020).

4. CONCLUSION

Recommendations for affirming the research paper's conclusions could state that the partial (combined) selection of crypto coin price assessments and individual crypto assets can reduce the expected return from the selection of the asset price so that this form of investment in crypto assets can reduce the level of observation of return on wealth from crypto assets for investors especially in expecting the chance on that investment (Cornil et al., 2019).

This study demonstrates that the BTC price investment weight indicator can increase the valuation of the price of the crypto selection. In contrast, crypto ETH can reduce the level of risk consideration by investors in the smart contract-based payment system in the cost of the contract on the ETH price selection. The USDT crypto has a return on assets over time that is unrelated to the evaluation of the price selection of crypto coins, leading to the conclusion that distinct price diversifications exist (Borri & Magistris, 2022; Bouri et al., 2020).

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