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THE ECONOMIC IMPLICATIONS OF BITCOIN AS A DIGITAL ASSET

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Abstract: This study investigates the relationship between Bitcoin, the first cryptocurrency, and US financial markets. To broadly represent US financial markets, two assets are considered: the S&P 500 (SPY) and Gold. The prices of these three assets are used to create a Vector Autoregression (VAR) model to show that the price behavior of the individual assets does not have a statistically significant relationship to Bitcoin (and vice-versa) due to the stark differences in the market structure these assets trade-in and the characteristics of the asset itself. The daily closing price data is sourced from the Intercontinental Exchange (ICE) and is transformed to a monthly level prior to the VAR model. This reduces the effects of outlier events and creates a dataset fit for longer-term analysis. While all three assets see long-term growth (year-over-year), independently, in the short-term (month-to-month), the VAR results suggest no statistical relationship between Bitcoin-S&P and Bitcoin-Gold. The relevance of this study can be seen in the context of portfolio theories.

Keywords: *Bitcoin, Cryptocurrency, Financial Markets, Vector Autoregression (VAR,) Portfolio Theory, Asset Diversification, Risk Management, Decentralized Finance (DeFi), Cryptocurrency Volatility, Economic Integration.*

1 Introduction

Because the subject of integration in financial markets is one that is hotly debated by a variety of investors and experts, this has been a fruitful field for research. Because of unexpected shifts in the dynamics of the market, there is a huge amount of room for study in the field of financial integration (Cavalcante, R. C., Brasileiro, R. C., Souza, V. L., Nobrega, J. P., & Oliveira, A. L., 2016). Since the decade of the 1980s, the globe has witnessed a rise in globalization, growth in foreign portfolio diversification, and the movement of capital. The phenomena of increased globalization have also contributed to the development of advanced communication mechanisms. There is a substantial amount of increase in financial integration during times of financial crisis, which gives rise to the issue of contagion. The variation in volatility spillover is a significant component that is contributing to the contagion in the current financial crisis (Bekaert & et al., 2014).

The globalization and liberalization of economies are necessary preconditions for the growth of equities markets. The financial markets are an essential component in the process of moving money from a sender to a recipient (Liow & et al, 2021). It is very vital to study the operation of capital markets as well as their expansion in order to have an understanding of the idea of financial volatility. Numerous studies from across the world have made use of this notion since oscillations and crises in one nation have an influence on other nations; for instance, a crisis in the United States will have a negative effect on nations whose economies are dependent on the stock market in that nation. Variability and volatility spillover are two terms that can be used interchangeably (Katusiime, 2022).

After the financial crisis of 2009, Satoshi Nakamoto was the one who first presented Bitcoin to the world. This is a digital phenomenon that involves software and protocols (Fanusie & et al, 2018). Cryptocurrency is the asset class with the highest market value despite the efforts of many imitators who have created hundreds of competing financial products. Bitcoin has a number of different methods to protect users against fraudulent activity. It

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delivers services that are distinct from those provided by other payment systems, which is one of its many distinctive characteristics. Although no firm can truly manage the service, businesses are welcome to participate. In essence, it is made with the convenience of the general population in mind (Chohan, U. W. , 2021).

Due to the fact that cryptocurrencies are not governed by any central authority, their use as an asset is entirely unique. Although currencies are not officially recognized as a category of assets, the profits generated by cryptocurrencies give the impression that they do. When it comes to the development of a financial portfolio, cryptocurrencies have the potential to fulfill a function that cannot be met by traditional assets (Saraswat & et al, 2017). This function is best suited for persons who enjoy taking risks and who are interested in acquiring an asset that is uncorrelated to other assets already present in the macroeconomy. If a new asset is developed that satisfies this requirement, it could be feasible, at least in principle, to construct a portfolio that reacts to shocks in the macro economy in a manner that is far less severe than that of contemporary portfolios. Cryptocurrencies by themselves are not necessarily beneficial in contemporary or postmodern portfolio theory; but, when held in conjunction with other assets, the diversification needs and possibility for economic cycles independent of either the national or global economy can be valuable. A VAR analysis is performed in order to determine whether or not the aforementioned criteria are satisfied by Bitcoin.

Following closely on each other, the Modern Portfolio Theory (often abbreviated as MPT) and the Postmodern Portfolio Theory (sometimes abbreviated as PMPT) are the two most recent developments in portfolio creation. (PMPT). In the beginning, the models were straightforward, and the examination of businesses was conducted on a fundamental level. The focus was mostly on answering the question, "Is there actual value in the asset?" Investors would gradually add to their portfolios over the course of time, basing their selections on the specific chances that presented themselves one at a time. MPT was a formalized method of evaluating a portfolio that was developed by Dr. Harry Markowitz. It evaluated a portfolio in terms of tradeoffs by looking at the complete portfolio at once. This is distinct from the way portfolios were first constructed, and it is also different from PMPT, as the objective of MPT is to lessen the degree to which the value of a portfolio varies from one point in time to another. If the volatility of an investment portfolio is kept to a minimum, then long-term growth may be achieved regardless of which phase of the business cycle the macro economy is now experiencing. The PMPT is a variant of the MPT that shifts the emphasis from minimizing upside risk to minimizing downside risk, or what are effectively the worst-case possibilities.

Types Of Portfolio Management

Some types of portfolio management are,

Active Portfolio Management

Dynamic portfolio board requires an elevated degree of skill in the business sectors. The primary objective of an asset manager implementing a functional strategy is to generate market returns that are superior to the overall market. The approach is characterized as 'dynamic' as it necessitates a continuous evaluation of the market to procure resources at undervalued prices and vend them when they exceed the norm. The methodology necessitates a rigorous analysis of the market through quantitative means, extensive expansion, and a comprehensive understanding of the business cycle.

The primary benefit of utilizing dynamic techniques is the possibility of generating returns that outperform the market. The system also provides flexibility in that the asset manager has the ability to modify their approach whenever necessary. Conversely, dynamic methodologies are known to incur significant costs due to frequent resource turnover. The effect of human mistakes is additionally a lot more prominent in dynamic systems. Dynamic strategies are suitable for seasoned investors who possess a greater risk appetite. The investors anticipate a higher level of risk-taking in order to generate greater returns. Frequently, individuals allocate a greater proportion of their capital to stocks in order to satisfy their desire for returns that outperform the market. This results in a higher concentration of capital in stocks.

Discretionary Portfolio Management

An alternative approach to managing portfolio managers grants the asset manager full autonomy over their clients' speculative choices. The individual in charge of customization makes all trading decisions with the aim of benefiting their clients and utilizing the system they deem most effective. This particular methodology should be imparted to individuals possessing substantial expertise and experience in endeavors. Investors who opt for supervisors are at ease with delegating their investment choices to an expert. The principal benefit of elective involvement is the transfer of authority over one's investment choices to an expert. This would facilitate matters considerably, particularly in the event of concurrence with the trading perspectives of one's supervisor.

If an individual prefers a more interactive approach toward their projects, then optional files may not be suitable for them. If cost is a concern, elective records may prove to be more limiting as elective managers tend to levy higher fees for their services. Currently, the Modern Portfolio Theory (MPT) is widely utilized as the primary instrument for developing investment portfolios. The principle underlying passive investment is utilized. Nevertheless, a significant number of investors aspire to enhance their returns beyond the scope of passive investing or mitigate their risk in a more comprehensive manner, or both. The pursuit of alpha, which refers to returns that exceed the market, is a fundamental principle that guides the management of actively managed portfolios. These portfolios are typically overseen by investment managers, with hedge funds being a notable example. Post-modern portfolio theory is utilized by portfolio managers to incorporate negative returns into their portfolio calculations.

2 Literature Review

The correlation between the returns of cryptocurrencies, the S&P 500, and gold has been the subject of academic inquiry since the mid-2010s, following the surge in the adoption of cryptocurrencies. According to Bohte and Rossini, the subject of cryptocurrency is gaining traction both within academic circles and beyond. The subject of cryptocurrencies has garnered significant attention, with its market value surging from approximately 19 billion US dollars in February 2018 to around 800 billion US dollars in December 2017. As a result, extensive research has been conducted on this topic. Following the inception of Bitcoin, a plethora of approximately one thousand cryptocurrencies emerged, presenting a novel avenue for investment among traders (1-3). The primary reason for this phenomenon can be attributed to the accessibility of market entry and its highly unstable nature, as noted by Zięba (12).

Various researchers have employed Vector Autoregressive (VAR) models to examine time series data, particularly in the realm of currency analysis. Bohte and Rossini (4) employed VARs with constant volatility to examine the forecasting ability of cryptocurrency time series. The data was collected for the sample span ranging from 8 August 2015 to 28 February 2019 and consisted of 1301 observations from four major cryptocurrencies, namely Bitcoin, Ethereum, Litecoin, and Ripple. Lin (3) conducted a study utilizing Vector Autoregression (VAR) models to investigate the causal relationship between the performance of multiple cryptocurrencies and investor attention. According to Al (2), the VAR analysis facilitates the exploration of the interrelationships among multiple variables of significance and the forecasting ability of a particular time series in comparison to another.

Modern Portfolio Theory

The portfolio selection methodology authored by Markowitz is commonly known as Modern Portfolio Theory. Markowitz's theory is centered on the fundamental principles of diversification, risk, and correlation, which are inherently interconnected. In the financial market, there exist two distinct categories of investors: those who are averse to risk and those who are inclined to take risks. Investors who are averse to risk tend to allocate their investments toward financial instruments that are considered safe while showing a preference for lower returns. Conversely, investors who are willing to take on greater risk tend to prioritize investments that offer higher returns, despite the increased level of risk involved.

The topic of diversification has been a productive subject of investigation for numerous investors. Investors who concentrate their investments on a single asset are at risk of losing their entire portfolio, thus necessitating the need for an optimal mix of investments. The diversification of a portfolio can effectively mitigate idiosyncratic risk. The process of globalization and advancements in technology have led to increased proximity among economies. The reduction of risk is achieved through the minimization of variability risk, as volatility serves to decrease risk. Based on the findings of a recent survey on blockchain data, it has been revealed that the total value of cryptocurrencies exceeds 13 billion.

The integration of finances has resulted in interconnectivity among global economies. The aim of integration is to facilitate the adoption of novel technologies and eliminate impediments to investment.

Efficient Frontier

The efficient portfolio also known as a financial tool is a set of investment portfolios that give the highest rate of return with the expected level of risk. Different assets have a different levels of risk and return. The efficient frontier is based on utility theory. The concept has been coined by a Swiss mathematician by whom he explained it with diagrammatical representation. In an efficient frontier, the y-axis and x-axis represent expected returns and risk levels. The theory is based on preference and usefulness.

Decentralise Finance

Decentralized finance eliminates the involvement of intermediaries such as banks, financial services, and institutions. It eradicates the service charges levied by diverse financial establishments. The utilization of the aforementioned resource is accessible to all individuals with an internet connection, without the requirement of any formal authorization from a governing entity. Individuals have the option to store their funds in a digital wallet as a means of safeguarding their finances, as opposed to depositing them in a traditional financial institution. The utilization of decentralized technology involves the implementation of cryptocurrency mechanics. The technical nature and complexity of DEFI can render it a challenging procedure to navigate. The presence of security vulnerabilities, coding errors, and malicious actors poses a significant financial risk. As per the latest blockchain data report, hackers have siphoned off over 13 million units of cryptocurrencies.

Data and Methodology

The utilization of vector autoregression analysis in portfolio management facilitates the modeling of interrelated variables with reciprocal causation and allows for the simulation of market responses to innovations in other markets. The term "autoregressive" pertains to the inclusion of past values of the dependent variable in the model equation. On the contrary, the term "vector" pertains to the inclusion of a set of two or more variables within the model. The process of constructing a Vector Autoregression (VAR) model involves verifying that the time series data is stationary after the first difference.

The provided dataset displays the daily closing prices of Bitcoin, SPY, and GLD in the stock markets from September 2014 to November 2021. The analysis of descriptive statistics reveals a significant variability in the valuation of Bitcoin. Table 1 presents the descriptive statistics. Descriptive statistics are utilized to generate a fundamental representation of data. Additionally, it can aid in identifying any potential outliers that may be present. Table 1 presents the statistical summary of three assets, including the minimum, maximum, and mean values, based on a sample size of 87 observations. In order to mitigate the impact of unpredictable or highly unstable occurrences, the time series data collected on a daily basis is consolidated into monthly intervals.

Table-1

Variable	Observations	Mean	Std. Dev.	Min	Max
Bitcoin	87	10264	15243	232	62116
S&P 500	87	276	71	191	467
Gold	87	133	23	102	185

A causality analysis is performed on the model and the viability for forecasting will be assessed. The Granger-causality analysis helps determine whether one variable can be used to forecast another. Multiple information criteria will be used to determine the optimal lag length.

The VAR model takes the following form:

$$Y_{1,t} = \alpha_1 + \beta_{11,1}Y_{1,t-1} + \beta_{12,1}Y_{2,t-1} + \beta_{13,1}Y_{3,t-1} + \beta_{11,2}Y_{1,t-2} + \beta_{12,2}Y_{2,t-2} + \beta_{13,2}Y_{3,t-2} + \epsilon_{1,t}$$
$$Y_{2,t} = \alpha_2 + \beta_{21,1}Y_{1,t-1} + \beta_{22,1}Y_{2,t-1} + \beta_{23,1}Y_{3,t-1} + \beta_{21,2}Y_{1,t-2} + \beta_{22,2}Y_{2,t-2} + \beta_{23,2}Y_{3,t-2} + \epsilon_{2,t}$$
$$Y_{3,t} = \alpha_3 + \beta_{31,1}Y_{1,t-1} + \beta_{32,1}Y_{2,t-1} + \beta_{33,1}Y_{3,t-1} + \beta_{31,2}Y_{1,t-2} + \beta_{32,2}Y_{2,t-2} + \beta_{33,2}Y_{3,t-2} + \epsilon_{3,t}$$

where Y_1 is the price of Bitcoin, Y_2 is the price of SPY, and Y_3 is the price of Gold. Each equation has the appropriate number of lags, as determined by the AIC, which is discussed further in the following section. Each equation also contains an error term. Since the logarithm of the first difference is used, the interpretation for the equations is as follows: a 1% change in an explanatory variable yields a percent change in the dependent variable on the following period, quantified by the coefficient of the explanatory variable (holding everything else constant). The interpretation can also be understood as a return on the asset.

The time-series data is sourced from the Intercontinental Exchange (ICE), which owns and operates multiple exchanges and financial technologies.

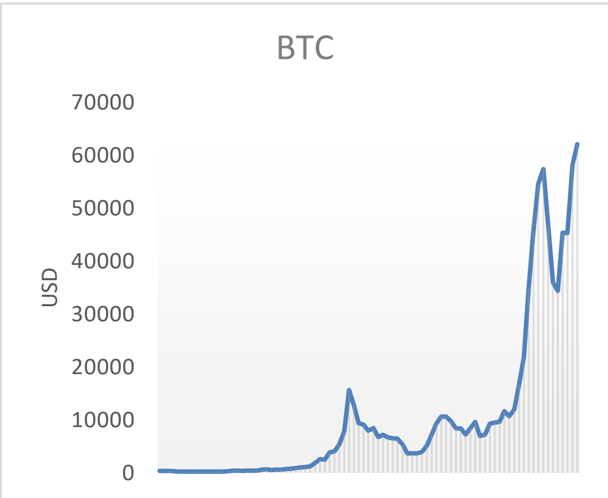
Results

a) Stationarity

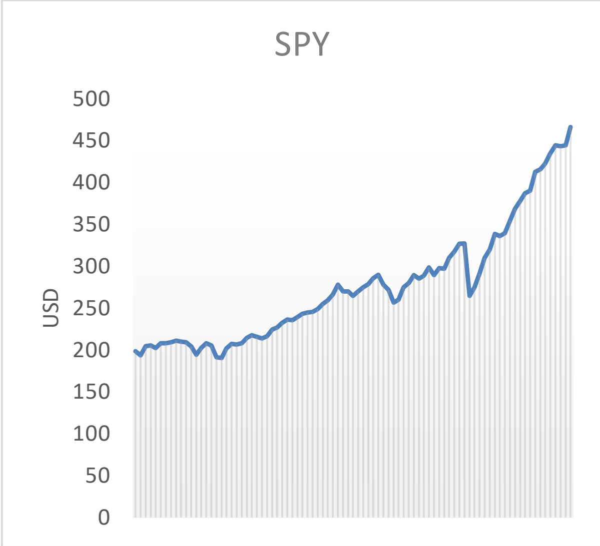
The prices for Bitcoin, SPY, and Gold are all non-stationary, due to their underlying growth trend. Graphs 1,2, and 3 show this (note the scale of the y-axis), from September 2014 to November 2021. To fit this data to the VAR model, the logarithm of the first difference is used. Using the Augmented Dickey-Fuller test with one lag, the null hypothesis of a unit root is rejected because the test statistic is higher than the critical value, at 1% significance.

Table 1

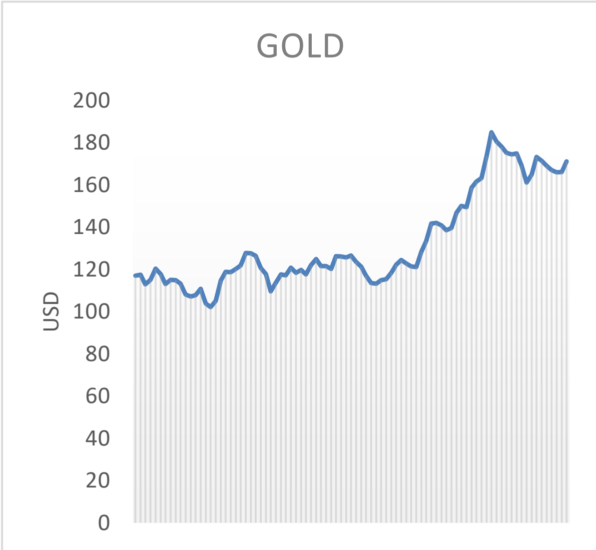
Data	Test Statistic	Critical Value at 1%
BTC	-5.298	-3.532
SPY	-7.304	-3.532
Gold	-6.596	-3.532



Graph-1



Graph-2



Graph-3

b) Optimal Lag Length

The AIC yields an optimal lag length of 1, whereas the HQIC and SBIC yield no optimal lags. To avoid misspecification of the model, one lag is chosen.

Lag	AIC	HQIC	SBIC
0	-8.357	-8.32*	-8.263
1	-8.418	-8.268	-8.041
2	-8.259	-7.996	-7.560

Table 2

c) VAR Model

The VAR Model shows the lack of significance between the coefficients involving Bitcoin. There is no level of significance where the lagged values of SPY and Gold help estimate the monthly return of Bitcoin, *ceteris paribus*. The same goes for lags of Bitcoin at a 5% level.

Table 3

	Coeffivient	Std. err.	Z	P>| z |	[95% conf.	Interval]
dlnBTC Equation						
dlnBTC						
L1.	0.334321	0.1106108	3.02	0.003	0.1175278	0.5511142
dlnSPY						
L1.	-0.2126349	0.5966945	-0.36	0.722	-1.382135	0.9568649
dlnGLD						
L1.	-0.54757	0.6483133	-0.84	0.398	-1.818241	0.7231007
Cons	0.00451943	0.0210292	2.15	0.032	0.0039778	0.0864108
dlnSPY Equation						
dlnBTC						
L1.	0.012626	0.0215874	0.58	0.599	-0.0296845	0.0549366
dlnSPY						
L1.	0.0268473	0.1164541	0.23	0.818	-0.2013986	0.2550931
dlnGLD						
L1.	0.1185196	0.1265283	0.94	0.349	-0.1294712	0/3665105
Cons	0.0088697	0.0041042	2.16	0.031	0.0008257	0.0169137
dlnGLD Equation						
dlnBTC						
L1.	0.029039	0.017668	1.64	0.1	-0.0055897	0.0636677
dlnSPY						
L1.	-0.2227937	0.0953109	-2.34	0.019	-0.4095997	-0.0359877
dlnGLD						
L1.	0.2642778	0.1035561	2.55	0.011	0.0612116	0.04672441
Cons	0.0037501	0.003359	1.12	0.264	-0.0028334	0.0103337

d) Causality Analysis

A Granger causal analysis is performed. Table 4 shows the Granger results. The results show that changes in SPY and Gold prices do not granger cause the other, and vice versa. This means lagged values of SPY and Gold are not useful for forecasting Bitcoin because changes in one period do not affect the subsequent period.

Table-4

Equation	Excluded	chi2	df	Prob > chi2
dlnBTC	dlnSPY	0.12699	1	0.722
dlnBTC	dlnGLD	0.71336	1	0.398
dlnBTC	ALL	0.88607	2	0.642
dlnSPY	dlnBTC	0.34208	1	0.559

dlnSPY	dlnGLD	0.87742	1	0.349
dlnSPY	ALL	1.0728	2	0.585
dlnGLD	dlnBTC	2.7014	1	0.1
dlnGLD	dlnSPY	5.4641	1	0.019
dlnGLD	ALL	6.128	2	0.047

e) Cointegration Test

Cointegration is a statistical strategy used to examine the long-run or for a certain time period correlation between two or more non-stationary time series. The approach aids in the determination of long-run parameters or equilibrium for two or more sets of variables. Using the Johansen Test for Cointegration on the logarithm of the time series, the trace statistic (12.53) is less than the 5% critical value (29.68) at rank 0, suggesting that there is no cointegrating series in the model. At the normal level of the dataset, there is cointegration at rank 1. Table 5 shows the results.

Table-5

Johansen test for cointegration					
Trend : Constant					**Number of obs = 85**
Sample: 3 thru 87					**Number of lags = 2**
Rank	**Params**		**LL Eigenvalue**	**Trace Statistics**	**Critical value 5%**
0	12	-1353.7393	.	31.3861	29.68
1	17	-1344.3119	0.19894	12.5313*_	15.41
2	20	-1338.496	0.12789	0.8997	3.76
3	21	-1338.0462	0.01053		

f) ARDL Model

As there is no cointegration present, we are able to run the ARDL model. ARDL model is able to measure both short and long-run effects. ARDL analysis used lags while analyzing the data. So, For ARDL first, we used to check the lags. First, we check the lags of Bitcoin our dependent variable then the lags of independent variables.

Table-6

Lag-order selection criteria								
Sample : 5 thru 87							**Number of obs = 83**	
Lag	**LL**	**LR**	**Df**	**P**	**FPE**	**AIC**	**HQIC**	**SBIC**
0	-917.83				2.4e+88	22.1522	22.1522	22.1696
1	-794.987	245.69	1	0.000	1.3e+07	19.2279	19.279	19.2628
2	-787.006	15.962	1	0.000	1.1e+07	19.0262	19.0714	19.1237
3	-786.734	.54338	1	0.461	1.1e+07	19.007	19.1007	19.1704
4	-782.215	9.0386	1	0.003	1.1e+o7*	18.969*	19.0276*	19.1147*

*optimal lag
Endogenous: btc
Exogenous: _cons

The results show that the optimal lag for Bitcoin is 4. After checking the lag for Bitcoin, we also check the lag of independent variables.
Lags of SPY
Table-7

Lag-order selection criteria								
Sample : 5 thru 87							**Number of obs = 83**	
Lag	**LL**	**LR**	**Df**	**P**	**FPE**	**AIC**	**HQIC**	**SBIC**
0	-470.665				5052.08	11.3654	11.3771	11.3946
1	-310.356	320.62*	1	0.000	108.721*	7.52665*	7.55007	7.63675
2	-310.297	.11807	1	0.731	111.216	7.54932	7.58445	7.66309
3	-310.181	2.2325	1	0.135	110.91	7.54652	7.59335	7.66309
4	-307.919	2.5224	1	0.112	110.222	7.54023	7.59877	7.68594

*optimal lag
Endogenous: SPY
Exogenous: _cons

Lags of SPY is 1.

Table-8

Lag-order selection criteria								
Sample : 5 thru 87							**Number of obs = 83**	
Lag	**LL**	**LR**	**Df**	**P**	**FPE**	**AIC**	**HQIC**	**SBIC**
0	-377.781				538.823	9.12726	9.13897	9.15641
1	-235.257	285.05	1	0.000	17.7994	5.71703	5.74045	5.77532
2	-232.178	6.1582*	1	0.013	16.93	5.66693	5.70206*	5.75436*
3	-230.822	2.7108	1	0.100	16.7864	5.65837*	5.7052	5.77494
4	-230.822	.00099	1	0.975	17.1968	5.68245	5.74099	5.82817

*optimal lag
Endogenous: gld
Exogenous: _cons

From these three lags analysis we find that the lag of BTC is 4, lag of SPY is 1, and lag of Gold is 3 using AIC criteria. Now we run ARDL model using these lags.

Table-9

ARDL(4,1,3) regression						
Sample 5 thru 87					**Number of obs**	= 83
					F(10, 72)	= 238.99
					Prob > F	= 0.0000
					R-squared	= 0.9708
					Adj R – squared	= 0.9667
Log likelihood = -771.25026					**Root MSE**	=2819.5159
Btc	**Coeffivient**	**Std. err.**	**t**	**P>| t |**	**[95% conf.**	**Interval]**
btc						
L1.	1.217975	.1143623	10.65	0.000	.9899977	1.445952
L2.	-.1790897	.1941638	-0.92	0.359	-.5661483	.3079688
L3.	-.4520476	.2130792	-2.12	0.037	-.8768132	-.027282
L4.	.2658606	.1307743	2.03	0.046	.0051668	.5265544
spy						

- -	79.31343	34.18002	2.32	0.023	11.1768	147.4501
L1.	-52.62362	34.09261	-1.54	0.127	-120.586	15.33875
gld						
--	-105.3291	81.15691	-1.30	0.198	-267.1124	56.45423
L1.	-17.71432	131.1023	-0.14	0.893	-279.062	243.6333
L2.	74.22059	131.9752	0.56	0.576	-188.8672	337.3084
L3.	78.69327	89.32969	0.88	0.381	-99.3822	256.7687
_cons	-9369.746	3055.339	-3.07	0.003	-15460.45	-3279.038

The results of the t statistic show the significance of the variable. The t stat of SPY is 1.54 which is less than 2 means SPY and Bitcoins have no short-term relationship. The same results are shown by Gold, there is also no significance. So, it is concluded that there is no short and long-run relation between Bitcoin, SPY, and Gold.

Conclusions

There was not enough evidence to suggest that the asset pairs Bitcoin-SPY and Bitcoin-Gold have a connection that is of a monthly-to-monthly nature. Both of these hypotheses were supported by the lack of evidence. On the other hand, it was demonstrated that both of these links were the product of chance occurrences. As a consequence of the findings, we have come to the conclusion that it is not practical to use this model for prediction, but that it is conceivable to use Bitcoin as a hedge against correlation and cointegration within a portfolio. This conclusion was reached as a result of the data that were presented. The observations led to the formation of this conclusion as a natural consequence. Because of the emphasis placed on decreasing variance and, more specifically, downside risk, the MPT and PMPT investment strategies may not find it to be as feasible to employ Bitcoin as their principal asset. This is particularly the case because of the emphasis placed on minimizing downside risk. This is a result of the importance put on reducing the risk of potential losses. Due to the high degree of volatility that Bitcoin possesses, it does not comply with those guidelines and should not be included in a portfolio unless the objective of the portfolio is to deliberately increase the amount of risk that it contains. Only those investors should hold it who are aware of this and who already have a portfolio that is risk-averse; those investors should not hold bitcoin who did not hold any risk-averse portfolio, since it is an investment choice that comes with a high risk and a high potential return. In a further study, the causal link between the three variables should be investigated using more VAR models in order to establish whether or not the results are comparable. In addition, conducting research on the connections between Bitcoin and other cryptocurrencies is another way to reduce the risk of investing in crypto assets.

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