Bulletin of Business and Economics, 13(1), 51-60
https://bbejournal.com
https://doi.org/10.61506/01.00173

Impact of Crypto Assets as Risk Diversifiers: A VAR-based Analysis of Portfolio Risk Reduction

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Abstract
This research aims to empirically investigate the portfolio risk associated with crypto assets. In other words, we want to investigate whether the inclusion of crypto assets in a portfolio can minimize the portfolio risk or not, because it is argued that there is a lower degree of correlation between crypto assets and traditional assets. In order to achieve our research objectives, we employ the Vector Autoregressive Model (VAR) by using five different asset classes. The first two variables are taken from the crypto assets, Bitcoin and Ethereum, and the remaining three variables for Gold, Crude Oil and VIX (Chicago Board Options Exchange's (CBOE) volatility index). Our research strategy will be based on an analysis for unit root, optimal lag selection, coefficient matrix, checking VAR stability, the Granger causality test, and impulse response function (IRF). Our findings suggest that none of the indicators of traditional assets drive and explain Bitcoin. We also found that only Bitcoin is significantly related to Ethereum. while none of the other variables are statistically useful to explain the variation in the Ethereum. Based on these findings it can be recommended that the inclusion of crypto assets into a portfolio reduces risk because none of the indicators of crypto assets are significantly related to the indicators of traditional assets.
Keywords: Portfolio risk, crypto assets, Bitcoin, ETH, Granger causality test, VAR, IRF

1. Introduction

This study investigates the risks associated with the portfolio of crypto assets in combination with equities, forex instruments, and commodity assets. That is, apart from crypto assets such as Bitcoin and Ethereum, this study includes Gold, EURO, Crude Oil price, and VIX index. A portfolio of crypto assets when combined with other financial assets can help the investor to reduce the portfolio risk (Aliu et al., 2021). One way to differentiate crypto assets from other financial assets is the higher volatility in returns of the crypto assets. Despite the higher volatility of returns, investors are embracing crypto assets primarily secure because advanced technology using crypto, cross country secure and decentralized access to the crypto assets. For instance, the overall crypto assets market capitalization increased from $759 billion in January 2018 to $1354 billion in May 2022. It shows a 78% percent growth in the overall market capitalization of crypto assets during the period (Grider et al., 2022).

It is argued that there is a low degree of correlation between crypto assets and traditional assets (Demertzis & Wolff, 2018). If it is true, then the claim that the inclusion of crypto assets in the portfolio is desirable for diversification appears to be valid. That is, a lower degree of correlation between crypto assets and traditional assets makes it desirable for investors to include crypto assets in a bid to diversify the portfolio. Apart from diversification benefits, crypto assets offer massive upside returns, and in recent decades even attracted many institutions to invest in crypto assets. Since the risk-return spectrum shows that crypto assets are on the higher bar in terms of risk, but at the same time, they are leading in terms of massive returns. In addition, the attention of investors diversifying from other assets or market to the crypto assets to be included in the portfolio of investors (Reiff, 2020; Ali et al., 2021; Sulehri et al., 2022). Together, diversification benefits, massive returns, and continued debasement of fiat money make it desirable for investors to include crypto assets in their portfolios.

There are different types of portfolio risk measures (e.g., standard deviation, CAPM, variance, Value at Risk (VaR), Vector Autoregressive Model (VAR)). Classically, the standard deviation of portfolio returns has been used as a risk measure. According to this measure, the risk would be higher if the standard deviation of returns around the mean is highly dispersed. However, it has been found that the returns of many financial assets including crypto assets are not normally distributed and for that reason, standard deviation as a measure of risk would be misleading. Apart from standard deviation, Capital Asset Pricing Model (CAPM) has been frequently applied to investigate the relationship between expected return and risk of a portfolio. As per CAPM, the expected return of a portfolio depends on the risk-free return, Beta the coefficient which is a measurement of the volatility, also known as the systematic risk, of an asset or portfolio in relation to the market as a whole. Risk premium which is the difference between market return and risk-free return. The worth considering component of the CAPM model is the Beta which measures the risk associated with returns or volatility of returns. When Beta equals 1 it shows that the expected return of the asset equals the average market return (Sulehri et al., 2023). In addition, the Value-at-Risk (VaR) approach has also been frequently applied to measure the portfolio risk. VaR is a probabilistic measure of minimum loss which is expected over a specific period of time. For instance, if the 90 percent one-year VaR is $10 million, one can say that there is 90 percent confidence that the portfolio risk over the next year is not more than 10 million (Risman et al., 2021).

1.1. Problem Statement

The significant growth of crypto assets in terms of their overall market capitalization has directed many researchers pay attention to exploring the risk associated with portfolios of crypto assets. The problem in this study is trying to explore is the risk associated with portfolio crypto assets. In this regard, we outline the following research questions.

1.2. Research Objectives

Many academics are focusing on the risk associated with a portfolio of crypto assets because of the rapid expansion of crypto assets in terms of market capitalization. In this research, we are looking at the risk associated with holding crypto assets in a portfolio. In this regard, we outline the following research questions:

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- What is the link between crypto assets and portfolio risk?
- To what extent does the inclusion of crypto assets minimize the portfolio risk.

1.3. Research Gap

Crypto assets and the global financial stability are related because the magnitude and structural vulnerabilities associated with crypto assets are riskier. The rapid market expansion and transnational character of crypto assets further (Risman, Mulyana, Silvatika, & Sulaeman, 2021) raise regulatory loopholes, fragmentation, or arbitrage risk. There it is imperative to explore the portfolio risk of crypto assets. The research gap of this study is based on the fact that we are using three different risk measures to explore the link between crypto assets and portfolio risk. The earlier studies related to crypto assets have analyzed the risks associated using standard deviation, CAPM, and VAR approach to measure the risk associated with the portfolio of crypto assets. Here in this research more attention has been given to Vector Autoregressive Model (VAR) which is best to measure the volatility of an asset and risk volatility.

2. Literature Review

The available literature on crypto assets and portfolio risk has many dimensions. The post-financial crisis era has seen a growing interest in assessing and measuring the hedging and safe haven properties of different classes of assets. For instance, hedging against a market downturn and safe heaven properties of crypto assets attracted the attention of many scholars as the two mentioned properties are quite helpful in reducing portfolio risk. Chemkha et al. (2021) analyze the effectiveness of Bitcoin and gold during and before the Covid-19 and explore the fact that both gold and Bitcoin are effective as hedging assets. It is argued that both gold and Bitcoin appeared to be weak safe heaven during the pandemic. However, Bouoiyour and Selmi (2017) revealed that Bitcoin contains both hedge and safe heaven properties for the US stock index. It implies that to cater to the downside risk of equity investment, the investor can include Bitcoin in their portfolio, and can decrease portfolio risk.

Another line of literature documented on crypto assets explores the fact that crypto assets can be used as a significant tool for portfolio diversification. Li and Yi (2019) argued that crypto assets are a good diversification tool because empirical evidence suggests that crypto assets have a lower degree of correlation with other financial assets such as stock prices, oil prices, and other currencies. In this regard, it has been suggested that the inclusion of crypto assets within an investment portfolio can provide an opportunity to maximize risk-adjusted returns. In addition, the narrowing attention of investors toward other financial assets during the Covid-19 allows the crypto assets to be included in the portfolio of investors (Reiff, 2020; Shair et al., 2021; Shair et al., 2023). However, Bakry et al. (2021) suggested that Bitcoin is a potential diversifier only in normal market conditions and a good option for risk-seeking investors compared to risk-averse investors.

The third strand of the literature revealed the vulnerabilities in the crypto assets market. Board (2022) enlisted the channels through which the vulnerabilities have severe implications for global financial stability. The report identifies various vulnerabilities such as technological frugality, liquidity, and maturity issues. The first channel is the exposure of the financial sector to the crypto assets such as financial entities and products that can be affected by crypto assets. The wealth effect is the second channel through which financial stability can be threatened primarily due to higher volatility in the returns of crypto assets. For instance, Grider (2022) offered an illustrative asset class risk and return frontier in which the crypto assets are on the higher risk-return spectrum. Whereas the equity instruments and government debt instruments in the middle and lower risk-return spectrum respectively. It implies that crypto assets offer higher returns but are associated with higher risk as compared to equity and government debt instruments.

3. Methodology

To achieve the academic research's objectives, we are using a quantitative research methodology. Our research strategy is based on estimating the VAR model to check the link between crypto assets and portfolio risk. In the first place, we conduct unit root analysis followed by the optimal lag selection criterion. Secondly, we provide a VAR coefficient matrix and check for both stability conditions and residual diagnostic. After that, we present the Granger causality test and interpret the impulse response functions of the selected variables.

3.1. Econometric Model

The accessible econometric models utilized in this sort of study include the Value-at-Risk (VaR) method, GARCH, and Vector Autoregressive Model (VAR), based on the information we gained by examining the current literature in this topic. However, we are employing the VAR model, which assumes that both sets of time series, i.e., daily annualized Log returns of Bitcoin and Ethereum, are stationary at level, which means that their characteristics are not dependent on time and mean, and their variance is stable over time. The Vector Autoregressive Model is an extension of univariate regression, often known as the single equation model, in which current values are dictated by lagged values from the previous year. Data description, forecasting, volatility, and model stability are the various components in the VAR. Each variable is represented as a vector.

$$Bt = \alpha 0 + \alpha 1\, Bt - 1 + \alpha 2Et - 1 + \alpha 3VIX\, t - 1 + \alpha 4goldt - 1 + \alpha 5Eurot - 1 + \alpha 6Crudeoil\, t - 1 + \mu 1t$$

(Equation 1 – Bitcoin)

$$Et = \alpha 0 + \alpha 1\, Bt - 1 + \alpha 2Et - 1 + \alpha 3VIX\, t - 1 + \alpha 4goldt - 1 + \alpha 5Eurot - 1 + \alpha 6Crudeoil\, t - 1 + \mu 1t$$

(Equation 2 - Ethereum)

$$VIX = \alpha 0 + \alpha 1\, Bt - 1 + \alpha 2Et - 1 + \alpha 3VIX\, t - 1 + \alpha 4goldt - 1 + \alpha 5Eurot - 1 + \alpha 6Crudeoil\, t - 1 + \mu 1t$$

(Equation 3 – VIX)

$$Gold = \alpha 0 + \alpha 1\, Bt - 1 + \alpha 2Et - 1 + \alpha 3VIX\, t - 1 + \alpha 4goldt - 1 + \alpha 5Eurot - 1 + \alpha 6Crudeoil\, t - 1 + \mu 1t$$

(Equation 4 - Gold)

$$Euro = \alpha 0 + \alpha 1\, Bt - 1 + \alpha 2Et - 1 + \alpha 3VIX\, t - 1 + \alpha 4goldt - 1 + \alpha 5Eurot - 1 + \alpha 6Crudeoil\, t - 1 + \mu 1t$$

(Equation 5 - EURO)

$$Crudeoil = \alpha 0 + \alpha 1\, Bt - 1 + \alpha 2Et - 1 + \alpha 3VIX\, t - 1 + \alpha 4goldt - 1 + \alpha 5Eurot - 1 + \alpha 6Crudeoil\, t - 1 + \mu 1t$$

(Equation 6 – Crude Oil)

Equations 1, 2, 3, 4, 5, and 6 represents the VAR model used in this study. We know VAR model is a multivariate time series model in which a feedback mechanism occurs between variables. In contrast to univariate model, VAR model assumes no dependent variable for the system and each variable can be dependent and independent at the same time. In other words, when two or more than two-time series linearly influence each other, then we can use VAR model and forecast the current and future value based on the past values of a series. For instance, equation 1 shows that Bitcoin as dependent variable is a function of its past values and past values of other variables in the system plus a constant term and residuals. In the same way, we assume Ethereum as dependent variable depends on its past values and past values of other variables plus a constant term and residuals. Since we have six variables in the model, therefore we have six equations in this system. However, due to multicollinearity issue we later drop the equation 5 during estimation.

3.2. Research Strategy

The first basic assumption of VAR model is that all the time series must be stationary. It implies that the statistical properties of the selected series must remain constant over time such as mean, variance, and autocorrelation. In the real world, time series usually exhibit unit root processes in which high jumps and downs frequently occur in the series. Unit root test allows a researcher to determine the stationarity of the series and in a mirror way, it is equivalent to saying that it determines the randomness of the series. One direct consequence is that high randomness invites sudden jumps and downs, and the objective of accurate forecasting cannot be achieved. Therefore, our first strategy is to check the stationarity of the selected series. We have used Augmented Dickey Fuller Test (ADF) with null hypothesis such that time series has unit root process.

Our second strategy is to select optimal lags for the model. It is also known as the optimal lag selection process. It would tell us how many lags are optimal to estimate the VAR model. The next strategy is about estimating the VAR model with optimal lags. A VAR model can be defined as a multivariate time series model in which a feedback mechanism occurs between variables. More specifically, the VAR model assumes no dependent variable for the system and each variable can be dependent and independent at the same time. The coefficient matrix of variables will be presented. We will check the statistical significance of each coefficient at 5% significance level. The coefficient tells us about the explanatory power of past values of a variable in determining its current and future value of a variable. The most important thing in the coefficient matrix are the probability values associated with each coefficient in the table. A less than 5% probability value implies that the coefficient is significant statistically. In other words, the magnitude of the relationship between variables is not a random pattern rather the relationship is significant statistically. Apart from coefficients and probability values, the coefficient matrix also contains standard errors of each coefficient. Standard error refers to the variability around the mean value. A high standard error indicates a less reliable mean or coefficient. It can be calculated as a coefficient divide by z-statistics.

Our fourth research strategy is to check the stability of the VAR model. Because the implications of a coefficient matrix become invalid if the model lacks stability. In simple words, the model will be stable if the model exhibits covariance stationarity. Covariance refers to joint variability of two random variables and measures the relationship between variance of two random variables. And when such joint variability fulfills the conditions of stationarity, we would call it covariance stationarity. The covariance becomes stationary if all the eigenvalues are less than 1 in an absolute term. In other words, the VAR model exhibits stability if all the eigenvalues are less than 1 in absolute terms and that time, we will achieve the objective of covariance stationarity.

In the next strategy, we will use the Granger causality test. The concept of causality in this test is based on prediction. In this test, if variable X Causes Y, then it implies that the past values of X can explain and predict the variation in Y. It tells us the pattern of correlation between variables and helps us predict the current value of a variable based on past values of another variable. By using the granger causality test, we can observe the correlation between the selected series. And our last strategy is graphically present impulse response function.

4. Results and discussion

In table 1, we provide the results of unit root analysis by using Augmented Dickey Fuller Test. One of the assumptions of the VAR model is that the model must be stationary and there must not be a unit root issue in the model. The validity of the VAR model directly depends on this assumption. Therefore, we have shown the unit root analysis in table 1. The results show that all selected variables in the model are stationary at the first difference and none of the variables are stationary at levels. It is important to note that the null hypothesis of the ADF test is such that there is a unit root in the series, and the rejection of the null hypothesis can be concluded as there is no unit root in the series. For instance, Ethereum is significant at 1%, 5%, and 10% levels of significance. Similarly, the probability value of Ethereum is less than 5% level of significance, and for that reason, we reject the null hypothesis. And we conclude that the series of ETH has no unit root at first difference. The same logic can be extended to all selected variables and we conclude that the model is stationary at first difference and we can apply the VAR model.

The second step before estimating the VAR model is to choose the optimal lags for the model. It is necessary because the VAR model assumes lag values of variables as the explanatory variables. For simplicity, the steric-values show the optimal lags as per each criterion. The last three criteria are the most widely used optimal selection-order criteria. The most interesting fact about these selection order criteria is that all they choose the lowest value as optimal lag. Specifically, all the mentioned criterion measures the goodness of fit and helps researcher to choose the best model among the alternatives.For instance, in the second lags, the , Akaike information criterion (AIC) criteria show that 45.122 is the lowest value in the series which suggests that the second lag is the optimal lag for the model. In the same way, the Hannan-quinn information cireterion (HQIC) criteria also suggest second lag as optimal lag for the model because the associated value is the smallest in the series. However, as per the nd Schwarz bayesian information cireterion (SBIC), the first lag is optimal. Therefore, we choose the first two lags as optimal lags for the model.

Table 1: Unit Root Analysis Augmented Dickey Fuller Test

ADF FOR		Test statistics	1% critical value	5% critical value	10% critical value	MacKinnon approximate p-value for	Stationarity level
ETH	Z(T)	-25.854	-3.442	-2.871	-2.570	0.000	Stationary (1)
BTC	Z(T)	-22.578	-3.442	-2.871	-2.570	0.000	Stationary (1)
VIX	Z(T)	-25.009	-3.442	-2.871	-2.570	0.000	Stationary (1)
Crude Oil	Z(T)	-33.553	-3.442	-2.871	-2.570	0.000	Stationary (1)
EURO	Z(T)	-18.335	-3.451	-2.876	-2.570	0.000	Stationary (1)
Gold	Z(T)	-24.126	-3.442	-2.871	-2.570	0.000	Stationary (1)

Table 2: Optimal Selection-order criteria

Sample: 1/11/2019 - 3/25/2022, but with gaps Number of observations = 140

Lags	LL	LR	df	P	FPE	AIC	HQIC	SBIC
1	-3164.76	2799.1	25	0.000	4.6e+13	45.6394	45.8956	46.2698*
2	-3103.6	122.32	25	0.000	2.7e+13*	45.1228*	45.5924*	46.2785
3	-3086.59	34.01	25	0.108	3.1e+13	45.237	45.9201	46.918
4	-3061.02	51.151*	25	0.002	3.1e+13	45.2288	46.1254	47.435

4.1. VAR estimation

In the third step, we estimate the VAR model using first and second lags as optimal lags for the model. In the upper portion of the table, we show the equations that have been estimated and their respective statistical significance. For instance, in the first equation, the dependent variable is BTC, while all the rest of the variables are treated as explanatory variables. The second column gives us the number of parameters in the equation. We know that the model has five variables and with two lags plus constant determines eleven parameters. The third column is about root mean square error, which shows the standard deviation of residuals. In the same way, the R square of the first equation is 0.99, which shows that the explanatory variables in the first equation explain 99% of the variation in BTC, including its lagged values. Finally, the probability value is also less than 5% significance, indicating that model 1 is well fitted. The second equation in the upper portion of table 3 assumes Gold as the dependent variable. The R square is for the second equation is again 99% with less 5% probability value indicating that model 2 is well fitted. Extending the same logic for equation 3, equation 4, and equation 5 shows that all five equations are statistically significant at 5% level of significance.

Table 3. VAR estimation

Equation	Parms	RMSE	R-sq	chi2	P>chi2
BTC	11	1298.03	0.9954	101681.9	0.0000
Gold	11	17.5007	0.9933	70277.08	0.0000
ETH	11	68.8484	0.9977	205707.3	0.0000
Crude Oil	11	1.68243	0.9911	52722.97	0.0000
VIX	11	2.38804	0.9376	7072.406	0.0000

	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
BTC						
BTC						
L1.	1.000	0.044	22.610	0.000	0.913	1.086
L2.	-0.014	0.044	-0.320	0.746	-0.102	0.073
Gold						
L1.	-0.993	3.310	-0.300	0.764	-7.482	5.495
L2.	2.297	3.320	0.690	0.489	-4.209	8.803
ETH						
L1.	-0.155	0.558	-0.280	0.781	-1.249	0.938
L2.	0.142	0.530	0.270	0.789	-0.897	1.181

Crude Oil						
L1.	13.494	23.178	0.580	0.560	-31.934	58.922
L2.	-12.304	22.011	-0.560	0.576	-55.445	30.837
VIX						
L1.	36.451	26.124	1.400	0.163	-14.751	87.653
L2.	-34.604	26.211	-1.320	0.187	-85.977	16.768
_cons	-1774.899	842.333	-2.110	0.035	-3425.841	-123.957
Gold						
BTC						
L1.	-0.001	0.001	-0.840	0.399	-0.002	0.001
L2.	0.001	0.001	1.090	0.275	-0.001	0.002
Gold						
L1.	0.872	0.045	19.530	0.000	0.784	0.959
L2.	0.118	0.045	2.650	0.008	0.031	0.206
ETH						
L1.	-0.018	0.008	-2.440	0.015	-0.033	-0.004
L2.	0.018	0.007	2.460	0.014	0.004	0.032
Crude Oil						
L1.	0.461	0.312	1.470	0.141	-0.152	1.073
L2.	-0.467	0.297	-1.570	0.116	-1.049	0.115
VIX						
L1.	-1.368	0.352	-3.880	0.000	-2.058	-0.677
L2.	1.140	0.353	3.230	0.001	0.448	1.833
_cons	18.417	11.357	1.620	0.105	-3.842	40.676
ETH						
BTC						
L1.	0.055	0.002	23.640	0.000	0.051	0.060
L2.	-0.054	0.002	-22.850	0.000	-0.059	-0.049
Gold						
L1.	0.109	0.176	0.620	0.535	-0.235	0.453
L2.	-0.163	0.176	-0.930	0.354	-0.508	0.182
ETH						
L1.	0.987	0.030	33.360	0.000	0.929	1.045
L2.	0.003	0.028	0.110	0.916	-0.052	0.058
Crude Oil						
L1.	0.717	1.229	0.580	0.560	-1.693	3.126
L2.	-0.642	1.167	-0.550	0.582	-2.931	1.646
VIX						
L1.	-1.560	1.386	-1.130	0.260	-4.276	1.156
L2.	1.624	1.390	1.170	0.243	-1.101	4.348
_cons	59.546	44.678	1.330	0.183	-28.021	147.114
Crude Oil						
BTC						
L1.	0.000	0.000	0.820	0.410	-0.000	0.000
L2.	-0.000	0.000	-1.200	0.231	-0.000	0.000
Gold						
L1.	-0.002	0.004	-0.500	0.616	-0.011	0.006

L2.	0.002	0.004	0.510	0.610	-0.006	0.011
ETH						
L1.	0.001	0.001	1.000	0.317	-0.001	0.002
L2.	-0.000	0.001	-0.450	0.656	-0.002	0.001
Crude Oil						
L1.	1.020	0.030	33.960	0.000	0.961	1.079
L2.	-0.040	0.029	-1.390	0.163	-0.096	0.016
VIX						
L1.	-0.029	0.034	-0.840	0.399	-0.095	0.038
L2.	0.015	0.034	0.450	0.650	-0.051	0.082
_cons	1.367	1.092	1.250	0.211	-0.773	3.507
VIX						
BTC						
L1.	-0.000	0.000	-1.870	0.062	-0.000	0.000
L2.	0.000	0.000	1.560	0.118	-0.000	0.000
Gold						
L1.	-0.001	0.006	-0.200	0.840	-0.013	0.011
L2.	0.004	0.006	0.670	0.502	-0.008	0.016
ETH						
L1.	0.000	0.001	0.030	0.972	-0.002	0.002
L2.	-0.000	0.001	-0.060	0.953	-0.002	0.002
Crude Oil						
L1.	-0.057	0.043	-1.350	0.178	-0.141	0.026
L2.	0.050	0.040	1.230	0.220	-0.030	0.129
VIX						
L1.	0.769	0.048	16.000	0.000	0.675	0.863
L2.	0.186	0.048	3.850	0.000	0.091	0.280
_cons	-2.756	1.550	-1.780	0.075	-5.793	0.281

In the lower part of the table, we present individual VAR coefficients for each variable. For instance, in the first equation, BTC is the dependent variable. We can see that only Lag 1 of the dependent variable is significant statistically while the second lag is not. In the same way, none of the other lags are significantly related to BTC. Based on this, it can be said that the BTC value at time t largely depends on its previous day's value. Apart from that, the constant of the first equation is also significantly related to BTC. It implies that the mean value of BTC can also explain the BTC value at time t.

Table 4: VAR Stable: Eigenvalue stability condition

Eigenvalue	Modulus
.9991374	.999137
.9868338+ .00348837i	.98684
.9868338- .00348837i	.98684
.9655605+ .01763986i	.965722
.9655605- .01763986i	.965722
.2346365	.234637
.07838175+ .1403649i	.160767
.07838175- .1403649i	.160767
.06744149+ .00866872i	.067996
.06744149- .00866872i	.067996

The second equation assumes Gold as the dependent variable, and we find two variables other than lagged values of the dependent variable are statistically significant. In other words, only BTC and Crude Oil are statistically insignificant, while ETH and VIX,

including lags of the dependent variable, are statistically significant. In the same way, the third equation assumes ETH as the dependent variable, and findings show that only BTC is significantly related to the dependent variable, including its lags. While none of the other variables are statistically useful to explain the variation in the dependent variable.
After estimating the VAR model, it is customary to check whether VAR satisfies stability conditions. Stability conditions are similar to the stationary conditions which we have identified in table 1. There are a total of 10 eigenvalues indicating the fact that we are using two lags for each variable. One way to check the stability conditions is to see whether the eigenvalues are inside or outside the unit circle. The unit circle in the table implies that the eigenvalue must not be greater than one. We can see that all the eigenvalues lie inside the unit circle and less than 1 and we conclude that VAR satisfies stability conditions.

Table 5: Granger causality Wald tests

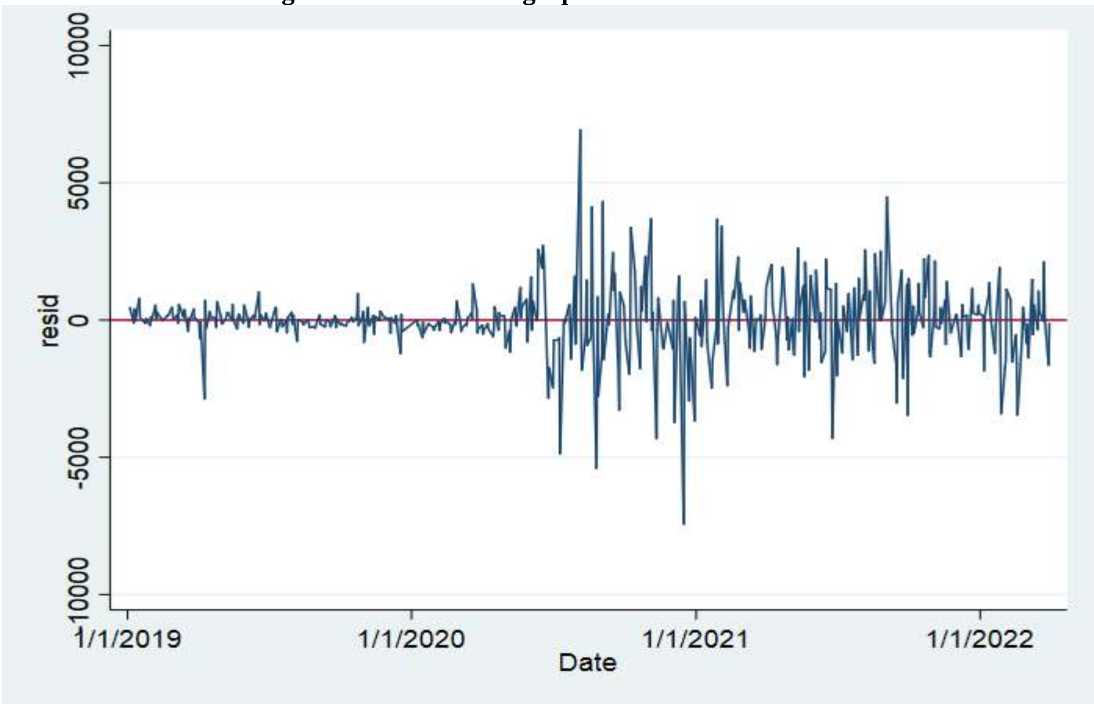
Equation	Excluded	chi2	Df	Prob>Chi2
BTC	Gold	4.926	2	0.085
BTC	ETH	0.078	2	0.962
BTC	Crude Oil	0.340	2	0.844
BTC	VIX	1.948	2	0.378
BTC	ALL	9.182	8	0.327
Gold	BTC	1.981	2	0.371
Gold	ETH	6.099	2	0.047
Gold	Crude Oil	2.543	2	0.280
Gold	VIX	17.567	2	0.000
Gold	ALL	30.989	8	0.000
ETH	BTC	558.820	2	0.000
ETH	Gold	3.466	2	0.177
ETH	Crude Oil	0.346	2	0.841
ETH	VIX	1.365	2	0.505
ETH	ALL	578.800	8	0.000
Crude Oil	BTC	3.396	2	0.183
Crude Oil	Gold	0.260	2	0.878
Crude Oil	ETH	5.853	2	0.054
Crude Oil	VIX	2.052	2	0.358
Crude Oil	ALL	9.044	8	0.339
VIX	BTC	4.530	2	0.104
VIX	Gold	6.928	2	0.031
VIX	ETH	0.012	2	0.994
VIX	Crude Oil	1.963	2	0.375
VIX	ALL	11.098	8	0.196

4.2. Granger causality

The next step in the VAR process is to check the Granger causality test. The basic purpose of the Granger causality test is to see whether lagged values of one variable help to predict other variables in the model. The null hypothesis of the Granger causality test is such that the first variable does not granger cause the second variable. And if we reject the null hypothesis entails that the first variable helps us to predict the second variable in the model.

For instance, BTC Granger causality test causes an impact on the price of Gold at 8% level of significance but BTC does not have an impact on any other variable in the model. However, the Gold granger causes an impact on the price of ETH and VIX but does not have an impact on the prices of any other variables in the model. In the same way, the ETH granger causality test causes an impact on the price of BTC but do not have an impact on any other variable's prices in the model. Similarly, the price of Crude oil granger causality test causes an impact on the price of ETH and price of VIX do have a significant impact on Gold prices and do not have significantly affect other variable's prices in the model.

Figure 1: Residual line graph around the mean



The next step is to check for residual diagnosis and to observe the possible autocorrelation between residuals. In figure 1, we have the residual line graphs, with the red horizontal line showing the mean value for residuals and the spread around the mean showing the standard deviation of residuals. We can see that roughly most of the residuals are around the mean and there is no sign of autocorrelation among residuals in the model.

4.3. Impulse Response Function

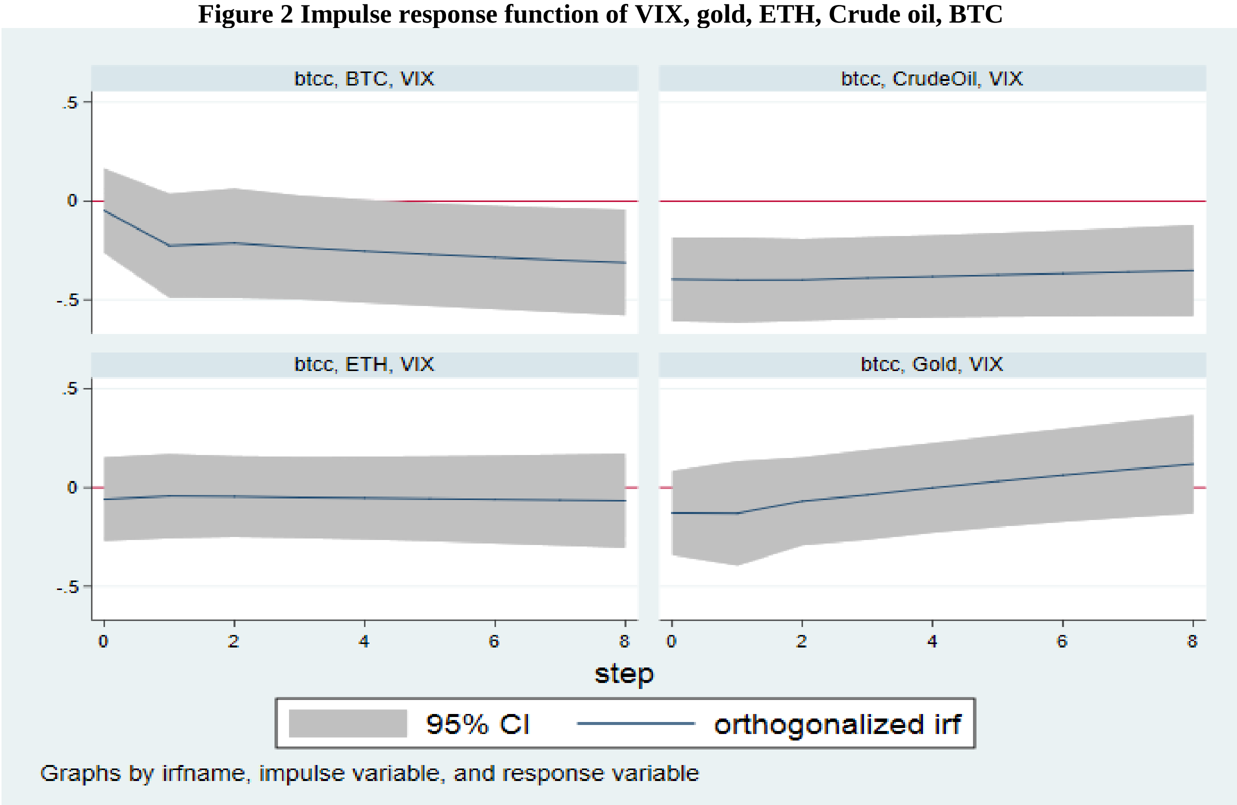
Impulse response function shows the effect of one variable on the other given the external shock to the system. For instance, in the first panel of figure 2, we have shown the effect of BTC on VIX given the external shock. The horizontal axis is measured by standard deviation. A one standard deviation shock BTC causes a significant decrease in VIX which is the response variable. This effect of BTC on VIX for a short period and after that the effect is disappeared because the response variable shows constant behavior. There is no impulse response function between Crude Oil and VIX and between ETH and VIX. However, the last panel shows an impulse response function between Gold and VIX. For instance, a one standard deviation shock to Gold causes a significant increase for the entire selected period. One can see that the curve is slowly moving upwards till the end.

5. Conclusion

This study aimed to investigate the link between crypto assets and portfolio risk. Alternatively, the basic goal is to explore whether the inclusion of crypto assets can minimize the portfolio risk or not. This study found that today's BTC value can be predicted based on its previous day's value. We found that only the first lag value of BTC is significantly related to the current value of the dependent variable. Apart from the first Lag value of BTC, we found no other lags of explanatory variables significantly related to the current value of the BTC. However, the constant term is significantly related to the current value of BTC. As a result, it can be concluded that both the first lag value and the mean value of BTC are helpful in predicting the current value of BTC. When we assume Gold as the dependent variable, we found that both ETH and VIX are significantly related to the dependent variable. It implies that both ETH and VIX are helpful in predicting the average value of Gold. In addition, the 1 year lagged value of Gold is also significantly related to the dependent variable. Unlike BTC, there are two explanatory variables that are helpful in explaining the variation in the dependent variable. In the third equation, we assumed ETH as the dependent variable and found that the 1 year lagged value of ETH is significantly related to its current value. However, none of the explanatory variables except BTC are significantly related to the current value of ETH. In fact, we found that both the selected lags of BTC can explain and predict the variation in ETH. The fourth and fifth equation also shows that none of the explanatory variables are significantly related to the Gold and VIX. Only the 1 year lagged value of Golf and VIX can significantly explain their current values. Apart from that, we checked the VAR stability condition and found that the model is stable as all the eigenvalues lie inside the unit circle.

In the next step of VAR process, we conducted the Granger causality test. We found that BTC granger causes Gold only at 8% significance level. However, BTC cannot granger causes any other variables in the model. We can say that lagged value of BTC helps us in predicting the average value of Gold. Results also indicates that Gold granger causes both ETH and VIX at 5% significance level. However, there is no other variable that is significant related to GOLD. We also found that ETH granger causes BTC AT 5% significance level. However, ETH do not granger causes any other variable in the model. Further, findings of granger causality test show that Crude oil granger causes ETH, and VIX granger causes gold. However, Gold and VIX do not granger causes other variables.

Figure 2 Impulse response function of VIX, gold, ETH, Crude oil, BTC



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