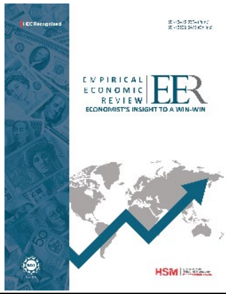
Empirical Economic Review (EER)
Volume 7 Issue 2, Fall 2024
ISSN(P): 2415-0304, ISSN(E): 2522-2465
Homepage: https://ojs.umt.edu.pk/index.php/eer

Article QR



Title:	**Spillover in Mean and Volatility from Bitcoin to other Cryptocurrencies**
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DOI:	https://doi.org/10.29145/eer.72.06
History:	Received: February 10, 2024, Revised: April 25, 2024, Accepted: October 22, 2024, Published: December 10, 2024
Citation:	Bashir, A., Javed, M. M., & Javed, M. (2024). Spillover in mean and volatility from Bitcoin to other cryptocurrencies. *Empirical Economic Review*, *7*(2), 133-144. https://doi.org/10.29145/eer.72.06
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Conflict of Interest:	Author(s) declared no conflict of interest

A publication of
Department of Economics and Statistics, Dr. Hasan Murad School of Management
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Spillover in Mean and Volatility from Bitcoin to other Cryptocurrencies

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Abstract

Worldwide interest in cryptocurrencies has grown significantly. Understanding the nature of cryptocurrency volatility is becoming increasingly important. Therefore, the current study aimed to examine the spillover in mean and volatility from Bitcoin (BTC) to other cryptocurrencies. Seven cryptocurrencies for the time period (2017-2023) were used in the study and they were chosen based on market capitalization. The ARMA (1,1) GARCH (1,1)-M model was utilized to measure the spillover in volatility and mean from BTC to other cryptocurrencies. According to the findings, there exists mean spillover from BTC to other digital currencies except one, that is, Tether. However, spillover in volatility exists from BTC to other cryptocurrencies. The study provided guidance to investors, portfolio managers, and policymakers to allocate assets and diversify their risks.

Keywords**:** ARMA-GARCH, cryptocurrencies, mean and volatility spillover

Introduction

Cryptocurrencies are becoming more and more popular these days. This is because they reduce risks and open up new avenues for stockholders, businesspeople and legislators (Hedegaard et al., 2023). During the last decade, a number of cryptocurrencies has risen multifold. Stepanova et al. (2024) are of the view that more than 10,000 currencies were in use by the end of 2023. Moreover, the combined market capitalization of all active cryptocurrencies exceeds USD 1.5 trillion. Nakamoto (2008) invented Bitcoin (BTC) employing blockchain technology. BTC is regarded as the leading player in virtual currency market, trailed by Litecoin (LTC), Ethereum (ETH), and other coins. ETH is regarded as the second most important cryptocurrency after BTC. The emergence of cryptocurrencies,

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especially BTC, has changed the financial landscape and also attracted considerable attention from experts and academics.

Digital currency, according to Ammous (2018), is the ideal substitute for cash and is a brand-new type of currency. The characteristics of several other financial assets, such as bonds or equities, are shared by cryptocurrency. According to Baur et al. (2018), cryptocurrency can be utilized as a medium of trade or as a tool to invest. The decentralized structure of cryptocurrencies has enhanced this allure. Due to its decentralization and autonomy, people from all walks of life are attracted to cryptocurrencies (Joshi et al., 2018).

The current study found its roots in Efficient Market Hypothesis (EMH). According to EMH, security prices fully reflect the information about the concerned stock. According to Fama (1970), investors may forecast the direction of security prices on the basis of information and might avoid any huge loss in the future. Investors face risks due to the open and frequently decentralized nature of the cryptocurrency market, which may have negative effects, such as unstable capital flows and increased sensitivity to changes in the global financial market. Integration within the cryptocurrency markets may reduce the options for diversification, leaving investors more vulnerable in times of crisis.

By concentrating on the influence of BTC on the mean and volatility of major cryptocurrencies, the current study aimed to fill the gap in literature on cryptocurrencies by taking data up to 2023. Furthermore, this study improved the understanding by examining how links between BTC and other cryptocurrencies may change over time using advanced econometric technique. The study is significant for both investors and academicians as it provides them with useful information to make well-informed decisions. Moreover, it would also help in reducing risks, especially for those who are interested in cryptocurrency portfolios. For academicians, it extends the existing literature by concentrating on the influence of BTC on the mean and volatility of major cryptocurrencies. The results provided a clear understanding of how volatility and mean spread from BTC to other significant cryptocurrencies through the GARCH modeling process. This makes them pertinent for fields, such as market regulation, risk management, market dynamics, and academic literature. The study aimed to clarify how volatility and mean of BTC are transmitted to other significant cryptocurrencies.

Literature Review

Elsayed and Sousa (2024) aimed to explore the relationship between dynamic spillovers of global financial policies and three main cryptocurrencies in four major economies of the world. They reported strong spillover effect from international monetary policies to cryptocurrencies in their sample. Kumah and Baafi (2024) analyzed the time-varying correlation among seven main cryptocurrencies during the COVID-19 pandemic. They observed that these currencies are highly interdependent on each other. Furthermore, they warned the investors to take extreme caution in trading these currencies due to their high interdependence.

Theiri (2024) analyzed the impact of geopolitics' uncertainty on cryptocurrency industry. A strong impact of geopolitics was observed on cryptocurrency market in all time-frames. Mensi et al. (2023) investigated quantile dependencies among five major cryptocurrencies and three major asset classes. Their study reported mixed results. Karimi et al. (2023) explored the spillover effect of cryptocurrencies on each other and on oil and gold markets. They reported that these cryptocurrencies have spillovers among themselves, however, spillover effects on gold and oil were rather negligible.

Saini et al. (2021) analyzed return and volatility spillovers in the BTC market. Findings demonstrated time-varying conditional correlations across cryptocurrencies and the importance of both GARCH and ARCH effects in predicting the conditional volatility. Kumar and Anandarao (2019) analyzed spillover in volatility among the four most popular cryptocurrencies and concluded that ETH and LTC experienced volatility spillover from BTC. Zięba et al. (2019) explored the interdependence of BTC with other cryptocurrencies. They drew the conclusion that changes in the price of BTC have no impact on the pricing of other cryptocurrencies. Koutmos (2018) examined the relationships between eighteen cryptocurrencies and determined that there existed spillover in volatility and return among main cryptocurrencies and that it became stronger over time. Additionally, BTC had a high spillover in volatility.

Urquhart (2017) analyzed the volatility of BTC market. The investigation came to conclusion that BTC had no leverage impact. Ghosh (2014) determined the volatility spillover in the Indian foreign currency market. The study identified volatility spillover effects in FX market of India. They observed that these different markets affected Indian FX market unequally. Chittedi (2012) investigated the connection between oil prices and the Indian stock market and concluded that stock prices had an effect on Indian oil prices. Hoveni and Bonga (2011) investigated the volatility spillover in South Africa's foreign currency market and equity market. They observed volatility spillover from stock to FX market.

Research Hypotheses

H1: There is a spillover in mean from BTC to other cryptocurrencies.

H2: There is a spillover in volatility from BTC to other cryptocurrencies.

Methodology and Data

Data Description

The study estimated the mean spillover and volatility spillover from BTC to other cryptocurrencies. Data for this study included the closing prices of each cryptocurrency, that is, BTC, ETH, Monero (XMR), Ripple (XRP), Tether (USTD), Dash (DASH), and LTC quoted in US dollars for the period ranges from 1st Mar, 2017 to 26th Jul, 2023. These currencies were chosen due to their larger market size in electronic currency market. The return formula was used to compute the return for each currency.

ṙt = log(ṕt/ṕt-1)

where, log = Logarithm, ṙt = constant compounding of a cryptocurrency return, ṕt = the current price of cryptocurrency, ṕt-1 = the past value of cryptocurrencies.

Research Methodology

An ARMA-GARCH model was employed in the current study to examine the spillover in mean and volatility between other cryptocurrencies and BTC. These spillovers were explored by ARMA (1,1) GARCH (1,1)-model. The ARMA-GARCH model combines volatility-based GARCH model with the mean-based ARMA model. The simultaneous analysis of volatility and mean spillover effects is made possible by this integrated model.

The two-stage ARMA-GARCH in mean model (Liu & Pan, 1997) is utilized to quantify how quickly volatility and mean spread from BTC to other cryptocurrencies. The 1st phase is modeling the BTC return series by utilizing ARMA-GARCH (1,1) model. The mean and volatility equation of cryptocurrency is specified below in eq.1 and 2 respectively

$$r_{x,t} = \beta_o + \beta_1.r_{x,t-1} + \beta_2.v_{x,t} + \beta_3.\varepsilon_{x,t-1} + \varepsilon_{x,t},\ \varepsilon_{x,,t} \sim N_{(0,vx,t)} \quad (1)$$

$$v_{x,t} = \gamma_o + \gamma_1.v_{x,t-1} + \gamma_2.\ \varepsilon^2_{x,t-1} \quad (2)$$

where, $r_{x,t}$ demonstrates each day's returns for BTC and $\varepsilon_{x,t}$ is error term, often known as the residual or unexpected return. Mostly, the correction of serial correlation in data is the main goal to include ARMA (1,1) GARCH structure in the model.

The standardized residual and its square from the 1st stage is obtained in the second stage. Afterwards, they are inserted into mean and volatility equation of other currencies using ARMA (1, 1)-GARCH (1, 1) method as follows:

$$ry_{,t} = \beta y_{,o} + \beta y_{,1.r}y_{,t-1} + \beta y_{2.v}y_{,t} + \beta y_{,3}.\ \varepsilon y_{,t-1} + \lambda y.\ \varepsilon y_{,t} + \varepsilon y_{,t},\ \varepsilon y_{,t},\ \sim N_{(0,\ v}y_{,t)} \quad (3)$$

$$vy_{,t} = \gamma\ y_{,o} + \gamma\ y_{,1}.vy_{,t-1} + \gamma\ y_{,2}.\ \varepsilon^2\ y_{,t-1} + \gamma\ y.e^2_{x,t} \quad (4)$$

where, spillover in mean impact from these causes is captured by the standardized error term for BTC, which is $\varepsilon_{x,t}$. The exogenous variable $e^2_{x,t}$ - the standardized error term's square is comprised of conditional volatility equation and is described as $e_{x,t} = \varepsilon_{x,t}/\sqrt{v_{x,t}}$ to investigate the volatility spillover.

Results and Discussion

The return series of seven significant cryptocurrencies was applied to various models in this chapter. Descriptive statistics were used in the initial step to examine the behavior of the data. Each dependent and independent variable was included in the analysis. BTC was the I.V and the D.Vs included ETH, USTD, XMR, XRP, DASH, and LTC.

Descriptive Statistics

The average, max., and min. daily returns for the cryptocurrencies are shown in Table 1, along with skewness and kurtosis, that is, BTC, ETH, XMR, XRP, USTD, DASH, and LTC.

Table 1

Descriptive Statistics

Variables	Bitcoin	Ethereum	Monero	Ripple	Tether	Dash	Litecoin
Mean	0.001357	0.001996	0.001104	0.002085	0.047306	-0.00014	0.001350
Median	0.001105	0.001111	0.002317	8.94e-05	0.000000	0.000149	-1.65E-05
Max.	0.227602	0.258599	0.435383	1.027995	0.078680	0.711032	0.606981
Min.	0.497278	0.589639	0.535391	0.652989	0.057470	-0.70570	-0.48678
SD	0.040323	0.053789	0.056340	0.071507	0.005210	0.063744	0.059663
Skewness	0.803637	0.593340	0.479328	1.988254	1.861593	0.126862	0.625492
Kurtosis	15.51263	12.27045	14.27621	34.93141	55.77955	22.68685	15.64976

According to market figures, the average returns of all currencies are positive except DASH. The mean returns are highest for USTD and minimum for DASH. However, median returns are highest for XMR and negative for LTC. The standard deviation is highest for XRP which indicates that XRP is more volatile and riskier and USTD has less standard deviation as compared to other currencies. This indicates that it is less volatile and has less risk, relative to other currencies. Skewness is positive for all cryptocurrencies which indicates more favorable returns. Kurtosis value of all cryptocurrencies is greater than 3 which means that data is peaked and shows the leptokurtic behavior for returns of these currencies. This shows that all of the study's currencies' log returns are more centered around the mean than around the normal distribution.

Spillover in Mean and Volatility from Bitcoin (BTC) to other Cryptocurrencies -GARCH Model

Using GARCH processes, the current study investigated the linkage of spillover in mean and spillover in volatility among BTC and other cryptocurrencies. The findings observed the transfer of volatility and mean from BTC to other cryptocurrencies utilizing GARCH processes.

Spillover in Mean from Bitcoin (BTC) to other Cryptocurrencies

The current study applied the ARMA-GARCH model and calculated the average spillover from BTC to other cryptocurrencies. By applying an ARMA (1, 1)-GARCH (1, 1) model, Table 2 identifies the parameters of the mean spillover from BTC to other cryptocurrencies along with their p-values.

Table 2

Spillover in Mean from BTC to other Cryptocurrencies

	Bitcoin	Ethereum	Monero	Ripple	Tether	Dash	Litecoin
βo	0.001212	0.002700	0.003153	0.000563	2.74E-06	-0.008680	0.00167
	(0.4740)	(0.0000)	(0.0002)	(0.2611)	(0.7799)	(0.0156)	(0.1233)
$\beta 1$	-1.491415	-0.845260	-0.20140	-0.00279	0.521087	-1.283395	-1.18979
	(0.0112)	(0.0004)	(0.1791)	(0.9885)	(0.0000)	(0.1127)	(0.0008)
$\beta 2$	2.437252	1.166544	-0.92388	-0.92701	-1.58073	1.819443	1.065046
	(0.0707)	(0.1333)	(0.1291)	(0.0000)	(0.3973)	(0.0327)	(0.1233)
$\beta 3$	1.453366	0.797922	0.084870	-0.08423	-0.66060	1.25979	1.139607
	(0.0134)	(0.0000)	(0.5774)	(0.6774)	(0.0000)	(0.12121)	(0.0011)
$\beta 4$	-	0.039234	0.034255	0.033624	-1.5E-05	0.002299	0.041863
		(0.0000)	(0.0000)	(0.0000)	(0.4392)	(0.0393)	(0.0000)

The $\beta 1$ for BTC, ETH, USTD, and LTC is significant which shows the market inefficiency. Therefore, the results of BTC cannot be forecasted through previous price patterns, while for XMR, XRP and DASH, are insignificant that shows market efficiency. This means that the returns of these cryptocurrencies may be predicted from historical price movements. The GARCH term $\beta 2$ is significant for BTC, XMR, and USTD which shows that the forecasted volatility cannot be used to predict today's returns. While for remaining, it is significant, depicting that forecasted volatility can be used to predict todays' returns. The error term $\beta 3$ for BTC, ETH, and USTD is significant, indicating that the previous shocks were interpreted into the present-day market's returns. While for XMR, XRP, DASH, and LTC $\beta 3$ is insignificant, indicating that the previous economic shocks could not be translated into present returns for these markets. The mean spillover $\beta 4$ is significant for ETH, XMR, XRP, DASH, and LTC, indicating the spillover in mean from BTC to these currencies. The positive sign of mean spillover shows that if returns of BTC change, then returns of these currencies would also move in the same direction. Higher returns in BTC result in higher returns for these currencies, while $\beta 4$ for USTD is insignificant which means that mean spillover does not exist from BTC to USTD. Higher returns in BTC result in lower returns for USTD. These results are in line with the findings of Kumah and Baafi (2024).

Spillover in Volatility from Bitcoin (BTC) to other Cryptocurrencies

By applying the ARMA-GARCH model, the current study aimed to ascertain the volatility spillover from BTC to other cryptocurrencies.

By employing ARMA (1, 1)-GARCH (1, 1) model, Table 3 identifies the variables influencing the volatility spillover from BTC to other cryptocurrencies. The study aimed to identify shocks in BTC and how these shocks transmit to other cryptocurrencies.

Table 3

Spillover in Volatility from Bitcoin (BTC) to other Cryptocurrencies

	Bitcoin	Ethereum	Monero	Ripple	Tether	Dash	Litecoin
γ	9.61E-05	-3.89E-06	4.45E-06	8.86E-05	-8.33E-09	0.000143	1.70E-05
o	(0.0000)	(0.0162)	(0.3387)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
$\gamma 1$	0.834293	0.749308	0.785546	0.419339	0.651034	0.850193	0.836454
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\gamma 2$	0.116271	0.205448	0.186728	0.704705	0.203762	0.118222	0.147532
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\gamma 3$	-	9.04E-08	1.06E-07	4.92E-07	1.69E-10	4.69E-08	5.39E-08
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0042)	(0.0000)

The GARCH term γ 1 is significant for all currencies since it demonstrates the volatility in these currencies' long-term trend. This means that historical volatility can be used to forecast current volatility. The residual term γ 2 is also significant for all currencies since it demonstrates how historical price behavior may be utilized to anticipate the current volatility. The value of $\gamma 1+ \gamma 2$ is close to 1 which means that in long-run persistence of volatility exists. The volatility spillover $\gamma 3$ is significant for all currencies which shows transmission of volatility from BTC to all these currencies. The volatility spillover for these currencies shows positive sign which means that volatility transmits positively from BTC to these currencies. Higher volatility in BTC results in higher volatility in these currencies. The results support the findings of Wajdi et al. (2020).

There are a number of reasons for this phenomenon which is why BTC effects other cryptocurrencies. Approximately, 40% of the market for cryptocurrencies is captured by BTC. Since it is the first and oldest type of cryptocurrency, it has the biggest market capitalization. The currency is also the most tradeable. The majority of cryptocurrency investors trade in BTC. Secondly, many companies have started accepting BTC as a payment. Therefore, BTC is the most tradeable currency in cryptocurrency markets. Due to this, all other cryptocurrencies, including BTC, are affected by changes in the price of BTC.

Conclusion

The current study aimed to examine the spillover in mean and spillover in volatility from BTC to other cryptocurrencies. Seven cryptocurrencies, for the time period (2017-2023), were used in the study and they were chosen based on market capitalization. The ARMA (1,1) GARCH (1,1)-M model was utilized to measure the spillover in volatility and spillover in mean from BTC to other cryptocurrencies. Mean spillover showed significant results for ETH, XMR, XRP, DASH, and LTC. It suggested that spillover in mean from BTC to XMR, LTC, ETH, XRP, and DASH exists. The positive values of spillover in mean for all these currencies showed that as BTC's performance grows better, so would ETH, XMR, XRP, DASH, and LTC's. As a result, the conclusion can be drawn that USTD offers a considerable potential for portfolio diversification**.** Similarly, the findings of spillover in volatility are positively significant for all currencies. The significant results indicate the existence of spillover in volatility from BTC to all other cryptocurrencies. Therefore, there would be less opportunity for portfolio diversification of these currencies.

Future Research Implications

This study provided guidance to investors, portfolio managers, and policymakers to allocate assets and diversify their risks. The currencies with less BTC spillover would offer better opportunities for diversification in portfolios. This is because there would be fewer risks in the context of those currencies since they are not impacted by any BTC spillover. The allocation of cryptocurrencies as well as portfolio management is significantly impacted by these findings. This study provided valuable knowledge to entrepreneurs, investors, and policymakers.

Conflict of Interest

The authors of the manuscript have no financial or non-financial conflict of interest in the subject matter or materials discussed in this manuscript.

Data Availability Statement

Data associated with this study will be provided by corresponding author upon reasonable request.

Funding Details

No funding has been received for this research.

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