

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

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 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 a 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.

19 **1. INTRODUCTION**

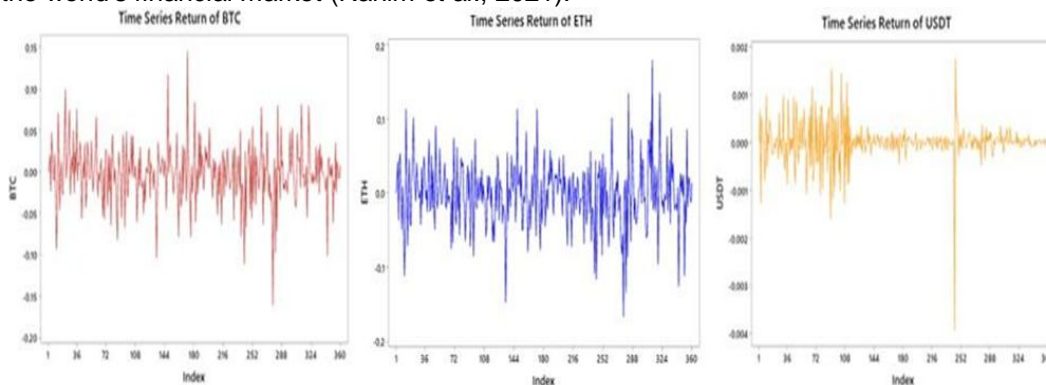
20 **1.1 Background of the Study**

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

31 **1.2 Research Problem**

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

38
39 However, fluctuations in the brief trading time circumstances associated with cryptocurrency
40 make it possible to hedge risky bets. From the findings in the field, crypto assets are more
41 similar to speculative investments rather than actual cash investments (Guesmi et al., 2019).
42 Due to the fact that cryptocurrency investments typically do not have a track record,
43 investors are therefore misinformed about the reasons and aims for investing in
44 cryptocurrency. Because of these drawbacks, bitcoin is a risky investment (although it
45 always tends to increase), particularly because it has not yet expanded throughout most of
46 the world's financial market (Rahim et al., 2021).



47
48 **Figure 1.** The returns in 1 the year 2021-2022 (September) on three cryptocurrencies
49

50 **1.3 Research Objectives**

51 Observations on a different crypto market revealed a return on investment for Ethereum
52 (ETH) tokens of 72.02 percent, followed by Bitcoin (BTC) tokens at 38.98 percent, and
53 Tether tokens (THT) tokens at 0.23 percent. This percentage is the potential rate of return on
54 top crypto investments based on the market return index by crypto throughout the trading

55 period compared to studies of other markets, such as investing in silver by 42.16 percent,
56 then copper by 20.75 percent, and gold by 8.54 percent (Abdelrhim et al., 2020).

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

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

71
72

73 2. MATERIAL AND METHODS

74 2.1 Material

75 2.1.1 Price And Asset Return At Time Unaffected

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

84

$$\Delta \ln P_t = \alpha + \varepsilon_t \sim \varepsilon_t := N(0, \sigma^2) \quad (1)$$

85

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

91

92 2.1.2 The Selection of Investment Price in Time (t)

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

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

103

$$\theta_t^{(i)} = \frac{W_t^{(i)}}{W_t} \quad (2)$$

104 Where $W_t^{(i)} = \Delta_t^{(i)} \cdot S_t^{(i)}$ is the value of investment assets that are in the i sequence in a row
105 table in a column and where W_t is the total value of the investment weight of asset prices in
106 the t -time sequence, meanwhile $\theta_t^{(i)}$ is a portfolio in self-financing or a singular portfolio in a
107 series vector (Fahim, 2019).

108

109 **2.1.2 Currency Contract Forward**

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

116

$$F_t = S_t - e^{rt} S_0, \quad 0 \leq t \leq T \quad (3)$$

117

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

122 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
123 execution results in one taking a short decision position on the security and a long decision
124 position from now on, or if each investor can deposit assets into a risk-free account at an
125 annual rate of r (interest rate), then the buyer will take a short decision position on the
126 security and a long decision position going forward.

127

128 **2.1.3 The Selection of Asset Price Assessment under Probability**

129 If the S_n asset price selection has been obtained in the return value of an asset, the asset's
130 price value can be changed to an undeveloped price value. Thus, the expectation of return
131 value R_i with price selection S_n is defined by $R_i := E[R_i]$ (Fahim, 2019) or the expectation of
132 $E[R_i]$ by R_i is shown to quantify the level of price return volatility in assets based on the
133 assets' estimated risk (Stavroyiannis, 2018).

$$R_\theta := \sum_{i=1}^N \theta_i R_i \quad (4)$$

134 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
135 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
136 the selection of asset price valuation under the decision of an investor can make the
137 probability of selection of funds distributed in the investment can be defined through the
138 consideration of portfolio weights $\theta_1, \dots, \theta_N$ which is straight on the formula θ_p .

139

140 Thus, there is a basic type of asset investment accompanied by expectation. This objective
141 might boost the likelihood of observing varied asset returns when investing (Cornil et al.,
142 2019).

143

144 **2.2. Methods**

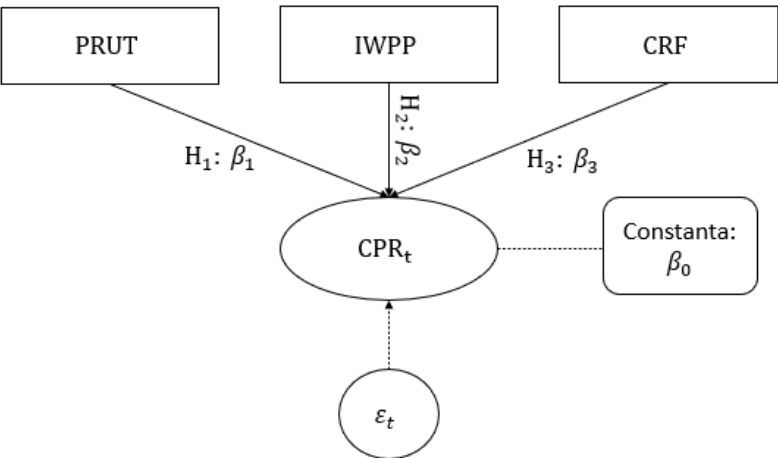
145 **2.2.1 Measurement**

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

194
 195 **2.2.5 Research Hypothesis Line**

196 Following the argumentation of Kabašinskas & Štutienė (2021), explaining the relationship
 197 between economics and finance in the fundamental principle of traditional financial markets
 198 that the determination of an asset price has a number of facts that have found opportunities
 199 in the form of profit-taking from several financial markets which cannot disappear in such a
 200 time fast. Therefore, crypto coin trading assets will have a good possibility of holding a
 201 cryptocurrency asset portfolio that continues to expand and adjusts from the rate of return by
 202 price selection constructed from the decisions of investor commitment (Quoc & Brisbane,
 203 2020).

204
 205 Figure 2 is the path of the hypothetical problem that has been emphasized in the literature
 206 through the preparation of writing variables. This path can be found by tracing **backward**
 207 from the statements modified by multiple authors to see the relationship to the formulation of
 208 earlier research.



209
 210

Figure 2. Hypothesis of Research Structure Writing Line

211 *2.2.3.1. The Relationship of Returns at Time Unrelated to Crypto Price Valuation*
 212 According to Borri & Magistris (2022), returns on crypto assets such as BTC would disburse
 213 funds with a profit rate in the shape of a sloping curve and may signal a surge in price
 214 movements (volatility) to tail risk as assessed by kurtosis yields. Thus, the price-return
 215 classification is a premium cryptocurrency or a cryptocurrency coin with variability on the
 216 high degree of price. Kececi (2020) highlighted that high variability risk can necessitate
 217 investors' capital strategies at a larger threat to overcome losses, causing crypto coin prices
 218 to fluctuate upwards and investors to employ a unique monitoring approach when selecting
 219 insecure crypto coins.

220
 221 H_1 : PRUT negatively affects the selection of crypto price valuation

222
 223 *2.2.3.2. The Relationship of Investment Weight Price Period to Crypto Price Valuation*
 224 According to Tenkam et al. (2022), the crypto market in 2009 spawned a diversification of
 225 digital financial portfolios that was efficiently spread across financial market classes. A

226 diverse price distribution promotes investors' assessment of the risk management of their
 227 crypto portfolio in terms of calculating risk with a return on wealth proportional to the number
 228 of assets invested.

229
 230 Guinda & Bhattacharyya, (2021) unearthed that 80% of crypto coin asset selection is
 231 positive, beginning with ETH crypto assets with bearish periods that have been proven to
 232 fluctuate in an erratic positive and negative direction when used to protect their portfolio
 233 capital at diversification considerations of the portfolio
 234 .

235 H_2 : IWPP positively affects the selection of crypto price valuation
 236

237 *2.2.3.3. Crypto Forward Relationship to Crypto Price Valuation*
 238 Crypto assets have the potential to generate interest effects in the amount of 4% on an
 239 annual basis if smart contracts based on crypto assets are used in maximum time and
 240 historically (Tien et al., 2020). Therefore, the implementation of smart contracts in contract
 241 fees associated with transactions between traditional and digital currencies results in risks
 242 that investors must consider regardless of the oversight provided by the blockchain linking
 243 them to payment systems. Hu et al. (2019) discovered that in a cryptocurrency market that
 244 fluctuates based on the payment price that is set between traders and buyers, hedging
 245 actions on smart contracts can significantly reduce the level of decision risk or become a
 246 (new) solution in the process of negotiating cryptocurrency prices with the usability at the
 247 time of receiving the annual interest effect.

248
 249 H_3 : CRF positively affects the selection of crypto price valuation
 250

251 3. RESULTS AND DISCUSSION

252 3.1 RESULTS

253 3.1.1 Descriptive Data Summary

254 Tables 1 and 2 are the data on the distribution of output variables and research samples that
 255 have been processed as descriptive statistical data reviews.

256 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			

257 σ : Standard deviation. ε_{err} : Standard error mean (S.E). μ : Data averaging

258 The output of Table 1 displays two independent indicators in the form of crypto investment
 259 period weight (IWPP) and forward contracts of crypto assets (CRF) in data proximity
 260 measured at standard deviation (σ) and measured price spread rate σ^2 (through variance)
 261 and it can be concluded that the predictor of the crypto price indicator is biased away from its
 262 mean value. Conversely, the findings of the crypto price appraisal (CPR) selection in the
 263 market are significantly over the sample's mean level.

264 According to Sheng & Shen's research (2020), the problem of portfolio valuation in
 265 cryptocurrency asset investment prices has different swings compared to other traditional

266 assets (IWPP). While crypto contracts have some security issues, investors (CRF) are
 267 concerned about the influence that price diversification will have on the market (bouri et al.,
 268 2020).

269 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	-	-11.56
ε_{err}	.0001	.0002	.0082	.0493	.0001	.0642	.0291	.0491	.0704	21.10	.0006	.00001
N	360				360				360			

270

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

276

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

282

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

290

291 **3.1.2 The interpretation of OLS model**

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

294 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 Result	.0000 Fixed-Effect

$R^* \quad .953$

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

296 Consequently, the evaluation of crypto price selection (Coeff.) is negative, or the selection
 297 effect of crypto prices can reduce the expected rate of return from a crypto asset based on
 298 the price of a risky currency by -5.75 percentage points (Stavroyiannis, 2018). So,
 299 hypothetically, the unrelated time return indicator (PRUT) is negative but insignificant at -
 300 0.1298.

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

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

310 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			

311

312 Sample regression as the results of the coefficient (CPR) for three cryptocurrencies is
 313 presented in table 4. These results show that investors' expectations of returns on the value
 314 of crypto assets can be reduced using these cryptocurrencies. Concurrently with the
 315 selection indicator for cryptocurrency coin investment price weights where (Tenkam et al.,
 316 2022) through the development of crypto assets up until now in investments that have the
 317 potential to be diversified by portfolio expectations can increase from cryptocurrency returns
 318 (IWPP +) to investor expectations which will decrease or make investors warier of investing
 319 in crypto assets (Guinda & Bhattacharyya, 2021).

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

327 **3.1.3 ARCH-GARCH Forecasting**

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

330

331

5. The Output of Variance Prediction Period Results

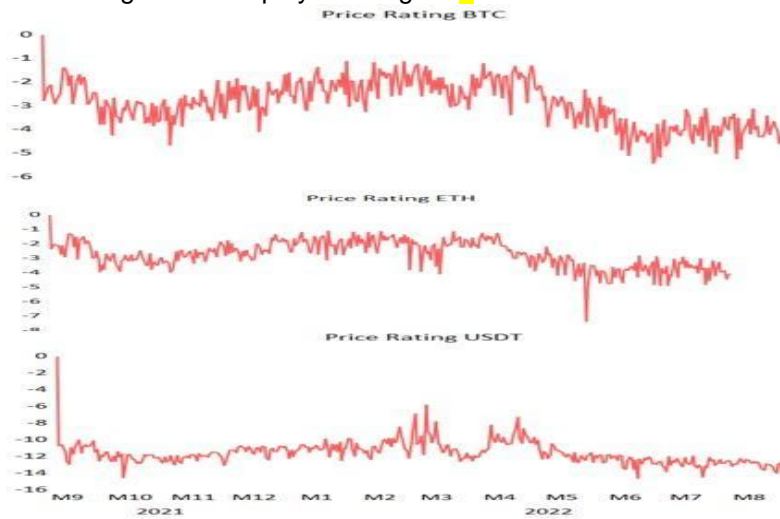
	Variable						Sample	DF
	BTC	Prob.	ETH	Prob.	USDT	Prob.		
Coeff. Variance	.0393	.1566	.0263	.1937	.7028	.0000	BTC	0.01**
Residual (-1) ²	.1605	.0203	.1909	.0059	.5412	.0000	ETH	0.01**
GARCH (-1)	.7921	.0000**	.7864	.0000**			USDT	0.01**
LM-ARCH								
F-Statistics	1.831	.1768	.1255	.7233	.0981	.7543		

332

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

333
334
335
336
337
338
339
340
341

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 3.



342

343

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

344
345
346
347
348
349

A plot of the test findings between the crypto price selection factors determined by three separate crypto samples is displayed in Figure 3. This plot demonstrates that the data contains elements that are stationary. Figure 4 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.

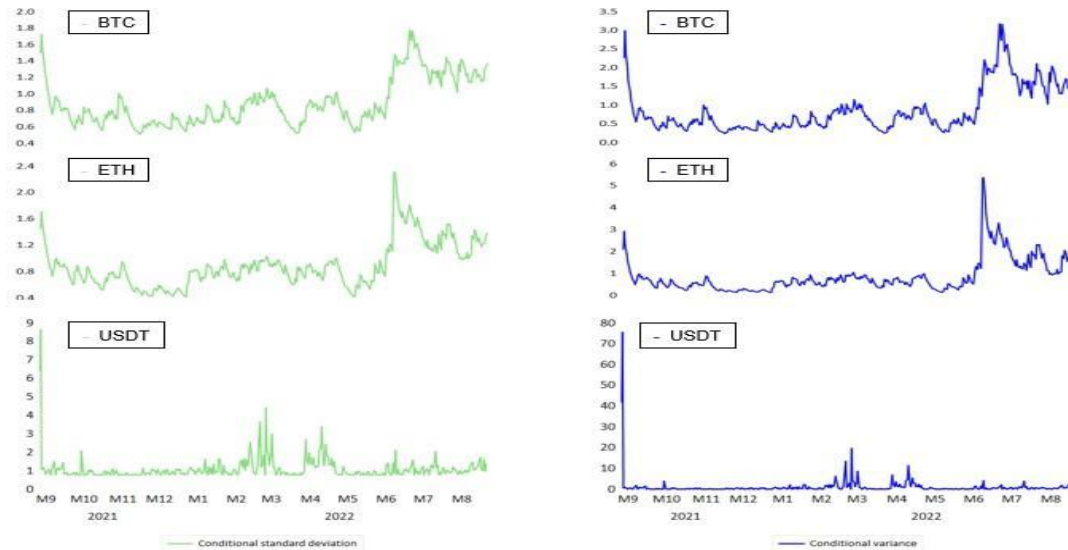


Figure 4. The Graphics of Volatility Prediction of ARCH-GARCH (Standard Deviation) (Left) with the Volatility Prediction of ARCH-GARCH (Variance) (Right)

350
351
352
353

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

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

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

369
370
371
372

3.2 Discussion

3.2.1 Interpretation of Regression

3.2.1.1 Full Sample Test Hypothesis

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

381 **3.2.1.2 Section Sample Test Hypothesis**

382 Based on the distinctions between the three altcoins according to Table 4, the CRF variable
383 in the ETH crypto asset is statistically negative -0.382, or according to findings (Hu et al.,
384 2019; Tien et al., 2020) in studies, it can be concluded that ETH tokens can reduce the level
385 of risk consideration by investors to the relationship of the payment system and by the
386 function of the ETH crypto smart contract to be negative (bearish) fluctuations. Yields can
387 also be determined by the combined influence of the three altcoins (Table 3), which has the
388 ability to diminish investors' consideration of the blockchain monitoring system during the
389 payment process or price selection transactions involving crypto coins.

390 Whereas the result in Table 3 of the PRUT variable panel output is appropriate or negative -
391 0.1298 but is not significant, the result in Table 4 of the USDT crypto token by the PRUT
392 variable or return on assets in time that is not related to the crypto price appraisal selection
393 (CPR) is positive by 0.0001 and is not significant. This is in contrast to the different results in
394 Table 3 of the PRUT variable panel output. As a result of these disparities, it is possible to
395 draw the conclusion that the combined price movements of the three altcoins have spikes
396 that are not the same as or inconsistent with (Borri & Magistris, 2022) where it is not typical
397 for the majority of crypto coins to experience high price variability.

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

405
406

407 **3.2.2 The Interpretation of ARCH-GARCH Forecast Output**

408 **3.2.2.1 Prediction Output**

409 Estimation of the selection of crypto coin price valuations on price proximity to the average
410 future crypto price valuation shown in Figure 4 as a result of GARCH (-1) predictions in BTC
411 and ETH assets respectively of 79.21% and 78.64% predictions made with ARCH-GARCH
412 levels (1, 0, 1) through variables (CPR) with contribution indicators (CPR) BTC and ETH
413 consisting of price returns in unrelated times (PRUT), crypto period investment weight
414 (IWPP) , with a crypto rate forward (CRF) it will have the opportunity to increase the
415 selection assessment of BTC and ETH crypto prices by 78.6% and 59.6% with the proximity
416 of various indicators (CPR) of BTC and ETH crypto prices which seem positive from the
417 average value crypto price selection assessment indicator.

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

426 **3.2.2.2 ARCH-GARCH Visualization Analysis**

427 The predicted distribution of price selection for BTC and ETH cryptocurrencies in Figure 4
428 (right) has a fluctuating price volatility surface. However, certain distribution predictions for
429 price selection for altcoin USDT do not vary with a sloping graphic surface pattern.
430 According to Table 2 (CPR), the statistical distribution of the price selection for the 3
431 cryptocurrencies for BTC and ETH is 87.6% and 87.0%, respectively, whereas USDT has an
432 unpredictable price selection of 0%.

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

438 **4. SUMMARY, CONCLUSION AND RECOMMENDATIONS**

439 **4.1 Summary of Findings Conclusion**

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

446 This study demonstrates **that the BTC price investment weight implication for the** indicator
447 can increase the valuation of the price of the crypto selection. In contrast, **effect from a**
448 **crypto ETH** can reduce the level of risk consideration by investors in the smart contract-
449 based payment system in the cost of the contract on the ETH price selection. The **indication**
450 **for USDT** crypto has a return on assets over time that is unrelated to the evaluation of the
451 price selection of crypto coins, leading to the conclusion that distinct price diversifications
452 exist.

453 **4.1 Recommendations**

454
455 **Based on this hypothesis, this research can determine that investors can perform the**
456 **evaluation process of the price level of crypto returns, and the cryptocurrencies such as**
457 **USDT can be an adequate means for investors to avoid high variability with the potentially**
458 **detrimental effect on their capital strategy, whereas ETH and BTC cryptocurrencies can**
459 **potentially produce the interest effect in the estimates of -0.38% negative and 1.48% positive**
460 **in annualized (historical) time, and some diverse crypto prices can be supportive for the**
461 **portfolio risk management at the level of returns proportional to the number of assets**
462 **invested to be chosen.**

463 **ACKNOWLEDGEMENTS**

464 Special gratitude goes to the Faculty of Economics and Business, Tanjungpura University.

465

466

467

468

469

470

471

472

473

474

REFERENCES

- Abdelrhim, M., Mohamed, M., & Farouh, M. (n.d.).** *Investment Opportunities in The Time Of (COVID-19) Spread: The Case of Cryptocurrencies and Metals Markets.*
<https://ssrn.com/abstract=3640333>
- Agung, G.N. (2009).** *TIME SERIES DATA ANALYSIS USING EIEWS.* Singapore: Wiley.
- Ahelegbey, D. F., Giudici, P., & Mojtahedi, F. (2022).** Crypto Asset Portfolio Selection. *FinTech*, 1(1), 63–71. <https://doi.org/10.3390/fintech1010005>

475 Alexander Carol. (2008). *Market Risk Analysis Volume I Quantitative Methods in Finance*.
476 Ankenbrand, T., & Bieri, D. (2018). Assessment of cryptocurrencies as an asset class by their
477 characteristics. *Investment Management and Financial Innovations*, 15(3), 169–181.
478 [https://doi.org/10.21511/imfi.15\(3\).2018.14](https://doi.org/10.21511/imfi.15(3).2018.14)

479 Boncz, I. (2015). Introduction to research methodology (Andor Sebestyén, Ed.; Imre Boncz).
480 European Union (Social Fund).

481 Borri, N., & Magistris, P. S. de. (2022). *Crypto Premium, Higher-Order Moments and Tail Risk*
482 *. <https://ssrn.com/abstract=3889169>

483 Bouri, E., Lucey, B., & Roubaud, D. (2020). Cryptocurrencies and the downside risk in equity
484 investments. *Finance Research Letters*, 33. <https://doi.org/10.1016/j.frl.2019.06.009>

485 Carpenter, A. (2016). *Portfolio Diversification with Bitcoin*.

486 Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the dynamic
487 relationships between cryptocurrencies and other financial assets. *Economics Letters*,
488 165, 28–34. <https://doi.org/10.1016/j.econlet.2018.01.004>

489 Cornil, Y., Hardisty, D. J., & Bart, Y. (2019). Easy, breezy, risky: Lay investors fail to diversify
490 because correlated assets feel more fluent and less risky. *Organizational Behavior and*
491 *Human Decision Processes*, 153, 103–117. <https://doi.org/10.1016/j.obhdp.2019.06.001>

492 Creswell John W. (2014). 115. *Qualitative, Quantitative, and Mixed Methods Approaches (*
493 *PDFDrive*).

494 Dietz, S., Bowen, A., Dixon, C., & Gradwell, P. (2016). Climate value at risk' of global financial
495 assets. *Nature Climate Change*, 6(7), 676–679. <https://doi.org/10.1038/nclimate2972>

496 Drokin, Y., & Zhitlukhin, M. (2020). Relative growth optimal strategies in an asset market
497 game. *Annals of Finance*, 16(4), 529–546. <https://doi.org/10.1007/s10436-020-00360-6>

498 Fahim, A. (2019). Introduction to Financial Mathematics. In *Introduction to Financial*
499 *Mathematics*. Florida State University Libraries. <https://doi.org/10.33009/financialmath1>

500 Guesmi, K., Saadi, S., Abid, I., & Ftiti, Z. (2019). Portfolio diversification with virtual currency:
501 Evidence from bitcoin. *International Review of Financial Analysis*, 63, 431–437.
502 <https://doi.org/10.1016/j.irfa.2018.03.004>

503 Guinda, M., & Bhattacharyya, R. (2021). *Using Principal Component Analysis on Crypto*
504 *Correlations to Build a Diversified Portfolio Using PCA on Crypto Correlations to Build a*
505 *Diversified Portfolio*. <https://ssrn.com/abstract=3918398>

506 Hu, Y. C., Lee, T. T., & Lam, C. (2019). A risk redistribution standard for practical
507 cryptocurrency payment. *Proceedings - 2019 IEEE International Conference on*
508 *Decentralized Applications and Infrastructures, DAPPCON 2019*, 89–99.
509 <https://doi.org/10.1109/DAPPCON.2019.00020>

510 Inci, A. C., & Lagasse, R. (2019). Cryptocurrencies: applications and investment opportunities.
511 *Journal of Capital Markets Studies*, 3(2), 98–112. [https://doi.org/10.1108/jcms-05-2019-](https://doi.org/10.1108/jcms-05-2019-0032)
512 0032

513 Judd, C. M., McClelland, G. H., & Ryan, C. S. (2017). *Data Analysis Third Edition: A Model*
514 *Comparison Approach to Regression, ANOVA, and Beyond*.
515 <https://doi.org/https://doi.org/10.4324/9781315744131>

516 Junghenn Hugo D. (2011). *Option Valuation A First Course in Financial Mathematics*.

517 Kabašinskas, A., & Štutienė, K. (2021). Key roles of crypto-exchanges in generating arbitrage
518 opportunities. *Entropy*, 23(4). <https://doi.org/10.3390/e23040455>

- 519 Kaya Soylu, P., Okur, M., Çatıkkaş, Ö., & Altıntig, Z. A. (2020). Long Memory in the Volatility
520 of Selected Cryptocurrencies: Bitcoin, Ethereum and Ripple. *Journal of Risk and*
521 *Financial Management*, 13(6), 107. <https://doi.org/10.3390/jrfm13060107>
- 522 Kececi, N. F. (2020). A comparative nonparametric analysis on cryptocurrency exchange rate
523 returns. *Pressacademia*, 12(1), 35–39.
524 <https://doi.org/10.17261/pressacademia.2020.1344>
- 525 Kim, S., & In, F. (2010). Portfolio allocation and the investment horizon: A multiscaling
526 approach. *Quantitative Finance*, 10(4), 443–453.
527 <https://doi.org/10.1080/14697680902960226>
- 528 Kozak, S., & Gajdek, S. (2021). Risk of Investment in Cryptocurrencies. *Economic and*
529 *Regional Studies / Studia Ekonomiczne i Regionalne*, 14(3), 294–304.
530 <https://doi.org/10.2478/ers-2021-0021>
- 531 Marczyk Geoffrey. (2005). *Essentials of Research Design and Methodology TEAM LinG-Live,*
532 *Informative, Non-cost and Genuine!*
- 533 Quoc, N., & Brisbane, K. (2020). *Conditional beta and uncertainty factor in the cryptocurrency*
534 *pricing model.*
- 535 Rahim, R. A., Ling, P. S., & Mohd Khalid, M. A. S. (2021). ASSESSING THE
536 PREDICTABILITY OF CRYPTOCURRENCY PRICES. *Malaysian Management Journal*,
537 25, 143–168. <https://doi.org/10.32890/mmj2021.25.6>
- 538 Sheng, D. L., & Shen, P. (2020). Portfolio Optimization with Asset-Liability Ratio Regulation
539 Constraints. *Complexity*, 2020. <https://doi.org/10.1155/2020/1435356>
- 540 Stavroyiannis, S. (2018). Value-at-risk and related measures for the Bitcoin. *Journal of Risk*
541 *Finance*, 19(2), 127–136. <https://doi.org/10.1108/JRF-07-2017-0115>
- 542 Sun, W., Dedahanov, A. T., Shin, H. Y., & Kim, K. S. (2020). Switching intention to crypto-
543 currency market: Factors predisposing some individuals to risky investment. *PLoS ONE*,
544 15(6). <https://doi.org/10.1371/journal.pone.0234155>
- 545 Tenkam, H. M., Mba, J. C., & Mwambi, S. M. (2022). Optimization and Diversification of
546 Cryptocurrency Portfolios: A Composite Copula-Based Approach. *Applied Sciences*
547 *(Switzerland)*, 12(13). <https://doi.org/10.3390/app12136408>
- 548 Tien, S. K., Wang, Y. T., Cai, Y. Z., & Tsai, M. H. (2020). Maximizing the Time Value of
549 Cryptocurrency in Smart Contracts with Decentralized Money Markets. *Proceedings -*
550 *2020 IEEE International Conference on Blockchain, Blockchain 2020*, 503–508.
551 <https://doi.org/10.1109/Blockchain50366.2020.00073>
- 552
- 553