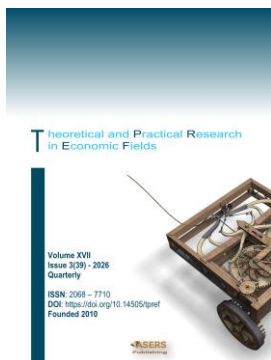


Cryptocurrency Investments: Evidence from Intra Market Interactions



Basim Alzugaiby¹ , Samira Ben Belgacem² ,
Moid U. Ahmad³ 

¹College of Business, Imam Mohammad Ibn Saud Islamic University, Saudi Arabia
baalzugaiby@imamu.edu.sa

²Faculty of Law, Economics and Management Sciences of Jendouba,
University of Jendouba, Tunisia

²Higher Institute of Management of Tunis (ISGT), LR99ES04 BESTMOD,
University of Tunis, Tunisia
kacem.samira@yahoo.fr

³Scholeio Consultants, Lucknow, India

scholeio.learn@gmail.com

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Abstract: The significance of cryptocurrency market to the global financial system motivated the study to probe the intra market dynamics by studying the prices, returns and volumes for five selected cryptocurrencies. The research is based on a sample of daily time series data on prices for the period January 2024 - March 2025. The research applied different types of regression including Vector Auto Regression along with causality analysis to draw inferences. A strong connection was observed between the returns of respective cryptocurrencies while a contrary trend was observed in correlation analysis. DogeCoin emerged as the cryptocurrency with most consistency in trends and relationships for the study variables. Additionally, the monthly portfolio return is observed to be more than the average daily return for four of the five cryptocurrencies studied.

Keywords: bitcoin; volumes; volatility; cryptocurrencies; returns.

JEL Classification: C32; C58; G12; G15.

Introduction

An IMF study paper (IMF,2019) defines cryptocurrencies as ‘Crypto assets are digital representations of value, made possible by advances in cryptography and distributed ledger technology (DLT)’. Blockchain technology, the backbone of most cryptocurrencies, provides a decentralized and immutable ledger that records transactions. Cryptocurrencies are decentralized digital assets that rely on cryptographic methods for securing transactions. Bitcoin was introduced by Satoshi Nakamoto (see Nakamoto, 2009), which led to the development of thousands of other digital currencies. As per an estimate on www.investing.com, the size of the cryptocurrency market (based on market capitalization) is around 2.17 trillion USD (as on August 17, 2026) with around 8059 different types of crypto currencies being traded across the globe. It is dominated by Bitcoin, which owns around 58.4% of the market share followed by Ethereum (10.5%).

Rapidly evolving cryptocurrency market attracts researchers to study different aspects of the financial instrument. There are different opinions if cryptocurrencies are financial assets and if the traditional financial policies and models are applicable on them also. Like other financial assets, cryptocurrencies are also connected and influence inter currency returns (Corbet *et al.*, 2018; Katsiampa, 2017). As high market capitalization stocks drag the inherent stock index, cryptocurrencies with large market share such as Bitcoin influence related indices and other cryptocurrency prices (Dimpfl & Elshiaty, 2021). Information flow (such as news or economic events) is also applicable in crypto market (Bianchi,2020) which yields in a common impact across different crypt assets, although this information transmission needs to be probed further. The unique feature of crypto assets where they can be traded with other crypto currencies, enhances their connectedness. Different cryptocurrencies being global digital assets can be traded on the same platform also, thus optimizing resources. The cryptocurrency market is self-regulated over block chains and thus different from traditional financial markets in terms of operations and counter party risks. Table 1 illustrates the latest data about the sample cryptocurrencies being used in the research.

Table 1. Data on selected cryptocurrencies

As on August 17, 2026 (US Dollars, approximate)		
	Market Capitalization	Price
Bitcoin	1.27 Trillion	63486
Ethereum	229 Billion	1904
ChainLink	7.1 Billion	9.5
DogeCoin	10.89 Billion	0.0702
GateToken	714 Million	6.7

Need for the study: Bringing cryptocurrencies to the mainstream will disrupt the existing investment management strategies. The notion that the fundamental price of Bitcoin is zero (Cheah & Fry, 2015) has encouraged much research to focus on the valuation of cryptocurrencies. The pricing mechanisms of cryptocurrency markets (Al Guindy, 2021), the drivers of volatility (Liu & Serletis, 2019) and the diversification potential of cryptocurrencies (Kurka, 2019) are some recent attempts. Bianchi (2020) investigates the key features of cryptocurrency returns and volatilities. Balcilar *et al.* (2017) study volatility and returns in cryptocurrency markets. Pele *et al.* (2023) used the dimensionality reduction techniques for the separation of cryptocurrencies from other assets. Thus, any research which adds to the existing understanding of valuation and pricing of cryptocurrencies will yield better investment decision making. The given research attempts to study cryptocurrencies with a focus on their returns, volumes, prices and inherent volatilities, which has not much been previously studied. The research aims to explain the interactions amongst the cryptocurrencies with the objective of enhancing its acceptability as a common investment avenue for individuals and portfolio managers.

1. Literature Review

Cryptocurrency is a new financial product which is yet to get a wider acceptability. There are inherent apprehensions about cryptocurrencies and thus different researcher have studied different aspects of it to encourage its usage in the mainstream portfolio management. Al Guindy (2021) did an event study and observed that days on which investors are 'distracted' because of some event, correspond to lower price volatility in cryptocurrency markets and that the increased investor attention to cryptocurrencies has the undesirable effect of increasing price volatility. Liu and Serletis (2019) found a statistically significant transmission of shocks and volatilities among the leading cryptocurrencies and a statistically significant spillover effects from the cryptocurrency market to other financial markets. Dimpfl & Elshiaty (2021) studied the size of cryptocurrency market and observed that 'Bitfinex' is the leading market for Bitcoin and Ripple, while 'Bitstamp' dominates for Ethereum and Litecoin. Bitcoin is the most dominant cryptocurrency and explains most of the volatility among the different cryptocurrencies (Dimpfl & Elshiaty, 2021). Kurka (2019) suggest that the unconditional connectedness between cryptocurrencies and traditional assets is negligible. However, conditional analysis uncovers periods of substantial shock transmission between Bitcoin and traditional assets. Bianchi (2020) found a mild relationship between returns on cryptocurrencies and commodities, and precious metals in particular while the volatility spillover was not observed in this relationship. Bianchi (2020) observed that the trading volume in cryptocurrencies is driven by past returns and that macroeconomic factors do not affect market activity in either the short term or the long term. Ghorbel & Jeribi (2021) found evidence of a higher volatility spillover between cryptocurrencies and lower volatility spillover between cryptocurrencies and financial assets. Corbet *et al.* (2018) found evidence that cryptocurrencies may offer diversification benefits for investors with short investment horizons. Pele *et al.* (2023) observed that the variation among cryptocurrencies, stocks, exchange rates, commodities, bonds, and real estate indexes can be explained by the tail, memory and moment factors of their log-returns. Balcilar *et al.* (2017) studied the dynamics between volume and returns and concluded that it is important in generating a better understanding of information dissemination in asset prices and improving forecasting ability. Katsiampa (2017) study the ability of several GARCH models to explain the Bitcoin price volatility and found the AR-CGARCH model as a good fit to the data. Cheah & Fry (2015) found that Bitcoin exhibits speculative bubbles. Clark *et al.* (2023) found evidence of limited predictive power of lagged commodity returns, while lagged Carbon Dioxide emissions significantly predict the returns of Bitcoin and Ethereum. On the contrary, environmental variables do not show any predictive power in the returns for stable coins (Tether and TrueUSD). Akyildirim *et al.* (2021) found that the average classification accuracy of four algorithms is consistently above the 50% threshold for all cryptocurrencies and for all durations implying a good fit of qualitative forecast in cryptocurrencies.

1.1 Cryptocurrency and Portfolio Investment

Boido and Aliano (2025) estimated that the portfolios with cryptocurrencies outperformed the non-cryptocurrency portfolios in terms of Sharpe Ratios, however, with an increased volatility. Zhou (2025) finds that Bitcoin delivers higher annualized returns than traditional assets like stocks, gold and USD index with significantly higher volatility and drawdowns. Terraza *et al.* (2024) confirms that Bitcoin's price volatility is driven partly by social media sentiment, distinguishing its dynamics from gold and stock markets. Lu *et al.* (2025) observed similar results for both return and volatility spillovers. They comment that highly industrialized countries tend to exert stronger spillover effects as origin countries while more agriculturalized countries exhibited weaker spillover effects as origin countries. Katsiampa (2017) comment that cryptocurrency's high returns may be explained as because of their high volatility. They are characterized by anonymity (Bariviera *et al.* 2017) and are prone to speculative bubbles (Cheah & Fry, 2015).

1.2 Research Gap and Novelty

Previous researchers have focussed less on the inclusion of cryptocurrencies in traditional portfolios (see Boido & Aliano, 2025; Doskočil & Budík, 2025). The research is novel in the context of the explanation it provides, and the arguments given for possible implications of cryptocurrency usage in the traditional investment management philosophy. The results from the risk-return analysis of a crypto based portfolio provide ample evidence in this direction.

There is limited research on valuation models for cryptocurrencies, which is largely considered as a speculative market. A trading volume-return (see Balcilar *et al.* 2017) model is commonly used by technical analysts and investors. Information bubbles may lead to spread contagion and weaken financial stability. Therefore, it is imperative to study the trends in price movements and spillover effects across cryptocurrencies markets and other asset classes to assess and manage the impact on investments. Considering the research gap and research objectives, the study evaluates three models (see equation 1,2 and 3). Here, 'i' varies from 1 to 5 as the counter for each of the five cryptocurrencies.

$$Return_i = Constant + \beta * Volume_i \quad (1)$$

$$Price_i = Constant + \beta * Volume_i \quad (2)$$

$$Return_i = Constant + \beta * Return_i \quad (3)$$

2. Materials and Methods

Clark *et al.* (2023) investigated the lead-lag relationship across the returns of four cryptocurrencies with a focus on the environment in forecasting. Akyildirim *et al.* (2021) also analysed the predictability of twelve cryptocurrencies at daily and minute level frequencies using the machine learning classification algorithms. Bianchi (2020) investigated the key features of cryptocurrency returns and volatilities. Ghorbel and Jeribi (2021) compare the volatilities of five cryptocurrencies, American indices, oil and gold. Ghorbel and Jeribi (2021) based their research on daily prices from the 2016 to 2020 while Balcilar *et al.* (2017) used daily data from the year 2011 to 2016. Corbet *et al.* (2018) study three popular cryptocurrencies and a variety of other financial assets in their research.

An understanding of volatility in returns and volumes is extremely relevant for an effective risk return trade off in investment management. Any study addressing this issue will surely add to the prowess and performance of investors, fund managers and policy makers. Thus, the primary research objective of the research is to dive deep into the intra cryptocurrency dynamics with a focus on volatility and spillover in returns and volumes. Additionally, the results from a risk-return trade-off for an all-cryptocurrency portfolio are also analysed.

Sample and data: Doskočil & Budík (2025) used the daily data for 10 cryptocurrencies for the time period January 2, 2021 to September 1, 2021 to develop a portfolio and evaluate its performance. Boido & Aliano (2025) studied the impact of cryptocurrencies in improving portfolio returns using weekly data for six years. The daily time series data has been extracted for five major cryptocurrencies (see Table 1 and 2) for the time period January 2024 to March 2025. To study the size effect, the cryptocurrencies were randomly selected to form a basket of cryptocurrencies with different sizes (market capitalization). Thus, two cryptocurrencies were selected with high market capitalization (Bitcoin and Ethereum), two with moderate capitalization (ChainLink and DogeCoin) and one with small capitalization (GateToken). The data source for the all the time series is Investing.com.

MS-Excel, SPSS 16.0 and Eviews 13.0 software have been used for data processing and analysis in the research. The Granger causality test (see Granger, 1987) is done to study the directional causality between volumes and returns of respective cryptocurrencies and also between returns amongst the five crypto currencies.

Two types of Vector Auto Regression (VAR) tests are conducted for cryptocurrency returns, one including volumes and returns and the other only on returns.

Here, the returns for all the sample markets and financial instruments have been calculated as Equation 4.

$$\text{Return} = \text{Log} [(P_t)/P_{t-1}] \quad (4)$$

A risk - return trade off analysis is also done for an all-cryptocurrency portfolio including the five sample cryptocurrencies with equal weights (20% each). Monthly portfolio returns are calculated as equation 5 while monthly portfolio risk is calculated as equation 6. Monthly calculations have been done on a non-continuous basis by dividing the study time period into 13 monthly estimates for portfolio risk and return. Sharpe's ratio has been calculated to evaluate overall risk in portfolio performance (see equation 7). The average of the US treasury's 3 months bond yield was considered as the risk-free rate. For the study time period it was calculated as 4.952%.

$$\sum_{i=1}^5 (W_i * R_i) \quad (5)$$

$$\sum_{i=1}^5 W_i^2 * \text{Variance}_i + \sum_{i=1}^5 \sum_{j=i+1}^5 (2 * W_i * \text{Variance}_i * \text{Covariance}_{i,j}) \quad (6)$$

$$\text{Sharpe ratio} = (\text{Portfolio return} - \text{Risk free return}) / \text{Portfolio risk} \quad (7)$$

Table 2. Data variables used in the study

Sl. No.	Variables	Code
1	Bitcoin price	BTC.Pr
2	Bitcoin volume	BTC.Vo
3	Bitcoin return	BTC.Rt
4	ChainLink price	Chn.Pr
5	ChainLink volume	Chn.Vo
6	ChainLink return	Chn.Rt
7	DogeCoin price	Dg.Pr
8	DogeCoin volume	Dg.Vo
9	DogeCoin return	Dg.Rt
10	Ethereum price	Eth.Pr
11	Ethereum volume	Eth.Vo
12	Ethereum return	Eth.Rt
13	GateToken price	Gat.Pr
14	GateToken volume	Gat.Vo
15	GateToken return	Gat.Rt

3. Research Results

This section reports and explains the results from analytical techniques as applied. The Chart 1 graphically illustrates the time series for the respective cryptocurrency return. Here, significant volatility is observed for all the five cryptocurrencies.

Table 3 illustrates the descriptive statistics. Here, 'N' indicates the number of observations in a time series. The maximum volatility was observed for the Ethereum price (Coefficient of Variation, CV=6.1) and the lowest was observed for the GateToken volume (CV=0.46). The lowest skewness was observed for Ethereum price (0.055) and the highest was observed for DogeCoin volume (2.92) and Ethereum volume (2.9). Additionally, all the variables indicated a positive skewness.

Analysing the descriptives for the returns, the highest volatility (CV= -649) with an almost zero mean return was observed for Ethereum. Ethereum returns were also observed as the riskiest crypto asset with a very high volatility and zero mean return. The average mean return for all the cryptocurrencies was observed as low with Ethereum indicating a negative daily mean return for the study time period. The maximum daily mean return was observed for ChainLink (12.5%).

Chart 1: Time series plot for respective returns

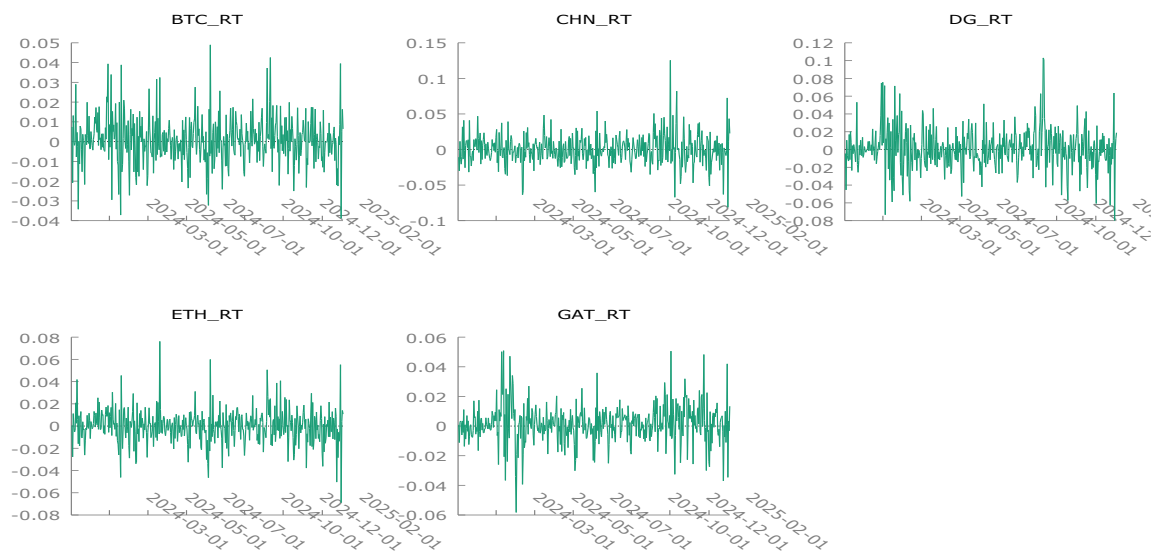


Table 3. Descriptive statistics for prices and volumes for the five cryptocurrencies

	N	Mean	Standard Deviation	Skewness	Kurtosis	CV
BTC.Pr	431	70646.36	17628.09	0.482	-0.77	4.008
BTC.Vol	431	85117.19	50334.45	1.811	5.264	1.691
Chn.Pr	431	16.16	4.35	0.677	-0.093	3.717
Chn.Vo	431	6619280.74	4905658.50	2.831	12.306	1.349
Dg.Pr	431	0.18	0.10	1.127	-0.005	1.781
DG.Vo	431	2917748074.25	2679411941.98	2.919	12.367	1.089
Eth.Pr	431	3030.21	497.53	0.055	-1.183	6.091
Eth.Vo	431	471515.68	318618.43	2.902	15.735	1.480
Gat.Pr	431	9.98	5.28	1.482	1.05	1.891
Gat.Vo	431	610080.16	1323047.27	9.22	116.307	0.461

Table 4. Descriptive statistics (returns)

	N	Minimum	Maximum	Mean	Standard Deviation	CV
BTC.rt	430	-0.039	0.049	0.00074	0.012	16.096
Chn.rt	430	-0.081	0.125	0.00011	0.021	193.891
Dg.rt	430	-0.080	0.103	0.00085	0.023	27.154
Eth.rt	430	-0.069	0.076	-0.00002	0.015	-649.350
Gat.rt	430	-0.058	0.051	0.00147	0.013	8.898

In Table 5 and Table 6 Pearson correlation coefficients have been reported. Most of the correlations were observed as statistically significant and positive. Additionally, almost all the positive correlations are found significant. The highest positive and significant correlation was observed between DogeCoin price and the BTC price (0.92) followed by BTC price with GateToken price (0.85). However, contrary results are observed in the correlation amongst returns and volumes for the five crypto currencies (Table 6). Only, the returns of ChainLink and DogeCoin were found to be significantly correlated with their volumes. Thus, a linear bivariate regression was applied between the returns and volumes for ChainLink and DogeCoin for further analysis (Table 7). Both the relationships were observed as significant but with low R-squared values.

Table 5. Correlations between cryptocurrency prices and volumes

	BTC.Pr	BTC.Vo	Chn.Pr	Chn.Vo	Dg.Pr	DG.Vo	Eth.Pr	Eth.Vo	Gat.Pr	Gat.Vo
<i>BTC.Pr</i>	1	.330**	.618**	.328**	.924**	.262**	.443**	.303**	.848**	.239**
<i>BTC.Vo</i>	.330**	1	.148**	.518**	.377**	.653**	.112*	.726**	.147**	.121*
<i>Chn.Pr</i>	.618**	.148**	1	.489**	.682**	.189**	.593**	.229**	.488**	.210**
<i>Chn.Vo</i>	.328**	.518**	.489**	1	.424**	.466**	.155**	.659**	.213**	.223**
<i>Dg.Pr</i>	.924**	.377**	.682**	.424**	1	.375**	.500**	.295**	.678**	.184**
<i>DG.Vo</i>	.262**	.653**	.189**	.466**	.375**	1	.306**	.577**	-0.018	.117*
<i>Eth.Pr</i>	.443**	.112*	.593**	.155**	.500**	.306**	1	0.061	0.081	0.081
<i>Eth.Vo</i>	.303**	.726**	.229**	.659**	.295**	.577**	0.061	1	.262**	.241**
<i>Gat.Pr</i>	.848**	.147**	.488**	.213**	.678**	-0.018	0.081	.262**	1	.302**
<i>Gat.Vo</i>	.239**	.121*	.210**	.223**	.184**	.117*	0.081	.241**	.302**	1
** Correlation is significant at the 0.01 level (2-tailed).										
* Correlation is significant at the 0.05 level (2-tailed).										

Table 6. Correlations between crypto returns and volumes

	BTC.rt	Chn.rt	Dg.rt	Eth.rt	Gat.rt
<i>BTC.Vo</i>	0.02	-0.027	0.01	-0.041	-0.075
<i>Chn.Vo</i>	-0.057	.135**	-0.089	-0.085	-0.025
<i>DG.Vo</i>	0.063	-0.005	.204**	-0.017	-0.006
<i>Eth.Vo</i>	-0.083	-0.076	-0.088	-0.069	-0.083
<i>Gat.Vo</i>	-0.004	0.006	-0.011	-0.019	0.045

Table 7. Regression results

Independent variable: ChainLink volume			
Dependent variable	R-squared(%)	p-value	Coefficient
ChinLink return	1.8	0.005	5.77E-10
Independent variable: DogeCoin volume			
DogeCoin return	4.1	0	1.76E-12

Table 8. Summary of VAR regressions (Dependent variable: respective returns)

Independent variable	Lag	R-squared(%)	p-value
<i>Bitcoin return and volume</i>	1	0.5	0.32
<i>ChainLink return and volume</i>	1	0.007	0.98
<i>DogeCoin return and volume</i>	1	1.8	0.02
<i>Ethereum return and volume</i>	1	0.4	0.39
<i>GateToken return and volume</i>	2	1.6	0.13

A Vector Auto Regression (VAR) analysis was done to understand the impact of lagged variables (Table 8). The optimum lags are determined considering the Schwarz Information Criteria (SIC) values. The VAR system indicated a significant relationship for DogeCoin only, which was further probed for impulse responses and Forecast Error Variance Decomposition (FEVD). The VAR estimates for DogeCoin are reported in Table 9.

Table 9. VAR estimates (Dependent variable: DogeCoin return)

	Coefficient	p-value
Constant	-0.001	0.26
DG return (lag 1)	0.063	0.2
DG volume (lag 1)	9.23	0.03

Table 10. Impulse responses to a one-standard error shock in DogeCoin volume

Time period	DogeCoin return	DogeCoin volume
1	0	1.64E+09
2	0.0015	1.25E+09
3	0.0012	9.72E+08
4	0.0009	7.56E+08
5	0.0007	5.87E+08
6	0.0005	4.56E+08
7	0.0005	3.54E+08
8	0.0004	2.75E+08
9	0.0003	2.13E+08
10	0.0002	1.66E+08

Table 11. FEVD decomposition of variance for DogeCoin return

Time period	DogeCoin return	DogeCoin volume
1	100	0
2	99.57	0.43
3	99.28	0.72
4	99.1	0.89
5	98.99	1.01
6	98.93	1.07
7	98.89	1.11
8	98.86	1.13
9	98.85	1.15
10	98.84	1.16

Table 12. Pairwise Granger causality tests (lag 1)

Null Hypothesis	p-value
BTC.Vo does not Granger Cause BTC.rt	0.4581
BTC.rt does not Granger Cause DG.rt	0.0104
BTC.rt does not Granger Cause DG.Vo	0.0166
BTC.rt does not Granger Cause Gat.rt	0.0087
BTC.rt does not Granger Cause Gat.Vo	0.0039
Chn.rt does not Granger Cause BTC.Vo	0.0033
Dg.Vo does not Granger Cause BTC.Vo	0.0016
BTC.Vo does not Granger Cause Dg.Vo	0.0048
Eth.rt does not Granger Cause BTC.Vo	0.0093
Gat.rt does not Granger Cause BTC.Vo	0.0043
Chn.Vo does not Granger Cause Chn.rt	0.9787
Chn.rt does not Granger Cause Eth.Vo	9.00E-05
Chn.rt does not Granger Cause Gat.Vo	0.0002
Chn.Vo does not Granger Cause Gat.rt	0.0082
Dg.Vo does not Granger Cause Dg.rt	0.0298
Dg.rt does not Granger Cause Gat.Vo	0.0004
Eth.Vo does not Granger Cause Dg.Vo	0.0086
Dg.Vo does not Granger Cause Eth.Vo	0.012
Dg.Vo does not Granger Cause Gat.rt	0.0618
Eth.Vo does not Granger Cause Eth.rt	0.3711
Eth.rt does not Granger Cause Eth.Vo	0.0003

Eth.rt does not Granger Cause Gat.rt	0.0065
Gat.Vo does not Granger Cause Eth.rt	0.6815
Eth.rt does not Granger Cause Gat.Vo	4.00E-06
Gat.rt does not Granger Cause Eth.Vo	9.00E-05
Gat.Vo does not Granger Cause Gat.rt	0.7345
Gat.rt does not Granger Cause Gat.Vo	0.0344

The causality results for the five sample cryptocurrencies are reported in Table 12 along with the other significant causalities. It is observed that only DogeCoin's volume significantly caused its returns. Although, a significant causality was observed for the returns of different cryptocurrencies implying an inherent flow of information amongst the returns for different cryptocurrencies. This needs to be further probed for dependencies and explanation through linear regressions and was taken up for further analysis.

Analysing the correlations amongst the returns, it is observed that all the correlations are significant at 99% level of confidence with coefficients more than 0.5 for all pairs. This implies that the cryptocurrency market returns move together and mostly in the same direction. This yields in a collective behaviour of the cryptocurrencies which may have a significant collective impact on other integrated financial markets. This is a novel finding from the research which may have large significance in inter market dynamics. This phenomenon was tested for robustness in a linear regression test (Table 14) where returns from each of the cryptocurrency were regressed over returns from another cryptocurrency. The results from bivariate linear regressions validated the findings from the correlation analysis. It is observed that all the bivariate regressions were statistically significant with moderate to high explanation (R-squared values). The highest R-squared value (64%) was observed when BTC returns were regressed over Ethereum returns. This phenomenon may be probed in future research for a more robust generality.

Table 13. Correlations amongst the crypto returns

	BTC.rt	Chn.rt	Dg.rt	Eth.rt	Gat.rt
BTC.rt	1	.629**	.791**	.801**	.590**
Chn.rt	.629**	1	.585**	.705**	.512**
Dg.rt	.791**	.585**	1	.710**	.548**
Eth.rt	.801**	.705**	.710**	1	.594**
Gat.rt	.590**	.512**	.548**	.594**	1

**** Correlation is significant at the 0.01 level (2-tailed).**

Table 14. Linear regression results for respective returns

	R-squared (%)	p-value	Coefficient
Dependent variable: BTC return			
ChainLink return	40	0	0.36
DogeCoin return	63	0	0.41
Ethereum return	64	0	0.63
GateToken return	35	0	0.54
Dependent variable: ChainLink Return			
BTC return	40	0	1.11
DogeCoin return	35	0	0.53
Ethereum return	50	0	0.97
GateToken return	26	0	0.82
Dependent variable: DogeCoin return			
BTC return	63	0	1.54
ChainLink return	34	0	0.64
Ethereum return	50	0	1.1
GateToken return	30	0	0.96

Dependent variable: Ethereum return			
BTC return	64	0	1.03
ChainLink return	50	0	0.51
DogeCoin return	50	0	0.47
GateToken return	35	0	0.69
Dependent variable: GateToken return			
BTC return	35	0	0.65
ChainLink return	26	0	0.32
DogeCoin return	30	0	0.31
Ethereum return	35	0	0.51

Chart 2: Portfolio risk-return trade off

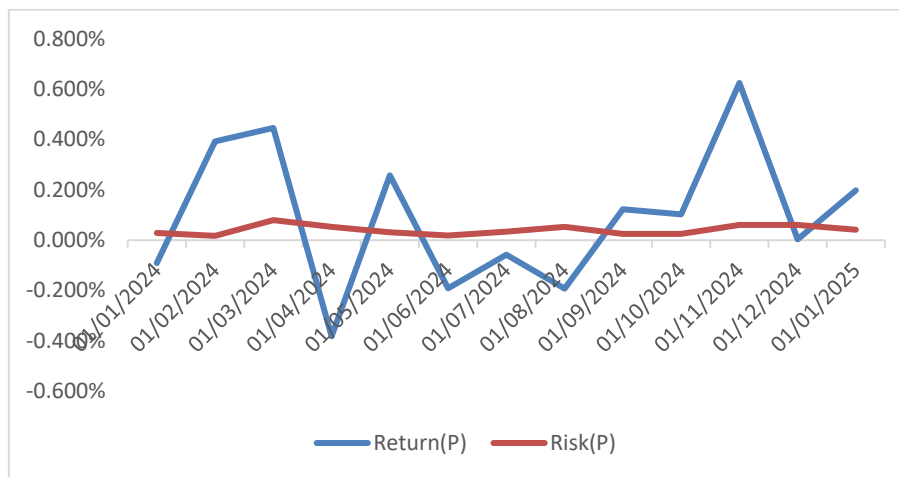


Table 15. Estimates for monthly portfolio risk and return

Month	Return	Risk	Sharpe ratio
January, 2024	-0.091%	0.029%	-173.83
February	0.393%	0.017%	-268.06
March	0.446%	0.080%	-56.30
April	-0.382%	0.053%	-100.60
May	0.258%	0.031%	-151.35
June	-0.192%	0.018%	-285.67
July	-0.058%	0.034%	-147.29
August	-0.192%	0.054%	-95.22
September	0.122%	0.025%	-193.12
October	0.102%	0.024%	-202.00
November	0.625%	0.061%	-70.90
December	0.003%	0.061%	-81.10
January, 2025	0.198%	0.042%	-113.14
Average	0.095%	0.041%	-118.41

It is observed that the average monthly portfolio return (0.095%) is more than the average return of four of the cryptocurrencies except GateToken (average return = 0.15%). Since the risk-free rate (4.952%) is more than monthly portfolio return, all the Sharpe ratio measures were observed as negative. However, the best performance was observed for March 2024 (-56.3 ratio).

Robustness test: To check for robustness amongst the interactions between the returns of the five cryptocurrencies, further unit root tests were performed. All the five return time series were found to be stationary

(Table 16) at level with order $I(0)$. Subsequently, a VAR analysis was done at lag 1. All the five variables were observed to be stationary, indicating stability in cryptocurrency returns.

Table 16. Unit root tests

Variable	ADF statistic	p-value	Decision	Order
BTC.rt	-22.012	<0.001	Reject unit root	$I(0)$
Chn.rt	-20.815	<0.001	Reject unit root	$I(0)$
Dg.rt	-18.968	<0.001	Reject unit root	$I(0)$
Eth.rt	-21.712	<0.001	Reject unit root	$I(0)$
Gat.rt	-12.732	<0.001	Reject unit root	$I(0)$

Table 17. VAR results

	Coefficient	p-value
Dependent variable(BTC.rt)		
Constant	0.001	0.261
BTC.rt(-1)	-0.134	0.163
Chn.rt(-1)	0.033	0.397
Dg.rt(-1)	0.055	0.192
Eth.rt(-1)	-0.100	0.159
Gat.rt(-1)	0.082	0.151
Dependent variable (Chn.rt)		
Constant	0.000	0.879
BTC.rt(-1)	-0.210	0.217
Chn.rt(-1)	0.031	0.66
Dg.rt(-1)	0.096	0.199
Eth.rt(-1)	-0.070	0.578
Gat.rt(-1)	0.033	0.747
Dependent variable (Dg.rt)		
Constant	0.001	0.55
BTC.rt(-1)	-0.450	0.015
Chn.rt(-1)	0.075	0.326
Dg.rt(-1)	0.218	0.007
Eth.rt(-1)	-0.131	0.341
Gat.rt(-1)	0.233	0.033
Dependent variable (Eth.rt)		
Constant	0.000	0.93
BTC.rt(-1)	-0.159	0.197
Chn.rt(-1)	0.037	0.47
Dg.rt(-1)	0.046	0.396
Eth.rt(-1)	-0.075	0.411
Gat.rt(-1)	0.079	0.282
Dependent variable (Gat.rt)		
Constant	0.001	0.036
BTC.rt(-1)	-0.182	0.08
Chn.rt(-1)	0.117	0.006
Dg.rt(-1)	0.052	0.255
Eth.rt(-1)	-0.188	0.015
Gat.rt(-1)	0.159	0.01

Subsequent VAR analysis (Table 17) indicated Dogecoin returns to depend on its lag (coefficient=0.22), lag of Bitcoin (coefficient= -0.45) and lag of GateToken (coefficient=0.033). Additionally, GateToken was observed to be affected by its lag and the lags of all other variables except Dogecoin(p-value=0.25). Here, the coefficients were negative for Bitcoin and Ethereum.

4. Discussion

Efficient Market Hypothesis (EMH) is one financial theory which has significant implication for financial markets. It explains the significance of information on related prices. If the past information (such as volume) can predict prices(returns) it is understood that the model follows a weak form of efficiency. This premise was evaluated in this research and interesting results were observed. The returns of ChainLink and Dogecoin were found to be significantly correlated with their volumes and hence validated the weak form of EMH.

Contributing to the findings from (Balcilar *et al.* 2017) and Liu and Serletis (2019), the study focussed on studying the intra cryptocurrency interactions between the volume and returns for the five sample cryptocurrencies (Table 1 and Table 2). Additionally, the study analysed the dynamics between the daily returns for the sample.

The time series data for the daily returns indicated presence of volatility for all the crypto assets. Ethereum was observed as the most-risky cryptocurrency with a very high volatility (CV=649) in daily returns and almost a zero-mean return. This was confirmed by the raw data descriptives for daily prices where the maximum volatility was observed for Ethereum price (CV=6.1). Here, the lowest volatility was observed for GateToken prices (CV=1.9) and Dogecoin prices (CV=1.8) along with lowest volatility in GateToken returns (CV=8.8). Also, the average mean return for all the cryptocurrencies was observed as low with Ethereum indicating a negative daily mean return for the period. The maximum daily mean return was observed for ChainLink (12.5%). Thus, GateToken and Dogecoin emerged as the cryptocurrencies with the lowest volatility and better returns while Ethereum emerged as the most volatile crypto asset of the five sample digital currencies. This finding is contrary to Dimpfl & Elshiaty (2021) where Bitcoin was observed as the most volatile cryptocurrency. This highlights the understanding that like other financial assets, the cryptocurrency volatility dynamics is also dependent on the sample time period and there are inherent events which have an impact on it. This also highlights a research gap and call for more event studies in the cryptocurrency market. All price and volume variables indicated a positive skewness indicating a presence of extreme values in the daily data. This further emphasizes the need for an event study in the cryptocurrency market.

The correlation analysis for the variables highlighted an interesting trend. Almost all the positive correlations between the prices and volume of the five cryptocurrencies are found as significant with the highest positive and significant correlation as between Dogecoin price and BTC price (0.92) followed by BTC price with GateToken price (0.85). However, contrary observations are demonstrated in the correlation amongst returns and volumes for the five crypto currencies (Table 4). Only, the returns of ChainLink and Dogecoin were found to be significantly correlated with their volumes. This highlighted an anomaly in the trend for prices and returns which calls for further studies focussed on this contrary trend. Here, to confirm this trend, a linear bivariate regression was applied between the returns and volumes for ChainLink and Dogecoin (Table 5). Both the relationships were observed as significant but with low R-squared values contrary to Akyildirim *et al.* (2021).

To check for robustness, Granger causality test was performed on returns, prices and volume of all the sample cryptocurrencies. It is observed that only Dogecoin's volume significantly caused its returns. Although a significant causality was observed for the returns of different cryptocurrencies implying an inherent flow of information amongst the returns for different cryptocurrencies (see Katsiampa, 2017). Thus, conforming to the findings from the descriptives, Dogecoin was observed as one cryptocurrency with better consistency in the trends and relationships amongst volumes, returns and prices. This needed to be further probed for dependencies and explanation through linear regressions and was taken up for further analysis.

Analysing the correlations amongst the returns, it is observed that all the correlations are significant at 99% level of confidence with coefficients more than 0.5 for all pairs. This implies that the cryptocurrency market returns move together and mostly in the same direction. This conforms to Ghorbel and Jeribi (2021) and Liu and Serletis (2019) where they observed a statistically significant transmission of shocks and volatilities among the sample cryptocurrencies. This yields in a collective behaviour of the cryptocurrencies which may have a significant collective impact on other integrated financial markets. This is a novel finding from the research which may have large significance in inter market dynamics. This phenomenon was tested for robustness in a linear regression test (Table 12) where returns from each of the cryptocurrency were regressed over returns from another cryptocurrency. The results from bivariate linear regressions validated the findings from the correlation analysis. It is observed that all the bivariate regressions were statistically significant with moderate to high explanation (R-squared values). The highest R-squared value (64%) was observed when BTC returns were regressed over Ethereum. This phenomenon

may be probed in future research for a more robust generality. Additional robustness tests were done on cryptocurrency returns by evaluating the lag effects through a VAR analysis (see Pele *et al.* 2023). All the five variables were observed to be stationary, indicating stability in cryptocurrency returns and thus can be considered for portfolio investments. This conforms to Doskocil and Budík (2025).

Subsequent VAR analysis (Table 17) indicated DogeCoin returns to depend on its lag (coefficient=0.22), lag of Bitcoin (coefficient= -0.45) and lag of GateToken (coefficient=0.033). Additionally, GateToken was observed to be affected by its lag and the lags of all other variables except Dogecoin(p-value=0.25). Here, the coefficients were observed negative for Bitcoin and Ethereum.

Bianchi (2020) observed that the trading volume for cryptocurrencies is driven by the past information conforming to weak form of EMH. Pele *et al.* (2023) also observed that the variation among cryptocurrencies is due to a lag effect. Cryptocurrencies have a dual nature in terms of investment performance as they bring instability as well as an opportunity for diversification (Boido & Aliano, 2025). This is contrary to Doskočil and Budík (2025) where they observed that a cryptocurrency investment portfolio demonstrated profits not only in the optimization period but also in the validation period. Considering the portfolio aspect of risk-return trade off, it is observed that the average monthly portfolio return (0.095%) is more than the average return of four of the cryptocurrencies except GateToken (average return = 0.15%). This implies the significance of diversification and investing in an all-cryptocurrency portfolio rather than investing into isolated cryptocurrencies.

Conclusion

The research aimed and successfully achieved to add more insights to the existing literature about the intra cryptocurrency dynamics. The focus of the study was on the relationship between crypto asset prices, volumes and their returns. Some interesting common trends were observed. A divergent trend was found between the correlations of crypto prices with their volumes and between crypto returns with their volumes. DogeCoin emerged as the cryptocurrency with most consistency in trends and relationships. Ethereum was observed as the most risky cryptocurrency with a very high volatility in daily returns and almost a zero mean return. GateToken and DogeCoin emerged as the cryptocurrencies with the lowest volatility and better returns. The linear regressions as well as the VAR systems, although statistically significant for selected variables could not explain much of the variance between prices and volumes and between volumes and returns, where maximum R-squared value(1.8%) was observed for DogeCoin returns over its volume on a one lag VAR. However, the bivariate linear regressions for crypto returns amongst themselves explained each other efficiently with the highest R-squared(64%) value between BTC and Ethereum returns. Significant causality was observed for the returns of different cryptocurrencies implying an inherent flow of information amongst the returns for different cryptocurrencies (see Katsiampa ,2017).

Further studies: Correlation and descriptive analysis indicated the presence of event shocks and calls for more event studies in the cryptocurrency market. The low R-squared values in regressions of volumes with returns and prices is a concern and further studies are needed with a focus on models aimed to improving this R-squared value. The diversification aspect of cryptocurrencies was highlighted and thus more studies are needed on the portfolios including cryptocurrencies. Previous researches have been sceptical on the portfolio performance of cryptocurrencies with mixed results (see Boido & Aliano, 2025; Doskočil & Budík, 2025). Thus, future studies should focus more on the portfolio aspect of cryptocurrencies (standalone and mixed portfolios).

Managerial implications: The findings from the research are expected to provide inputs to policymakers and decision makers to seriously consider cryptocurrency markets as part of the international business and trade. The managers and policy makers should consider inherent and underlying events and consider lag values for significant relationships. Return is a better estimator than price and should be preferred in financial models by managers.

Declarations

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Credit Authorship Contribution Statement:

Basim Alzugaiby: Project administration, Writing – original draft, Supervision, Writing – review and editing.

Samira Ben Belgacem: Project administration, Writing – original draft, Supervision, Writing – review and editing.

Moid U. Ahmad: Conceptualization, Investigation, Methodology, Project administration, Software, Formal analysis, Writing – original draft, Supervision, Data curation, Validation, Writing – review and editing, Visualization.

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