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Building A Portfolio Under Economic Uncertainty

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Abstract: This study explores how the returns and volatility of stocks, gold, bonds, and Bitcoin (BTC) respond to movements in inflation, interest rates (SBI), and exchange rates. To capture inter-asset relationships, the Granger Causality Test was applied, while GARCH modeling was used to evaluate hedging behavior under normal market conditions. An investment portfolio was then formulated using the Arbitrage Pricing Model (APT), comprising 28% stocks, 16.28% gold, 26.76% bonds, and the remaining proportion in BTC, delivering an estimated return of 0.0178 with optimized risk. The dataset covers monthly trading activity from 2018 to 2023 as in-sample observations, with an additional seven months used for out-of-sample validation. The results reveal that BTC returns correlate with those of gold and bonds, while stock volatility shows a link to BTC volatility. Gold consistently serves as a hedge against macroeconomic variables, whereas bonds primarily act as a portfolio diversifier. These findings underscore the relative stability of gold and bonds as instruments for risk mitigation against BTC's inherent volatility. Viewed through a sustainability lens, incorporating gold and bonds into the portfolio enhances resilience, lowers systemic risk, and supports long-term financial sustainability, aligning investment strategies with responsible and stable wealth management.

Keywords: arbitrage pricing theory, bitcoin, gold, safe-haven assets, sustainable investment.

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INTRODUCTION

Over the past five years, numerous events have intensified the dynamics of economic changes, leading to increased uncertainty in the markets (Liu, 2021; Karanasos et al., 2022; Hu et al., 2023). The emergence of information asymmetry, particularly in risky assets, has generated both negative and positive sentiments, resulting in asset price anomalies (Goel et al., 2021; Dhaoui & Bourouis, 2022; Polat, 2023). The Jakarta Stock Exchange Composite Index (JKSE) recorded its lowest value in five years at 4,538.93 in March 2020, a decline of 16.76%, coinciding with the onset of the COVID-19 pandemic (Zainuri et al., 2021). Rising food prices, industrial working hour restrictions, and increased inflation contributed to negative market sentiment, deterring investors from entering the stock market.

Arshanapalli et al. (2006) stated that bond and stock prices are interconnected, with both typically responding to announcements of labor market, industrial, and Producer Price Index data as investors anticipate abnormal returns. When Bank Indonesia raised interest rates consecutively from August to December 2022 as part of economic recovery measures, bond and stock prices experienced a decline. Investors seeking positive returns shifted to alternative assets offering higher profitability.

Gold price dynamics have shown a systematic positive response to macroeconomic shocks and uncertainties in government policies (Selmi et al., 2018). Previous studies concluded that gold serves as a safe haven against monetary policies and the U.S. dollar (Capie et al., 2005), maintaining purchasing power during periods of uncertainty, offering long-term benefits, and providing high liquidity (Terraza et al., 2024). During stock market contractions, gold has experienced positive rallies, reaching its second-highest value in two centuries of global gold price history at $2,074 per ounce on August 6, 2020. Investors shifted away from stocks to safer assets, such as gold or bonds, in a phenomenon known as flight-to-safety (Chen et al., 2023).

In addition to gold, investors have also turned to Bitcoin (BTC), often referred to as digital gold (Baur & Hoang, 2021; Rotta & Paraná, 2022; Malladi, 2023). Rising global inflation and the U.S. Federal Reserve's continued money printing have bolstered positive sentiment toward BTC. Its price surged significantly in May 2020 to IDR 152,659,981 after plummeting to IDR 61,073,112 in March 2020. Selmi et al. (2018) explained that BTC attracts investors due to global uncertainty and a loss of trust in the stability of the banking system. BTC is considered highly resilient, with its price unaffected by government or central bank policies (Köse et al., 2024; Paule-Vianez et al., 2020). Its value is solely determined by market demand and supply, making it a highly speculative and risky asset.

Investors must carefully construct their asset portfolios to navigate various economic uncertainties that can heighten asset price volatility. Portfolio construction involves several factors, including 1) Asset valuation and allocation, which consider inter-asset relationships and their complexity in response to macroeconomic changes; 2) Investment objectives; and 3) Asset diversification, achieved by combining varying levels of risk within a portfolio. The relationships among assets serve as indicators of an asset's role in preserving or enhancing the value of a diversified portfolio (Adrian et al., 2015). An asset is classified as a hedge asset if it has a negative or no correlation with other assets under normal conditions, while an asset is deemed a safe haven if it exhibits a negative or no correlation with other assets during extreme conditions (Elie et al., 2017; Khamis & Aassouli, 2023). A defining characteristic of safe-haven assets is their ability to preserve or reduce losses in an investor's portfolio during extreme scenarios.

This study aims to construct the best investment portfolio for moderate investors amidst economic uncertainties driven by inflation, exchange rate fluctuations, and bank interest rate changes. The assets examined include stocks, gold, BTC, and Indonesia's 10-year government bonds. The first step involves employing the Granger Causality test to investigate inter-asset relationships. Following Köse et al. (2024), this test examines the short-term effects between paired assets. If the current price of one asset is influenced by the past price of another, it can be concluded that the two asset prices are interrelated. Subsequently, assets are evaluated using the Arbitrage Pricing Theory (APT) method, which assumes that asset prices are influenced by systematic risks that cannot be diversified and unsystematic risks that can be eliminated in a well-diversified portfolio (Cont, 2001; Roll & Ross, 1995). Time-series regression with the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is employed to analyze the partial risk sensitivity of assets to the three economic changes, while cross-sectional regression with the Autoregressive Moving Average (ARMA) model is used to perform similar analyses simultaneously (Amtiran et al., 2017; Campbell et al., 1997).

The APT method is applied in asset valuation to identify arbitrage opportunities, achieving additional returns at the same level of risk. The results of both regression analyses are used to determine the weight of each asset in the arbitrage portfolio. The next step involves forming the optimal investment portfolio by combining the asset weights in the arbitrage portfolio with those in the initial portfolio, which is equally weighted. The resulting restructured weights will provide the best return for investors at the same level of risk as before.

We recognize that numerous prior studies have constructed portfolios using similar methods; however, to our knowledge, no such research has been conducted in Indonesia. As a developing country in Southeast Asia, Indonesia has a large potential investor base requiring optimal investment portfolio options. Additionally, Indonesia's stock market demonstrates significant growth yet remains fragile to sentiment, making it an intriguing area of study. A novel aspect of this study is the inclusion of BTC as part of the portfolio, an asset typically avoided by conservative and risk-averse investors but increasingly favored by moderate and aggressive investors. The greatest challenge lies in the potential for high standard deviation values within the portfolio. To address this, we test the performance of the constructed portfolio model using out-of-sample data. The model's accuracy is measured using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), with lower values indicating better performance.

This research provides practical advantages by helping investors select instruments that stabilize portfolio value or mitigate losses. By understanding asset risk levels, investors can assess return sensitivities and identify close substitutes among assets with similar risk profiles. The ability to choose instruments and determine their composition is a critical tool for investors aiming to optimize returns within their risk tolerance.

METHODS

This study uses secondary data in the form of monthly transaction data of stock trading, gold, 10-year Indonesian government bonds (sourced from http://www.investing.com), and BTC (sourced from https://www.coindesk.com/price/BTC/) as investment instruments available to investors. Three of these instruments are often considered safe-haven or hedge investments, while the other instrument, stocks, is a high-risk asset with balanced returns. Inflation data, exchange rates, and Bank Indonesia interest rates (SBI) were downloaded from the websites of the Indonesian Central Bureau of Statistics (Badan Pusat Statistik) and Bank Indonesia. The risk-free rate used in this study is the coupon rate of the SBR010 Government Bond. The time frame used in this study is from January 1, 2018, to July 31, 2024. The measurement of variables used in this study can be seen in Table 1 and is based on Arshad et al. (2023), Paule-Vianez et al. (2020), and Amtiran et al. (2017).

We acknowledge that during this period, the COVID-19 pandemic occurred from 2020 to 2022, leading to high volatility and uncertainty in the prices of instruments in the market. Therefore, we divided the data into two parts:

The training data, from January 1, 2018, to December 31, 2023, referred to as in-sample data. This data is used to build a more firm and solid portfolio under conditions of another financial crisis.

The testing data, from January 1, 2024, to July 31, 2024, referred to as out-sample data. This data is used to test the model that has been developed.

The data analysis process began with testing all variables for stationarity using the Augmented Dickey-Fuller (ADF) test and the correlogram analysis. The ADF test was employed to identify significant lags, patterns of autocorrelation, seasonality, and cyclicality. The null hypothesis (H_0) states that the data is non-stationary or contains a unit root, while the alternative hypothesis (H_1) asserts that the data is stationary (no unit root).

If the p-value from the test is less than the significance level (< 0.05), H_0 is rejected, indicating that the data is stationary. Conversely, if the p-value > 0.05, H_0 is accepted, and the data must be differenced to achieve stationarity and eliminate the unit root.

Table 1 Measurement of Variables Used in the Analysis

Variable	Indicator	Measurement	Scale
Return of Investment (R_i)	Rm (For Stock) Rg (For Gold) Rb (For Bond) Rbtc (For BTC)	$R_i = \frac{P_{i.t} - P_{i.t-1}}{P_{i.t-1}}$	Ratio
Expected Return (ER_i)	ERm (For Stock) ERg (For Gold) ERb (For Bond) ERbtc (For BTC)	$ER_i = R_i - R_t$	Ratio
Inflation (Inf)	Consumer Price Index	$Inf = \frac{IHK_t - IHK_{t-1}}{IHK_{t-1}}$	Ratio
Exchange Rate (Exc)	Rp/USD	$Exc = \frac{Rp_t - Rp_{t-1}}{Rp_{t-1}}$	Ratio
Interest Rate (SBI)	SBI 1/Month	$SBI = \frac{SBI_t}{12}$	Ratio

Note: Ri represents the return on asset i hence Pi.t is closing price of asset (i) on month t and Pi.t–1 is closing price of asset (1) on month t– 1. Rf is risk free rate and we use coupons of Indonesia Government Bond number SBR010. ERi is the difference beetwen actual return minus risk free rate (Rf). Consumer Price Index on month t is symbolized by IHKt hence IHKt–1 is Consumer Price Index on month t-1. Indonesian Rupiah exchange rate against US dollar on month t is symbolized by Rpt and Rpt–1 is Indonesian Rupiah exchange rate against US dollar on month t -1. SBIt is interest rate of Indonesia Central Bank on month t.

The next step involves testing the causal relationship between assets by following the study of Köse et al. (2024) using in-sample data. The Granger Causality test is employed to evaluate whether an uncertainty variable can be used to predict the dependent variable in the time series data, with a monthly period over the research timeframe.

$$Y_t = \alpha + \sum_{i=1}^{k} \beta_i Y_{t-1} + \sum_{j=1}^{k} \gamma_i X_{t-j} + \epsilon_t \text{ .... (1)}$$

If Y_t is the dependent variable, then α is the model constant. The variable X_{t-j} represents the predictive variable tested against Y_t. The influence of the lagged *Y* at *t–i* is indicated by the coefficient β_i and γ_i is the influence of the lagged X at *t–j*. If $\gamma_i \neq 0$, then X has predictive power over Y, and vice versa.

The Exc, Inf, and SBI were forecasted using the simple exponential smoothing method, after the relationships were mapped. This method predicts future values based on past patterns by smoothing out irregular data components through weighted averages of past observations. Miasary & Rachmawati (2023) uses the smoothed results as a subtractor from the actual value of the risk factor in the APT method, which is considered as the surprise factor. The formula is:

$$S_{t+1} = \alpha Y_t + (1-\alpha) S_t \text{ .... (2)}$$

Where S_{t+1} represents the prediction for the upcoming period while S_t is the current forecast derived from the previous period and Y_t is the actual value in the current period. The advantage of this method is that it uses data without trends or seasonality and assigns decreasing weights to longer-term observations, making it more responsive to the uncertainties of systematic risk. Next, all the asset prices are evaluated using the APT.

In the APT method, the expected return of asset *i* is determined based on its exposure to all considered risk factors. Its value is derived from the difference between the actual return and the risk-free rate. The sensitivity of an asset's return to changes in systematic risks is analyzed using time series and cross-sectional data, as illustrated by the formula:

$$R_i = ER_i + \beta_{i.1}f_1 + \beta_{i.2}f_2 + \beta_{i.3}f_3 + \ldots + \beta_{i.k}f_k + \varepsilon_i \quad \text{.......................... (3)}$$

$$ER_i = R_f + \beta_{i.1}F_1 + \beta_{i.2}F_2 = \beta_{i.3}F_3 + \ldots + \beta_{i.k}F_k \quad \text{.......................... (4)}$$

$\beta_{.i.(1,2\ldots k)}$ represents the sensitivity of instrument *i* to a set of *k* specific factors, and $f_{1,2\ldots k}$ refers to the surprise factors. These values are calculated as the actual values minus the predicted values. Meanwhile, excess return only reflects the additional return generated by $\beta_{.i.(1,2\ldots k)}$, focusing solely on the risk premium as compensation for the systematic risk taken. However, this factorial model does not yet describe the equilibrium condition of the model, necessitating a cross-sectional regression between the expected return and the systematic risk of each factor for the investment instruments. $f_{1,2\ldots k}$ are loading factors that calculated from the expected return of the instruments and factor *k* minus *Rf* as seen in formula 4.

In assessing asset prices, univariate GARCH regression was applied to all in-sample data instruments with the aim of estimating volatility over time to serve as a risk mitigation step and for price derivatives (Arshad et al., 2023; Baur & Lucey, 2010; Köse et al., 2024). The basic formula for GARCH (p, q) is specifically presented as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-1}^2 \text{ where } \omega > 0, |\alpha_i + \beta_j| < 1 \quad \text{.......................... (5)}$$

If σ_t^2 is the predicted variance value for period t, then ω is a constant in the model that captures the long-term average volatility. ε_t represents the error or residual at time t, while α_i is the coefficient that squares the residual from the previous period ε_{t-1}^2 and β_i is the coefficient for the conditional variance that multiplies the volatility from the previous period σ_{t-1}^2. GARCH requires that $|\alpha_i + \beta_j| < 1$, meaning that all variables must be stationary. However, we employ GARCH (0,1), where the equation only has one component, which is volatility, formulated as follows:

$$\sigma_t^2 = \omega + \beta_1 \sigma_{t-1}^2 \quad \text{.......................... (6)}$$

The equation above shows that the predicted variance is only based on past variance volatility, indicating the persistence of volatility. However, the influence of residuals is indirectly used as an indicator of surprise or shock in the predicted value. These estimated results are used to detect the hedging role of each instrument under normal conditions. The hypothesis posits that an asset serves as a hedge if the p-value in the GARCH model is below the significant level at (< 0.05) and the variable's coefficient is negative. Conversely, an asset functions as a diversifier if the p-value is below the significance level (< 0.05), but the coefficient is positive. However, the accuracy of the model requires consideration of the complex behavior of asset returns. This is essential to develop a more reliable model for risk assessment and performance prediction. Key tests include autocorrelation analysis and the examination of the return distribution. An asset pricing model is said to exhibit fat tails if its kurtosis exceeds 3, indicating a leptokurtic distribution with sharper peaks and more frequent extreme changes than a normal distribution. However, the model can still be considered stable if the kurtosis remains below 10. Additionally, skewness serves as another critical indicator, measuring asymmetrical risk that is not captured by volatility. If the skewness value falls within the range of −0.5 to 0.5, the asset pricing model demonstrates a tendency toward portfolio return stability, with minimal asymmetric risk.

The GARCH model that has been developed from the in-sample data will be applied to forecast volatility in returns and prices for the out-sample data. The GARCH method is highly effective for forecasting and capturing high and fluctuating volatility. The residual variance from the previous period is a good predictor for forecasting the volatility of returns and instrument prices in future periods. The accuracy of our forecast is measured using the Root Mean Square Error (RMSE) and Mean Absolute Error (MAPE) values. The smaller the resulting values, the better the model's performance. The RMSE and MAE formulas we use are as shown below, where N is the number of samples, and $\widehat{R}_t$ is the forecasted return or price.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(R_t - \widehat{R}_t)^2} \qquad MAE = \frac{\sum(R_t - \widehat{R}_t)}{N}$$

The next step involves constructing an arbitrage portfolio based on several key assumption 1) The investors will not inject additional capital into the portfolio, denoted by $\sum_{i=1}^{n} w_i = 0$, where w_i is the weight of each instrument into portfolio, 2) the arbitrage portfolio should have no sensitivity to systematic risk factors, expressed by $\sum_{i=1}^{n} w_i \beta_i = 0$ where β_i is weighted average sensitivity of assets within portfolio and 3) The portfolio is structured to yield positive expected returns, mathematically validated by $\sum_{i=1}^{n} w_i \overline{R_t} > 0$, where $\overline{R_t}$ is expected return.

RESULTS AND DISCUSSION

A descriptive analysis of all variables was conducted, as detailed in Table 2, with several key points highlighted.

Table 2 Descriptive Analysis

	Rm	Rg	Rb	Rbtc	Exc	Inf	SBI
Mean	0.00214	0.00678	0.00124	0.04109	0.00354	−0.00304	0.00389
Median	0.00431	−0.00368	0.00571	0.00023	0.00219	−0.00671	0.00396
Max	0.09442	0.09718	0.14811	0.60846	0.03247	0.28155	0.00500
Min	−0.16758	−0.06996	−0.08546	−0.37325	−0.02925	−0.30275	0.00014
Std.Dev	0.03925	0.03839	0.04251	0.21076	0.01372	0.11238	0.00094
Skew	−1.07506	0.34145	0.39031	0.35412	−0.27401	0.17228	−0.81621
Kurtosis	6.76807	2.41795	4.12593	2.74918	2.76637	3.23433	4.55215
JB	55.67995	2.38181	5.55307	1.66998	1.04992	0.51368	15.01046

Source: Processed by Author

Notably, BTC is a highly speculative asset with significant volatility, exhibiting a substantial disparity between its maximum at 0.60846 and minimum values at −0.37325. This condition supports the research by Köse et al. (2024), Selmi et al. (2018), and Terraza et al. (2024), which stated the similar result. Gold provides an average return of 0.00678, the second highest after bitcoin meanwhile bonds provided an average return of 0.00124 and the maximum return at 0.14811 and minimum at –0.08546. Arshanapalli et al. (2006) noted an inverse relationship between bond volatility and returns. Stocks offer an average return of 0.007434 which is the second highest among all instruments. Adrian et al. (2015) noted that increased stock volatility leads investors to expect higher returns, whereas bond returns decrease as investors are compensated with higher coupon rates. During periods of high stock volatility, investors tend to favor bonds over stocks called flight-to-safety.

The data distribution indicates that market returns are not normally distributed, characterized by a left-skewed tail, whereas volatility is observed to be right-skewed with leptokurtic kurtosis. In contrast, the return distributions for gold and bitcoin are found to be approximately normal, with right-skewed skewness and leptokurtic volatility distributions for both. Bond returns are identified as non-normally distributed, exhibiting leptokurtic skewness and kurtosis. These conditions suggest the presence of outliers in both return and volatility data. To address this, the Mahalanobis method will be applied to detect these outliers, and the outlier values will be replaced with the mean values.

The exchange rate experienced a significant negative contraction in May 2020, with a minimum return of –0.02925, while average returns remained positive at 0.00354, attributed to Indonesia's managed floating exchange rate system. Price stability has been maintained through Central Bank interventions in the spot market, DNDF market, and government securities buybacks. Following Fisher's theory, monetary policy adjustments were made post-COVID-19 to address inflation, supply chain issues, and rising energy prices, with the SBI rate increased from 3.50% in June 2022 to 4.75% in September 2022 and reaching 6.25% by April 2024. The average SBI return is recorded at 0.00389, while inflation averages –0.00304, indicating effective monetary policies in reducing essential goods prices. Distribution analysis shows that exchange rate and inflation data are normally distributed, while SBI data is leptokurtic with a value of 15.01046.

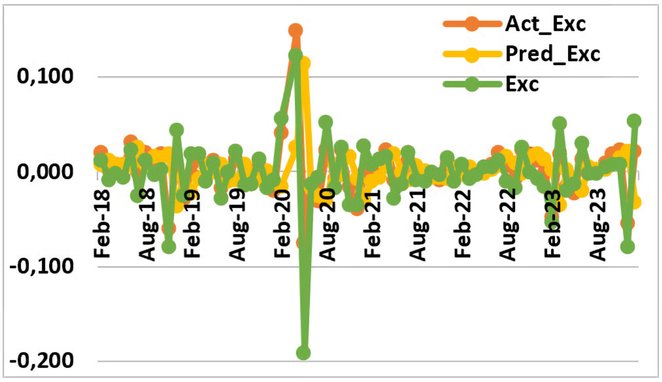
Next, the surprise values for the factors Exc, Inf, and SBI were determined using the exponential smoothing method in EViews 13. This method was selected for its effectiveness in short-term forecasting, which aligns with the analysis. The results are presented in Figure 1.

After structuring the surprise factors and variables, a stationarity test was performed using the ADF Test to ensure constant variance and mean for model stability. As shown in Table 3, all variables except SBI were stationary at the level, with a probability value of 0.0000. First differences were applied to the SBI variable, resulting in a probability value below the significance threshold.

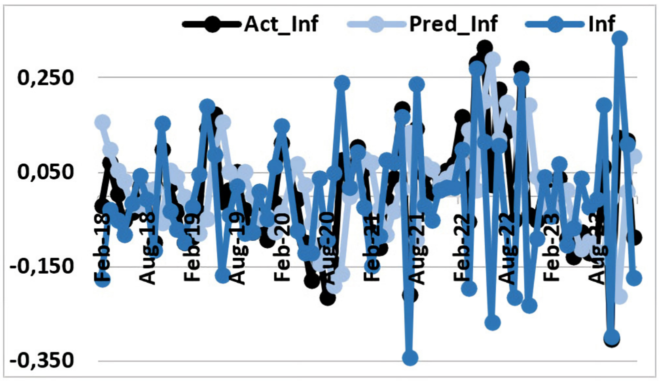
Table 3 Unit Test Roots Using ADF-Test

Var	Level		1st Differences		Var	Level		1st Differences	
	t-stat	Prob	t-stat	Prob		t-stat	Prob	t-stat	Prob
Rm	–7.6996	0.0000			Vb	–3.8007	0.0045		
Rg	–9.7548	0.0000			Vbtc	–6.3534	0.0000		
Rb	–7.8943	0.0000			Exc	–9.4378	0.0000		
Rbtc	–6.8974	0.0000			Inf	–7.0533	0.0000		
Vm	–5.4990	0.0000			DSBI	–1.3716	0.5912	–4.0015	0.0025
Vg	–6.0199	0.0000							

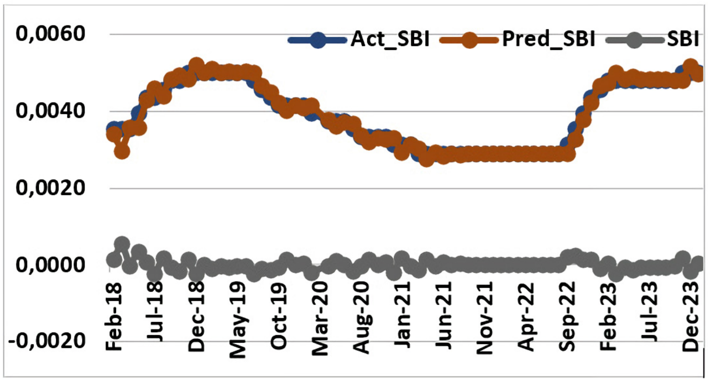
Source: Processed by Author. ADF Test has using maximum Lag = 11



Exchange Surprise Factor



Inflation Surprise Factor



SBI Surprise Factor

Note: The average returns for Act_Exc, Act_Inf, and Act_SBI are 0.0023, 0.0036, and 0.0039, respectively. The values for Pred_Exc, Pred_Inf, and Pred_SBI were obtained using the exponential smoothing method. The surprise factors for Exc, Inf, and SBI have averages of –0.0003, –0.0081, and 0.0001, respectively.

Figure 1 Exc, Inf and SBI Surprise Factors

A Granger Causality test was conducted on the returns of each pair of instruments using a lag length of 3. As shown in Table 4, only two short-term relationships were identified: gold and bond returns influencing BTC returns, but not vice versa. These findings align with studies by Arshad et al. (2023), Baur & Lucey (2010), and Terraza et al. (2024), which highlight the connection between gold and BTC. However, the results differ from Chen et al. (2023), as aggressive investors in Indonesia appear to favor BTC over gold and bonds due to the latter's lower returns. The absence of a relationship between stock market returns and the returns of gold, government bonds, and BTC was observed, indicating that each instrument moves independently without mutual influence during normal market conditions (Iqbal, 2017). It was concluded that a decline in stock prices prompts a shift by investors, particularly aggressive ones, toward BTC, which is characterized by highly volatile price movements.

Table 4 Granger Causality Test

Null Hypothesis:	F-Stat	Prob.
RIG does not Granger Cause RIM	0.3011	0.8244
RIM does not Granger Cause RIG	0.6822	0.5663
Null Hypothesis:	F-Stat	Prob.
RIB does not Granger Cause RIM	0.3643	0.7790
RIM does not Granger Cause RIB	0.6212	0.6040
Null Hypothesis:	F-Stat	Prob.
RIBTC does not Granger Cause RIM	0.1032	0.9579
RIM does not Granger Cause RIBTC	0.6697	0.5739
Null Hypothesis:	F-Stat	Prob.
RIB does not Granger Cause RIG	0.5266	0.6657
RIG does not Granger Cause RIB	0.5285	0.6644
Null Hypothesis:	F-Stat	Prob.
RIBTC does not Granger Cause RIG	0.1670	0.9183
RIG does not Granger Cause RIBTC	2.4983	0.0680*
Null Hypothesis:	F-Stat	Prob.
RIBTC does not Granger Cause RIB	0.4810	0.6967
RIB does not Granger Cause RIBTC	2.4796	0.0695*

Note: We have tested dependent variable across another dependent variable using maximum lag 12. A variable denotes by * indicates that it is significant at a probability level greater than 0.05.

Source: Processed by Author.

The subsequent phase involved verifying the hedging capabilities of the four instruments against economic uncertainty using the GARCH (0,1) model, as shown in Table 5. The value of βExc at –1.1436 and βInf at –0.0585 indicates a significant negative relationship between Rm and both the exchange rate and inflation, but no significant relationship with the SBI. Stock returns were concluded to function as a strong hedge against changes in the exchange rate and inflation, consistent with findings by Iqbal (2017), Amtiran et al. (2017), Chen et al. (2023), and Maghrebi et al. (2006). However, these results contradicted ChinZara (2011), who identified a diversifier function through a significant positive relationship. The value of ω at 5.35 x 10^–5 with a probability < 0.05 indicates the presence of persistent conditional volatility, meaning that, in the absence of sudden shocks, stock volatility remains at ω. In the mean-variance equation, the value of β at 0.9406 with a probability below 0.05 indicates that shocks from the previous period will affect current return volatility. These findings show that in developing countries like Indonesia, the stock market is sensitive to changes in Exc, Inf, and SBI.

The volatility of gold returns also serves as a strong hedge against Exc, as indicated by a significantly negative value. Meanwhile its only acts as weak hedge against Inf and SBI. It was also found that the prediction of gold returns is influenced by the persistent conditional variance, shown by the significant value of ω at 0.0002, and by the volatility of the previous period, with a value of 0.0909. A value approaching 1 indicates a persistent effect, leading us to conclude that gold can help preserve an investor's portfolio value during currency depreciation. The results are consistent with Paule-Vianez et al. (2020), Baur & Lucey (2010), and Baur & McDermott (2009).

The research findings indicate that Rb serve as a diversifier against Exc and Inf, as evidenced by the significant βExc values of 1.1910 and βInf 0.0996. Additionally, Rb acts as a weak hedge against SBI. When the rupiah appreciates and inflation rises, bond prices decrease, driven by positive market sentiment. Investors benefit from increased returns as compensation for the price decline. This condition can be leveraged to gradually accumulate bonds as an alternative investment asset under normal market conditions.

Lastly, Rbtc was identified as a strong hedge against Exc and a weak hedge against Inf or SBI. This condition is demonstrated by the positive actual returns observed during the study period. These findings are aligned with previous research stating that BTC is resistant to inflation (Arshad et al., 2023) and monetary policy (Paule-Vianez et al., 2020). BTC returns are influenced solely by market supply, demand, and availability. However, BTC prices were found to be correlated with both positive and negative news, particularly involving fraud and hacking incidents, which can generate negative sentiment (Köse et al., 2024). The insignificant ω values of Rb and Rbtc volatility indicate that both variances are persistently influenced by volatility from the previous period, as reflected by the β values in their respective GARCH equations.

Table 5 GARCH Estimation Result

	C	β_{Exc}	β_{Inf}	β_{DSBI}	Variance Equation		AIC	ARCH-LM
					ω	β		
Rm	0.0110	−1.1436	−0.0585	26.4462	5.35×10^{-5}	0.9406	−4.1887	0.1046
	(0.0149)**	(0.0000)*	(0.0124)**	(0.2640)	(0.0387)*	(0.0000)*		
Rg	0.0106	−1.3825	0.0098	22.8724	0.0002	0.9090	−3.7734	0.3836
	(0.0002)*	(0.0000)*	(0.7905)	(0.3842)	(0.0642)*	(0.0000)*		
Rb	−0.0073	1.1910	0.0996	−8.0945	0.0002	0.8131	−3.8121	0.6161
	(0.0000)*	(0.0001)*	(0.0019)*	(0.6781)	(0.6705)	(0.0757)***		
Rbtc	0.0516	−2.7089	−0.0870	−272.4830	0.0045	0.8681	−0.3092	0.7537
	(0.0990)***	(0.0878)***	(0.6692)	(0.2208)	(0.1251)	(0.0000)*		

Note: In the return regression analysis, variable C represents the instrument expected return while in the volatility regression, it signifies expected volatility. The coefficients β*Exc*, β*Inf* , and β*DSBI* represent the effects of exchange rate, inflation, and interest rate on the instrument, respectively. The numbers below these coefficients show the p-values from the regression outcomes. A * denotes significance at the 1% level, ** denotes significance at the 5% level, and *** denotes significance at the 10% level.

Source: Processed by Author.

The results in Table 5 show that GARCH (0,1) is significant in all tests, with probability values below the significance level and insignificant GARCH coefficients. The variance at time t is influenced by the variance of the previous period (t– 1). This suggests that return and price volatility in the current period affect future volatility. The return variance in GARCH shows persistent volatility over time. All models were tested for heteroscedasticity using the ARCH-LM test and confirmed not to have it, as Prob. F > 0.05. The low AIC values indicate that GARCH (0,1) is suitable for predicting the relationship between return volatility and instrument movements.

The GARCH (0,1) model was applied to out-of-sample data to test the developed model. The RMSE and MAE values for in-sample and out-sample data were compared, as shown in Table 6. The results show that all out-sample RMSE values are smaller, except for gold. For MAE, all out-sample data had smaller values, except for gold and bonds. These results suggest that the developed model is robust and effective for assessing the mean return and variance of the instruments.

Table 6 Forward Testing of GARCH Model

Indicators	Stock		Gold		Bond		Btc	
	In-Sample	Out-Sample	In-Sample	Out-Sample	In-Sample	Out-Sample	In-Sample	Out-Sample
RMSE	0.0268	0.0022*	0.0320	0.0371	0.0384	0.0306*	0.1880	0.1841*
MAE	0.0203	0.0186*	0.0250	0.0329	0.0326	0.0233	0.155	0.1310*

Source: Processed by Authors

A cross-sectional test was conducted to validate the factor loadings using panel data regression on ARMA (3,0), with the results shown in Table 7. Expected return was used as the dependent variable, and the loading factors were the independent variables, as outlined in Equation (4) of the methodology.

Table 7 Cross Sectional Result

Variable	Coefficient	Std. Error	t-Statistic	Prob (>|t|)
C	0.00057	0.00716	0.07902	0.93710
DRf	13.95689	31.68150	0.44054	0.66004
Exc	−0.24017	0.10505	−2.28620	0.02333**
Inf	−0.19006	0.02962	−6.41658	0.00000*
DSBI	20.94218	23.31436	0.89825	0.37017

Note: The analysis was conducted using panel data OLS with the Fixed Effect Model approach. To address issues of heteroskedasticity and autocorrelation, we applied specific weights to the observations (GLS Period Weight). The model successfully passed the classical assumption tests required for the above methods. The prob (>|t|) indicates the probability values, where values marked with * denote variables significant at the 1% level, and those marked with ** indicate significance at the 5% level.

Source: Processed by Author.

Table 7 shows that the expected return desired by investors is influenced by exchange rate fluctuations and inflation, but not by interest rates. The model is as follows:

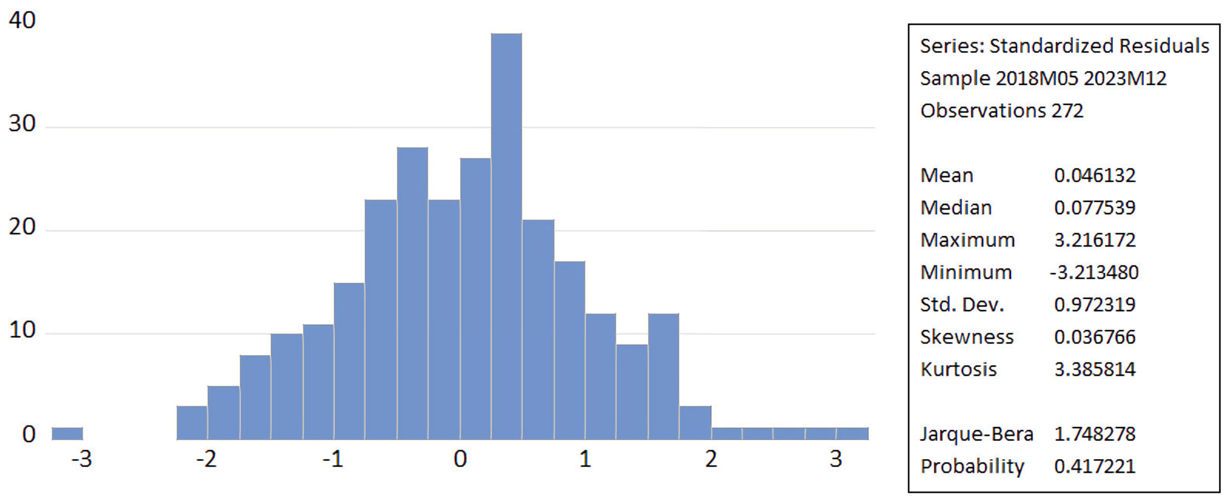
$$ERp = R_f + \beta_{Exc} F_{Exc} + \beta_{Inf} F_{Inf}$$

$$ERp = 0.00596 - 0.2402 F_{Exc} - 0.1901 F_{Inf}$$

Based on the model, if all factor loadings are 0, a return of 0.00596, equivalent to the risk-free rate, is expected. A 1%-rupiah depreciation increases the portfolio return by 0.2402, while a 1% decrease in inflation risk raises the return by 0.1901. Interest rate changes can be anticipated to minimize portfolio impact, and the government's ability to stabilize the exchange rate and control inflation is identified as crucial for investors.

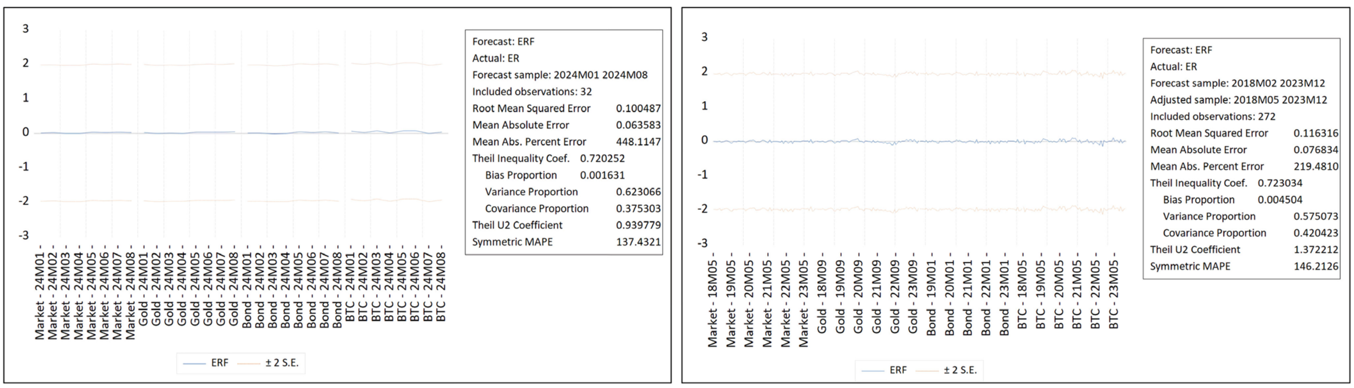
The complexity of asset return behavior was analyzed by examining tail shape, kurtosis, and skewness, as shown in Figure 2. A skewness value of 0.036766 indicates stable returns with no significant asymmetry in systematic risk. Idiosyncratic risk, however, should be managed through portfolio diversification. The kurtosis value of 3.385814 indicates a leptokurtic peak, suggesting fat tails within a normal range. The Jarque-Bera statistic of 1.748278 and a p-value of 0.417221 confirm that the asset pricing model follows a normal distribution. The model demonstrates stability, despite extreme changes within acceptable limits. The R-squared value of 0.2385 shows that 23.85% of the dependent variable is explained by the independent variables, with the remainder explained by other factors. The standard deviation of 0.9751 indicates a reasonably accurate model.

Similar to the GARCH model, forward testing was conducted on the portfolio model to evaluate its robustness and stability. The same methodology was applied to the testing data, and the results are presented in Figure 3. No significant differences were found between the RMSE and MAE values of the training and testing datasets, indicating that the asset pricing model is robust and stable.



Source: Processed by Authors

Figure 2 Output of Normality Test



In-sample Data

Out-sample Data

Source: Processed by Author

Figure 3 Forward Testing of Output of Asset Pricing Model

The APT method evaluates asset pricing based on the law of one price, which states that assets with the same systematic risk should have the same price (Zhang, 2023). This principle allows investors to exploit arbitrage opportunities by taking long positions in undervalued assets and short positions in overvalued ones, earning risk-free profits from price inefficiencies. Over time, the market corrects these inefficiencies, restoring asset prices to their fair values. An arbitrage portfolio is constructed based on variables, as shown in Table 8.

Construction of arbitrage portfolio based on the expected returns (Eri), the significant coefficient of surprised factors ($F_{1,\ 2\dots\ k}$), analyzed using GARCH (0,1) and the significant coefficient of loading factors, ($F_{1,\ 2\dots\ k}$) analyzed using ARMA (3,0) in normal condition, as shown in Table 9.

Table 8 Expected Return and Loading Factors

	ER	β_{Exc}	β_{Inf}	β_{DSBI}	F_{Exc}	F_{Inf}	β_{SBI}
Rm	0.011	−1.1436	−0.0585		−0.2402	−0.1901	
Rg	0.0106	−1.3825			−0.2402	−0.1901	
Rb	−0.0073	1.191	0.0996		−0.2402	−0.1901	
Rbtc	0.0516	−2.7089			−0.2402	−0.1901	

Source: Processed by Author.

Based on Table 8, arbitrage portfolio built by formulas below:

$$W_{Rm} + W_{Rg} + W_{Rb} + W_{Rbtc} = 0$$

$$-1.1436\ W_{rm} - 1.3825\ W_{rg} + 1.191\ W_{rb} - 2.7089\ W_{Rbtc} = 0$$

$$-0.0585\ W_{rm} + 0.0996\ W_{rb} = 0$$

An arbitrage portfolio is used to maximize returns without increasing risk. In the old portfolio, funds were equally allocated across four instruments. By adding an arbitrage portfolio, a new investment portfolio is created, as shown in Table 9, optimizing returns while maintaining the same risk level. Asset weights in the initial portfolio are adjusted using weights derived from the arbitrage portfolio based on cross-sectional regression. This approach improves diversification and risk optimization, enabling abnormal returns without additional capital investment.

Table 9 Investment Portfolio

Instruments	Old Portfolio				Arbitrage Portfolio	Investment Portfolio			
	W_i	ER_p	β_{Exc}	β_{Inf}		W_i	ER_p	β_{Exc}	β_{Inf}
Stock	0.25	0.00275	−0.06004	−0.04752	0.0300	0.28000	0.00308	−0.06725	−0.05322
Gold	0.25	0.00265	−0.06004	−0.04752	−0.0873	0.16280	0.00173	−0.03910	−0.03094
Bond	0.25	−0.00183	−0.06004	−0.04752	0.0176	0.26760	-0.00195	−0.06427	−0.05086
BTC	0.25	0.01290	−0.06004	−0.04752	0.0396	0.28960	0.01494	−0.06955	−0.05504
TOTAL	1.00	0.01648	−0.24017	−0.19006		1.00	0.01780	−0.24017	−0.19006

Source: Processed by Author.

In the investment portfolio (Table 9), gold allocation is reduced from 25% to 16.28%, while stock allocation increases to 28%. BTC allocation rises to 28.96%, and bonds increase to 26.76%. The expected return improves from 0.01648 to 0.01780, with systematic risk exposure remaining the same. Gold is recommended for shorting due to its disproportionate risk-to-return ratio, consistent with Baur & Lucey (2010) and Bakry et al., 2021. Long positions in stocks, bonds, and Bitcoin are advised for higher future returns. The findings indicate no flight-to-safety behavior among Indonesian investors, aligning with the Granger Causality Test results but contrasting with Chen et al. (2023). This supports the hypothesis that gold's low returns are less attractive to Indonesian investors.

CONCLUSION

The increasing volatility of financial markets over the past decade, driven by global economic uncertainties, highlights the necessity for investment strategies that emphasize inter-asset relationships and systematic risk control. The findings of this study indicate that gold and long-term government bonds remain reliable safe-haven assets, whereas Bitcoin (BTC), despite its significant price swings, exhibits short-term correlations with these traditional instruments and provides a partial hedge against currency depreciation. From a practical perspective, portfolio diversification emerges as a crucial approach, with an optimal composition of approximately 16.28% gold, 26.76% bonds, 28% stocks, and 28.96% BTC. Moderate and aggressive investors may complement this allocation with dynamic risk-management tools such as stop-loss and profit-target mechanisms. In contrast, conservative investors are advised to minimize exposure to high-risk assets and prioritize shorter-duration bonds. For Indonesia's market context, equities in the consumer and mining sectors are particularly attractive as they tend to benefit from currency movements. The originality of this research lies in its integration of four distinct asset classes: gold, bonds, equities, and BTC within a single portfolio framework, analyzed under the influence of key macroeconomic factors such as exchange rates, inflation, and interest rates. These factors account for only 23.85% of return variability, suggesting that additional systemic and behavioral variables remain unexplored. Future research should incorporate investor risk-profiling, broader macroeconomic indicators, and non-financial drivers such as geopolitical risks and market sentiment. Moreover, embedding sustainability considerations within portfolio strategies is becoming imperative. Incorporating green bonds and equities that adhere to Environmental, Social, and Governance (ESG) standards could enable investors to achieve both financial performance and long-term environmental and social objectives. Such an approach would strengthen portfolio resilience, align with global sustainability goals, and create a more balanced paradigm for investment management in an increasingly uncertain economic environment.

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