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Research article

Mutual coupling between stock market and cryptocurrencies

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ABSTRACT

We examine the relationship between the top five cryptos and the U.S. S&P500 index from January 2018 to December 2021. We use the novel General-to-specific Vector Autoregression (GETS VAR) and traditional Vector Autoregression (VAR) model to analyze the short- and long-run, cumulative impulse-response, and Granger causality test between S&P500 returns and the returns of Bitcoin, Ethereum, Ripple, Binance and Tether. Additionally, we used the Diebold and Yilmaz (DY) spillover index of variance decomposition to validate our findings. Evidence from the analysis suggests positive short- and long-run effects of historical S&P500 returns on Bitcoin, Ethereum, Ripple, and Tether returns—and negative short- and long-run effects of the historical returns of Bitcoin, Ethereum, Ripple, Binance, and Tether on S&P500 returns. Alternatively, evidence suggests a negative short- and long-run effect of historical S&P500 returns on Binance returns. The cumulative test of impulse-response indicates a shock in historical S&P500 returns stimulates a positive response from cryptocurrency returns while a shock in historical crypto returns triggers a negative response from S&P500 returns. Empirical evidence of bi-directional causality between S&P500 returns and crypto returns suggest the mutual coupling of these market. Although, S&P500 returns have high-intensity spillover effects on crypto returns than crypto returns have on S&P500. This contradicts the fundamental attribute of cryptocurrencies for hedging and diversification of assets to reduce risk exposure. Our findings demonstrate the need to monitor and implement appropriate regulatory policies in the crypto market to mitigate the potential risks of financial contagion.

1. Introduction

In recent years, the emergence of cryptocurrency—a blockchain technology that facilitates peer-to-peer (p2p) commerce seeking to revolutionize financial markets has attracted widespread attention. Unlike fiat, cryptocurrency allows for secure, fast, and anonymous transactions without a central or commercial bank. We investigated the relationship between the stock market and cryptocurrencies. Bitcoin was the first cryptocurrency currency and was proposed by Satoshi Nakamoto during the 2008 financial crisis in direct response to the perceived deep fundamental problem associated with the fiat money system [1]. The total market capitalization of more than 18, 000 cryptocurrencies stood at ~ US$1,7 trillion as of March 7, 2022—with bitcoin's market capitalization of ~US$725 billion accounting for 42.3% of the total crypto market dominance followed by Ethereum and Tether with a market capitalization of ~US$303

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billion, ~US$80 billion—corresponding to the market dominance of 17.7%, and 4.6% respectively [2]. In July 2016, bitcoin appreciated by 5000% after the global influx of individuals, retailers, and institutional investors [3]. Simultaneously, the stock market, measured by the S&P500 index, has appreciated about 190% over the last decade and about 60% over the last five years. In this paper, we analyze the relationship between the stock market and the five largest cryptocurrencies using the novel general-to-specific vector autoregression (GETS-VAR) as well as a traditional VAR model [4].

While critics call these cryptocurrencies speculative commodities, bubbles, and Ponzi schemes [5–7], supporters of virtual currencies predict the potential replacement of fiat currencies [8]. However, most empirical studies have described Bitcoin as an investment asset due to its high price volatility, implying it cannot be used as a medium of exchange [9,10]. The price volatility in the crypto space has often undermined its ability to serve as a medium of exchange to store value in the long-run [9]. Contrary to conventional assets such as fiat, shares, bond, and commodities—the cryptocurrency market's high degree of price volatility has prompted financial experts, policymakers, and academicians to question the fundamentals of cryptocurrencies as either a medium of exchange or investment vehicle [11,12]. The price volatility of cryptocurrencies is related to the efficiency and liquidity of the cryptocurrencies, see Refs. [13–17]. We analyze how the stock market affects the price volatility of cryptocurrencies, as well as how cryptocurrencies affect the stock market.

The experience of frequent financial crises such as the sub-prime crisis in 2009, illustrates how a collapse of one market can spill over to another market. This has led to an increasing interest in empirical studies of financial contagion. It is reported that the default of one market may cause uncertainty among investors in other markets to rebalance their risk exposure through short position and decline in investment which may affect the liquidity in the market [18]. Additionally, the study infers that financial contagion among markets influences investors' decision-making that may further worsen the financial crisis [19]. Given the speculative nature of Bitcoin, the risks of market contagion and spillover to the conventional market cause fear, as suggested in numerous scientific papers [19,20]. Some academic and financial experts have classified cryptocurrency from its genesis as a financial bubble that may burst in the long run with potential risks of spilling over into other financial market [21,22]. However, the crypto ecosystem has transformed the financial landscape in numerous ways, from decentralizing financial transactions to enabling new forms of financing and facilitating cross-border payments. While the crypto ecosystem is still in its early stages, it has the potential to reshape the financial industry in ways that we are only beginning to understand [23]. This game-changing crypto ecosystem has enabled new and innovative financial products and services such as decentralized finance (DeFi), Web3, metaverse, non-fungible token (NFT), and game finance (GameFi). For example, the DeFi platforms built on top of blockchain technology, offer a wide range of financial services including borrowing and lending, trading, and yield farming, all without the need for intermediaries or traditional financial institutions [24].

In recent years, the crypto market has experienced rapid growth in adoption in the mainstream market amid investors' appetite for risks, thus affecting the unique pool of investors compared to the conventional market. This coupled with large market capitalization, crypto leverage trading, and large Venture Capital funding for crypto startups has increased the nexus between crypto-assets and conventional assets particularly the stock market [25,26]. For instance, the daily correction coefficients of Bitcoin and the U.S. S&P 500 index jumped from 0.01 in 2018-19 to 0.36 in 2020-21 as assets rise and fall together. Additionally, evidence suggests that the correlation between crypto and stocks are higher than between stocks and other assets such as gold, and investment bond [27]. Given the unregulated or weak regulated nature of the crypto market, a potential spillover may lead to contagion risks exposure across the financial market, particularly in some emerging markets where crypto transactions have reached a macro critical level [28]. Yet, recent literature examining the extent of interconnectedness, relationships, and potential coupling between crypto and stock markets is limited. For example, the existing literature found no relationship between crypto and conventional markets (i.e., stock market) see [29–33]. However, only a few studies have confirmed the coupling relationship between crypto and conventional markets [34–36]. This inconsistency in findings may be associated with differences in data period covering the post-pandemic period that was characterized by rapid growth in adoption that compromised the unique pool of investors in the cryptocurrency market. Against the backdrop of inconsistent empirical underpinnings, we show that there is a significant short- and long-run relationship, cumulative impulse-response, and Granger causality between cryptocurrencies and the stock market. Here, we use the novel General-to-specific Vector Autoregression (GET-VAR) technique that controls for high dimensionality, high volatility, overparameterization, and threshold effects that hamper the existing traditional Vector Autoregression (VAR) model reported in the literature.

The research objectives seek to answer questions based on the expected utility and investor sentiment theories. The expected utility theory suggests that—investors allocate their funds between safe and risky assets, investors will buy some assets if the price is less than the expected value and will short the assets when the price is greater than the expected value [37], whereas investor sentiment theory suggests investors' beliefs and emotions can drive changes in market price and increase short-term deviation from the intrinsic value [38]. Thus, our research questions include first, are there short- and long-run effects of S&P500 returns on Bitcoin, Ethereum, Ripple, Binance, and Tether returns and vice versa? Second, what is the cumulative impulse-response of S&P500 returns on Bitcoin, Ethereum, Ripple, Binance, and Tether returns and vice versa? Third, are there steady-state effects of S&P500 on Bitcoin, Ethereum, Ripple, Binance, and Tether returns and vice versa? Our empirical evidence demonstrates that S&P500 returns have positive short-, long-run, and cumulative impulse-response effects on Bitcoin, Ethereum, Ripple, Binance, and Tether returns. Additionally, our study validates the existence of bidirectional causality showing S&P500 returns exhibit significant spillover effects on Bitcoin, Ethereum, and Ripple returns. From a financial policy perspective, our study suggests the coupling of cryptos and the stock market, thus, regulators may strengthen oversight and regulations to mitigate potential financial contagion like previous financial crises.

1.1. Literature review

The significant adaptation of cryptocurrency over the past decades is a manifestation of a new era of financial innovation based on virtual financial assets markets [12]. Speculation by investors has often triggered an upward price movement of Bitcoin with extreme returns, which financial experts label it a financial bubble [12]. Previous studies suggest the categorization of Bitcoin as a speculative commodity rather than a currency for commerce [6,7,39]. For example, the US Department of Justice opened a criminal investigation in 2018 on suspicion of cryptocurrency manipulation through illegal means, which spiked prices and increased market volatility [40]. Alternatively, empirical evidence shows that speculative trading is not directly related to the drastic fluctuation of the bitcoin market [41]. Evidence from other studies indicates that the trading volume of Bitcoin is positively related to the size of the speculative bubble [42]. Yet, another study suggested that the quantitative value of bitcoins is just a claim of numbers without underlining value [43]. Several scientific papers have compared cryptocurrencies, particularly Bitcoin to Gold, due to conceptual similarities such as mining, and their limited value supply & demand. The Bitcoin total supply on the smart contract is limited to 21 million without the central bank controlling the supply [33]. Interestingly, a study reported bitcoin correlation with gold commodity at specific periods, suggesting potential as risk diversification assets [44]. However, a study indicates that the conditional diversification benefit of gold to G7 equity markets offered a significantly better benefit than Bitcoin [45].

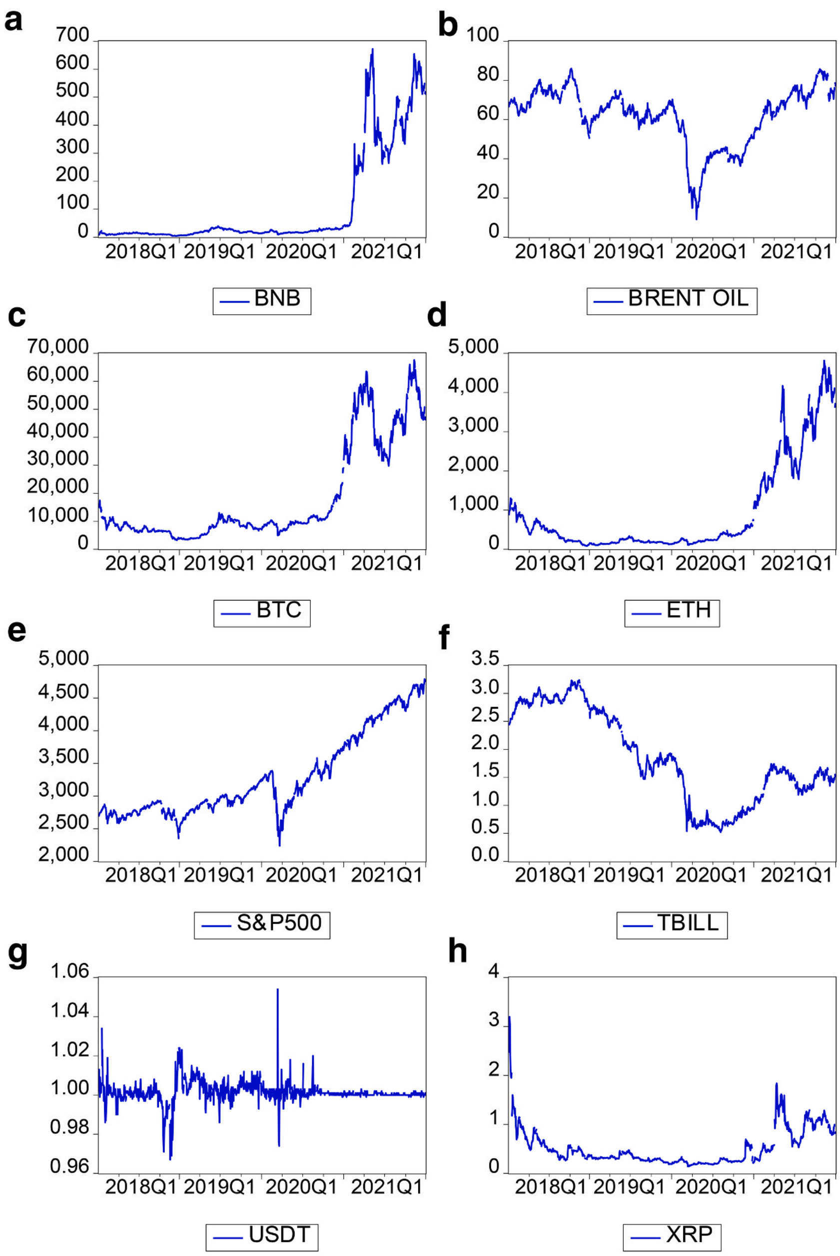

Fig. 1. Price trends of sampled variables. (a) Binance (BNB) (b) Brent oil returns (BRENT OIL) (c) Bitcoin (BTC) (d) Ethereum (ETH) (e) S&P500 (S&P500) (f) U.S. Treasury bill (TBILL) (g) Tether (USDT) (h) Ripple (XRP).

Previous studies suggest cryptocurrencies are not connected to traditional assets, which may be due to the differences in the pool of investors. For example, the stock market involves more institutional investors as compared to the crypto market with younger investors [29,30]. Some studies suggest that, unlike the conventional market, the crypto market seems to be less dependent on traditional indicators and financial variables [30,46]. An empirical study using the DCC-GARCH model indicates that the cross-correlation of the crypto market with the conventional market is evolving over time but is weak, supporting the literature on crypto assets' suitability for diversification [33]. Another study shows a weak correlation between Bitcoin and the traditional market, suggesting Bitcoin is a good diversification asset [31]. However, studies focus mainly on Bitcoin with only a few empirical studies expanding the scope to include other Altcoins [29,34]. The analysis of the spillover effect between cryptocurrencies and traditional assets shows evidence of isolation between these assets, which may offer diversification benefits in a short-term investment [29]. Other studies adopted the generalized VAR with invariant forecast-error variance decomposition to examine the total and directional spillover between cryptocurrency and benchmark indices [47]. The empirical findings show the drastic volatility in the bitcoin price movement undermines the ability to estimate its intrinsic value over the horizon [48].

2. Data and methodology

Our dataset consists of the daily closing price of the five largest crypto assets by market capitalization namely Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Binance (BNB), and Tether (USDT) as of December 31st, 2021 [2]. The stock market is captured by the US S&P500 index, and we also include the Brent oil price, as well as the 10-year U.S treasury bill as control variables to account for the possible impact of variations in commodity prices and financial condition on assets prices [34]. The US S&P500 tracks the performance of 500 large companies in leading industries and represents a broad cross-section of the U.S. economy and is widely considered representative of the overall stock market [49]. Tether (USDT) is a stable coin used in this study to provide insight into the inflow and outflow of funds in the market and as a tool for hedging against the volatility of the crypto market [50]. For this reason, the USDT is likely to be more sensitive to the movement of price in the crypto market. Fig. 1 presents a time series plot of the sampled variables. The daily datasets are in U.S. dollar currency and span from the period January 2018 to December 2021, excluding non-trading days for the purpose of uniformity (Fig. 1). Data on cryptocurrencies (Bitcoin, Ethereum, Ripple, Binance, and Tether) were retrieved from Yahoo Finance, whereas data on Brent oil, and U.S. 10-year treasury bill were retrieved from the U.S. Federal Reserve Bank of St. Louis [51, 52]. Additionally, the U.S. S&P500 was retrieved from Investing market indices [53]. The baseline specification of this study considers S&P500 index as an endogenous variable whereas cryptocurrencies and the control variables are used as dependent variables. We define returns (R χ_t) as the simple daily changes in the closing price (χ_t-χ_{t-1}) divided by the lag of the closing price of the variable (χ_{t-1}), i.e., [R $\chi_t = (\chi_t\text{-}\chi_{t-1})/(\chi_{t-1})$].

2.1. Methodology

This study employed the novel general-to-specific (GETS) VAR estimation technique that improves the traditional VAR model by controlling for potential overparameterization, and extreme volatilities. The GETS-VAR examines short- and long-run effects, Granger causality, and cumulative impulse-response of each variable in the dataset alongside diagnostics to validate the true causal statistical inferences [4]. The proposed GETS model is more efficient with improved statistical interpretation than the traditional VAR developed on ordinary least squares (OLS) [54]. Thus, the traditional VAR may exhibit potential evidence of overparameterization with multiple variables and high-order VAR, yielding weak statistical inferences [55]. The GETS-VAR model first estimates the parameters for the full specification VAR (i.e., traditional VAR) before arriving at the best-balanced parsimonious GETS version with robust estimates. Subsequently, we used this novel GETS-VAR model to examine the following hypotheses: the US S&P500 return has no effect on BTC, ETH, XRP, BNB, and USDT returns; BTC, ETH, XRP, BNB, and USDT returns have no effect on the US S&P500 returns. The GETS-VAR model specification to test the hypotheses can be expressed as:

$$\chi_t = \sum_{i=1}^{2} \pi_{1i}\chi_{t-i} + \sum_{i=1}^{2} \beta_{1i}\mathscr{Y}_{t-1} + \mathscr{Z}\theta_1 + \mathscr{Z}\alpha_1 + \varepsilon_{\chi_t} \tag{1}$$

$$\mathscr{Y}_t = \sum_{i=1}^{2} \pi_{2i}\chi_{t-i} + \sum_{i=1}^{2} \beta_{2i}\mathscr{Y}_{t-1} + \mathscr{Z}\theta_2 + \mathscr{Z}\alpha_2 + \varepsilon_{\mathscr{Y}t} \tag{2}$$

where x_t and y_t represent the causality between the paired variables at time t. x_t consists of Bitcoin returns (RBTC), Ethereum returns (RETH), Ripple returns (RXRP), Binance returns (RBNB), and Tether returns (RUSDT). y_t is the U.S. stock returns (RS&P500), whereas z denotes the vector of exogenous control variables namely Brent oil returns (RBRENTOIL), and 10-year U.S. treasury bill (RTBILL). $\pi, \beta, \theta,$ and α represent the estimated parameters while ε denotes the error term. The vector autoregression selection order criteria (VARSOC) was used in selecting the optimal lags for the estimated models. Using a combination of information criteria such as Akaike's information criterion (AIC), Hannan and Quinn information criterion (HQIC), Schwarz's Bayesian information criterion (SBIC), and final prediction error (FPE), an optimal lag length of 3 was selected. After the selection of prerequisite lags to investigate the causality of y on x and x on y, we tested the combined statistical significance of β_1 and π_2 parameters in equation (1) and equation (2), *respectively*. We define the short-run relationship of y on x, and x *on* y denoted by M_{yx}, and M_{xy} respectively, by using empirical specification (3–4) expressed as:

$$M_{yx} = \sum_{i=1}^{2} \beta_{1i} \tag{3}$$

$$M_{xy} = \sum_{i=1}^{2} \pi_{2i} \tag{4}$$

Additionally, the long-run effect $N_{yx}\,|N_{xy}$ of $y|x$ on $x|y$ (5–6) can be expressed as:

$$N_{yx} = \frac{\sum_{i=1}^{2} \beta_{1i}}{1 - \sum_{i=1}^{2} \pi_{1i}} \tag{5}$$

$$N_{xy} = \frac{\sum_{i=1}^{2} \pi_{2i}}{1 - \sum_{i=1}^{2} \beta_{2i}} \tag{6}$$

Cumulative-impulse response ($Q_{yx}|Q_{yx}$) simultaneously measures the reaction and dynamic effect of $y|x$ on $x|y$ (7–8) expressed as:

$$Q_{yx} = \frac{\sum_{i=1}^{2} \beta_{1i}}{\left(1 - \sum_{i=1}^{2} \pi_{1i}\right)\left(1 - \sum_{i=1}^{2} \beta_{2i}\right) - \sum_{i=1}^{2} \beta_{1i} \times \sum_{i=1}^{2} \pi_{2i}} \tag{7}$$

$$Q_{yx} = \frac{\sum_{i=1}^{2} \pi_{2i}}{\left(1 - \sum_{i=1}^{2} \pi_{1i}\right)\left(1 - \sum_{i=1}^{2} \beta_{2i}\right) - \sum_{i=1}^{2} \beta_{1i} \times \sum_{i=1}^{2} \pi_{2i}} \tag{8}$$

The traditional OLS VAR uses the balanced approach with the same lag length for the main variables whereas general-to-specific VAR adopts the near-VAR approach to eliminate some lagged variables with statistically insignificant estimates based on the threshold of Haitovsky rule in each of the equations [55,56]. Thus, the lag length of GETS-VAR is unbalanced and can be different from each variable in the equation. The statistical inferences examine the effect of short-, long-run, and cumulative-impulse response estimates using the delta method [55]. The step-by-step implementation of the method is expounded in Asali [4].

For validation of the spillover estimates, we employed the novel Diebold and Yilmaz (DY) spillover index to construct the return spillover index using the variance decomposition of the forecasted error [47]. The generalized model is presented below for brevity: Considering the N-dimensional random vector VAR(p).

$$r_t = \Sigma_{i=1}^{p} \beta_i x_{t-1} + \varepsilon_t \tag{9}$$

where $\varepsilon = (\varepsilon_{1t}, \varepsilon_{2t} \ldots\ldots \varepsilon_{nt})$ is a white noise vector that is assumed to be independent and identically distributed disturbances. The moving average of equation (9) is denoted by $r_t = \Sigma_{i=0}^{\infty} \theta_i \varepsilon_{t-i}$, where r represents a vector of return volatilities. The $N \times N$ is a parameter matrices θ_i obeys the recursion $\theta_i = \beta_1 \theta_{i-1} + \beta_2 \theta_{i-2} \ldots \ldots \beta_p \theta_{i-p}$. A detailed description of the model can be found in Diebold and Yilmaz [47].

3. Results & discussion

3.1. Descriptive statistics

The summary statistics showing the characteristics of sampled returns are presented in Table 1. It can be observed that RBNB (0.0075) has the highest average returns followed by both RBTC and RETH (0.0024). The average returns are insightful, as it indicates a trend of the daily returns. Excluding USDT (a stable coin), all cryptocurrencies experience a high level of volatility in their mean

Table 1
Descriptive statistical analysis.

Statistics	RS&P500	RBTC	RETH	RXRP	RBNB	RUSDT	RBRENTOIL	RTBILL
Mean	0.0005	0.0024	0.0024	0.0023	0.0075	0.0001	0.0022	0.0006
Median	0.0015	0.0014	0.0004	0.0000	0.0020	0.0000	0.0023	0.0000
Maximum	0.0929	0.1819	0.1894	0.3804	0.6976	0.0551	0.5099	0.4074
Minimum	−0.1198	−0.3717	−0.4235	−0.3275	−0.4190	−0.0512	−0.4747	−0.1957
Std Dev	0.0135	0.0428	0.0539	0.0621	0.0691	0.0049	0.0405	0.0392
Variance	0.0002	0.0018	0.0029	0.0039	0.0048	0.0000	0.0016	0.0015
Skewness	−1.3970	−0.6500	−0.6987	0.7492	2.3235	0.5332	1.2565	2.4924
Kurtosis	20.6605	11.9894	9.6124	9.5633	27.4643	41.9577	72.0194	33.9928
Jarque-Bera	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	752	752	752	752	752	752	752	752
R&SP500	1							
RBTC	−0.1196	1						
RETH	−0.1042	0.8370	1					
RXRP	−0.0471	0.6571	0.7216	1				
RBNB	−0.0920	0.6084	0.6010	0.5168	1			
RUSDT	0.2371	−0.0371	−0.0601	−0.0389	−0.0607	1		
RBRENTOIL	0.0152	0.1008	0.0917	0.0446	0.0357	−0.0849	1	
RTBILL	−0.0936	0.0203	−0.0041	0.0017	0.0058	−0.0535	0.1519	1

returns than BTC (i.e., based on the observed standard deviation). The excess kurtosis (i.e., leptokurtic distribution) reveals that the dataset has more frequent and extreme outliers in the order RBRENTOIL > RUSDT > RTBILL > RBNB > RS&P500> RBTC > RETH > RXRP. This justifies the adoption of the GETS-VAR technique rather than the traditional VAR model used in the literature. There is evidence of a negative correlation between the daily returns of cryptocurrencies and S&P500 apart from USDT, which is a stable coin pegged against the U.S. dollar rate. The calculated returns for the sample series violate the Jarque-Bera test and reject the null hypothesis of the normality assumption ($p < 0.05$).

3.2. Unit root test

Table 2 presents the unit root properties of the sample variable series using Phillips-Perron (PP) and Augmented Dickey-Fuller (ADF) tests for stationarity to control spurious regression, ascertain integration order, and obtain robust statistical inferences [57, 58]. The PP and ADF unit root tests failed to reject the null hypothesis of unit root of all variables in their raw form. However, the computed returns of all variables in Table 2 reject the null hypothesis of unit root at *p-value* < 0.01 for both PP and ADF tests. Thus, the sampled variables are I(0) processes.

Traditional VAR estimated parameters of short- and long-run, cumulative impulse-response, and Granger causality test indicate a weak statistical inference due to high dimensionality, high volatility, overparameterization, and threshold effect of the dataset (see Appendix A). The GETS-VAR results show the relationship between S&P500 and cryptocurrencies (Bitcoin, Ethereum, Ripple, Binance, and Tether). The estimated coefficients along with their standard errors in squared bracket are presented in Table 3. The estimated short-run effect shows a 1% increase in the historical returns of S&P500 stimulate BTC and USDT returns by 0.54%, and 0.07% at $p < 0.05$ and $p < 0.10$, respectively. The SP500 historical returns indicate a positive insignificant short-run effect on ETH and XRP returns but negative insignificant effects on BNB returns. Evidence of the positive short-run effect of lagged S&P500 returns on BTC, ETH, XRP, and USDT returns may be due to the exponential adoption of cryptocurrency. For example, the U.S. Federal Reserve allowed Exchange Traded Funds (ETFs) backed by Bitcoin or other cryptocurrencies to hold future contracts on the account of the firm's investment portfolio, such as Proshare Bitcoin Strategy ETF, Simplify U.S. Equity Plus GBTC ETF, and Valkyrie Bitcoin Strategy ETF. In 2022, Global Venture Capitalists (VCs) provided ~ US$15 billion in funds for the incubation or expansion of projects in recent years to take advantage of opportunities in the crypto and blockchain industry such as Web3, DAO, decentralized finance (DeFi) and centralized finance (CeFi) applications—that provide secured and faster transactions disrupting traditional banking systems [26]. This sudden growth has increased the nexus between the cryptocurrency market and the traditional stock market in recent years. Our empirical evidence contradicts the finding that suggests cryptocurrencies can be used as hedging or diversification tools against traditional markets in the short-term [29].

Evidence from the result shows the short-run negative effect of historical cryptocurrency returns on SP500 returns. Growth in BTC and ETH returns by 1% implies a decline in S&P500 returns by 0.08–0.10% at $p < 0.05$. The XRP returns indicate a negative coefficient of 0.09% on S&P500 returns at $p < 0.01$. Although, BNB and USDT returns reveal a negative effect on the return of S&P500 respectively, at an insignificant level—implying 1% increase in Binance and Tether decrease the returns of S&P500 by 0.03% and 0.41% respectively. Because investors and financial institutions are mostly driven by higher returns based on the risk aversion theory, evidence of a negative short-run effect of cryptocurrency returns on S&P500 returns may be associated with investor confidence for higher gains. Thus, funds are moved from the conventional market to the cryptocurrency market to take advantage of the historical bull market in cryptocurrencies, however, funds are retracted in crypto bear markets. Additionally, the historical S&P500 returns, BTC, ETH, XRP, and BNB have a positive effect on their own returns in the short run at an insignificant level, whereas the historical USDT returns have a significant positive short-run effect on its own returns. This implies that the historical returns of S&P500, BTC, ETH, XRP, and BNB cannot predict their own returns.

There is evidence of a positive long-run inertia effect of historical S&P500 returns on BTC, ETH, XRP, and USDT return. For example, 1% increase in the lag of SP500 returns will spur BTC and USDT returns by 0.55% and 0.02%, respectively. Additionally, 1% change in historical S&P500 returns increases ETH and XRP returns by 0.87–1.21% (both at insignificant levels). However, 1% increase in the lag of S&P500 returns decreases BNB returns by 0.03% in the long run ($p > 0.5$). This implies that a bull run in the equity market equips investors with excess returns and confidence to invest in other growing volatile markets such as cryptocurrencies. Historical BTC, ETH, XRP, BNB, and USDT returns stimulate a negative long-run inertia effect on S&P500 returns. The first indication

Table 2
Unit root test.

Data series	Dickey-Fuller Test	Phillips-Perron
	level	level
RS&P500	−26.38***	−26.34***
RBTC	−25.00***	−25.07***
RETH	−26.05***	−26.18***
RXRP	−23.85***	−23.83***
RBNB	−21.17***	−21.22***
RUSDT	−35.88***	−38.54***
RBRENTOIL	−30.85***	−29.44***
RTBILL	−23.04***	−23.24***

Note: *** denote the rejection of the null hypothesis of unit root test at a significance level of 1%.

Table 3
Results from general-to-specific (GETS) vector autoregression (VAR).

Short run	RSP500	RBTC	RETH	RXRP	RBNB	RUSDT
$RSP500_{t-1}$	0.13	0.54**	0.79	1.12	−0.25	0.07*
Std. Error	[0.30]	[0.27]	[0.56]	[0.75]	[0.50]	[0.23]
$RBTC_{t-1}$	−0.08**	0.01				
Std. Error	[0.04]	[0.08]				
$RETH_{t-1}$	−0.10**		0.10			
Std. Error	[0.02]		[0.09]			
$RXRP_{t-1}$	−0.09***			0.07		
Std. Error	[0.03]			[0.09]		
$RBNB_{t-1}$	−0.03					
Std. Error	[0.02]					
$RUSDT_{t-1}$	−0.41					−1.86***
Std. Error	[0.52]					[0.25]
Long run						
$RSP500_{t-1}$		0.55*	0.87	1.21	−0.03	0.02*
Std. Error		[0.30]	[0.62]	[0.80]	[0.02]	[0.01]
$RBTC_{t-1}$	−0.09*					
Std. Error	[0.06]					
$RETH_{t-1}$	−0.06*					
Std. Error	[0.04]					
$RXRP_{t-1}$	−0.11**					
Std. Error	[0.05]					
$RBNB_{t-1}$	−0.25					
Std. Error	[0.50]					
$RUSDT_{t-1}$	−0.38					
Std. Error	[0.46]					
CIR						
$RSP500_{t-1}$		−0.09*	−0.06	−0.10**	−0.29	−0.13
Std. Error		[0.05]	[0.04]	[0.04]	[0.61]	[0.16]
$RBTC_{t-1}$	0.60					
Std. Error	[0.38]					
$RETH_{t-1}$	1.01					
Std. Error	[0.78]					
$RXRP_{t-1}$	1.29					
Std. Error	[0.87]					
$RBNB_{t-1}$	−0.03					
Std. Error	[0.03]					
$RUSDT_{t-1}$	0.02					
Std. Error	[0.01]					

Note: *, **, ***, denote 10%, 5%, and 1% significance level; parenthesis represent standard error [std. error].

shows that 1% increase in historical XRP returns declines S&P500 returns by 0.11% at $p < 0.05$ whereas 1% increase in the lag of BTC and ETH returns triggers a decrease in S&P500 returns by 0.06–0.09%. However, 1% increase in historical BNB and USDT returns decreases S&P500 returns by 0.25–0.38% ($p>0.5$). This is consistent with the finding in the short-run, where investors and financial institutions move funds from the stock market into cryptocurrency during a bull market. The empirical evidence from the short- and long-run suggests a coupling effect between cryptocurrency and the conventional market, hence, cannot be used for hedging and diversification option to reduce the risk exposure from the stock market. Our findings contradict previous empirical literature that suggests the portfolio diversification potential of crypto assets [31,33].

The cumulative-impulse response violates the estimated short- and long-run effects at a weak significant level. We observe that a shock in the lag of S&P500 returns triggers a negative response from cryptocurrencies. For example, 1% shock in historical S&P500 returns decreases BTC, ETH, XRP, BNB, and USDT returns by 0.06–0.29%, with BTC and XRP showing a significant negative response to shocks in the lag of S&P500 returns. This implies that S&P500 returns affect cryptocurrency returns particularly BTC, the dominant cryptocurrency based on market capitalization. In contrast, a shock in historical BTC, ETH, XRP, BNB, and USDT returns has insignificant positive effects on S&P500 returns. Evidence from the findings implies that a shock in the stock market stimulates a negative response in the crypto market while a shock in the crypto market causes a positive response in the stock market. This indicates the influence of external factors in the crypto market, which may be due to fear of uncertainty, risk aversion, and high price volatility. Thus, an outflow of gains in the bull crypto market to mitigate the high risks exposure experienced in the crypto bear market.

We examined the direction of causality between S&P500, Bitcoin, Ethereum, Ripple, Binance, and Tether returns using the GETS-VAR Granger model while controlling for brent oil returns and the U.S. Treasury bill (Fig. 2). We observe bidirectional causality between S&P500 returns and cryptocurrency returns excluding BNB (i.e., BTC, ETH, XRP, and USDT). Evidence suggests spillover in both directions from equity to the crypto market at high intensity and vice versa at low intensity in recent years. For example, the Granger causality test suggests a causal effect from BTC to S&P500 by 4.32% at a weak significance level, whereas the causal effect from S&P500 to BTC by 3.86% at *p-value* < 0.05. Similarly, the causal effect from ETH, and XRP to S&P500 by 4.44–9.12%

respectively, at 5% significance level, whereas the causal effect from S&P500 to ETH and XRP by 16.98–18.70% respectively, at *p-value* < 0.01.

Additionally, we observe a higher estimate of the causality from USDT to S&P500 by 18.29% at *p-value* < 0.01 compared to the causality from S&P500 to USDT by 3.62% at a weak significance level. Empirical evidence from the Granger causality test indicates a significant causal effect from S&P500 to BNB, ETH, XRP, and vice versa. It is worth noting that the high spillover reported between USDT and S&P500 may be associated with the use of the stable coin for facilitating the inflow and outflow of funds from the crypto market. The findings suggest the coupling of stock market and crypto, which may increase future financial contagion risks. This could be associated with several factors that increase the nexus between cryptocurrency and the conventional market through the growing acceptance of crypto as investment assets among retailers and institutional investors. The findings are consistent with the investor risk aversion and sentimental theory that suggests investors may move funds due to high volatility or when there is a general sense of high risks among investors to a safer investment option [59]. Additionally, the rapid mainstream adoption of crypto-related platforms such as Metaverse, and usage of cryptocurrency particularly Bitcoin as a legal tender in countries such as El-Salvador, and Central Africa Republic, and the rise in VC investment in crypto and blockchain see Refs. [2,25,26]. These findings are consistent with the correlation and spillover between S&P500 returns and Bitcoin post-pandemic years reported in the literature [34,36]. Besides, a study that used the expectile-based approach reported the presence of downside spillover between BTC and stocks, bonds, currencies, and commodities [36].

The results presented in Table 4 using the DY spillover index provide the full sample spillover analyses for S&P500, BTC, ETH, XRP, BNB, USDT, Brent oil, and Tbill returns. All the results are based on estimated contributions to the forecast error variance of the "to-from" decomposition of the spillover index. We observe the highest directional spillover contribution from the returns of S&P500 to USDT by 22% of the error variance forecasting 10 weeks ahead. The returns of BTC and ETH report a spillover contribution of 15% from the returns of S&P500, followed by the returns of XRP and BNB at 8% and 7%, respectively. This implies the return spillover from S&P500 to USDT is larger than S&P500 to other cryptocurrencies. However, we observe a low directional spillover contribution from the returns of cryptocurrencies to the S&P500 returns. This reveals a high intensity of spillover contribution from the S&P500 returns to cryptocurrencies, but a lower spillover contribution from the returns of cryptocurrencies to S&P500. The total non-directional spillover suggests that on average for each of the five sampled groups, the S&P500, USDT, and the controls (Brent oil and Tbill) had the highest total spillover (i.e., 17%) of the volatility forecasted error variance. The summary in Table 4 simply shows that the total non-directional spillover is quite low whereas the directional spillover is average. The DY spillover index results are consistent with our previous findings using the GETS-VAR model that indicates bi-directional spillover of S&P500 and cryptocurrencies, but with high-intensity spillover contribution from S&P500 to cryptocurrencies and low spillover contribution to the other direction.

4. Conclusion

The rapid growth in market capitalization of cryptocurrency assets is caused by an influx in adoption from individuals, retailers, and institutional investors. The growth era of the cryptocurrency market particularly during the global pandemic has witnessed a

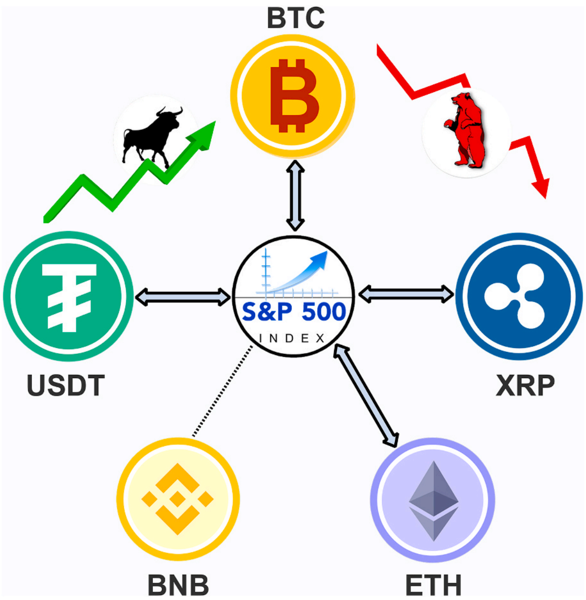

Fig. 2. GETS-VAR Granger causality between S&P500, Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Binance (BNB), and Tether (USDT) returns while controlling for brent oil returns and the U.S. Treasury bill. Legend: The short dashes (**....**) denote no causality whereas the double-headed arrow (⇔) represents bidirectional causality.

Table 4
Validation of results using the DY spillover index.

Estimates	RSP500	RBTC	RBRENTOIL	RBILL	Directional from Others
RSP500	94.2	2.6	3.1	0.1	5.8
RBTC	15	84.6	0.3	0.1	15.4
RBRENTOIL	13.3	4.6	81.6	0.5	18.4
RBILL	9.9	1.3	1.3	87.5	12.5
Directional to Others	38.2	8.4	4.8	0.7	52.1
Directional including Own	132.4	93	86.4	88.2	13.00%
	RSP500	**RETH**	**RBRENTOIL**	**RBILL**	**Directional from Others**
RSP500	95.8	1.1	3	0.1	4.2
RETH	15	84.6	0.3	0.1	15.4
RBRENTOIL	13.4	3.5	82.6	0.5	17.4
RBILL	10	2.1	1.3	86.7	13.3
Directional to Others	38.4	6.6	4.7	0.7	50.4
Directional including Own	134.1	91.2	87.3	87.4	12.60%
	RSP500	**RXRP**	**RBRENTOIL**	**RBILL**	**Directional from Others**
RSP500	95.9	0.9	3.1	0.1	4.1
RXRP	8	90.2	0.2	1.6	9.8
RBRENTOIL	13.3	2.2	84.2	0.4	15.8
RBILL	9.8	1.2	1.2	87.9	12.1
Directional to Others	31.1	4.2	4.4	2.1	41.9
Directional including Own	127	94.4	88.6	90	10.50%
	RSP500	**RBNB**	**RBRENTOIL**	**RBILL**	**Directional from Others**
RSP500	94.7	2.2	3	0.1	5.3
RBNB	7.1	92.6	0.3	0.1	7.4
RBRENTOIL	13.1	3	83.4	0.5	16.6
RBILL	9.8	0.8	1.2	88.2	11.8
Directional to Others	30	6	4.5	0.7	41.2
Directional including Own	124.7	98.6	87.8	88.9	10.30%
	RSP500	**RUSDT**	**RBRENTOIL**	**RBILL**	**Directional from Others**
RSP500	91.5	5	2.6	0.9	8.5
RUSDT	21.7	69.8	0.1	8.3	30.2
RBRENTOIL	13.9	3.7	81.4	1.1	18.6
RBILL	8.7	0.8	1.4	89.1	10.9
Directional to Others	44.3	9.5	4.1	10.3	68.1
Directional including Own	135.8	79.3	85.5	99.4	17.00%

Note: The column sum labeled "Directional to Others" and row sums labeled "Directional from Others", the total spillover index appears at the lower right corner for each of the five sampled groups in Table 4.

paradigm shift from the typical decoupled crypto market to a coupled market with the conventional market (such as the stock market). Against this backdrop, we investigated the short- and long-run relationships, cumulative impulse-response, and Granger causality between S&P500 and cryptocurrency returns (BTC, ETH, XRP, BNB, and USDT) using the traditional VAR and novel GETS-VAR. Our empirical evidence using the GETS-VAR suggests a significant positive short- and long-run effect of historical S&P500 returns on BTC and USDT returns, but insignificant positive short- and long-run effects on ETH and XRP returns. Evidence reveals insignificant negative short- and long-run effects of S&P500 returns on BNB returns. This implies the coupling of crypto and conventional markets amid the growing demand. In contrast, the empirical analysis suggests a significant negative short- and long-run effect of historical BTC, ETH, and XRP on S&P500 returns. Additionally, evidence shows insignificant negative short- and long-run effects of lagged BNB and USDT on S&P500 returns. The negative short- and long-run effects suggest the movement of funds from the stock market into the crypto bull market due to potential high returns but vice versa in the crypto bear market based on the risk aversion theory.

Our cumulative impulse-response shows a shock in historical S&P500 returns stimulates a negative effect from cryptocurrency returns, whereas a shock in historical crypto returns triggers a positive effect from S&P500 returns. Empirical evidence from the Granger causality test suggests bidirectional causality between S&P500 and cryptocurrency returns. We observe significant spillover from lagged S&P500 returns to BTC, ETH, XRP, and USDT returns and vice versa. Yet, a superior spillover effect was observed from S&P500 returns to crypto returns whereas a weak spillover effect was observed from crypto returns to S&P500 returns. As such, a deep decline in S&P500 returns can increase investors' risk aversion and trigger a fall in investments in cryptocurrencies. Additionally, market sentiment may be transmitted from the stock market to the crypto market in a nontrivial way. This implies the mutual coupling of the crypto market to the conventional market. The analysis herein contradicts the hedging and diversification potential of cryptocurrencies. This coupling may be influenced by several factors including the growing utility of crypto, investors' sentiment, funds injections from Venture Capital firms, increase in investors and institutions, ease in mobility of capital from one market to another, mainstream adoption, and rise in crypto asset price attributable to high demand.

Given the growing mutual coupling between crypto and conventional markets, there is a potential risk of increasing financial contagion. Hence, policymakers and regulators could review their approach towards crypto assets, to guide the existing and startups to control the potential risks of contagion. The drawback of this study is that since crypto assets are relatively new, the limited historical data available makes it difficult to draw a robust conclusion. This study employed S&P500 (the widely tracked market) and crypto assets, yet, may not be the true representative of the global market. Thus, further research could be undertaken to examine the nexus between crypto assets and major financial market benchmark indexes. This will further strengthen the limited literature on decoupling crypto from the conventional market.

Author contribution statement

Maruf Yakubu Ahmed: Conceived and designed the analysis; Analyzed and interpreted the data; Contributed analysis tools or data; Wrote the paper.

Samuel Asumadu Sarkodie: Conceived and designed the analysis; Analyzed and interpreted the data; Contributed analysis tools or data; Wrote the paper.

Thomas Leirvik: Contributed analysis tools or data; Wrote the paper.

Data availability statement

Data included in article/supplementary material/referenced in article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.heliyon.2023.e16179.

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