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Stock Market Response to Investment in Cryptocurrencies in United State: A Dynamic ARDL Simulation Approach

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Abstract

Virtual assets and currency sector are becoming increasingly intertwined. According to new IMF research, the correlation of crypto assets with traditional holdings like equities has increased dramatically as usage has grown, limiting their risk perception investment opportunities, and raising the danger of spillover across financial markets. Theoretical and empirical findings concerning cryptocurrencies and stock market behaviour have been misleading thereby putting policy makers at a crossroads. This paper therefore examines the response of stock market to investment in cryptocurrencies in the US stock market. Monthly data covering the period between February 2016 to February 2022 was used. The answer was achieved using novel dynamic autoregressive-distributed lag (ARDL) simulation techniques along with the Breitung and Candelon causality test. Findings revealed that cryptocurrencies impacted positively on the US stock market. Secondly, investment in Bitcoin and Ethereum is a good predictor of stock market while no evidence of causality between investment in ripple and stock market indices in the US stock market. Thirdly, a long-run relationship exists between investment in cryptocurrencies and behaviour of stock market indices in the United State, and that investment in cryptocurrencies has a significant long-run increasing effect on stock prices in United State.

Subject Areas

Business Finance and Investment

Keywords

Cryptocurrencies, Stock Market, Dynamic ARDL Simulation

1. Introduction

Cryptocurrencies are a globally spreading phenomenon that is frequently and also prominently addressed by the media, venture capitalists, financial and governmental institutions alike [1]. The recent emergence of cryptocurrencies as a new class of financial assets consequently offers a new opportunity to investigate several as yet unexplored aspects of cryptocurrencies. In empirical finance, the role of cryptocurrency markets has grown rapidly in recent years gaining a lot of attention from among academic scholars, the media, government institutions and the finance industry. The upsurge in cryptocurrencies and rapid development of cryptocurrency markets have been attributed to the recent sharp increase in Bitcoin, Ethereum and Ripple trading volume leading to a comprehensive literature on cryptocurrency markets [1].

The cryptocurrency market is seen as a significant fintech advancement that streamlines transactions and serves as a valuable medium of exchange [2]. Such a cryptocurrency has carved out a niche for itself in the worldwide financial markets, owing to its quick development and expansion. In 2018, the cryptocurrency market's market capitalization reached $139 billion, with over 250,000 transactions every day [3]. When compared to the warmer months, the Bitcoin market cap achieved an all-time high in April 2021, having grown by over 1000 billion dollars. Since then, the market capitalization has fallen, reaching around $600 billion at the end of June 2021.

Cryptocurrency is a relatively new phenomenon that is attracting a lot of interest. Crypto assets like Bitcoin and Ethereum have little association with key market indices prior to the deadly Covid-19 pandemic. They were considered to help mitigate risk and function as a protection against volatility as regards other asset classes. However, this changed in early 2020, following the unprecedented central bank crisis reactions. Cryptocurrency prices and stock prices in the United States have both risen as a result of improved global financial circumstances and increased risk appetite among investors. Increased crypto-stocks correlation boosts the prospect of investor attitude spillovers between asset classes, according to the IMF Report (2022) [4]. On the one hand, it is built on a fundamentally novel technology whose future is unknown, but which, in its current form, performs similar activities to other, more traditional assets [5].

Cryptocurrencies gained worldwide attention in 2017 as their prices skyrocketed, prompting investors to pour a large portion of their savings into these new sorts of financial assets. The price excitement, however, could not be sustained, and the crypto price market crashed at the end of 2018. This extreme volatility in the cryptocurrency demonstrates the dangers of investing in this form of asset. Many theoretical and empirical studies that investigated the link between volatility of cryptocurrencies and the behaviour of investment in other assets have reported high volatility as a key determinant of investment behaviour in the market of cryptocurrencies [6]. However, due to a lack of awareness of the nature of cryptocurrencies as investment assets, scholars and experts opined that appropriate returns may not be available [7]. Because of the extreme volatility of cryptocurrencies, Raza, Ahmed, and Aloui, (2022) proposed that investments require a high level of risk [8]. As a result, investors who choose to invest in various markets ought to have a thorough grasp of how cryptocurrencies' returns, and volatility behave.

Although much study has been done to determine the impact of cryptocurrencies on stock market performance, there is no evidence of the stock market's reaction to investment in cryptocurrencies in the literature. Also, empirical findings over the years have been inconclusive. For example, some scholars [9] [10] [11] have argued that cryptocurrencies have a significant positive effect on the stock market indices by moving in the same direction. However, studies by Conlon, Corbet and McGee in 2020 [12] opined that Bitcoin and Ethereum are not safe havens for almost all the stock market indices during the COVID-19 market turmoil and have an adverse effect on the behaviour of the stock market. A study on the relationship between cryptocurrency market and the performance of stock market in the Middle East and North Africa (MENA) region found a mixed result [13]. While cryptocurrency market improves the performance of stock market for countries that have flexibility in the application of the Islamic Sharia rules, the opposite was the case with countries that adhere strictly to Islamic Sharia rules.

This inconclusive result has put policy makers at a crossroads as to how to make a decision concerning investment in cryptocurrencies while also allowing the stock market to thrive. Therefore, the question that one may need to ask is, how does the stock market respond to investment in crypto assets? What effect does investment in cryptocurrencies has on the stock market indices and what is the direction of causality between cryptocurrencies and stock prices. The aim of this paper, therefore, is to investigate the response of stock market to investment in cryptocurrencies using the US stock market.

This paper contributes to existing literature by employing the novel dynamic ARDL simulation estimation technique to investigate the response of stock market to investment in cryptocurrencies in the United State stock market which is assumed to be one of the leading markets in the world. Secondly, the use of the frequency domain causality test as proposed by Breitung and Candelon in investigating the direction of causality between investment in cryptocurrency and stock market indices as opposed to the time domain Granger causality is usually employed by most studies in the literature [14].

Aside from the introduction, the rest of the paper is structured as follows: Section 2 reviews relevant literature, Section 3 presents the model specification, data description and estimation technique employed in the study, The discussion of the empirical results is presented in Section 4 while Section 5 concludes and provide policy implications.

2. Literature Review

2.1. Cryptocurrencies

A cryptocurrency is a digital currency that is based on electronic communication and is meant to function as a medium of exchange with the use of encryption to prevent counterfeiting and fraudulent transactions [15]. A cryptocurrency is a digital money intended to be used as a means of exchange [9]. Cryptocurrency is defined as a digital money that relies on the principles of encryption to process and validate digital transactions [16]. Cryptocurrency transactions are fast to consummate and have low transaction costs. The digital currencies operate on fully decentralized systems and as such bypass financial controllers and regulations. The main types of cryptocurrencies are Bitcoin, Ethereum, Binance Coin, Cardano, Ripple and Tether [17]. The price volatility of cryptocurrencies, as well as the significant energy consumption of mining activities and their application in criminal activities, all contributes to drawbacks to the general adoption of cryptocurrencies as a global means of exchange [18].

2.2. Components of Cryptocurrencies

Cryptocurrencies run on blockchain technology for its attractiveness and usefulness. Blockchain is, as its name implies, a collection of interconnected blocks or an online ledger. Each block comprises a collection of transactions that each network member has independently validated. Every new block must be validated by each node before being confirmed, making forging transaction histories nearly impossible. The contents of an online ledger must be agreed upon by the whole network of a single node, or computer, that keeps a copy of the ledger.

Generally, there are three components of cryptocurrency. The protocol is a computer code that specifies how participants can transact, a ledger that stores the history of transactions, and a decentralized network of participants that update, store, and read the ledger of transactions. These three components also allow cryptocurrencies to operate on a digital peer-to-peer base of exchange by which individuals move currencies from their accounts to the account of others without the need for a central authority to execute the exchange, thus, providing a financial exchange system devoid of a Central Bank or regulating Institution [19].

2.3. The Stock Market

A stock market is a venue where publicly traded corporations' shares are traded. The stock market is a network of exchanges where investors can buy and sell securities such as stocks and bonds [20]. The stock market provides a platform for companies to raise capital to fund their operations by selling shares of stock on the stock market, producing and sustaining wealth for individual investors. In a stock market environment, the primary market is where corporations raise cash by selling shares to the general public in an initial public offering (IPO).

After securities are sold in the primary market, they are traded in the secondary market, where one investor buys shares from another at the current market price or whatever price the buyer and seller agree on. The regulatory authority oversees the secondary market or stock exchanges.

2.4. Functions of the Stock Market

Beyond providing a base for companies to raise funds for operations and continuity, the stock market functions can be broken down into four [21]; control, creation, combination and compensation.

1) **Control:** The separation of managerial authority over corporate resource allocation choices from ownership of the corporation's publicly traded shares is made possible by a stock-market listing.

2) **Cash:** The stock market can be used to raise public funds through an initial public offering (IPO) and one or more secondary public offerings. It may, however, serve a negative cash function through payout to shareholders.

3) **Creation:** Existence of stock markets makes it possible for a start-up company to do an initial public offering (IPO) on the stock market in three to five years motivates private equity (*i.e.*, venture capital) to participate in new company formation.

4) **Combination:** To finance mergers and acquisitions, the stock market allows business shares to be used as a currency rather than cash.

5) **Compensation:** Employee remuneration in the form of stock purchase plans, stock options, or stock awards can be paid in stock rather than cash if the company is listed on the stock exchange.

Under the stock market is the stock exchange. A stock exchange is a centralized marketplace in which financial securities, shares of publicly traded companies, commodities, derivatives and other financial instruments are traded. There are two major stock exchanges in the United States; New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX).

3. Empirical Review

Gil-Alana, Abakah & Rojo (2020) investigate the relationship between cryptocurrencies and stock market indices. The study analysed the connection between the statistical properties of six main market cryptocurrencies and six stock market indices. The cryptocurrencies selected for the study area are Bitcoin, Ethereum, Litecoin, Tether, Ripple and Stellar. A fractional integration technique was used to analyse data. The unit root test results show variables under study to be integrated in mixed order. Final result suggests that no cointegrating relationships between the six cryptocurrencies being studied. Also, the study found no evidence of cointegration between stock market indices and cryptocurrencies which implies that cryptocurrencies have no association with the mainstream financial and economic assets [1].

The volatility and return spillover between cryptocurrencies and stock markets were assessed [22]. The paper analysed daily data covering the period from March 2013 to March 2018. Variables analysed in the study were bitcoin price and stock index prices for five major stock markets (FTSE 100, S & P 500, CAC 40, DAX 30, and Nikkei 225). A multivariate Vector Autoregressive Moving Average (VARMA) AGARCH model was used to estimate data. Results indicate the presence of volatility spillovers in all the five markets which implies that investors migrate their investments to cryptocurrencies between peaks and troughs of the stock market to maximize profits.

The effects of macro-financial indicators on the price volatility of cryptocurrencies in the United States were examined using a panel approach; financial time series data for the period August 2016 to April 2019 were analysed using a Seemingly Unrelated Regressions (SUR) model. Macro-financial variables used in the study were S & P 500 stock market index, gold price, oil price, 2-year benchmark US Bond interest rate and US Dollar index. The study used prices of Bitcoin, Litecoin, Ethereum, and Ripple to proxy cryptocurrencies. Analysis of results indicates a positive relationship between increases in gold price, oil price, S&P 500 index and the prices of cryptocurrencies. Further analysis suggests an adverse relationship between US bond interest rate and US Dollar index which implies that investors may find a safe haven in cryptocurrencies when the US dollar is devalued or US Bond yield decreases.

The determining factors of the prices of the most invested five crypto assets were investigated in relation to the stock market (SP500 index), gold prices, and interest rates in the United States [17]. Secondary time series data over a period of nine years (2010-2018) was analysed. The cryptocurrencies studied were Bitcoin, Ether, Dash, Litecoin, and Monero. Findings suggest that market beta, trading volume, and volatility are significant determinants of crypto prices in both short and long-run. Also, the US Stock market returns (SP500) index was found to have a positive (albeit weak) long-run impact on Bitcoin, Ethereum, and Litcoin, and a negative relationship with the cryptocurrencies in the short run.

The relationship between cryptocurrencies and exchange rates was analyzed and the study used secondary data between 14 February 2014 to 7 March 2018 [23]. A range of fiat currencies was used in the study some of which are Thai Baht, Taiwan Dollar, and Chinese Yuan, while data on cryptocurrency assets, Litecoin, Monero, Bitcoin, Ethereum, Ripple, and Dash were also analysed. A multivariate regression and Granger causality test was employed to analyse data. Evidence suggests that the Thai Baht, Taiwan Dollar, and Chinese Yuan are significantly linked to the six major cryptocurrencies now available to investors around the world.

Hung (2020) investigates the nexus between Bitcoin prices and major stock indices in the Asia-Pacific [23]. The paper studied daily data from Bitcoin (BIT), Bitcoin Futures (BITF), two major stock markets (S & P 500 and Euronext (ENX), and stock index prices of five stock markets in the Asia-Pacific region (Australia (ASX), Hong Kong (HSCI), Japan (NIKKIE), New Zealand (NZ), Singapore (STI). Data analysed covered February 2012 to August 2019. Analysis of data was carried out using a Wavelet transform model. Findings revealed a significant unidirectional association from Bitcoin to the selected Asia-Pacific stock markets in the short, medium, and long-run.

A group of scholars analysed the effects of cryptocurrencies on equity portfolio's performance, and domestic currency. The objective of the paper was to confirm the existence of and effectiveness of hedging in cryptocurrency markets. They focused on analyzing secondary data on five cryptocurrencies (Bitcoin, Ethereum, Monero, Ripple, and Litecoin), equity indices in Aisa (Indonesia, Malaysia, Vietnam, Thailand, and the Philippines), and iShares ETF MSCI World. The asymmetric generalized dynamic conditional correlation (AG-DCC) GARCH was used to analyse data. Findings revealed that cryptocurrencies have a negligible positive hedging effectiveness [24].

Ghorbel & Jeribi (2021) [24] investigates the relationship between volatility in cryptocurrencies and other financial assets. Daily secondary data from 2016 to 2020 on adjusted closing-price of Bitcoin, Dash, Ethereum, Monero, and Ripple cryptocurrencies as well as American Stock indexes returns, oil (WTI), and gold prices were analysed. A Dynamic Conditional Correlation (DCC) GARCH Model and a BEKK-GARCH Model was used to analyse data. Results show that cryptocurrencies exhibit higher volatility spillovers than financial assets. Additionally, results suggest that US investors considered gold and Bitcoin as hedges prior to coronavirus outbreak.

4. Data and Methodology

4.1. Data

To achieve the study objective, a structured monthly data from February 2016 to February 2022 is used for the empirical analysis. The constructed dataset includes stock market indices measured by stock prices, which is the dependent variable. The independent variables are Bitcoin, Ripple and Ethereum. However, exchange rate was added, since it is generally regarded as determinants of stock price indices as supported by (Mattera, Di Sciorio, & Trinidad-Segovia, 2022 [25]: Zubair, 2013 [26]). The data on US S&P were retrieved from https://www.investing.com/ Monthly data on exchange US exchange rate was retrieved from https://www.imf.org/external/np/fin/data/param_rms_mth.aspx while data on Bitcoin, Ripple and Ethereum are sourced from https://www.cryptodatadownload.com/data/

4.2. Methodology

4.2.1. ARDL Model

As rightly stated by Jordan and Philips (2018) [27], the ARDL model of Pesaran, Shin and Smith (2001) [28] stands as an important model for testing relevant theories. As supported by Jordan and Philips, therefore, this approach is employed in investigating the response of US stock market to investment in cryptocurrencies. Evidence has shown that the ARDL estimation technique produces reliable and consistent results irrespective of whether our data series are stationary at levels I(0) or after their first difference I(1) or mutually co-integrated. A study by Harris and Sollis [29] opined that the procedure also gives estimates that are capable of reducing the problems posed by endogeneity in regression. However, the conventional ARDL technique is faced with two major weaknesses. First its approach to bounds testing as regards cointegration may declare the absence of cointegration even when present for small samples (say time points less than or equal to 80) thereby misleading some empirical results. More so, the conventional ARDL models regularly possess complex dynamic structures that are characterized by first differences and lags of first differences, several lags, concurrent values and so on. This complexity makes it difficult in the interpretation of the impacts of the independent variable on the regressors [14].

As a result, Jordan and Phillips (2018) [27] suggested a novel dynamic ARDL technique that is adaptable enough to support the dynamic simulation of various ARDL models. The dynamic simulations performed report the importance of the findings through counterfactual possibilities, rather than the typical hypothesis testing of parameter estimations. The dynamic ARDL model used in this study is specified as follows:

$$\ln SMP_t = \beta_0 + \beta_1 \ln BTC_t + \beta_2 \ln EXCR_t + \varepsilon_t \tag{1}$$

$$\ln SMP_t = \beta_0 + \beta_1 \ln ETH_t + \beta_2 \ln EXCR_t + \varepsilon_t \tag{2}$$

$$\ln SMP_t = \beta_0 + \beta_1 \ln RPL_t + \beta_2 \ln EXCR_t + \varepsilon_t \tag{3}$$

$$\ln SMP_t = \beta_0 + \beta_1 \ln CRYP_t + \beta_2 \ln EXCR_t + \varepsilon_t \tag{4}$$

where $\ln SMP$ is the log of US stock price (S & P 500), $\ln BTC$ represents the price of Bitcoin, $\ln RPL$ is the price for Ripple, $\ln ETH$ represents price for Ethereum, $\ln CRYP$ represents the combined value of the measures of cryptocurrencies (Bitcoin, Ethereum and Ripple) computed by Principal Component Analysis (PCA), and $\ln EXCR$ represent exchange rate

The error correction form for the dynamic ARDL simulations of the econometric models defined in Equations (5)-(8) is as follows:

$$\begin{aligned} \ln SMP_t = \beta_0 + \beta_1 \Delta \ln SMP_{t-1} + \beta_2 \Delta \ln BTC_t + \beta_3 \ln EXCR_t \\ + \beta_4 \Delta \ln EXCR_{t-1} + \beta_5 \Delta \ln EXCR_{t-2} + \varepsilon_t \end{aligned} \tag{5}$$

$$\begin{aligned} \ln SMP_t = \beta_0 + \beta_1 \Delta \ln SMP_{t-1} + \beta_2 \Delta \ln ETH_t + \beta_3 \ln EXCR_t \\ + \beta_4 \Delta \ln EXCR_{t-1} + \beta_5 \Delta \ln EXCR_{t-2} + \varepsilon_t \end{aligned} \tag{6}$$

$$\begin{aligned} \ln SMP_t = \beta_0 + \beta_1 \Delta \ln SMP_{t-1} + \beta_2 \Delta \ln RPL_{t-2} + \beta_3 \ln EXCR_t \\ + \beta_4 \Delta \ln EXCR_{t-1} + \beta_5 \Delta \ln EXCR_{t-2} + \varepsilon_t \end{aligned} \tag{7}$$

$$\begin{aligned} \ln SMP_t = \beta_0 + \beta_1 \Delta \ln SMP_t + \beta_2 \Delta \ln RPL_t + \beta_3 \ln EXCR_t \\ + \beta_4 \Delta \ln EXCR_{t-1} + \beta_5 \Delta \ln EXCR_{t-2} + \varepsilon_t \end{aligned} \tag{8}$$

4.2.2. Causality Test

We also test for Granger causality between these parameters to create a pattern of link between cryptocurrency investment and stock market investing. We use the Breitung and Candelon's Granger causality test in the frequency domain [30] In this study, the approach is preferred because it outperforms alternative time domain approaches in the following ways: it produces better results for short-term series with seasonal and other potential economic episodes, it is more suitable for non-linear series, and it can reflect causal relations at various frequencies. As a result, we employ this causality test to see if investing in cryptocurrencies at frequency ω serves as a useful predictor of the component of stock market at the same frequency one period ahead.

Following the simplifications made by Breitung and Candelon, linear restrictions are placed on the coefficients of the first component of a VAR model (1) as follows:

$$\ln SM_t = \alpha_1 \ln SM_{t-1} + \cdots + \alpha_p \ln SM_{t-p} + \beta_1 \ln CRYP_{t-1} + \cdots + \beta_p \ln SM_{t-p} + \varepsilon_t \quad (9)$$

Here, α and β represent lag polynomial coefficients, and the hypothesis $M_{\ln SM \to \ln CRYP}(w) = 0$ equals the linear restriction. $H_0 : R(w)\beta = 0$. Where $\beta = \left[\beta_1, \cdots, \beta_p\right]'$ = vector of the coefficients of $\ln CRYP_t$, and $R(\omega) = \begin{bmatrix} \cos(w)\cos(2w)\cdots\cos(pw) \\ \sin(w)\sin(2w)\cdots\sin(pw) \end{bmatrix}$.

5. Results and Discussion

5.1. Empirical Result

5.1.1. Descriptive Statistics

The descriptive analysis of data for the study as shown in **Table 1** below indicates that the mean values for Bitcoin, Ripple, Exchange rate, stock market price, and Ethereum are \$14377.81 \$0.412, \$3040, \$114.13, and \$762.60 respectively. The minimum and maximum values for the cryptocurrencies used are \$448.50, \$0.006, \$8.00, and \$61309.60, \$1.98, \$4628.90 for Bitcoin, Ripple and Ethereum respectively. The minimum exchange rate for US based on the period used was \$107.65 while the maximum value was \$123.30. However, the stock market price recorded a minimum value of \$2085.3 and the highest value within the period was \$4766.18.

5.1.2. Preliminary Analysis

A study carried out by Sarkodie and Owusu recommended that certain conditions must be met before conducting novel dynamic ARDL simulations in any research for the results to be unbiased [30]. First, the dependent variable must be stationary only after its first difference I(1), whereas the independent variable must be integrated with an of either order zero I(0) or after first difference I(1) but not with an of order two I(2) or higher. To be considered as a third condition, the dependent and independent variables must have a long-term relationship. To determine the conditions, the Augmented Dickey-Fuller Unit root test [31] and the Phillips-Perron test [32] unit root tests were conducted on both the dependent and independent variables. **Table 2** presents the outcome showing that the target variable Stock Market (SM) was stationary only after its first difference and the independent variables were all in line integrating at either level I (0) or after their first difference I(1) with none of the variables stationary after their second difference only. Based on the outcome, the first and second conditions that permit the use of dynamic ARDL simulation are satisfied.

The third condition is that long run relationship must exist between the variables. To ensure that this condition is met, the bound cointegration test by Pesaran, Shin and Smith [28] was employed, and the result is reported in **Table 3**. The test has three critical values as proposed by Kripfganz and Schneider [33]

Table 1. Descriptive analysis of variables.

Variable	Mean	Std. Dev	Min	Max
BTC	14377.81	16660.38	448.50	61309.60
RPL	0.412	0.386	0.006	1.98
SM	3040.35	736.40	2085.3	4766.18
EXR	114.13	3,178	107.65	123.30
ETH	762.60	1123.39	8.00	4628.90

Table 2. Unit root test.

Variable	PP	PP	ADF	ADF
	Level	First Diff	Level	First Diff
SM	−0.413	−9.647***	−0.649	−9.027***
	(0.900)	(0.000)	(0.852)	(0.000)
RPL	−2.011	−8.982***	−2.036	−8.987***
	(0.282)	(0.000)	(0.271)	(0.000)
BTC	−1.622	−6.976***	−1.643	−6.933***
	(0.466)	(0.000)	(0.454)	(0.000)
ETH	−1.522	−7.015***	−1.432	−6.896***
	(0.517)	(0.000)	(0.562)	(0.000)
EXR	−1.992	−4.757***	−2.932**	−5.574***
	(0.289)	(0.000)	(0.047)	(0.000)
CRYP	−1.119	−8.911***	−1.236	−8.792***
	(0.704)	(0.000)	(0.654)	(0.000)

Note: 1) *** and ** denote significance at 1% and 5% respectively 2) intercept and trend is the specification employed with Schwarz Info Criterion’.

Table 3. PSS Bound cointegration test.

Model	F-Stat.	10%		5%		1%	
		I(0)	I(1)	I(0)	I(1)	I(0)	I(1)
SM = f(RPL, EXR)	211.24***	2.838	3.898	3.408	4.55	4.725	6.08
SM = f(ETH, EXR)	202.33***						
SM = f(BIT, EXR)	244.17***						
SM = f(CRY, EXR)	876.00***						

Note: *** denotes rejection of the null hypothesis of no cointegration.

with both lower and upper bound using F-statistics. As reported in the table, the F-statistic (211.21***, 202.33***, 244.17*** and 876.00***) generated by the test for all the model used are greater than the upper bound critical value at 1% significance level. Hence, the null hypothesis of no long run relationship between the dependent and independent variables is rejected. This confirmation that cryptocurrencies, along with the other control variable, have a long-run relationship with stock market indices in the US stock market. This stands as a clear indication that cryptocurrencies in any form affect stock market behavior in the long run in the United State. The confirmation of the long run confirmed the use of the dynamic ARDL simulation.

5.2. ARDL Regression Result

5.2.1. Short Run and Long Estimate

After establishing that all the requisite preconditions for employing the novel dynamic ARDL simulation have been met, the method was employed to investigate the short- and long-run effects of cryptocurrencies on stock market indices along with the counterfactual shock arising from the investment in crypto assets. **Table 4** and **Table 5** shows the short-run and long-run estimates respectively.

As reported in **Table 4**, the short run estimates show that cryptocurrencies measures (Bitcoin, Ripple and Ethereum show a positive impact on US stock market. Specifically, percentage increase in investment in Bitcoin, Ripple and Ethereum will increase stock market indices by 0.029%, 0.002%, and 0.013% respectively in the short run. However, in the long run, percentage increase in the cryptocurrency's measures will raise US stock market indices by 0.173%, 0.106% and 0.134% respectively. The result shows that the effect of cryptocurrencies on the US stock market indices is higher in the long run than in the short run as seen by their coefficient in the long run. The result was however significant both in the short run and in the long run. with $\rho < 0.01,$ indicating that cryptocurrency assets are major determinants of stock market behaviour in the United State. Therefore, contrary to the findings of (Gil-Alana, Abakah & Rojo, 2020 [1]; Conlon, Corbet, & McGee, 2020 [12]) the study supported the outcome of (İçellioğlu & Öner, 2019 [9]; Susilo, Wahyudi, Pangestuti, Nugroho, & Robiyanto 2020 [10]; Giudici, Milne, & Vinogradov, 2020 [11]) that investment in cryptocurrencies has no adverse effect on the behaviour of the stock market indices. This is also in accordance with a report by the International Monetary Fund (IMF) from 2022 [4], which found that cryptocurrency and stock market indices rose and fell in lockstep. In addition, contrary to popular belief, the greater relationship between Bitcoin and equities has grown higher than the link between stocks and other assets such as gold, investment-grade credit bonds, and major currencies, showing that risk diversification benefits are limited.

The combined effect of cryptocurrencies after computed using the Principal Component Analysis (PCA) shows a positive and significant impact on the stock market. As reported in **Table 4** and **Table 5**. A percentage increase in cryptocurrencies will raise stock market by 0.128% in the short – run and 0.659 in the long run. The result was significant both in the short run and long run.

In terms of exchange rate, the result shows an inverse relationship with stock market in the short run both after the first and second periods lagged. Specifically, a percentage increase in exchange rate will reduce stock market prices by

Table 4. Short run estimate.

Model	Variable	Coefficient	t-Stat	Prob
Bitcoin Model	D(BTC)	0.029***	2.910	0.005
	D(EXR)	−1.22**	−2.499	0.015
	D(EXR(−1)	0.810*	1.571	0.099
	CointEq(−1)	−0.167***	−2.914	0.005
Ethereum Model	D(ETH)	0.013*	1.798	0.077
	D(EXR)	−1.156**	−2.199	0.032
	D(EXR(−1)	0.810*	1.571	0.099
	CointEq(−1)	−0.092**	−1.855	0.068
Ripple Model	D(RPL)	0.002	0.567	0.572
	D(EXR)	−1.416***	−2.725	0.008
	D(EXR(−1)	1.025**	2.014	0.048
	CointEq(−1)	−0.025	−2.780	0.023
CRYP Model	D(CRYP)	0.128	3.566	0.000
	D(EXR)	−0.731	−1.749	0.085
	D(EXR(−1)	−0.186	−3.543	0.000
	CointEq(−1)	−0.186	−3.643	0.000

Note: ***, ** and * denotes significance at 1%, 5% and 10% respectively.

Table 5. Long run estimate.

Model	Variable	Coefficient	t-Stat	Prob
Bitcoin Model	lnBTC	0.173***	7.712	0.000
	lnEXR	1.016	0.920	0.356
	C	0.736	0.326	0.745
Ethereum Model	lnETH	0.134***	4.012	0.000
	lnEXR	2.426**	1.162	0.250
	C	1.799*	0.417	0.678
Ripple Model	lnRPL	0.106	0.814	0.419
	lnEXR	1.335	0.171	0.865
	C	0.977	0.060	0.952
CRYP Model	lnCRYP	0.659***	8.736	0.000
	lnEXR	3.117***	3.258	0.002
	C	−3.298	−1.667	0.100

0.731% and 0.186%. Surprisingly, the impact was positive in the long run with a percentage increase raising the stock price by 3.117%. The result was significant both in the short and long-run.

Surprisingly, the effect of exchange rate on the stock prices was negative and significant in the short run.

5.2.2. Predicted Effects of Counterfactual Shocks to Cryptocurrencies on Stock the US Stock Market

Finally, in Figures 1-4, the expected consequences of a one standard deviation counterfactual shock to cryptocurrency investment on stock prices are simulated and presented. Figure 1 depicts the impact of one standard deviation shock to lnBTC on lnSM, both positive and negative. The first graph in Figure 1 depicts that a positive shock to lnBTC will cause a sharp increase in lnSM in the short run to a sustained long-run value of approximately 3.82. The second graph indicates that a negative shock to lnBTC causes a large drop in lnSM in the short run, eventually reaching a long-run value of 1.28. These findings show that a positive shock on Bitcoin investment causes the stock market to respond positively, whereas a negative shock causes the stock market to respond negatively. As a result, the stock market in the United States moves in the same direction with investment in bitcoin in the United State.

In Figure 2, we plot the effects of positive and negative one standard deviation shocks to lnETH on lnSM. As shown in the first graph, a positive one standard deviation shock in lnETH significantly increase stock market prices in the short run and raises it to a sustained long run value of 3.81. As shown in the second graph a negative one standard deviation shock to lnETH lowers lnSM in the short-run and raises it to a sustained long-run value of about 3.42. The findings confirm IMF report that Ethereum and Bitcoin moves in the same direction with the stock market indices in the United State.

Figure 3 plots the response of US stock market price (lnSM) on positive and negative one standard deviation shocks to investment in Ripple (lnRPL). As shown in the first graph, a positive one standard deviation shock in lnRPL reduces lnSM slowly to a sustained long-run value of about 3.82. Surprisingly, as plotted in the second graph, a negative one standard deviation shock to lnRPL also raises lnSM to approximately 3.84 in the long run. The results show that investment in Ripple has no serious correlation with the pattern of behaviour of the US stock market behaviour.

Similarly, in Figure 4, where the combined measures of cryptocurrencies (Bitcoin, Ripple and Ethereum) were computed using the PCA, the effect of a one standard deviation of a positive shock to lnCRYP raises stock market prices while negative shock to cryptocurrency reduces the stock prices. This shows that stock market responds positively to a positive shock to investment in cryptocurrencies in the United State and negatively to a negative shock.

5.3. Causality Test Result

The causal relations between investment in cryptocurrencies and stock market are viewed through the Breitung and Candelon (2006) [14] Granger causality testing in frequency domain. Figures 5-7 below present the frequency domain causality graphs the test results reveals that investment in Bitcoin and Ethereum

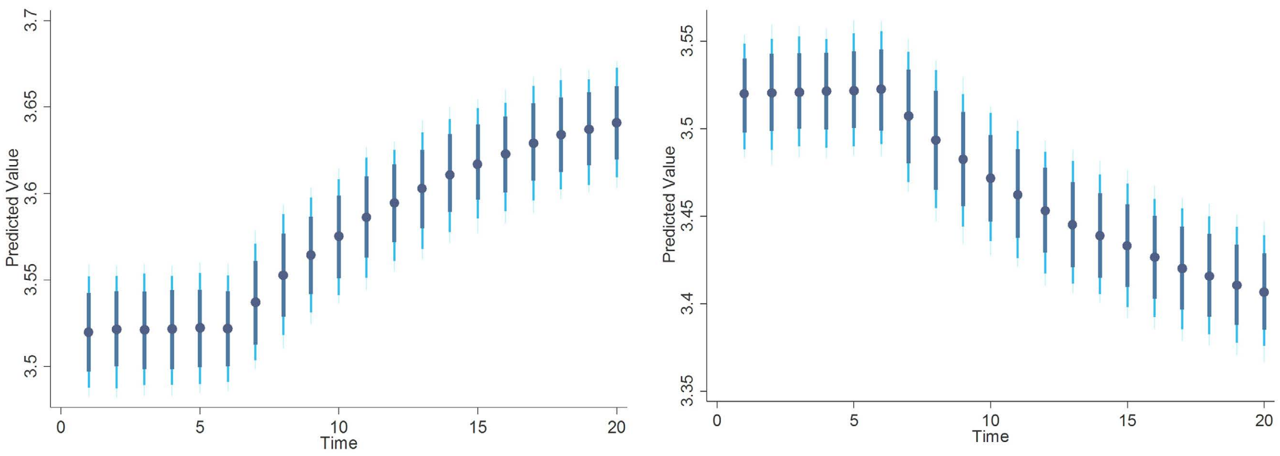

Figure 1. The projected effect of a 1 shock in lnBTC on lnSM is represented graphically. The dark patches represent expected mean values, whilst the blue lines, from darkest to lightest, reflect the 75 percent, 90 percent, and 95 percent confidence intervals, respectively.

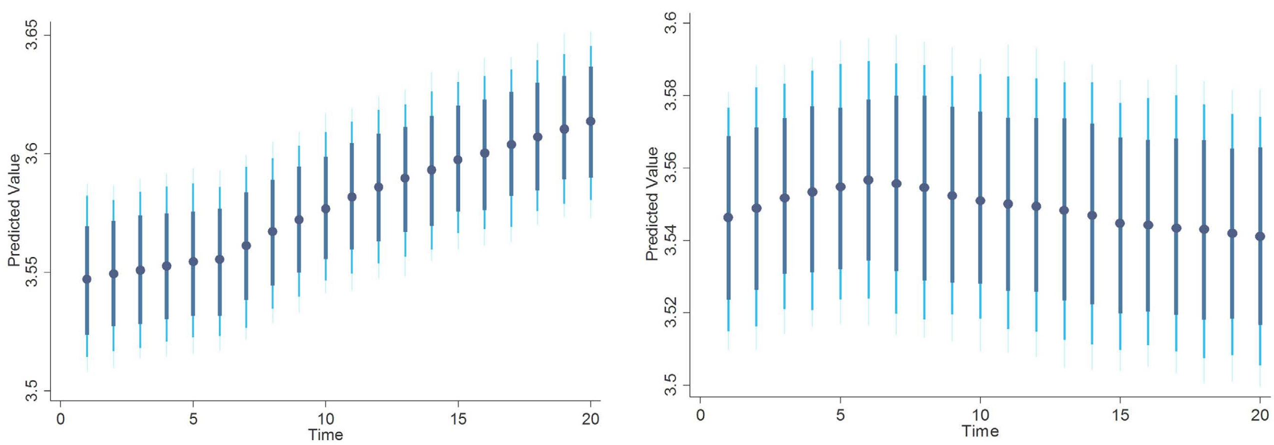

Figure 2. The projected effect of a 1 shock in lnETH on lnSM is represented graphically. The dark patches represent expected mean values, whilst the blue lines, from darkest to lightest, reflect the 75 percent, 90 percent, and 95 percent confidence intervals, respectively.

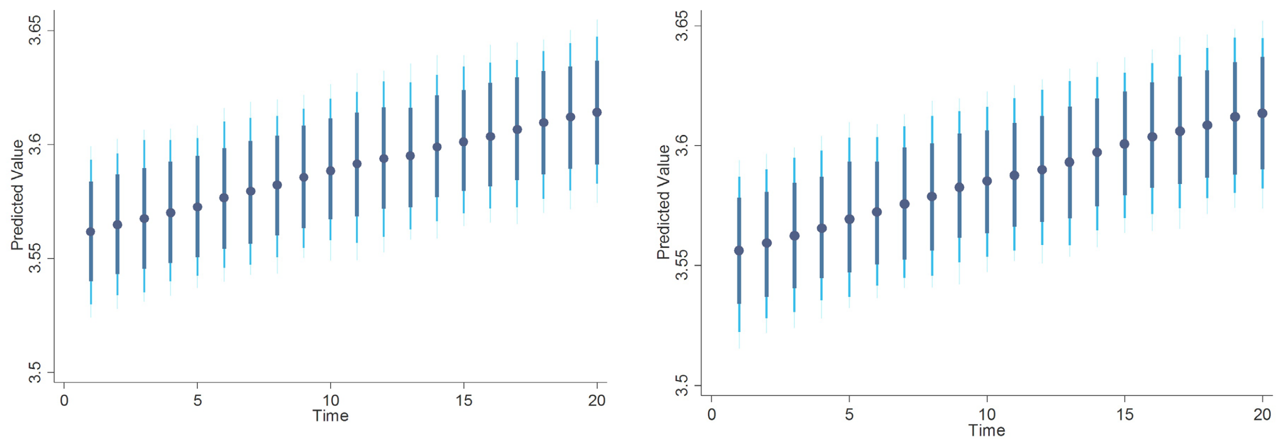

Figure 3. The projected effect of a 1 shock in lnRPL on lnSM is represented graphically. The dark patches represent expected mean values, whilst the blue lines, from darkest to lightest, reflect the 75 percent, 90 percent, and 95 percent confidence intervals, respectively.

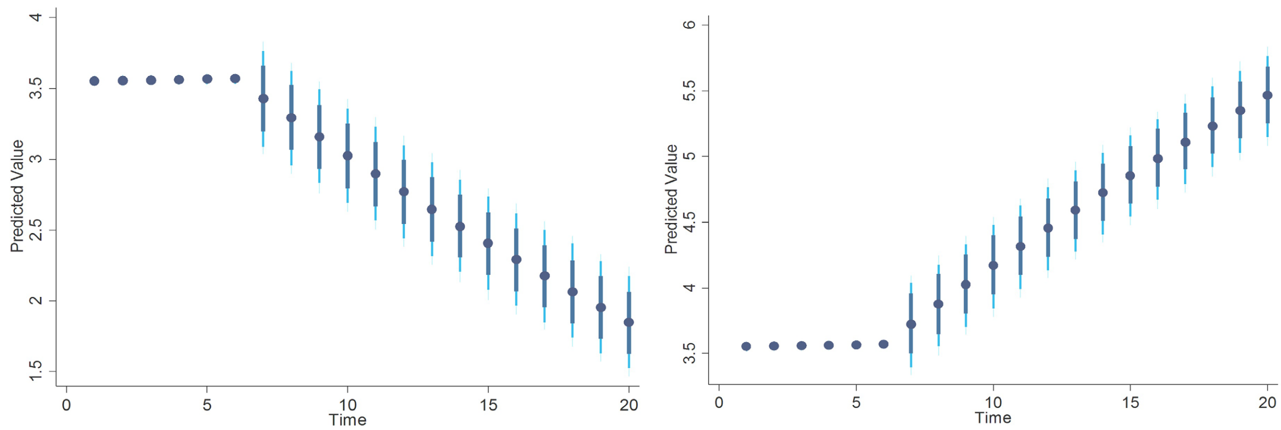

Figure 4. The projected effect of a 1 shock in lnCRYP on lnSM is represented graphically. The dark patches represent expected mean values, whilst the blue lines, from darkest to lightest, reflect the 75 percent, 90 percent, and 95 percent confidence intervals, respectively.

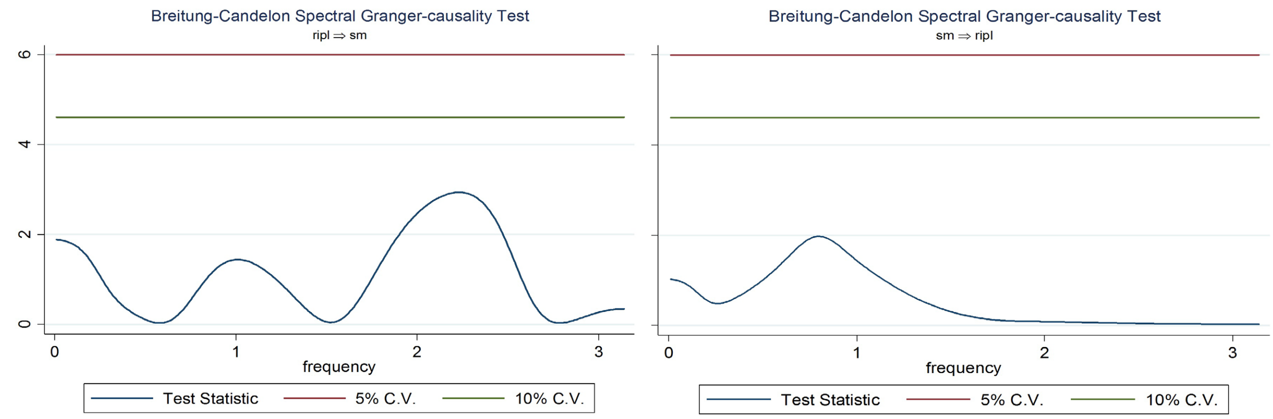

Figure 5. Direction of causality between Ripple and Stock Market.

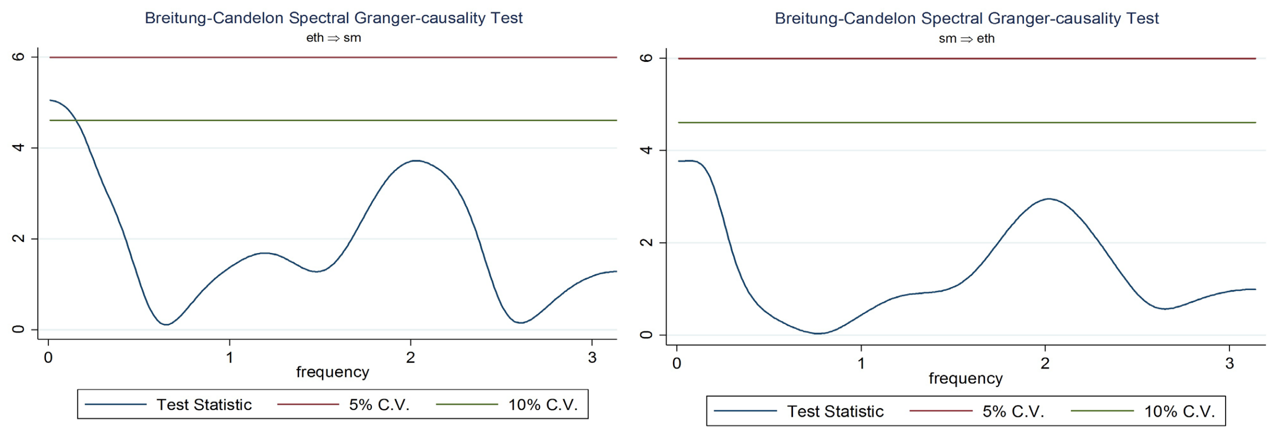

Figure 6. Direction of causality between Ethereum and Stock Market.

is able to predict stock market in the Unite State at various frequencies without any feedback effect. However, there exists no direction of causality between investment in Ripple and stock market implying that investment in Ripple is not a major predictor of the US stock market.

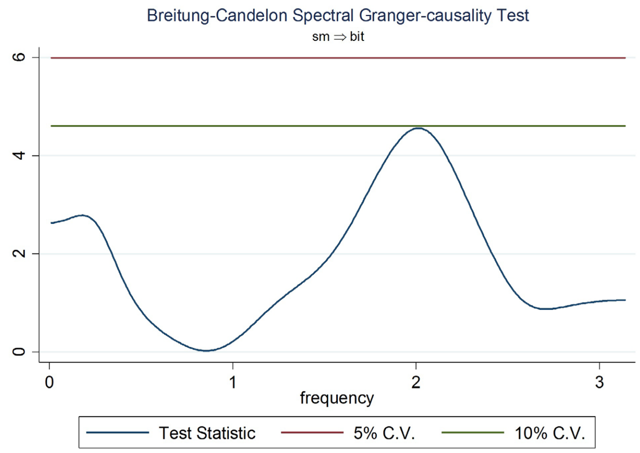

Figure 7. Direction of causality between Bitcoin and Stock Market.

6. Conclusion and Policy Implications

The volatility of cryptocurrencies in the recent time and time horizon is the center point for investment decisions even in the stock market. However, attention is not often drawn to the response of the stock market as a result of investment in cryptocurrencies to determine whether it stands as a blessing or a curse to the behaviour of the stock market indices. Thus, the paper investigates the response of the US stock market to investment in cryptocurrencies using the novel dynamic ARDL simulation techniques that have the ability to determine the effect of a shock on a variable. Using the modified Pesaran *et al.* (2001) [28] bounds test with Kripfganz and Schneider (2018) [33] critical values we found that a long-run relationship exists between the US stock market indices and investment in cryptocurrencies. Both the short-run and long-run result revealed a positive effect of investment in cryptocurrencies and stock market indices. The simulations also revealed that investment in cryptocurrencies has a significant long-run increasing effect on the behaviour of the stock market indices in the United State.

The findings from this study lead to the conclusion that investment in cryptocurrency by investors in the United State is an important source of improvement in the US stock market behaviour. This is possible either because increasing investment in cryptocurrency does not distort the intention of investors that are risk averted to withdraw from investing in the stock market, or because it creates a need for risk premiums to be factored into investment in the stock market.

Conflicts of Interest

The author declares no conflicts of interest.

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