The Impact of Returns and Influence of Crypto Assets on Different Asset Classes

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Abstract

The inception of financial digital assets has attracted young, innovative and tech savvy entrepreneurs, which created the foundation for a new breed of investors. The participants of this ecosystem went through some paradigm shifts till they captured the attention of institutional investors. This market event has pushed the digital markets to new levels and forced the ecosystem to adapt to a traditional investment methodology.

This paper will analyze the relationship of crypto assets with other traditional and alternative asset classes, from the perspective of their returns. The aim of this study is to analysis and explore the impact of the investment behavior, over other asset classes, of the participants which operate in dynamic, volatile and high-risk digital markets.

We will try to assess how the returns generated in this novel asset class can influence the possibility of portfolio diversification, which extends towards traditional finance world and other alternative markets.

Key words: Financial Digital Assets, Crypto Assets, Volatility, Returns
J.E.L. classification: G12, C52, D40, F32, F60

1. Introduction

Crypto assets have emerged in the recent years as a mainstream asset class within the spectrum of alternative investments. These assets have transformed and influenced the financial markets rapidly, having millennials and Gen Z as its main promotors. The popularity of these assets has led a dynamic growth within different financial institutions and SMEs, which have engaged using blockchain technology along with the usability and implementations of crypto assets. Most of the statistics that have been reported, indicate that the returns generated by financial digital assets represent the most important and major factor in this proliferation.

Based on the above, we can clearly say that the profits generated by this volatile market attracts new investors and, because of this, the volumes of trading and the participants to this new ecosystem, have been constantly increasing.

The learning curve of crypto assets trading has been steep, as many individuals become more familiar with the digital markets. A consequence of the traders acquisition, is directly proportional with the confidence and motivation for trading other alternative assets, such as metals, commodities and stocks.

This research study investigates the impact of the returns of crypto assets over the metals, stocks and commodities' returns. This analysis will also comprehend whether this impact is positive or negative and what is the magnitude of this influence.

The objective of the research is to compute the impact of these returns from the crypto assets and how it influences the metals, stocks and commodities market behavior. The hypothesis of the study is based on the principle that higher returns from crypto assets, increase the returns on metals, stocks and commodities through improved acknowledgement and understanding of different markets and asset classes.

2. Literature review

In this section, we present a segment of the literature review of the previous studies conducted related to crypto assets, in order to find a research gap on the impact of returns of crypto assets which influence traditional and alternative assets.

Originally, Bitcoin and blockchain technology were approached by Satoshi Nakamoto in Bitcoin's whitepaper from October 2008. Generally, decentralized control systems and cryptography are essential technologies of cryptocurrencies that are used by crypto assets to facilitate security, verification of transactions and also to create additional, similar or more complex assets (Wang, 2021). While Bitcoin and other cryptocurrencies took years for acknowledgement and to become popular, in the recent years they have rapidly expanded and continue to proliferate on the internet, along with other innovations within the space of Blockchain and Distributed Ledger Technology (DLT) (Madey, 2017). Since the acknowledgement of the crypto assets, as a native and innovative asset class, multiple research studies have been conducted.

So far, many research efforts have been performed to evaluate crypto assets' relation with traditional assets through a Value-at-Risk (VAR) methodology. Stavros Stavroyiannis (2018) examined the VAR model and related measures for Bitcoin. He compared the findings with Standard and Poor's SP500 Index and the gold spot price time series. A GJR-GARCH model was implemented, in which the residuals follow the standardized Pearson type-IV distribution. A large variety of VAR measures and back testing criteria were implemented. It was found that Bitcoin was a highly volatile, violating the VAR measures more than the other crypto assets (Stavroyiannis, 2018).

The COVID-19 pandemic consequences provided the first widespread bear market conditions since the inception of crypto assets. Conlon et al. (2020) tested the widely mooted safe haven properties of Bitcoin, Ethereum and Tether from the perspective of international equity index investors. Bitcoin and Ethereum are not a safe haven for the majority of international equity markets examined, with their inclusion for a portfolio downside risk. As Tether successfully maintained its peg to the US dollar, it acted as a safe haven investment for all of the international indices examined.

Similarly, many other researchers put their efforts to analyze VAR for crypto assets. Akkuş & Dergisi (2020) modelled to forecast the cryptocurrency market volatility and VAR dynamics of bitcoin. Khairunnisa et al. (2022) performed a study to analyze cryptocurrency risk analysis during the covid-19 pandemic, where the VAR approach was used. Tan et al. (2021) investigated VAR and returns of cryptocurrencies before and after the crash: long-run relations and fractional cointegration. VAR model of cryptocurrencies has also been evaluated by Boako et al. (2019), Hrytsiuk et al. (2019), Khairunnisa et al. (2022), Stavroyiannis (2018), Trucíos et al. (2020) and Uyar & Kahraman (2019).

Caferra & Vidal-Tomás (2021) examined the behavior of cryptocurrencies and stock markets during the COVID-19 pandemic through the wavelet coherence approach and Markov switching to an autoregressive model. The results showed that a financial contagion scenario was observed in March, since both cryptocurrency and stock prices fell steeply. Despite this turn-down, cryptocurrencies promptly rebounded, while stock markets were trapped in the bear phase. It was observed that the price dynamics during the pandemic depend on the type of the market and the investment behavior.

The examination of the impact of financial digital assets' market on the stock market performance is very important to evaluate the relationship between the incorporated assets. Sami & Abdallah, (2021) analyzed comparative analysis to distinguish the crypto assets and the stock market impact between Gulf countries and other economies in the region. The analysis used the information of crypto assets and the stock market indices of the Gulf countries. Granger causality testing and regression analysis were applied using the instrumental variable with generalized method of moments. The results indicated that there was a significant relationship between the crypto market and the stock market performance in the MENA region. Contrarily, increase in the crypto assets returns reduces the stock market performance. On the other hand, for the non-Gulf the stock market performance had direct relationship with crypto assets' returns.

Gil-Alana et al. (2020) investigated the stochastic properties of six major crypto assets and their bilateral linkages with six stock market indices using fractional integration techniques. Concerning bivariate results within the financial digital assets and testing for cointegration, no evidence cointegration between the six crypto assets was found, which implies that the crypto market is decoupled from the mainstream financial and economic assets. The findings indicated that the significant role of crypto assets in investor portfolios, as they serve as a diversification option for investors, confirming that crypto assets is a new investment asset class. To evaluate sentiment spillover and price dynamics: information flow in the financial digital assets and stock market, Caferra (2022) employed vector autoregressive model and found direct relation of crypto assets with economy.

The literature review suggests a significant gap for the current research study. Based on the fact that this is a valid research topic within the spectrum of alternative and traditional assets, we believe that a study to investigate the relationship among crypto assets, stocks, metals and commodities, is approachable.

3. Data used in the study

To proceed with the study, time series daily data from February 2017 till February 2022 has been used which were downloaded from Yahoo Finance. The total number of observations utilized, after excluding missing data, is 1022.

Four types of asset classes have been used in this study which are constructed by the author from other multiple sub-classes or components. These classes are composed of crypto assets, stocks, metals and commodities. Detailed classification of the asset classes used are presented in table below:

Table no. 1 Asset Classes and Sub-Classes used in the study

#	**Asset Class**	**Sub-Class classification and details**
1	Crypto Assets	Weighted average daily return on 4 crypto assets [*Bitcoin, , Ethereum, Litecoin, Binance Coin*]
2	Stocks	Weighted average daily return on 5 stocks [*Google (Alphabet Inc.), Amazon, Apple, Ford Motor Company, Microsoft Corporation*]
3	Metals	Weighted average daily return on 5 metals [*Rhodium, Gold, Copper, Iridium, Silver*]
4	Commodities	Weighted average daily return on 5 commodities [*Coffee, Cotton, Crude oil, Sugar, Soybean*]

Source: Author's creation

As stated above, each asset class consists of further different components or sub-classes. The weights are created as a share of total volume. Let V be the total volume of trades of crypto assets, stock, metals or commodities included in this study and V_{ij} is the volume of the sub-classes. The weight for crypto assets W_{ij} will be:

$$W_{ij} = \frac{V_{ij}}{V}$$

Where i represents the asset class and j represents the sub-class. The weighted average daily return is computed as follow:

$$X_{wj} = W_j * R_j$$

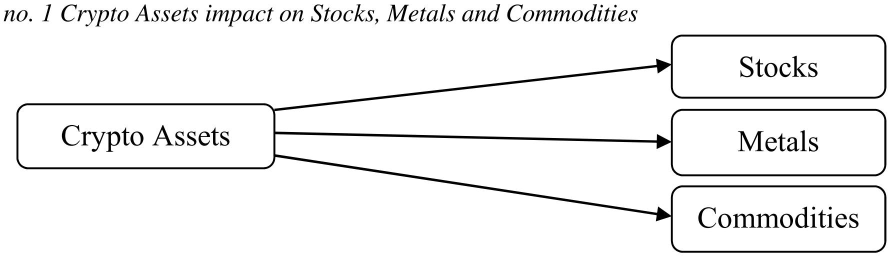
Where R is daily return and X_{wj} is the symbol used for weighted average.

3. Research methodology

We start from the premise that the returns of crypto assets are considered to have an impact on the returns of metals, stock and commodities. Crypto assets have yielded high positive returns, which gives the new investors, confidence in approaching this new alternative markets. With vast learning methods, which are free and accessible, the technological divergence, along with the innovation acumen and trading knowledge, will improve, and new skills can be achieved. Over time, the new alternative markets' investors will get a sufficient level of information, knowledge and trading skills, in order to generate profits from crypto assets. These accumulated skills and profits, will clearly boost their confidence to invest in other markets such as stocks, metals, or commodities. Contrary to this, after a bad performing session within the crypto assets' market, if the results are not as per their expectations, the learning curve for advancing their trading acumen towards other assets, will decrease. Hence, they will not try interacting with any other alternative or traditional assets. As a conclusion of our theory, we will analyze the returns from crypto assets and quantify the exerted impact on the returns of other assets from the perspective of new markets investors. We are assessing the influence of crypto assets, based on the volume of trading and their returns, to identify the impact on other assets which can lead to more complex phenomena, correlations and divergences.

Diagrammatically, this can be presented as follow:

Figure no. 1 Crypto Assets impact on Stocks, Metals and Commodities



Source: Author's creation

In order to advance with our approach, we will engage a Multivariate GARCH model (MGARCH). The ARCH model was developed by Engle (1982) to incorporate conditional heteroscedasticity. This model went through different transformations to solve specific problems. Bauwens et al. (2006), Bollerslev et al. (1988), R. Engle (2009), Silvennoinen & Teräsvirta (2009) and Tim Bollerslev, Robert Engle et al. (1993) detail on Multivariate GARCH (MGARCH) models. A general mathematical equation of MGARCH model is given below:

$$Y_t = BX_t + \varepsilon_t$$

$$\varepsilon_t = H_t^{1/2} + v_t$$

Y_t is an $M \times 1$ vector of dependent variables, B is an $M \times K$ matrix of parameters, X_t is a $K \times 1$ vector of independent variables, which may contain lags of dependent variables; $H_t^{1/2}$ is the Cholesky factor of the time varying conditional covariance matrix H_t, and V_t is an $M \times 1$ vector of zero-mean, unit-variance, independent and identically distributed innovations.

This general MGARCH model transformed by Bollerslev (1990) to a Constant Conditional Correlation (CCC) model in which correlation matrix is time-invariant. This model is simple and have fewer parameters for estimation. However, it may be too restrictive in some empirical studies. Keeping in view these restrictions, R. Engle (2002) proposed Dynamic Conditional Correlation (DCC) MGARCH model where conditional quasi-correlations are used. The next significant addition to MGARCH model was made by Tse & Tsui (2002). In this model in which the conditional correlations at each period are a weighted sum of a time-invariant component, a measure of recent correlations among the residuals, and last period's conditional correlations. Therefore, this model is called Varying Conditional Correlation (VCC).

After the estimation of these three models (CCC, DCC, and VCC) it is important to select the best model for the current dataset. For the purpose of our study, different tests have been developed such as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and Lagrange Multiplier (LM) test. These criteria are estimators of prediction error. In other words, these tests estimated the quality of any estimated model performed in our study. A model which generates lower value of AIC/BIC is considered better because it has lower prediction errors. The best model is selected based on the results of these tests. The next section presents the results of the models and once the model selection has been performed, Spiro-Wilk test of normality is applied to confirm that the error terms generated from the selected model are normally distributed. Another problem of time series data is the serial correlation of the error terms. In this case the error term of current period represents an association with the error term from a previous period. To test the absence of the serial correlation, Q-test is applied. The p-value greater than 5% indicates absence of the related problem.

4. Findings

In this section we will present the results and interpretation with regards to the current analysis and study. We will start with descriptive statistics which will be explained, followed by model selection criteria and detailed analysis of selected model.

4.1. Descriptive Statistics

As previously explained, for the purpose of this study, we have selected a number of assets based on their market capitalization, influence, heritage and prestige, from different sectors of traditional and digital markets.

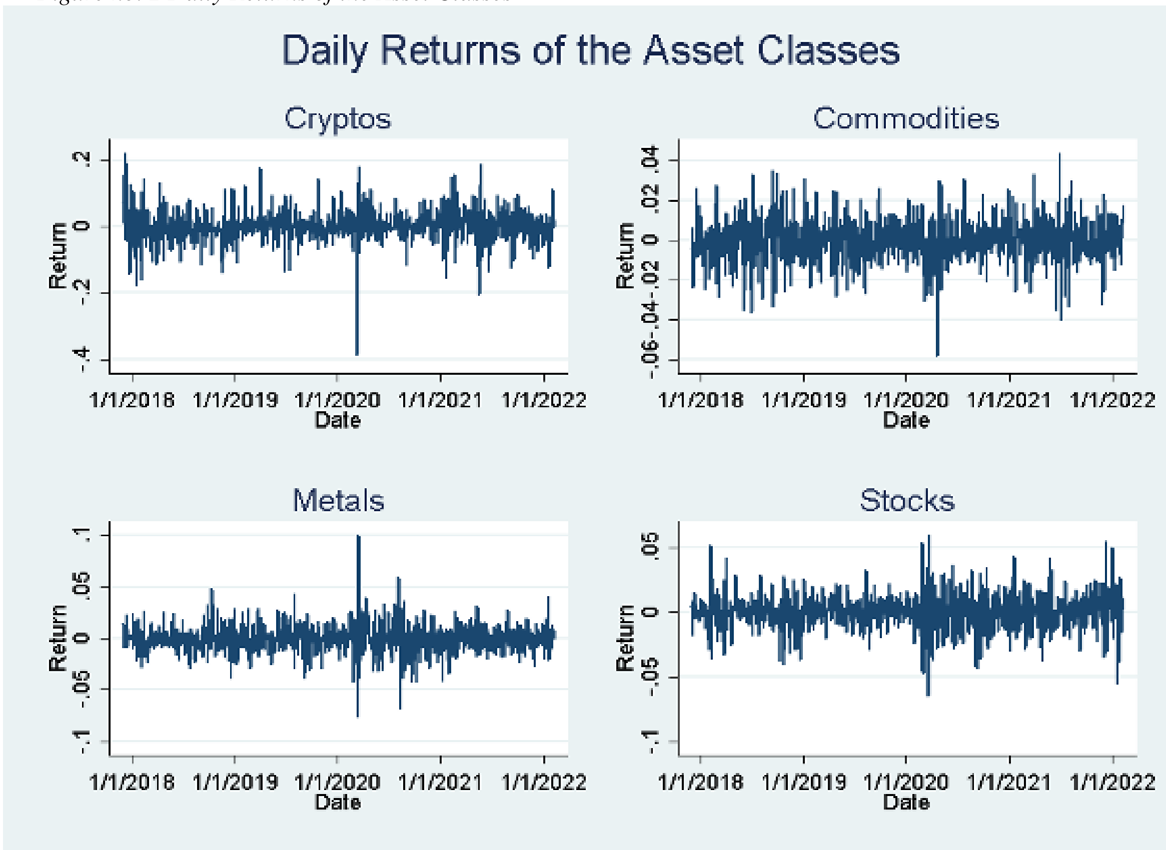
Table no. 2 Descriptive Statistics

Asset Class	Obs	Mean	Std. Dev.	Min	Max
Cryptos	1022	.0027	.0474	-.3852	.2218
Commodities	1022	-.0003	.011	-.0582	.0437
Metals	1022	-.0002	.0135	-.0765	.0998
Stocks	1022	.0003	.0136	-.0648	.0592

Source: Author’s creation

Table 2 presents descriptive statistics of the asset classes used in this research: crypto assets, commodities, metals, and stocks. The descriptive statistics include total number of observations, mean value, standard deviation, minimum, and maximum. The average return of crypto assets, commodities, metals and stocks is 0.27%, -0.03%, -0.02% and 0.03% respectively. Commodities and Metals have negative average return while average returns from Stocks and Crypto Assets are positive. The Crypto Assets have highest average return among the four asset classes. The maximum return of cryptos is 22.18% while minimum return is -38.52%. The maximum returns of commodities, metals and stocks is 4.37%, 9.98% and 5.92% respectively. The standard deviations of all of the four asset classes is greater than mean values. This indicates greater spread/volatility in the returns. The visual presentation of the average return of all asset classes is presented in Figure 2. Commodities have lowest volatility among the variables while cryptos have highest volatility.

Figure no. 2 Daily Returns of the Asset Classes



Source: Author's creation

Table no. 3 Matrix of correlations

Variables	(1)	(2)	(3)	(4)
(1) Cryptos	1.0000			
(2) Commodities	0.0726	1.0000		
(3) Metals	0.0848	0.0813	1.0000	
(4) Stocks	0.1271	0.1167	0.1318	1.0000

Source: Author's creation

Table 3 presents the matrix of correlation between the Asset Classes. The correlation coefficient ranges between -1 and +1. The values closer to zero indicates weak leaner correlation and value near 1 indicates a strong correlation. The linear correlation among the four asset classes is close to zero which indicates that all of the variables have a linearly weak correlation.

4.2. Results of the Modelling

Following the methodology presented in previous section, Multivariate GARCH (MGARCH) model is applied. Within the MGARCH three models have been analyzed. The best model is than selected based on AIC, BIC, and Log Likelihood (LL) of the model. The best model for the same dataset produces minimum AIC/BIC values and improves significance of the coefficients and model as a whole. According to these criteria, the model which produces lowest AIC/BIC values or highest LL is considered the best model. The results of the criteria for three models have been presented in table 4. According to the selection criteria, Dynamic Conditional Correlational (DCC) model is the most suitable model among the three models. It produced lowest AIC/BIC values and highest LL values.

Table no. 4 Model Selection Criteria

Model	Obs	LL(model)	Df	AIC	BIC
CCC	1,021	9220.405	24	-18392.81	-18274.52
DCC	1,021	9227.539	26	-18403.08	-18272.94
VCC	1,021	9226.220	26	-18400.44	-18272.30

Source: Author's creation

After the DCC model has been selected based on model selection criteria stated above, the model statistics of the most suitable model (DCC) are presented in table 5. The number of observations used in the analysis are 1021. One observation is less than total observations that is because of inclusion of lagged variable in the analysis. Chi-Sq value of Wald test is 29.37 and its corresponding p-value is 0.0006 which is below 0.05. This indicated that the overall the model is statistically significant.

Table no. 5 Model Statistics

Mean dependent var	0.0003	SD dependent var	0.0136
Number of obs.	1021	Chi-square	29.37
Prob > chi2	0.0006	Akaike crit. (AIC)	-18403.08

Source: Author's creation

Table no. 6 Dynamic Conditional Correlation MGARCH model

Equation	Asset Class	Coef.	t-value	p-value	[95% Conf	Interval]	Sig
Eq1:Commodities							
	Cryptos	.019	2.65	.008	.005	.0334	***
	L.Cryptos	.0151	2.10	.0362	.001	.0293	**
	L.Commodities	-.0397	-1.19	.2332	-.105	.0256	
	Constant	-.0002	-0.49	.6226	-.0008	.0005	
ARCH Commodities							
	L.Arch	.0593	3.76	.0002	.0284	.0902	***
	L.Garch	.8838	29.18	0.000	.8245	.9432	***
	Constant	6.87e-06	2.61	.009	1.71e-06	0.000012	**
Eq2:Metals							
	Cryptos	.0183	2.23	.0255	.0022	.0343	**
	L.Cryptos	.0152	1.93	.0541	-.0003	.0306	*
	L.Metals	-.0053	-0.16	.8722	-.0692	.0587	
	Constant	-.0002	-0.64	.5232	-.001	.0005	
ARCH Metals							
	L.Arch	.0714	4.30	0	.0389	.1039	***
	L.Garch	.8881	31.38	0	.8326	.9435	***
	Constant	0.000	2.43	.0151	0.000	0.000	**
Eq3:Stocks							
	Cryptos	.0228	2.97	.003	.0078	.0379	***
	L.Cryptos	.0077	1.01	.3137	-.0072	.0226	
	L.Stocks	-.0671	-1.99	.0462	-.1331	-.0011	**
	Constant	.0007	2.04	.0412	0	.0014	**
ARCH Stocks							
	L.Arch	.1213	5.25	0	.076	.1666	***
	L.Garhc	.8504	33.15	0	.8001	.9006	***
	Constant	0.000	3.09	.002	0.000	0.000	***
Correlations							
Commodities, Metals		.0809	1.16	.2456	-.0557	.2176	
Commodities, Stocks		.1379	2.00	.0457	.0027	.2732	**
Metals, Stocks		.0628	0.89	.3741	-.0757	.2014	
Adjustment							
	lambda1	.0136	2.38	.0175	.0024	.0249	**
	lambda2	.9723	65.32	0	.9431	1.0015	***

Source: Author's creation

The coefficients of DCC MGARCH model are presented in table 6. The model produces coefficients of independent variables, ARCH and GARCH terms, correlations and adjustments. Similarly for each coefficient the table presents its t-value, p-value, confidence interval, and significance (columns). According to the results, cryptos have statistically significant and positive contemporary effect on commodities, stocks and metals. This indicated that an increase in return from cryptos leads to a better return from stocks, commodities and metals. Crypto Assets have highest impact on stocks and lowest impact on commodities.

First column of the table 6 represents different equations estimated using DCC model. The first equation is for commodities followed by its ARCH equation. The return on crypto assets have positive impact on the returns of commodities. Its magnitude is 0.019 and it is statistically significant at 1% level of significance. The impact of lag of crypto assets on returns of commodities is positive and representative with regards to a 5% level of significance. The equation ARCH commodities is modelled on ARCH term and GARCH term. The ARCH term indicates that volatility or variance of error term is a linear function of previous error terms. The GARCH term is included to overcome the problem of autocorrelation in the variance of error. Both of the coefficients are significant at a 1% level of significance. The constant term is also valid at a 5% level of significance.

The second equation presents impact of returns on crypto assets on metals. The crypto assets have positive and significant impact on return of metals and it is statistically significant at a 5% level of significance. The lagged effect of cryptos on metals is minimal at a 5% level of significance, but we can note that it is still positive. The variance of metals has ARCH and GARCH term and both of the coefficients are statistically valid at a 1% level of significance.

The last equation presents the coefficients for the stocks equation. The contemporary effect of crypto assets on stocks is positive and statistically significant at a 1% level of significance. However, its lagged effect is unsubstantial at a 5% level of significance. Contrary to the previous equations, the lagged effect of the dependent variable of stocks, is negative and statistically significant. The variance of stock has significant ARCH and GARCH term.

The correlations between the pairs are insignificant except commodities and stocks, which are significant at a 5% level of significant. This means that the return of this pair is correlated, though the coefficient of correlation indicates not a very strong correlation.

$\lambda 1$ and $\lambda 2$ are parameters that govern the dynamics of conditional quasi-correlations. $\lambda 1$ and $\lambda 2$ are positive (non-negative) and satisfy $0 \leq \lambda 1 + \lambda 2 < 1$. In other words, their sum must be between 0 and 1. In this analysis, both of these parameters are statistically valid, important and satisfy the conditions. This means that the covariances and correlations between the variables are dynamic rather than constant. These parameters further endorse our DCC model.

Table no. 7 Shapiro-Wilk W test for normal data

Variable	**Obs**	**W**	**V**	**Z**	**Prob>z**
R_Commodities	1,021	0.9852	9.4920	5.5780	0.0000
R_Metals	1,021	0.9596	25.9740	8.0730	0.0000
R_Stocks	1,021	0.9720	17.9740	7.1600	0.0000

Source: Author's creation

Table 7 presents Shapiro-wilk tests to check the normality of the residuals from the three equations. The p-value for all of the three tests is below .05 therefore we can reject the null hypothesis of non-normal error terms from the equations.

Table no. 8 Serial Correlations Test for Residuals from Metals

LAG	AC	PAC	Q	Prob>Q
1	-0.0182	-0.0182	.33942	0.5602
2	-0.0374	-0.0378	1.7741	0.4119
3	0.0312	0.0298	2.7712	0.4283
4	-0.0258	-0.0262	3.455	0.4848
5	0.0722	0.0739	8.8161	0.1166
6	0.0131	0.0127	8.9919	0.1740
7	0.0100	0.0179	9.0942	0.2460
8	-0.0112	-0.0153	9.2239	0.3238
9	0.0191	0.0231	9.5997	0.3838
10	0.0259	0.0200	10.294	0.4151

Source: Author's creation

Table no. 9 Serial Correlations Test for Residuals from Stocks

LAG	AC	PAC	Q	Prob>Q
1	-0.0457	-0.0457	2.1345	0.144
2	-0.0495	-0.0517	4.6428	0.0981
3	-0.0031	-0.0078	4.6526	0.1991
4	0.0121	0.0091	4.8021	0.3082
5	0.031	0.0318	5.7914	0.327
6	-0.0093	-0.0052	5.8811	0.4366
7	0.0087	0.0113	5.9592	0.5445
8	-0.0565	-0.0571	9.2487	0.3218
9	0.0111	0.0053	9.3754	0.4034
10	0.0038	-0.0016	9.3903	0.4955

Source: Author's creation

Table no. 10 Serial Correlations Test for Residuals from Commodities

LAG	AC	PAC	Q	Prob>Q
1	0.0222	0.0223	0.50615	0.4768
2	0.0852	0.085	7.9468	0.0188
3	-0.0081	-0.0119	8.0138	0.0457
4	0.0171	0.0103	8.3124	0.0808
5	-0.0003	0.0009	8.3125	0.1398
6	0.0115	0.0092	8.4488	0.207
7	0.0452	0.0456	10.552	0.1594
8	-0.0293	-0.0331	11.435	0.1782
9	0.0105	0.0046	11.549	0.24
10	-0.0077	-0.0021	11.61	0.312

Source: Author's creation

To further authenticate the model, serial correlation tests are presented in tables 8-10. The Q statistic and its corresponding p-value indicates no sign of the presence of serial correlation. The p-values are above 5% level of significance therefore we can reject the null hypothesis of presence of serial correlation up to lag 10 and conclude that residuals from the equations are serially independent.

5. Conclusions

Financial digital assets have been integrated within the investment environment as a novel alternative asset class. Most of the research performed on crypto assets have been from the perspective of understanding the performance of these assets, under the pressure of different traditional factors, which are thoroughly analyzed in the traditional finance world. As correlations, divergences and spillover effects have been a common subject of study, we wanted to assess how crypto assets influence and impact other asset classes.

Based on the overview of the descriptive statistics, crypto assets have highest aggregate average return among the four asset classes taken in consideration in this study. The standard deviation of the crypto returns is 0.031 which is relatively high. The value of aggregate average return suggests that investments in crypto assets is the most suitable option, from all the asset classes which were investigated. However, due to high standard deviation, there is a high risk associated to this asset class as well, which indicates that the investors must be careful in their decisions when considering allocations.

The developed MGARCH model is analyzed and tested using three models named; CCC, DCC and VCC. The most suitable model is DCC which is selected based on log likelihood, AIC and BIC. The MGARCH-DCC model is further tested for autocorrelation, heteroscedasticity and normality. The normality test rejects the null hypothesis and indicated that all of the three equations in the DCC generated normal residuals. The normal residuals are necessary for efficient and un-biased coefficients. Furthermore, there is no serial correlation between residuals and residuals are free from heteroscedasticity.

The MGARCH-DCC model analyzed three equations and the model is statistically significant and valid. Most of the coefficients of the model are statistically representative at a conventional 5% level of significance. The model analyzes contemporaneous impact of returns of crypto assets on metals, stocks and commodities. We have found that the returns of crypto assets have significant and positive impact on all the other asset classes studied in this research. This indicates that as the returns of cryptos provide a positive results, their influence for the other asset classes will create a momentum of interest from its main participants.

Another aspect drawn from our research is that the investment behavior of the participants within the crypto asset class is different from other traditional and alternative asset classes. This ecosystem is mainly composed of millennials and Gen Z investors who are tech savvy and can tolerate high risk scenarios. The investors generated by this new asset class differentiate themselves from the traditional finance world, as they understand and research technological innovations. The technological gap identified with the investors associated within these asset classes, is quite high and is directly proportional with the risk appetite. These are important factors to be considered, as we believe their acumen and cumulated knowledge in these digital markets create all the necessary conditions for them to diversify and interact with other financial markets.

The field of financial digital assets has been struggling with the adoption and acknowledgement of these assets for quite some time, and as a result, institutional and mature investors started paying attention to these digital markets quite late. An influx of capital was seen from the traditional finance world within the recent years, especially within the COVID-19 period.

As financial digital assets became a mainstream class within the spectrum of alternative assets, and many financial players invested in the space, we could clearly see signs of correlation with traditional market, especially in distressed periods. Our approach for this study, comes from the angle of understanding how the profile of a crypto assets' investor, interacts and impacts with other asset classes, especially coming for a novel, infant and dynamic environment which is representative for the financial digital asset class.

We can conclude that the investment methodology has not changed and, clearly, the investors which perform in high-risk digital markets, will always try to diversify their allocations. Based on our results, the exodus towards different investment fields is happening, but at a slow rate and in an organic way. The factors which affect these movement patterns are many, but the returns generated by crypto assets remains a major one. The volatility encountered in the digital markets cannot be matched by alternative and traditional markets, thus the returns and risks are different. We believe that as these new digital markets will mature, we will see a more stable and solid investment climate.

With stability, regulations and safety nets, the investment landscape will change and will accommodate a wide range of investment profiles.

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