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How do cryptocurrency features determine their dynamic volatility and co-movements with stocks?

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ABSTRACT
Whilst previous studies have primarily focused on the hedge effects and co-movements between cryptos and traditional assets, cryptos' features that are associated with hedge effects and co-movements have often been neglected in extant studies. This research aims to investigate how specific cryptocurrency features influence their dynamic volatility and co-movements with stock markets. Using cointegration analysis and Granger causality tests, we explore the hedge effects and co-movement between the top 100 cryptos and eight leading stock markets. Additionally, we use logistic regression models to assess the role of crypto-specific features in driving these dynamics. We find that consensus mechanisms and having limited supply are key features influencing co-movements during and after the Covid-19 pandemic, while acting as a means of payment predominantly affects co-movement after the pandemic. We highlight cryptos underlying characteristics and functionalities that could significantly affect their demand and people's attitudes toward them. Based on finance theory, these differing characteristics could affect cryptos' versatility thereby impacting their demand, pricing, hedge effects and co-movement in their returns compared to stock returns. This paper makes significant theoretical contributions by addressing the role of crypto features in their co-movements and hedge effects on representative stock markets.

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1. Introduction

This study explores cryptos' functional and fundamental features that are linked to their co-movement with traditional assets. Cryptos are progressively popular among individual and corporate investors (Balcilar et al., 2017) and are drawing increasing attention from policymakers, regulators, law-enforcement agents, and financial institutions (Blandin et al., 2019). Extant literature has investigated the links between cryptos and stock market dynamics using several statistical models, but findings remain inconsistent. Some studies (Diniz-Maganini et al., 2021; Jeribi et al., 2021; Kliber, 2022; Tiwari et al., 2019) suggest that popular cryptos such as Bitcoin, Ethereum, Dash, Monero, Ripple, Stellar, and Litecoin, can serve as a 'safe-haven' (i.e. hedging instrument) for representative stock markets such as S&P500, NASDAQ, and EURO STOXX, providing opportunities for risk diversification. Other studies (Ahmed et al., 2023; Bejaoui et al., 2023; Jiang et al., 2021; Li & Miu, 2023) are more circumspect about cryptos hedging claims. Whilst previous studies have focused on the co-movements between cryptos and traditional assets, how crypto features determine their dynamic volatility and co-movements with stock markets remains an unanswered question. This study is devoted to answering this important question. Given that cryptos are unlike stocks where the market automatically recognises the fundamental factors in asset pricing, the effects of cryptos' fundamental features on their pricing require specific empirical consideration.

Two critical limitations in the extant literature on cryptos' safe haven and co-movement with other asset classes have left significant gaps in our understanding of the crypto market's dynamics. First, existing studies have predominantly focused on a limited subset of the popular cryptos, typically nine to

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twelve, such as Bitcoin and Ethereum, and their co-movement with major stock markets. Yet, there are over 8985 cryptos in circulation and around 420 million crypto users across the globe. Although these few leading cryptos have the largest market capitalisation and constitute over 54% of the cryptos market, they represent only a fraction of the 8985 cryptos in circulation today. This narrow focus may lead to sample bias and result in an incomplete picture of the crypto market. This paper investigates a broader crypto landscape and involves the mid-tier and smaller cryptos to provide a holistic appreciation of the dynamics of the cryptos market. Such a deeper understanding could help us build better typologies of the cryptos market and inform cryptos market structure and regulations.

Second, our study integrates critical features of cryptos, features that are often neglected in extant studies, to examine their role in hedge effects and co-movement dynamics. Although they have a common basis in Blockchain technology, cryptos are highly heterogeneous in terms of their operational mechanisms, functionalities and user appeal. For example, many investors in cryptos have realised that cryptos with proof of work (PoW) mechanism as against proof of stake (PoS) have significantly high energy consumption for validation leading to their avoidance due to their poor environmental sustainability credentials. Similarly, cryptos with smart contract capabilities or being attached to a stablecoin are seemingly more efficient and desirable than those without. Beyond these, several cryptos are developed to executive specific activities for example, Dapp coin coordinates activity for applications on blockchains that provide services such as data storage, trading, lending, and online games, Non-fungible Tokens (NFT) are used for the tokenization of assets and DeFi are used to provide direct access to financial services without disclosing the user's identity. Based on finance theory, these differing characteristics could potentially affect cryptos' versatility thereby impacting their demand, pricing, and whether they exhibit hedge effects and co-movement in their returns compared to stock returns.

To provide empirical evidence on the link between cryptos features and their returns co-movement, we collect daily close prices of cryptos based on market capitalisation and eight representative stock markets (i.e. the US, the UK, Spain, France, Italy, Germany, Vietnam, and China) from the birth of each crypto till 15 May 2024. First, we examine the hedge effectiveness and the dynamic co-movements between cryptos and stock markets using co-integration and Granger causality test. We then use logistic regression models to explore the key features of the cryptos' safe-haven properties and co-movement with representative stock markets. Given that our sample also covered the Covid-19 period, we conducted further analysis to test the validity of our results under time-varying conditions of the pandemic.

Our findings show that 23, 32, and 24 (out of the 100) cryptos examined demonstrate safe-haven properties for different stock markets, while 42, 50, and 76 (out of 100) cryptos examined show significant co-movements with those stock markets before, during, and after the Covid-19 pandemic respectively. Among the top 10 leading cryptos, only USDC could serve as a safe haven for seven stock markets before the Covid-19 pandemic. During the Covid-19 pandemic, USDT and USDC demonstrated safe-haven features for 5 and 7 stock markets, respectively. After the Covid-19 pandemic, USDC and USDT served as safe havens for the same 5 stock markets. Other leading cryptos, such as Bitcoin, Ethereum, Ripple, Dash, Tether, and Monero did not show safe-haven features for any of the eight stock markets. Furthermore, leading cryptos such as Bitcoin, Ethereum, Binance coin, and XRP showed co-movement with more stock markets after the Covid-19 pandemic than during and before. Consensus mechanisms and having limited supply are key crypto features that are associated with co-movements during and after the Covid-19 pandemic while acting as a means of payment appeared as a feature associated with co-movement after the Covid-19 pandemic. These findings also provide important insight for potential cryptos market regulation to recognise the use cases and the features of the cryptos rather than a generalised regulation regime.

Our paper makes three contributions to the literature. First, it extends the scope of analysis by moving beyond the narrow focus on dominant cryptos, providing a deeper and comprehensive overview of the spillover and co-movement between top 100 cryptos and representative stock markets. Expanding the coverage of the cryptos implied that we could explore a variety of their use cases including crypto such as decentralised application (Dapp) coins, decentralised finance (Defi) coins, non-fungible tokens (NFT), and a means of exchange and payments. Using a larger pool of cryptos also affords the chance to accommodate a variety of cryptos features such as consensus mechanisms, implementation of initial coin offering (ICO), limited maximum supply, manufactured as stablecoins, made as privacy coins, and deployment on EVM. Secondly, this study advanced the literature by systematically integrating cryptos unique features into analysis of their co-movement with stock markets. Unlike prior studies, which have largely treated cryptos as a homogenous asset class, we provide a differentiated approach that accounts for their underlying technological and functional distinctions. This is because cryptos are different from stock markets while their fundamental and functional features are not automatically priced into their valuation. Thirdly, this study provides additional empirical evidence on the information-driven asset co-movement in contrast to the traditional frictionless and rational-driven motivation. We thus, show that there is a difference in investors' attitude to cryptos based on their use cases and whether they provide additional information by way of their unique features. The rest of the paper is structured as follows; Section 2 presents the literature review. Section 3 explains the data and econometric models. Section 4 presents the results. Section 5 discusses the results and Section 6 concludes.

2. Literature review

Information theory provides the most intuitive theoretical underpinning for expecting co-movements between asset classes and across markets. On this, Grossman and Stiglitz (1980) have shown that information affects asset pricing. Assuming that information is exogenously determined, they argue that increased information quality leads to better asset pricing. Barberis et al. (2005: page 284) distinguished between traditional and non-traditional causes of stock co-movement. From a traditional viewpoint, assuming frictionless economies and rational investors, they suggest that stock co-movements only ever reflect co-movements in stock fundamentals. An alternative view suggests that co-movements could be information driven. Advancing this, Veldkamp (2006a) argues that information could be endogenously determined and *that it has a high fixed cost but a low marginal cost of replication*. This implies that buying it in bulk makes it cheaper for all market participants who could leverage the same information leading to *information herding*, a precursor to herd behaviour in financial markets. According to Veldkamp (2006b), if information cost remains high even with high demand, investors will cherry-pick their information needs and only follow a limited number of assets. In such a situation, information shock will not lead to a significant change in behaviour and there will be fewer assets' co-movements. However, shock on cheap information and high-demand assets will gravitate investors toward common behaviour, ultimately leading to co-movements in asset pricing as investors recognise homogenous information in asset prices.

Beyond stocks, studies exploring co-movements in cryptos are gaining momentum, and some have examined cross-assets co-movements. Extant literature (Bouri et al., 2017; Just & Echaust, 2024; Shahzad et al., 2020; Stensås et al., 2019) on the co-movements between cryptos and stock performance can be divided into three categories. First, studies comparing co-movements between asset classes (cryptos vs stock and other traditional asset classes) based on the level of economic development (i.e. developed vs emerging or developing economies). Second, studies analysing co-movements amongst asset classes including cryptos based on their time horizon (i.e. between short-term and long-term horizons), and finally, studies exploring co-movements between cryptos and traditional assets during stable and unstable periods (e.g. Pandemic, Global Financial Crisis, Asian Crisis, etc).

In terms of different economic systems, dynamic conditional correlation (DCC) models, vector autoregression models, and quantile coherency approaches have been used to identify the correlation between cryptos and stock markets in different economic contexts. Findings suggest that Bitcoin is a safe haven and can serve as a strong hedge for developed markets such as Canada (Shahzad et al., 2020), emerging markets such as Brazil, Russia, India, China, South Korea, and other Asian countries, as well as developing market such as Zimbabwe (Stensås et al., 2019). However, it has proven to be a poor hedge instrument against the G7 stock markets (Bouri et al., 2017; Stensås et al., 2019). Similarly, Just and Echaust (2024) report that Bitcoin, Ethereum, Cardano, Binance, and Ripple do not have safe-haven properties for stock markets in G7 and BRICS countries. Ahmed et al. (2023) also found that Bitcoin, Ethereum, Tether, and Ripple have a mutual coupling with US stock markets, meaning that they do not have diversification potential for the US market.

Studies (Diniz-Maganini et al., 2021; Kliber, 2022; Kumar & Padakandla, 2022) exploring the timeliness of the co-movements of cryptos with stocks have often used wavelet coherence methods and GARCH models. For example, Kliber (2022) suggests that Bitcoin and Ethereum are safe-haven assets for the US stock market during 2020–2022, although the hedging performance varied over time and depended on the investment horizon. Diniz-Maganini et al. (2021) found that Bitcoin was a safe haven for MSCI World stocks when the time scale exceeded 3 months. Kumar and Padakandla (2022) demonstrate that Bitcoin had short-run and long-run safe-haven properties for NASDAQ and EURO STOXX, as well as short-run safe-haven features for NSE50.

In terms of economic periods, researchers demonstrate that some cryptos, especially Bitcoin and Ethereum, can be considered safe-haven assets for stock markets such as MSCI World stocks, NASDAQ, and Euro Stocks in certain periods. The co-movements and spillovers between cryptos and other asset classes seem to depend on the certainty in the wider economy. On this, Jeribi et al. (2021) find that Ripple and Dash presented safe-haven features for all BRICS markets before the Covid-19 pandemic, while Bitcoin, Ethereum, Monero, Dash, and Ripple acted as safe-havens for Brazilian, Russian, and Chinese stock markets during the pandemic. Maitra et al. (2022) find that the Covid-19 pandemic has increased the risk spillovers from Bitcoin and Ethereum to stock market returns so that cryptos could not serve as a hedge for stock markets during uncertainty. The examined stock markets in Maitra's study include the S&P 500, FTSE 100, CAC40, DAX30, FTSE MIB, IBEX35, Nikkei 225 of Japan, and SSE composite index of China. Post-pandemic et al. (2018) conclude that Bitcoin did not correlate with the S&P 500 both during periods of financial turmoil and normal times, thereby providing a hedging opportunity in these periods. Bejaoui et al. (2023) argue that the co-movements between emerging stock markets (i.e. Gulf and BRICS) and cryptos (i.e. Bitcoin, Ethereum, Monero, Gold, True, and Tether) tend to be different but insignificant against extremely stressful and unexpected events. Rubbaniy et al. (2024) identified stable hedge effectiveness of equity market indices and cryptos. Meanwhile, Cao and Celik (2021) demonstrate that Bitcoin call option value increases with the money supply growth rate while Wu et al. (2021) found that Bitcoin spot and futures prices exhibit long memory properties. Overall, extant studies have been silent on the features of cryptos that are linked to their co-movements.

3. Methodology

3.1. Data

There were 8985 active cryptos in the market as of 11th June 2024 (Coinmarketcap.com, 2024). We select the top 100 cryptos based on their market capitalisation. We also collect the daily closing prices for these cryptos from the birth of each crypto till 15th May 2024. We collect information regarding the fundamental and functional features of each crypto from the publicly available databases such as Coinmarketcap and their official websites. The stock market indexes include S&P500, IBEX35, FTSE100, FTSEMIB, CAC40, DAX, Vietnam ETF, and SSE, which are representative stock markets from the United States (US), Spain, United Kingdom (UK), Italy, France, Germany, Vietnam and China, respectively. The stock markets in the Big 5 European countries, including Spain, the UK, Italy, France, and Germany (Yoo et al., 2022), along with the US play dominant roles in the global economy (Wadhwani, 1999). Moreover, Vietnam ranks 1st in crypto adoption in 2023, while China is the largest country that has banned cryptos, these provide additional justifications for their inclusion in the study

The earliest available data was for Bitcoin whose daily price was available from 19th July 2010. We collect the daily closing prices of the above-mentioned eight stock markets from the publicly available database Yahoo Finance covering the period between 19 July 2010 to 15 May 2024 due to data constraints. To investigate the impacts of the COVID-19 pandemic we divide the time series data into 3 periods, before 11 March 2020 (pre-pandemic), from 11 March 2020 to 29 October 2021 (pandemic), and after 29 October 2021 (post pandemic). 11 March 2020 was the date WHO declared COVID-19 a pandemic while 29 October 2021 was the date when vaccination was completed in most of the developed countries (Oanh, 2022).

We estimate the daily return of each crypto and stock market using Equation 1.

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}} \tag{1}$$

where P is the asset price and t is the time period.

3.2. Augmented Dickey-fuller (ADF) test and Phillips-Perron test

Stationarity is a prior criterion for examining hedging effectiveness and Granger causality between cryptos and the stock market and can be examined using Augmented Dicky Fuller (ADF) test (Dickey & Fuller, 1979) and Phillips-Perron test (Phillips, 1988). Compared to the original Dicky-Fuller test, the ADF test includes lagged difference terms of the reliant variable to make a parametric correction, as shown in Equation 2.

$$\Delta R_t = c + bt + aR_{t-1} + d_1\Delta R_{t-1} + d_2\Delta R_{t-2} + \ldots + d_n\Delta R_{t-n} + e_t \tag{2}$$

where R_{t-i} is lag i of time series (i.e. daily return) of each asset (i.e. crypto or stock market), ΔR_t is the first difference of the daily returns at time step t-1.

The null hypothesis of the ADF test assumes the presence of a unit root, which means that $a=1$. If the time-series daily return of an asset is stationary, the estimated p-value will be smaller than the significance level (i.e. p-value < 0.05) so the null hypothesis will be rejected. To further verify the robustness of the results obtained from ADF tests, we conducted the Phillips-Perron test that the time series, i.e. daily return of an asset is integrated with order 1, as shown in Equation 3.

$$R_t = c + aR_{t-1} + e_t \tag{3}$$

3.3. Ordinary least squares (OLS) regression for safe-haven property and hedge effectiveness

A hedge is an asset which, on average, is negatively correlated with other assets in a portfolio and which maintains its safe asset properties over the long run (Kopyl & Lee, 2016). A safe haven is an asset that is negatively correlated with other assets during periods of market crisis. OLS regression has been commonly employed in financial studies to assess hedge and safe-haven properties. Following Baur and Lucey (2010), Baur and McDermott (2010), we use OLS regression models to obtain the constant optimum hedge ratio between different cryptos and stock markets (Ederington, 1979), as shown in Equation 4.

$$\boldsymbol{R}^s = a + \beta\boldsymbol{R}^c + e \tag{4}$$

where a and β are the regression parameters, while e is the error term. $\boldsymbol{R}^c$ is the daily return of a crypto, which is the independent variable. $\boldsymbol{R}^s$ is the daily return of a stock market, which is the dependent variable. β represents the hedge ratio. Hedge effectiveness is measured by the coefficient of determination R^2 of the regression between the daily return of cryptos and stock markets, which indicates the maximum risk reduction potential of a hedge. A higher R^2 value indicates better hedging effectiveness. A crypto is a safe-haven if its p-value from the OLS regression is smaller than 0.05 for the corresponding stock market.

3.4. Granger causality test and co-movement feature

Cryptos and stock markets exhibit dynamic behaviours that may evolve over time. Granger causality determines whether past values of stock market returns contain predictive information about crypto returns (Granger, 1969). This is essential for understanding co-movement, as it highlights whether one asset's behaviour influences the other. Following Matar et al. (2021), Jang and Sul (2002) and Li et al. (2015), we use the Granger causality test to examine the Granger causality connection between each crypto and the selected stock markets. Granger causality is a measurable feedback concept that is generally utilised in prediction models. The Granger causality test can indicate the existence of co-movement between cryptos and stock markets, as shown in Equation 5.

$$R_t^s = a + \beta_1 R_{t-1}^s + \beta_2 R_{t-2}^s + \ldots + \beta_p R_{t-p}^s + c_1 R_{t-1}^c + c_2 R_{t-2}^c + \ldots + c_q R_{t-q}^c + e_t \tag{5}$$

where R_t^s and R_t^c are the daily stock market and crypto returns at time step t, respectively. The null hypothesis of Granger causality test will be verified if $c_1 = c_2 = \ldots = c_q$, which means that crypto daily return R_t^c is not able to Granger cause stock market daily return R_t^s. If at least one of the β coefficient is significant (i.e. $p < 0.05$), the alternative hypothesis of Granger causality test is verified, meaning that crypto daily return R_t^c does Granger cause stock market daily return R_t^s. Overall, if the p-value of the Granger causality test is smaller than 0.05, the crypto demonstrates a significant co-movement with the corresponding stock market.

3.5. Logistic regression model

Furthermore, we use logistic regression models to identify the key fundamental and functional features that are associated with the safe-haven property and dynamic co-movements between cryptos and stock markets. The independent variables include consensus mechanism (*CS*) i.e. whether the cryptos uses PoW or PoS, whether the crypto has limited maximum supply (*MS*) or not, whether the crypto is made as a stablecoin (*S*) or not, whether the crypto is made as a privacy coin (*PC*) or not, whether the crypto is deployed upon EVM (*EVM*) or not, and the functional features of crypto (*F*). The features of the cryptos are introduced in Section 2.3. Each independent variable is adopted as a binary or dummy variable. The dependent variable of the logistic regression model is a binary variable to indicate whether there exists significant co-movement between each crypto and stock market. The logistic regression model assumes that the logit of the probability of whether the cryptocurrency has co-movement with the stock market can be modelled as a linear combination of the independent variables (Nick & Campbell, 2007). The logit is given by:

$$logit\left(P(Y=1|X)\right)=\log\left(\frac{P(Y=1|X)}{1-P(Y=1|X)}\right)=\beta_0+\beta_1X_1+\beta_2X_2+\ldots+\beta_kX_k \tag{5}$$

Where:

$P(Y=1|X)$ is the probability of the co-movement with the stock market given the independent variables (i.e. $X_1=CM, X_2=SC, X_3=ICO, X_4=LS, X_5=S, X_6=PC, X_7=EVM, X_8=F$).

β_0 is the intercept.

$\beta_1, \beta_2, \ldots, \beta_k$ are the coefficients of the independent variables $X_1, X_2, \ldots, X_k$.

Therefore, the probability that the dependent variable $Y=1$ is modelled using the logistic function:

$$P(Y=1|X)=\frac{1}{1+e^{-(\beta_0+\beta_1+X_1+\beta_2+X_2+\ldots\beta_kX_k)}} \tag{6}$$

This function maps any real-valued number into the interval (0,1), making it suitable for probability estimation.

4. Results

4.1. Descriptive summary of the stock market and cryptos

The descriptive statistics of the close price and daily return for the eight stock markets and the top 10 cryptos are summarised in Tables 1 and 2, respectively. In terms of close prices, the Italian stock market FTSEMIB and Vietnamese ETF have the largest and smallest average value and standard deviation of the close prices, respectively. Meanwhile, Bitcoin and Tron have the largest and smallest average values and standard deviation, respectively. The kurtosis of the 8 stock markets is smaller than 3, meaning that the distribution has lighter tails and flatter peaks than the normal distribution. The kurtosis of 49% of the cryptos are also smaller than 3. These cryptos include Bitcoin, Ethereum, Binance Coin, Solana, and TRON. The other 51% of the cryptos have a kurtosis value larger than 3, meaning that the distribution has heavier tails and sharper peaks than the normal distribution. These cryptos include Tether, Ripple, USD Coin, Dogecoin and Cardano. The skewness of most stock markets (except for IBEX35 and FTSE100) and all cryptos is larger than 0, meaning that the time-series data of daily close prices has a longer tail on the right side. The *p*-value of Jarque Beras of all stock markets and cryptos is smaller than 0.01, meaning that all the time series data do not follow the normal distribution.

Table 1. Descriptive summary of daily close prices of stock markets and cryptos.

	Count	Mean	SD	Min	Max	Kurtosis	Skewness	Jarque Beras	*p*-value of Jarque Beras
Stock market									
S&P500	3616	2600.27	1129.64	1022.58	5308.15	−0.88	0.53	284.68	0.000
IBEX35	367	9249.57	1150.60	5956.30	12222.50	−0.37	−0.22	51.12	0.000
FTSE100	3626	6699.36	745.51	4805.80	8445.80	−0.92	−0.35	202.87	0.000
FTSEMIB	3651	21215.82	3995.39	12363.00	35366.00	0.64	0.56	253.90	0.000
CAC40	3674	5027.65	1235.60	2781.68	8239.99	−0.53	0.51	203.16	0.000
DAX	3646	11066.32	3203.18	5072.33	18869.36	−0.91	0.01	126.67	0.000
Vietnam ETF	3616	17.49	3.67	9.70	30.00	0.05	0.68	283.10	0.000
SSE	3483	2934.47	504.46	1950.01	5166.35	0.76	0.17	98.33	0.000
Cryptos									
BTC	3529	16226.75	17993.52	178.10	73083.50	0.36	1.18	254.14	0.000
ETH	2380	1338.85	1166.25	84.31	4812.09	−0.35	0.78	128671.34	0.000
USDT	2380	1.00	0.01	0.97	1.08	35.70	2.66	220.00	0.000
BNB	2380	182.96	184.34	1.51	675.68	−0.74	0.64	17440.20	0.000
XRP	2380	0.52	0.33	0.14	3.38	12.24	2.59	16217.86	0.000
USDC	2047	1.00	0.01	0.97	1.04	12.87	2.52	5325.24	0.000
DOGE	2380	0.07	0.09	0.00	0.68	6.03	2.10	2618.12	0.000
ADA	2380	0.47	0.56	0.02	2.97	3.46	1.90	502.31	0.000
SOL	1497	53.22	58.23	0.52	258.93	0.86	1.35	176.49	0.000
TRX	2380	0.05	0.03	0.00	0.22	−0.05	0.67	1720.15	0.000

Table 2. Descriptive summary of daily return of stock markets and cryptos.

	Count	Mean	SD	Min	Max	Kurtosis	Skewness	Jarque Beras	*p*-value of Jarque Beras
Stock market									
S&P500	3615	0.05	1.10	−11.98	−0.38	12.29	−0.49	22,840	0.000
IBEX35	3673	0.01	1.37	−14.06	−0.67	10.58	−0.26	17,107	0.000
FTSE100	3625	0.02	1.00	−10.87	−0.45	8.77	−0.49	11,724	0.000
FTSEMIB	3650	0.02	1.51	−16.93	−0.71	9.03	−0.67	12,644	0.000
CAC40	3673	0.03	1.25	−12.28	−0.55	7.42	−0.32	8456	0.000
DAX	3645	0.04	1.24	−12.24	−0.52	7.19	−0.31	7881	0.000
Vietnam ETF	3615	−0.01	1.56	−10.71	−0.82	2.98	−0.29	1379	0.000
SSE	3482	0.01	1.27	−8.49	−0.56	6.00	−0.72	5511	0.000
Cryptos									
BTC	3528	0.21	3.68	−37.17	−1.25	7.48	−0.13	8214	0.000
ETH	2379	0.20	4.66	−42.35	−1.87	6.18	−0.21	3781	0.000
USDT	2379	0.00	0.40	−5.12	−0.05	59.76	1.16	352,975	0.000
BNB	2379	0.38	5.52	−41.90	−1.78	25.83	2.03	67,467	0.000
XRP	2379	0.22	6.29	−42.33	−2.11	34.44	3.14	120,977	0.000
USDC	2046	0.00	0.33	−3.65	−0.03	40.52	0.59	139370	0.000
DOGE	2379	0.50	10.08	−40.26	−2.28	654.65	19.46	42452621	0.000
ADA	2379	0.31	6.84	−39.57	−2.67	87.57	5.32	768,177	0.000
SOL	1496	0.59	7.10	−42.28	−3.20	5.00	0.51	1609	0.000
TRX	2379	0.38	7.00	−40.73	−2.03	86.67	5.70	754,265	0.000

Regarding daily return, the US stock market S&P500 and Vietnamese ETF have the largest and smallest average values, while the Vietnamese ETF and UK FTSE100 have the largest and smallest standard deviations, respectively. Meanwhile, Solana and USDT, USDC have the largest and smallest average values and standard deviations, respectively. The kurtosis for most of the stock markets and cryptos is larger than 3, meaning that the distribution has heavier tails and sharper peaks than the normal distribution. The skewness for all the stock markets is smaller than zero, meaning that the time-series data of daily return has a longer tail on the left side. On the contrary, the skewness for most of the cryptos is larger than zero, meaning that the time-series data of daily return has a longer tail on the right side. The p-value of Jarque Beras of all stock markets and cryptos is smaller than 0.01, meaning that all the time series data do not follow the normal distribution.

4.2. Results of the ADF test and phillips test

For illustration purposes, the ADF test and Phillips test results of the daily return for the eight stock markets and the top 10 cryptos are summarised in Table 3. The p-values of both the ADF test and the Phillips test are smaller than 0.01. This demonstrates the stationarity of each crypto and stock market,

Table 3. Results of ADF test and Phillips test.

	ADF test		Phillips test			ADF test		Phillips test	
Stock market	*t*-value	*p*-value	*t*-value	*t*-value	Cryptos	t-value	*p*-value	*t*-value	*p*-value
S&P500	−13.03	0.000	−67.91	0.000	BTC	−59.30	0.000	−59.43	0.000
IBEX35	−21.66	0.000	−58.49	0.000	ETH	−14.14	0.000	−49.64	0.000
FTSE100	−13.58	0.000	−59.92	0.000	USDT	−16.54	0.000	−126.30	0.000
FTSEMIB	−31.17	0.000	−62.18	0.000	BNB	−10.24	0.000	−47.70	0.000
CAC40	−22.08	0.000	−60.38	0.000	XRP	−9.85	0.000	−48.02	0.000
DAX	−21.72	0.000	−58.92	0.000	USDC	−12.70	0.000	−113.82	0.000
Vietnam ETF	−60.70	0.000	−60.69	0.000	DOGE	−7.58	0.000	−45.49	0.000
SSE	−10.94	0.000	−56.58	0.000	ADA	−8.55	0.000	−49.62	0.000

meaning that the OLS regression models, and Granger causality tests can be conducted using these sets of crypto and stock market data.

4.3. Hedge effects between cryptos and stock markets

We use OLS regression models to examine the hedge effectiveness between stock markets and cryptos. We summarise the hedge ratio (beta), R^2, and p-value for the cryptos that have significant hedge effects with stock markets in Table 4 below. A negative hedge ratio (beta) indicates that the crypto's return moves inversely to the stock market's return, meaning the crypto can serve as a safe haven. A p-value of the OLS regression model smaller than 0.05 indicates a significant hedge effect between the corresponding crypto and the stock market. The R^2 value measures the proportion of variance in the crypto's returns that is explained by the stock market's return.

Before the COVID-19 pandemic, USDC is the only crypto among the top 10 cryptos serving as a safe-haven for seven stock markets (i.e. S&P500, IBEX35, FTSE100, CAC40, DAX, Vietnam ETF, and SSE). During the COVID-19 pandemic, USDC stopped showing safe-haven features for SSE, but showed safe-haven features for FTSEMIB, and continued showing safe-haven features for the other stock markets. USDT show safe-haven features for all 8 stock markets. SOL showed a safe haven feature for the Chinese stock market SSE only. After the COVID-19 pandemic, USDC and USDT continued showing safe-haven features for IBEX35, FTSE100, FTSEMIB, CAC40, and DAX, while they stopped showing safe-haven features for the other stock markets. The other leading cryptos, such as Bitcoin, Ethereum, Ripple, Dash, Tether, and Monero did not show safe haven features for any of the studied stock markets. This implies that only stablecoins such as USDC and USDT are suitable diversification for traditional stock markets most of the time, while other leading cryptos failed to fulfil such functionality. Still focusing on before the COVID-19 pandemic, there were only 11, 14, 12, 12, 12, 11, 10, and 10 (out of 100) cryptos demonstrating safe haven properties on US, Spanish, UK, Italian, French, German, Vietnam, and Chinese stock markets, respectively.

During the COVID-19 pandemic, there were only 9, 14, 15, 10, 11, 10, 10, and 23 (out of 100) cryptos showing safe haven properties on US, Spanish, UK, Italian, French, German, Vietnam, and Chinese stock markets, respectively. After the COVID-19 pandemic, there were only 4, 16, 9, 11, 11, 11, 8, and 9 (out of 100) cryptos demonstrating safe haven properties on US, Spanish, UK, Italian, French, German, Vietnam, and Chinese stock markets, respectively. The fact that only a smaller number of cryptos can serve as safe haven properties on these exchanges may be because most cryptos are still young and speculative investors looked for quick gains rather than long-term investment. Also, hacking, technological flaws, and operational risks may have led to sudden drops in crypto values, reducing the appetite to hold them in lieu of traditional assets. Meanwhile, the COVID-19 pandemic has made more cryptos act as safe havens for UK and Chinese stock markets, given the number of cryptos demonstrating hedge effects for these markets; for example, this increased from 10 to 23 for the Chinese stock. However, the number of cryptos acting as safe havens for US and Chinese stock markets reduced dramatically after the COVID-19 pandemic (i.e. from 9 and 23 to 4 and 9, respectively), while the number of cryptos acting as safe havens for the Spanish stock market slightly increased (i.e. from 14 to 16). This implies that most investors turn to cryptos as diversifications during the pandemic, especially in China.

However, we found that most cryptos are no longer suitable as safe haven for traditional stock markets after the pandemic period, indicating a transient demand for cryptos fuelled by the pandemic. The

Table 4. Hedge ratio and R^2 coefficient between stock markets and cryptos.

	S&P500			IBEX35			FTSE100			FTSEMIB			CAC40			DAX			Vietnam ETF			SSE		
Cryptos	Hedge ratio	*p*-value	R^2	Hedge ratio	*p*-value	R^2	Hedge ratio	*p*-value	R^2	Hedge ratio	*p*-value	R^2	Hedge ratio	*p*-value	R^2	Hedge ratio	*p*-value	R^2	Hedge ratio	*p*-value	R^2	Hedge ratio	*p*-value	R^2
Pre-Covid pandemic																								
USDC	−0.094	0.000	0.001	−0.031	0.000	0.000	−0.053	0.000	0.001	0.062	0.547	0.001	−0.061	0.000	0.001	−0.035	0.000	0.000	−0.087	0.000	0.001	−0.178	0.000	0.004
LTC	0.005	0.000	0.001	−0.002	0.000	0.000	0.002	0.000	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.002	0.000	0.000	0.010	0.000	0.002	0.002	0.000	0.000
MATIC	0.003	0.092	0.001	0.004	0.921	0.002	0.000	0.000	0.000	−0.003	0.914	0.000	−0.001	0.000	0.000	−0.001	0.048	0.000	0.005	0.000	0.002	−0.001	0.000	0.000
WBTC	−0.002	0.018	0.000	−0.001	0.806	0.000	−0.001	0.000	0.000	0.004	0.892	0.000	−0.001	0.000	0.000	−0.003	0.000	0.000	0.000	0.000	0.000	0.028	0.000	0.009
DAI	−0.259	0.740	0.029	−0.197	0.000	0.022	−0.228	0.000	0.034	−0.306	0.993	0.035	−0.271	0.000	0.043	−0.242	0.000	0.034	−0.091	0.000	0.006	−0.034	0.000	0.001
LEO	−0.004	0.116	0.000	0.003	0.960	0.000	0.012	0.824	0.001	0.022	0.986	0.002	−0.007	0.000	0.000	−0.003	0.000	0.000	−0.005	0.000	0.000	−0.004	0.000	0.000
UNI	0.001	0.071	0.001	0.001	0.000	0.000	0.001	0.000	0.001	0.001	0.994	0.001	0.000	0.000	0.000	0.001	0.000	0.000	−0.001	0.000	0.001	0.003	0.000	0.007
TUSD	−0.007	0.000	0.000	−0.053	0.000	0.001	0.011	0.000	0.000	−0.083	0.000	0.002	0.018	0.000	0.000	−0.057	0.000	0.001	−0.038	0.000	0.000	−0.045	0.000	0.001
CRO	−0.001	0.006	0.000	0.000	0.609	0.000	0.001	0.000	0.000	0.003	0.942	0.001	0.001	0.000	0.000	−0.001	0.000	0.000	0.003	0.000	0.001	−0.001	0.000	0.000
ARB	0.001	0.000	0.000	0.004	0.000	0.004	0.003	0.000	0.002	0.005	0.009	0.004	0.003	0.000	0.003	0.003	0.000	0.003	−0.001	0.000	0.000	0.003	0.000	0.002
QNT	−0.002	0.000	0.000	−0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.471	0.000	0.000	0.000	0.000	0.000	0.000	0.000	−0.004	0.000	0.001	0.008	0.000	0.005
ALGO	0.017	0.022	0.011	−0.002	0.968	0.000	−0.006	0.000	0.002	−0.016	0.987	0.008	−0.009	0.000	0.004	−0.009	0.000	0.004	0.003	0.000	0.000	0.007	0.000	0.003
SNX	−0.010	0.000	0.007	−0.008	0.000	0.007	−0.008	0.000	0.008	−0.009	0.000	0.006	−0.008	0.000	0.006	−0.007	0.000	0.005	−0.012	0.000	0.008	−0.001	0.000	0.000
RPL	−0.001	0.000	0.000	−0.004	0.000	0.004	0.000	0.000	0.000	−0.001	0.426	0.000	−0.001	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	−0.004	0.000	0.002
KAVA	0.053	0.344	0.032	0.025	0.000	0.009	0.025	0.000	0.010	−0.001	0.993	0.000	0.017	0.000	0.004	0.026	0.000	0.010	0.030	0.000	0.015	0.048	0.000	0.039
CHZ	0.007	0.236	0.003	0.010	0.000	0.007	−0.002	0.000	0.000	0.007	0.989	0.003	0.008	0.000	0.004	0.007	0.000	0.004	0.010	0.000	0.007	0.004	0.000	0.001
KCS	0.011	0.000	0.006	−0.001	0.000	0.000	0.004	0.000	0.001	0.001	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.000	0.012	0.000	0.005	0.012	0.000	0.007
USDP	−0.202	0.000	0.004	−0.052	0.000	0.000	−0.073	0.000	0.001	−0.174	0.501	0.003	−0.096	0.000	0.001	−0.074	0.000	0.001	−0.174	0.000	0.003	−0.512	0.000	0.023
COMP	0.001	0.000	0.007	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.000	0.013	0.001	0.000	0.001
ZEC	0.006	0.000	0.001	0.000	0.000	0.000	0.007	0.000	0.002	0.005	0.000	0.001	0.007	0.000	0.002	0.005	0.000	0.001	0.012	0.000	0.003	0.012	0.000	0.004
LUNC	0.011	0.390	0.003	0.015	0.977	0.007	0.012	0.924	0.005	0.016	0.987	0.005	0.020	0.968	0.012	0.016	0.923	0.008	0.020	0.000	0.014	−0.002	0.000	0.000
BTT	0.006	0.023	0.001	0.001	0.813	0.000	−0.002	0.000	0.000	−0.003	0.891	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.011	0.000	0.003	0.023	0.000	0.009
GUSD	−0.059	0.000	0.004	−0.068	0.000	0.007	−0.061	0.000	0.007	−0.091	0.537	0.008	−0.073	0.000	0.008	−0.060	0.000	0.005	−0.004	0.000	0.000	0.015	0.000	0.000
During Covid pandemic																								
USDT	−1.101	0.000	0.105	−0.995	0.000	0.082	−0.720	0.000	0.060	−1.275	0.000	0.137	−0.763	0.000	0.055	−0.718	0.000	0.047	−0.648	0.000	0.032	−0.029	0.000	0.000
USDC	−0.999	0.000	0.069	−1.188	0.000	0.091	−0.751	0.000	0.051	−1.298	0.000	0.111	−0.800	0.000	0.047	−0.689	0.000	0.034	−0.591	0.000	0.021	0.025	0.000	0.000
SOL	0.009	0.000	0.012	0.007	0.000	0.007	0.003	0.000	0.002	0.010	0.000	0.013	0.007	0.000	0.008	0.006	0.000	0.006	0.001	0.000	0.000	−0.003	0.000	0.004
DOT	0.031	0.000	0.077	0.016	0.000	0.013	0.014	0.000	0.015	0.029	0.000	0.046	0.023	0.000	0.034	0.030	0.000	0.053	0.033	0.000	0.053	0.000	0.000	0.000
SHIB	−0.003	0.000	0.008	0.007	0.000	0.028	0.002	0.000	0.006	0.004	0.000	0.010	0.002	0.000	0.005	0.002	0.000	0.002	0.003	0.002	0.006	−0.001	0.000	0.001
DAI	0.050	0.000	0.001	−0.237	0.000	0.014	−0.171	0.000	0.010	−0.112	0.000	0.003	−0.234	0.000	0.016	−0.269	0.000	0.020	−0.170	0.000	0.007	−0.188	0.000	0.022
LEO	−0.006	0.000	0.000	0.003	0.000	0.000	−0.010	0.000	0.001	−0.003	0.000	0.000	−0.004	0.000	0.000	0.001	0.000	0.000	0.002	0.000	0.000	−0.011	0.000	0.002
UNI	−0.002	0.000	0.002	0.000	0.000	0.000	−0.001	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	−0.002	0.000	0.002	−0.001	0.000	0.001
BUSD	−0.986	0.000	0.090	−0.952	0.000	0.079	−0.700	0.000	0.059	−1.234	0.000	0.135	−0.694	0.000	0.048	−0.631	0.000	0.038	−0.491	0.000	0.020	0.066	0.000	0.001
TUSD	−1.148	0.000	0.098	−1.094	0.000	0.083	−0.810	0.000	0.064	−1.369	0.000	0.133	−0.789	0.000	0.049	−0.739	0.000	0.041	−0.600	0.000	0.024	0.055	0.000	0.001
FIL	0.004	0.000	0.001	−0.003	0.000	0.000	−0.005	0.000	0.002	0.002	0.000	0.000	−0.007	0.000	0.003	−0.006	0.000	0.002	−0.003	0.000	0.000	0.003	0.000	0.001
ICP	0.024	0.000	0.104	0.012	0.000	0.015	0.010	0.000	0.019	0.021	0.000	0.049	0.015	0.000	0.029	0.019	0.000	0.047	0.026	0.012	0.056	−0.001	0.000	0.000
ARB	0.006	0.000	0.004	0.000	0.000	0.000	−0.001	0.000	0.000	0.003	0.000	0.001	0.004	0.000	0.002	0.004	0.000	0.002	0.004	0.000	0.002	0.000	0.000	0.000
GRT	−0.001	0.000	0.003	−0.001	0.000	0.005	0.000	0.000	0.000	−0.001	0.000	0.004	0.000	0.000	0.001	0.000	0.000	0.001	−0.001	0.000	0.005	0.000	0.000	0.000
XDC	0.044	0.000	0.063	0.041	0.000	0.054	0.035	0.000	0.055	0.044	0.000	0.062	0.034	0.000	0.042	0.033	0.000	0.038	0.043	0.000	0.055	−0.002	0.000	0.000
ALGO	0.064	0.000	0.099	0.046	0.000	0.050	0.037	0.000	0.043	0.061	0.000	0.089	0.043	0.000	0.050	0.047	0.000	0.056	0.061	0.000	0.081	−0.003	0.000	0.001
SAND	0.012	0.000	0.021	0.003	0.000	0.001	0.005	0.000	0.003	0.008	0.000	0.006	0.009	0.000	0.009	0.013	0.000	0.021	0.008	0.000	0.006	−0.001	0.000	0.000
XEC	0.005	0.520	0.011	−0.003	0.000	0.002	0.001	0.000	0.000	0.004	0.000	0.003	0.000	0.000	0.000	0.000	0.000	0.000	0.014	0.000	0.033	−0.001	0.000	0.000
USDP	−0.913	0.000	0.079	−0.899	0.000	0.072	−0.579	0.000	0.042	−1.106	0.000	0.111	−0.590	0.000	0.035	−0.539	0.000	0.028	−0.512	0.000	0.022	0.065	0.000	0.001
GALA	0.002	0.000	0.002	0.002	0.000	0.001	0.001	0.000	0.000	0.003	0.000	0.005	0.002	0.000	0.001	0.002	0.000	0.003	0.003	0.000	0.004	0.000	0.000	0.000

(*Continued*)

Table 4. Continued.

	S&P500			IBEX35			FTSE100			FTSEMIB			CAC40			DAX			Vietnam ETF			SSE		
Cryptos	Hedge ratio	*p*-value	R^2	Hedge ratio	*p*-value	R^2	Hedge ratio	*p*-value	R^2	Hedge ratio	*p*-value	R^2	Hedge ratio	*p*-value	R^2	Hedge ratio	*p*-value	R^2	Hedge ratio	*p*-value	R^2	Hedge ratio	*p*-value	R^2
CRV	0.016	0.000	0.041	0.002	0.000	0.000	0.003	0.000	0.001	0.009	0.000	0.010	0.005	0.000	0.003	0.012	0.000	0.017	0.016	0.000	0.023	−0.005	0.000	0.003
COMP	0.000	0.000	0.010	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.004	0.000	0.000	0.000	0.000	0.000	0.000
PAXG	0.336	0.000	0.066	−0.003	0.000	0.000	0.049	0.000	0.002	0.100	0.000	0.006	0.047	0.000	0.001	0.105	0.000	0.007	0.210	0.000	0.023	0.040	0.000	0.002
XAUT	0.216	0.000	0.019	−0.050	0.000	0.001	0.058	0.000	0.002	−0.015	0.000	0.000	0.012	0.000	0.000	0.108	0.000	0.005	0.245	0.000	0.022	0.138	0.000	0.019
GMX	0.005	0.000	0.019	0.000	0.000	0.000	−0.003	0.000	0.010	0.002	0.000	0.001	0.003	0.000	0.004	0.003	0.000	0.009	−0.004	0.000	0.008	−0.003	0.000	0.006
CSPR	0.008	0.000	0.022	0.013	0.000	0.034	0.011	0.000	0.039	0.019	0.000	0.068	0.014	0.000	0.045	0.013	0.000	0.041	0.010	0.007	0.016	0.000	0.000	0.000
FXS	0.007	0.000	0.015	0.000	0.000	0.000	−0.001	0.000	0.000	0.001	0.000	0.000	0.002	0.000	0.001	−0.001	0.000	0.000	0.008	0.000	0.009	0.004	0.000	0.003
TWT	0.001	0.000	0.000	−0.003	0.000	0.001	−0.001	0.000	0.000	−0.002	0.000	0.000	−0.001	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.001	0.009	0.000	0.014
BONE	0.001	0.000	0.003	0.000	0.000	0.000	0.001	0.000	0.002	0.002	0.000	0.005	0.001	0.000	0.000	0.002	0.000	0.003	0.001	0.000	0.002	−0.001	0.000	0.001
GUSD	0.238	0.000	0.063	0.143	0.000	0.022	0.095	0.000	0.013	0.205	0.000	0.046	0.075	0.000	0.007	0.056	0.000	0.004	0.159	0.000	0.025	−0.074	0.000	0.015
WOO	0.011	0.000	0.056	0.005	0.000	0.005	0.008	0.000	0.022	0.007	0.000	0.014	0.006	0.000	0.010	0.008	0.000	0.017	0.009	0.000	0.017	−0.003	0.000	0.003
1INCH	0.016	0.000	0.039	0.009	0.000	0.007	0.005	0.000	0.004	0.020	0.000	0.039	0.009	0.000	0.012	0.017	0.000	0.034	0.014	0.000	0.012	−0.006	0.000	0.004
Post-Covid pandemic																								
USDT	1.814	0.000	0.005	−0.484	0.000	0.000	−0.347	0.000	0.000	−0.419	0.000	0.000	−0.988	0.000	0.001	−0.490	0.000	0.000	0.596	0.000	0.000	0.161	0.000	0.000
USDC	0.178	0.000	0.000	−1.751	0.000	0.005	−1.747	0.000	0.007	−1.704	0.000	0.003	−1.422	0.000	0.003	−1.147	0.000	0.002	0.254	0.000	0.000	1.290	0.000	0.003
DAI	0.235	0.000	0.001	−0.079	0.000	0.000	0.002	0.000	0.000	−0.254	0.000	0.001	−0.235	0.000	0.001	−0.302	0.000	0.002	−0.410	0.000	0.002	0.348	0.000	0.003
UNI	0.000	0.000	0.007	0.000	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.003	0.000	0.000	0.000
BUSD	0.053	0.000	0.000	0.482	0.000	0.004	0.176	0.000	0.001	0.418	0.000	0.002	0.334	0.000	0.002	0.316	0.000	0.002	0.523	0.000	0.003	−0.003	0.000	0.000
TUSD	0.149	0.000	0.001	−0.019	0.000	0.000	0.140	0.000	0.001	0.072	0.000	0.000	0.031	0.000	0.000	0.098	0.000	0.000	−0.260	0.000	0.001	0.482	0.000	0.012
XMR	0.086	0.000	0.099	0.036	0.000	0.020	0.022	0.000	0.011	0.038	0.000	0.017	0.034	0.000	0.017	0.034	0.000	0.016	0.039	0.000	0.012	−0.009	0.000	0.002
MNT	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.001	0.002	0.000	0.009	−0.001	0.000	0.009
APT	0.002	0.000	0.001	0.004	0.000	0.003	0.001	0.000	0.000	0.004	0.000	0.002	0.003	0.000	0.001	0.005	0.000	0.003	0.002	0.000	0.000	0.000	0.000	0.000
ARB	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.007	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000
OP	0.000	0.000	0.001	0.000	0.000	0.002	0.000	0.000	0.002	0.000	0.000	0.002	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.005	0.009	0.000	0.003
GRT	0.067	0.000	0.118	0.061	0.000	0.068	0.040	0.000	0.047	0.069	0.000	0.062	0.072	0.000	0.075	0.075	0.000	0.079	0.044	0.000	0.057	−0.012	0.000	0.005
STX	0.000	0.000	0.000	0.000	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.005	0.000	0.000	0.006	0.000	0.000	0.004	0.000	0.000	0.000	0.000	0.000	0.000
IMX	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.001	0.000	0.003	0.000	0.000	0.001
USDD	0.623	0.000	0.022	0.020	0.000	0.000	0.072	0.000	0.001	−0.023	0.000	0.000	0.062	0.000	0.000	0.050	0.000	0.000	0.400	0.000	0.005	0.010	0.000	0.000
APE	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.007	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000
PEPE	0.008	0.000	0.015	−0.001	0.000	0.001	−0.003	0.000	0.011	0.005	0.000	0.009	−0.001	0.000	0.001	−0.001	0.000	0.000	0.008	0.002	0.010	0.003	0.000	0.004
PAXG	0.147	0.000	0.012	−0.022	0.000	0.000	−0.015	0.000	0.000	0.025	0.000	0.000	0.004	0.000	0.000	0.016	0.000	0.000	0.115	0.000	0.004	0.138	0.000	0.015
XAUT	0.169	0.000	0.014	−0.040	0.000	0.001	−0.016	0.000	0.000	0.019	0.000	0.000	−0.010	0.000	0.000	0.002	0.000	0.000	0.128	0.000	0.005	0.164	0.000	0.018
LUNC	0.008	0.000	0.006	−0.002	0.000	0.000	0.000	0.000	0.000	−0.001	0.000	0.000	−0.002	0.000	0.000	−0.003	0.000	0.001	0.013	0.000	0.009	−0.005	0.000	0.003
GMX	−0.002	0.000	0.005	−0.001	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	−0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000
SUI	0.001	0.000	0.002	0.001	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.002	0.000	0.000	0.000	0.001	0.000	0.001	−0.001	0.000	0.005
ARP	0.052	0.000	0.094	0.018	0.000	0.015	0.017	0.000	0.018	0.030	0.000	0.029	0.028	0.000	0.030	0.027	0.000	0.027	0.031	0.000	0.019	−0.001	0.000	0.000
GUSD	0.127	0.000	0.002	−0.049	0.000	0.000	−0.110	0.000	0.003	−0.078	0.000	0.001	−0.037	0.000	0.000	0.001	0.000	0.000	−0.055	0.000	0.000	0.075	0.000	0.001

type of cryptos that act as safe-haven for the stock markets also keeps changing during different periods, meaning that there is no single solution to finding a safe haven for stock markets from cryptos. For example, USDC, DAI, and TUSD constantly act as a safe haven for IBEX35 before, during, and after the COVID-19 pandemic, while USDC and DAI constantly act as a safe haven for CAC40 and DAX, but DAI and TUSD constantly act as a safe haven for Vietnam ETF. Meanwhile, USDC and DAI are the only cryptos that constantly act as a safe haven for FTSE100 and FTSEMIB, respectively. It is interesting to note that USDC, TUSD, and DAI are all pegged to fiat currency, and the peg is maintained through various mechanisms to ensure stability and minimise price fluctuation.

4.4. Co-movement between cryptos and stock markets

A Granger causality test with a *p*-value smaller than 0.05 indicates a significant co-movement between two time-series data. The heatmap of the *p*-value of the Granger causality test result presents the co-movement between the eight stock markets and 100 cryptos, as shown in Figure 1. A *p*-value smaller than 0.05 (i.e.showing in dark blue) indicates significant co-movement between a crypto and a stock market, meaning that there is less than 5% chance that the observed correlation is due to random variation. Light blue, orange, and red mean that there is no evidence to suggest that there exist any co-movements between a crypto and stock market. Especially, red means that the *p*-value is larger than 0.9 and there is a 90% chance that the observed correlation is due to random variation.

Before the COVID-19 pandemic, there were 42, 21, 21, 18, 28, 28, 31, and 33 (out of 100) cryptos showing significant co-movement with the selected stock markets in this study (S&P500, IBEX35, FTSE100, FTSEMIB, CAC40, DAX, Vietnam ETF, and SSE stock markets), respectively. USDC, HBAR, XAUT, TWT, BONE, and DASH showed significant co-movement with all eight stock markets. Moreover, Bitcoin showed significant co-movement with the US, Spanish, Italian, French, German, Vietnam, and Chinese stock markets, while Ethereum only demonstrated significant co-movement with the US, Spanish, French, German, and Vietnam stock markets. Binance coin only showed significant co-movement with US and Chinese stock markets, while XRP only showed significant co-movement with Vietnam and Chinese stock markets.

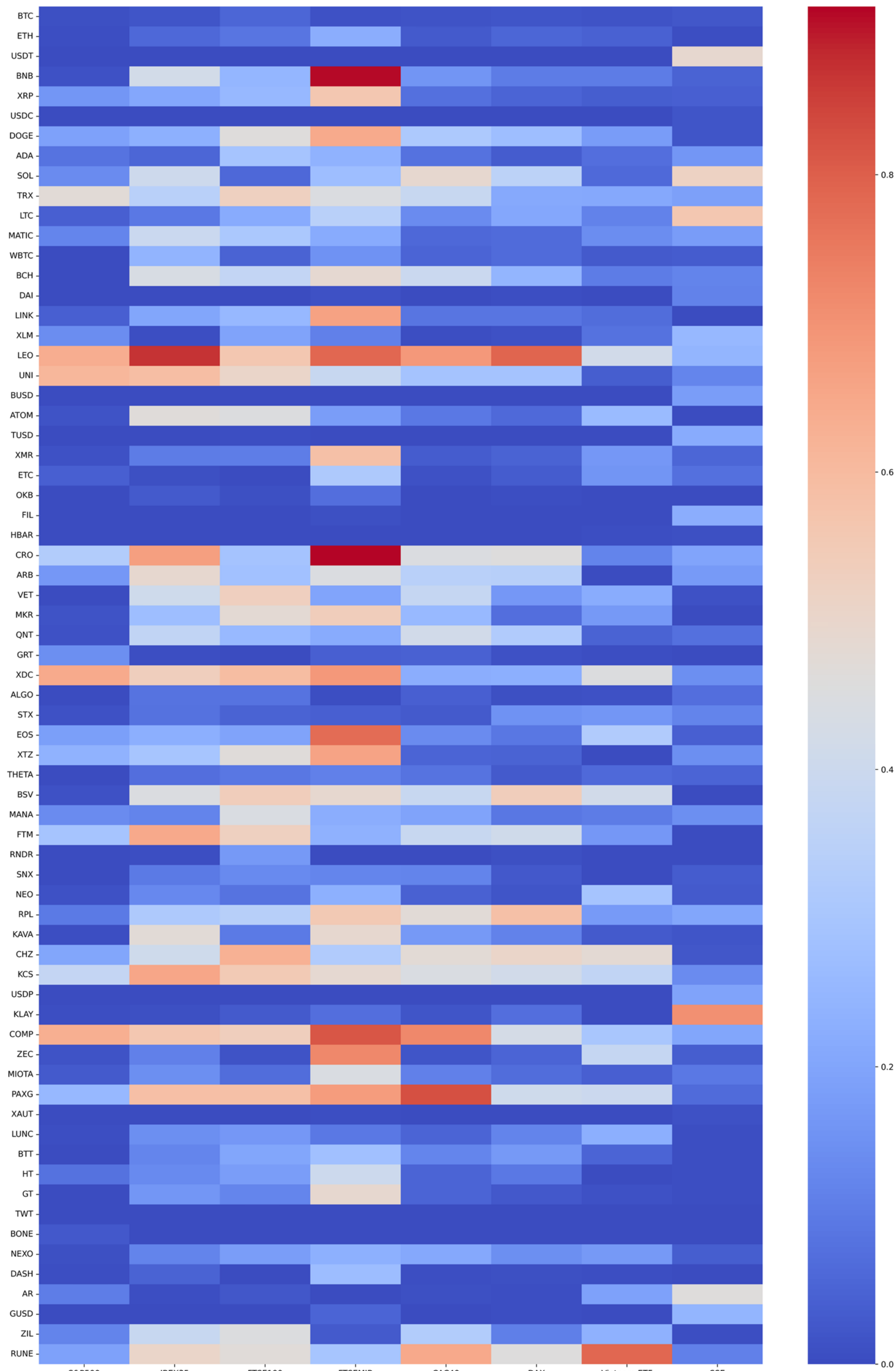
During the COVID-19 pandemic, there were 33, 19, 33, 40, 28, 30, 35, and 59 (out of 100) cryptos showing significant co-movement with the selected markets. Only CRO and XEC showed significant co-movement with all eight stock markets. Bitcoin showed significant co-movement with the UK, Italian, French, and Chinese stock markets, while Ethereum showed significant co-movement with Italian, French, German, and Chinese stock markets. Binance coin only showed significant co-movement with the German stock market, while XRP only showed significant co-movement with the US and Vietnam stock markets.

After the COVID-19 pandemic, there were 25, 37, 60, 33, 67, 54, 76 and 54 (out of 100) cryptos showing significant co-movement with the selected markets. Bitcoin, Ethereum, AVAX, OKB, GRT, EGLD, FTM, WOO, and RUNE demonstrated significant co-movement with stock markets in all eight countries. XRP demonstrated significant co-movement with the UK, French, German, Vietnam, and Chinese stock markets, while Binance coin demonstrated significant co-movement with Spanish, UK, French, German, and Vietnam stock markets.

We find that many cryptos began to show co-movement with stock markets during and after the COVID-19 pandemic, especially for IBEX35, FTSE100, FTSEMIB, CAC40, DAX, Vietnam ETF, and SEE. Only the S&P500 showed co-movement with fewer number of cryptos after the COVID-19 pandemic. These indicate that more cryptos began to show the same volatility trend as representative stock markets after the COVID-19 pandemic, so most cryptos are not able to act as safe havens for stock markets. Meanwhile, leading cryptos such as Bitcoin, Ethereum, Binance coin, and XRP began to show co-movement with a larger number of stock markets after the COVID-19 pandemic reducing their potential to act as safe-haven. It also implies that leading cryptos began to have the same price volatility trend as traditional stock markets, potentially indicating their maturity.

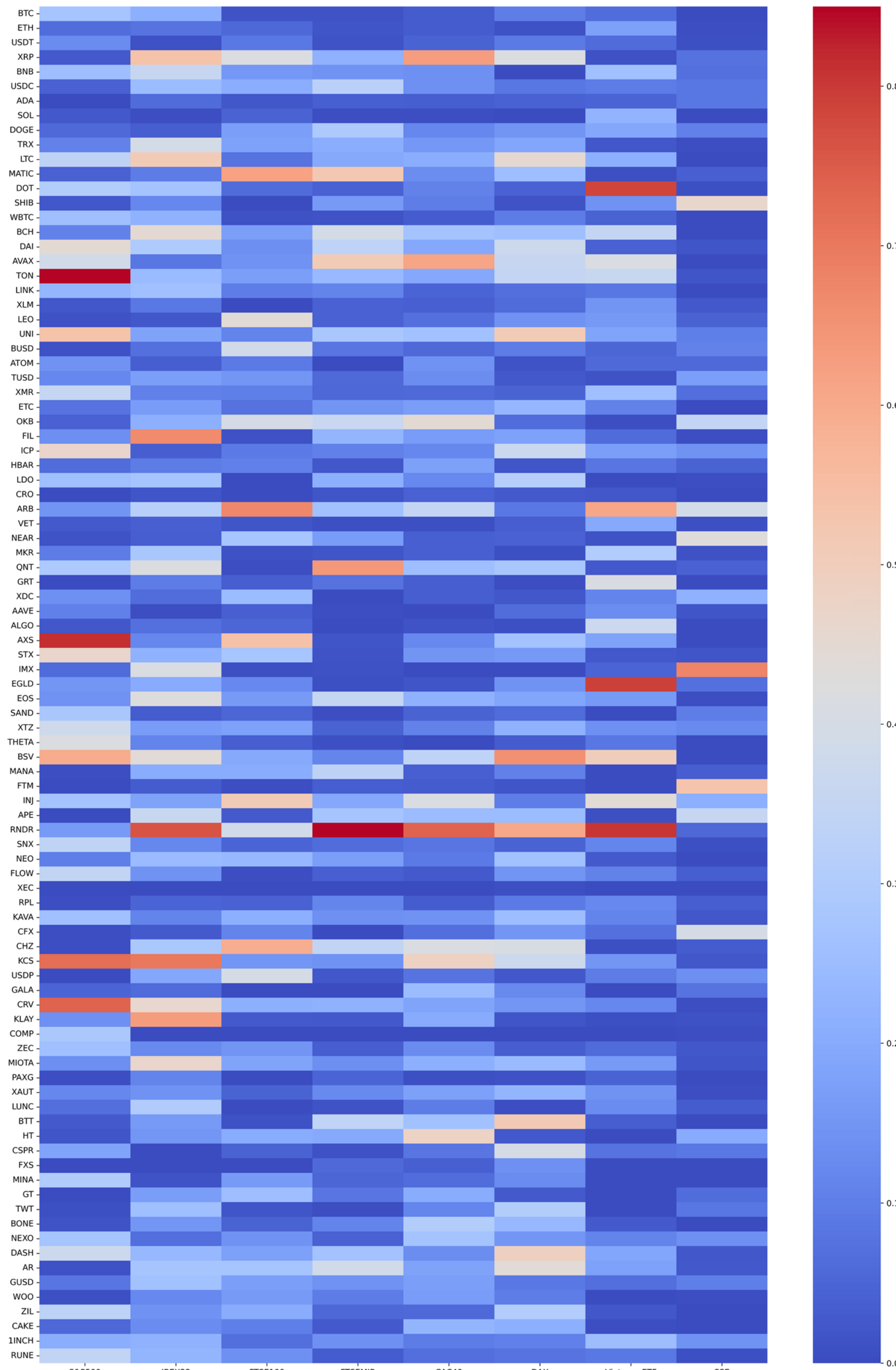
4.5. Logistic regression model analysis

Our 100 cryptos consisted of 27 Dapp coins, 24 Defi coins, 10 NFT coins, 3 utility coins, and 36 cryptos used as a means of exchange and payment. In terms of consensus mechanisms, 17, 59, and 24 cryptos



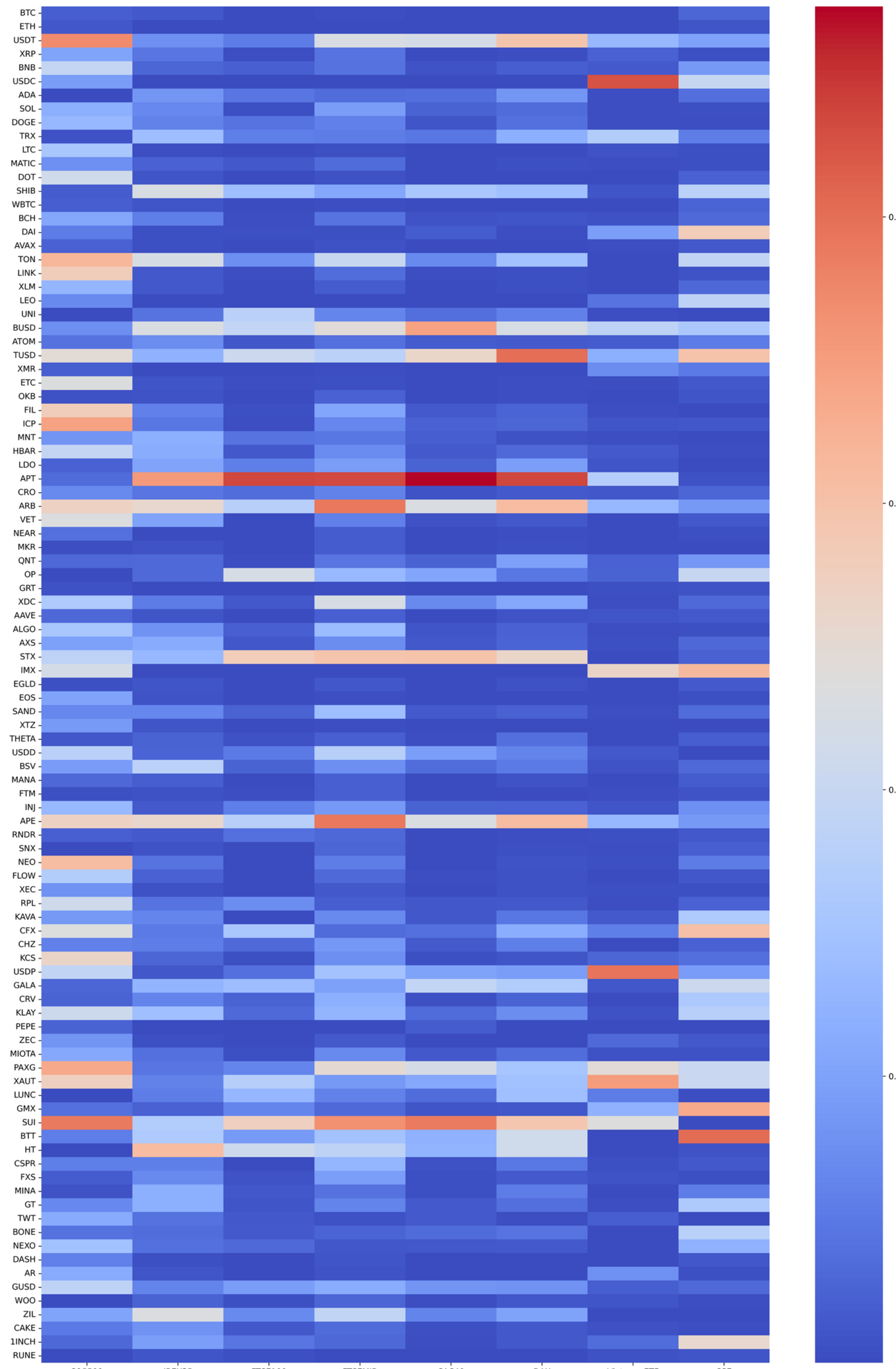
(a) Before the COVID-19 pandemic

Figure 1. Heat map of the *p*-value of the Granger causality test.
(a) Before the COVID-19 pandemic.
(b) During the COVID-19 pandemic.
(c) After the COVID-19 pandemic.



(b) During the COVID-19 pandemic

Figure 1. Continued.



(c) After the COVID-19 pandemic

Figure 1. Continued.

used PoW, PoS, and other alternative sustainable consensus mechanisms, respectively. 76 out of the 100 cryptos have limited maximum supply, 17 are manufactured as stablecoins, 5 are made as privacy coins, and 8 were deployed on EVM, respectively.

Tables 5, 6, and 7 summarised the logistic regression model results between crypto features and their hedge effects on the stock markets before, during, and after the COVID-19 pandemic. Table 5 presents the results before the COVID-19 pandemic, showing that only the adoption of the PoS mechanism and deployment on EVM were associated with a cryptos being a safe haven for DAX and SSE, respectively. These imply that German and Chinese investors seem to consider PoS and EVM as important features that make cryptos sustainable during the early stages of cryptos. Table 6 for during the COVID-19 pandemic showed that none of the features are associated with cryptos being a safe haven for any of the stock markets. This may be because investors are more concerned about secured return and low fluctuation performance rather than the functionality and fundamental features of the cryptos during the volatile periods.

Table 7 presents the result after the COVID-19 pandemic, showing that being used as a Defi coin became a feature associated with crypto being safe haven for IBEX35 and FTSE100. These suggest that Spanish and UK investors consider Defi as a promising future for sustainable financial markets. The adoption of the PoS mechanism seem to be associated with cryptos being a safe haven for FTSEMIB, suggesting that Italian investors seem to see cryptos as environmental-friendly investments if these cryptos use the PoS mechanism. Being adopted as a means of payment is associated with cryptos being a safe haven for Vietnam ETF, suggesting that Vietnamese investors see cryptos as important payment methods.

Table 5. Correlation: Crypto features and hedge effects with stock markets before the COVID-19 pandemic.

Stocks	Parameter	Intercept	PoS	PoW	Limited supply	Stablecoin	Privacy coin	EVM	Defi coin	Means of payment	NFT coin
S&P500	Coefficient	−6.198	1.767	0.859	0.321	0.960	0.117	1.571	−31.851	0.853	0.971
	Standard error	2.750	1.252	1.656	0.886	0.855	1.883	1.900	1.02×10^{7}	1.282	1.335
	p value	0.024**	0.158	0.604	0.717	0.262	0.950	0.409	1.000	0.506	0.467
	t value	−2.254	1.412	0.519	0.363	1.122	0.062	0.827	0.000	0.665	0.727
IBEX35	Coefficient	−6.099	1.846	1.239	0.172	0.740	0.148	1.678	0.589	−26.611	1.211
	Standard error	2.512	1.252	1.499	0.789	0.795	1.664	1.694	1.383	708614	1.328
	p value	0.015**	0.140	0.409	0.827	0.351	0.929	0.322	0.670	1.000	0.362
	t value	−2.428	1.475	0.826	0.219	0.932	0.089	0.990	0.426	0.000	0.911
FTSE100	Coefficient	−3.640	0.189	−0.602	0.448	1.012	−0.280	0.861	−22.182	0.091	1.272
	Standard error	1.653	0.802	1.294	0.774	0.761	1.279	1.279	92533	1.235	0.962
	p value	0.028**	0.814	0.642	0.563	0.184	0.827	0.501	1.000	0.941	0.186
	t value	−2.202	0.236	−0.466	0.579	1.330	−0.219	0.674	0.000	0.073	1.322
FTSEMIB	Coefficient	−85.493	38.681	5.290	24.143	0.572	19.725	20.604	N.A.	N.A.	N.A.
	Standard error	1.78×10^{5}	57328	2.13×10^{7}	1.44×10^{5}	1.306	50258	50258	N.A.	N.A.	N.A.
	p value	1.000	0.999	1.000	1.000	0.662	1.000	1.000	N.A.	N.A.	N.A.
	t value	0.000	0.001	0.000	0.000	0.438	0.000	0.000	N.A.	N.A.	N.A.
CAC40	Coefficient	−4.064	0.991	0.029	−0.139	1.192	0.334	1.317	−20.064	0.193	0.555
	Standard error	1.797	0.918	1.373	0.747	0.751	1.332	1.351	25816	1.207	0.884
	p value	0.024**	0.280	0.983	0.852	0.113	0.802	0.330	0.999	0.873	0.530
	t value	−2.261	1.080	0.021	−0.187	1.586	0.251	0.975	−0.001	0.160	0.627
DAX	Coefficient	−6.579	2.220	1.314	−0.177	1.241	−0.143	1.991	−19.699	1.870	1.918
	Standard error	2.664	1.258	1.698	0.841	0.881	1.788	1.782	27473	1.134	1.279
	p value	0.014**	0.078*	0.439	0.833	0.159	0.936	0.264	0.999	0.099	0.134
	t value	−2.470	1.764	0.774	−0.211	1.409	−0.080	1.118	−0.001	1.649	1.500
Vietnam ETF	Coefficient	−4.850	1.752	−20.505	0.302	0.430	0.347	2.365	N.A.	N.A.	N.A.
	Standard error	2.239	1.223	44943	0.824	0.824	1.533	1.552	N.A.	N.A.	N.A.
	p value	0.030**	0.152	1.000	0.714	0.602	0.821	0.128	N.A.	N.A.	N.A.
	t value	−2.167	1.432	0.000	0.367	0.522	0.226	1.524	N.A.	N.A.	N.A.
SSE	Coefficient	−5.175	1.955	−21.315	−0.352	0.951	0.208	2.783	N.A.	N.A.	N.A.
	Standard error	2.347	1.236	76133	0.833	0.921	1.605	1.651	N.A.	N.A.	N.A.
	p value	0.027**	0.114	1.000	0.673	0.302	0.897	0.092*	N.A.	N.A.	N.A.
	t value	−2.205	1.581	0.000	−0.422	1.032	0.130	1.686	N.A.	N.A.	N.A.

Table 6. Correlation: Crypto features and hedge effects with stock markets during the Covid-19 pandemic.

Stocks	Parameter	Intercept	PoS	PoW	Limited supply	Stablecoin	Privacy coin
S&P500	Coefficient	−5.086	1.510	0.897	−0.313	1.500	0.042
	Standard error	2.204	1.257	1.627	0.861	0.971	1.481
	p value	0.021**	0.230	0.581	0.716	0.122	0.978
	t value	−2.308	1.201	0.551	−0.363	1.546	0.028
IBEX35	Coefficient	−2.627	0.486	0.748	−0.958	0.385	−0.393
	Standard error	1.344	0.875	1.145	0.764	0.753	1.029
	p value	0.051*	0.579	0.513	0.210	0.610	0.703
	t value	−1.954	0.556	0.654	−1.253	0.511	−0.381
FTSE100	Coefficient	−2.309	0.186	−0.850	−0.646	0.662	0.015
	Standard error	1.197	0.717	1.223	0.654	0.676	0.975
	p value	0.054*	0.796	0.487	0.323	0.328	0.987
	t value	−1.929	0.259	−0.695	−0.988	0.979	0.016
FTSEMIB	Coefficient	−4.878	1.793	1.274	−0.595	0.911	−0.153
	Standard error	2.184	1.283	1.693	0.877	0.939	1.463
	p value	0.025**	0.162	0.452	0.497	0.332	0.917
	t value	−2.234	1.397	0.753	−0.679	0.970	−0.104
CAC40	Coefficient	−3.805	0.778	0.014	−0.377	1.347	−0.184
	Standard error	1.637	0.944	1.401	0.777	0.864	1.197
	p value	0.020**	0.410	0.992	0.628	0.119	0.878
	t value	−2.325	0.824	0.010	−0.485	1.558	−0.153
DAX	Coefficient	−2.548	−0.319	−0.367	−0.397	0.782	−0.907
	Standard error	1.407	0.901	1.394	0.867	0.896	1.140
	p value	0.070*	0.723	0.792	0.647	0.383	0.426
	t value	−1.811	−0.354	−0.263	−0.458	0.873	−0.796
Vietnam ETF	Coefficient	−2.798	−0.214	−0.512	−0.499	1.236	−0.616
	Standard error	1.406	0.860	1.338	0.828	0.889	1.119
	p value	0.047**	0.803	0.702	0.547	0.164	0.582
	t value	−1.989	−0.249	−0.383	−0.603	1.390	−0.551
SSE	Coefficient	−1.707	0.377	−0.654	0.022	−0.037	0.406
	Standard error	0.992	0.599	0.915	0.519	0.506	0.845
	p value	0.085*	0.529	0.475	0.966	0.941	0.631
	t value	−1.722	0.629	−0.714	0.043	−0.074	0.480

Tables 8 and 9 summarised the logistic regression model results between cryptos' fundamental factors, functionalities, and their co-movement with the stock markets during and after the Covid-19 pandemic, respectively. During the COVID-19 pandemic, the adoption of PoW consensus had a significant positive effect on crypto co-movement with FTSEMIB, while having limited maximum supply had a significant negative effect on crypto co-movement with FTSEMIB. The adoption of PoW consensus also had a significant positive effect on crypto co-movement with CAC40. This indicates that Italian and French investors care most about the environmental-friendly and inflation features of cryptos. However, there were no fundamental factor or functional feature that demonstrated a significant effect on crypto co-movement with S&P500, IBEX35, FTSE100, DAX, Vietnam ETF, and SSE stock markets.

After the COVID-19 pandemic, acting as a means of payment had a significant positive effect on crypto co-movement with S&P500, IBEX35, and DAX. When cryptocurrencies are widely used as a means of payment, they become more integrated with traditional financial systems and markets in the US, Spain, and Germany. This integration seems to lead to a higher correlation between the performance of cryptos and traditional assets as economic activities and financial flows show similar behaviour. Moreover, increased adoption of cryptos for payments can lead to greater liquidity in the crypto markets, which makes cryptos more sensitive to changes in the broader financial markets. Having a limited maximum supply has significant positive effect on cryptos co-movement with FTSE100 and CAC30. This may be because institutional investors are increasingly adopting cryptos with a capped supply as part of their investment strategies. The consensus mechanism has a significant effect on cryptos co-movement with FTSEMIB. This indicates that investors might be worried about the intensive energy consumption of cryptos, which makes their investment intention in cryptos similar to traditional stock markets.

Table 10 summarised the association between the fundamental factors and functional features of crypto hedge effects and co-movements with the stock market. No fundamental factors or functional features are associated with the hedge effects between S&P500, CAC40, and cryptos, as well as co-movements between S&P500 and cryptos. The hedge effects between other stock markets and cryptos are affected by only one fundamental factor or functional feature. The co-movements between CAC40

Table 7. Correlation: Crypto features and hedge effects with stock markets after the COVID-19 pandemic.

Stocks	Parameter	Intercept	PoS	PoW	Limited supply	Stablecoin	EVM	Defi coin	Means of payment	NFT coin
S&P500	Coefficient	−32.468	−1.651	−0.392	0.378	−1.547	N.A.	N.A.	N.A.	N.A.
	Standard error	3815375	1.332	1.304	1.153	1.244	N.A.	N.A.	N.A.	N.A.
	p value	1.000	0.215	0.764	0.743	0.213	N.A.	N.A.	N.A.	N.A.
	t value	0.000	−1.240	−0.300	0.328	−1.244	N.A.	N.A.	N.A.	N.A.
IBEX35	Coefficient	−2.564	0.877	−0.012	−0.583	−1.092	0.359	2.850	1.234	−0.666
	Standard error	1.366	0.822	1.328	0.734	0.752	1.100	1.195	1.086	1.013
	p value	0.060*	0.286	0.993	0.427	0.146	0.744	0.017**	0.256	0.511
	t value	−1.877	1.067	−0.009	−0.794	−1.452	0.326	2.384	1.136	−0.658
FTSE100	Coefficient	−2.199	−0.580	−0.539	−1.558	0.040	−0.487	2.897	1.568	−24.192
	Standard error	1.500	0.927	1.347	1.125	0.984	1.303	1.456	1.460	86300
	p value	0.143	0.532	0.689	0.166	0.968	0.709	0.047**	0.283	1.000
	t value	−1.466	−0.626	−0.400	−1.385	0.040	−0.373	1.989	1.074	0.000
FTSEMIB	Coefficient	−1.409	−1.631	−1.609	1.305	−0.850	−0.987	1.197	0.694	−0.098
	Standard error	1.482	0.903	1.372	0.903	0.860	1.190	1.194	1.276	1.111
	p value	0.342	0.071*	0.241	0.148	0.323	0.407	0.316	0.587	0.929
	t value	−0.950	−1.807	−1.172	1.445	−0.989	−0.830	1.003	0.543	−0.088
CAC40	Coefficient	−2.334	0.017	−0.461	−0.098	−0.746	−0.321	1.598	0.569	0.363
	Standard error	1.546	0.860	1.347	0.776	0.815	1.214	1.233	1.240	1.066
	p value	0.131	0.984	0.732	0.900	0.360	0.792	0.195	0.646	0.734
	t value	−1.509	0.020	−0.342	−0.126	−0.915	−0.264	1.296	0.459	0.340
DAX	Coefficient	−2.359	0.080	−0.103	−0.390	−0.959	0.511	1.806	1.328	−0.069
	Standard error	1.433	0.815	1.311	0.771	0.810	1.181	1.244	1.042	0.969
	p value	0.100*	0.922	0.937	0.613	0.236	0.665	0.147	0.203	0.943
	t value	−1.646	0.098	−0.079	−0.505	−1.184	0.433	1.451	1.274	−0.071
Vietnam ETF	Coefficient	−5.035	1.020	1.550	1.016	−1.627	0.846	2.800	2.745	−0.547
	Standard error	2.428	1.211	1.689	1.010	1.065	1.782	1.947	1.306	1.229
	p value	0.038**	0.400	0.359	0.315	0.126	0.635	0.150	0.036**	0.657
	t value	−2.074	0.842	0.918	1.006	−1.528	0.475	1.438	2.102	−0.445
SSE	Coefficient	−3.080	0.244	0.464	−0.358	0.208	1.003	1.010	−26.912	−0.265
	Standard error	1.674	0.974	1.146	0.801	0.762	1.356	1.396	719548	0.999
	p value	0.066*	0.802	0.685	0.655	0.785	0.460	0.469	1.000	0.791
	t value	−1.841	0.251	0.405	−0.447	0.273	0.740	0.724	0.000	−0.265

and cryptos are affected by the most studied fundamental factors and functional features (5), followed by FTSEMIB (4), Vietnam ETF (3), IBEX35 (2), FTSE100 (2), and SSE (2). Moreover, using the PoS mechanism, having limited supply, and being used as a means of payment are the most important factors that are associated with the hedge effects and co-movements between cryptos and stock markets during different periods of time, followed by using the PoW mechanism and being adopted as privacy coin or Defi coin.

5. Discussion

Regarding safe haven features, our study is consistent with Będowska-Sójka and Kliber (2021), who demonstrate that Bitcoin is a weak haven for the S&P 500. We also demonstrated that Bitcoin is a poor hedge instrument against the G7 stock markets, this is consistent with the results from Bouri et al. (2017) and Stensås et al. (2019). Moreover, similar to Maitra et al. (2022), we find that Bitcoin and Ethereum do not function as safe-haven assets for major indices, including the S&P 500, FTSE 100, CAC 40, DAX, FTSE MIB, IBEX, and SSE. Furthermore, our study aligns well with the outcome of Ahmed et al. (2023), who illustrated that Bitcoin, Ethereum, Tether and Ripple are not able to serve as a safe haven for the US market.

In terms of co-movement behaviours, our Granger causality tests reveal significant co-movement between Bitcoin, Ethereum, and US stock markets, aligning well with findings from Wang et al. (2022). Additionally, we agree with Mgadmi et al. (2023) that Bitcoin, Ethereum, Ripple demonstrate co-movement

Table 8. Correlation: Crypto features and co-movement with stock markets during the Covid-19 pandemic.

Stocks	Parameter	Intercept	PoS	PoW	Limited supply	Stablecoin	Privacy coin	EVM	Defi coin	Means of payment	NFT coin
S&P500	Coefficient	−0.526	−0.494	−1.149	0.452	0.360	−138.546	1.747	−1.184	0.603	0.229
	Standard error	0.968	0.597	0.821	0.810	0.920	1.798	0.990	0.729	0.623	0.791
	p value	0.587	0.407	0.162	0.577	0.695	1.000	0.077	0.104	0.333	0.772
	t value	−0.544	−0.828	−1.400	0.558	0.391	0.000	1.766	−1.624	0.968	0.289
IBEX35	Coefficient	−1.030	−0.041	0.491	−0.015	0.191	1.078	0.784	−0.468	−1.066	−1.246
	Standard error	0.973	0.679	0.874	0.823	0.997	1.022	0.957	0.703	0.726	1.160
	p value	0.290	0.952	0.575	0.986	0.848	0.292	0.412	0.505	0.142	0.283
	t value	−1.059	−0.060	0.561	−0.018	0.192	1.055	0.820	−0.666	−1.469	−1.074
FTSE100	Coefficient	−0.192	0.350	−0.036	−0.757	−0.952	−340.194	−0.466	0.483	0.062	0.670
	Standard error	0.902	0.587	0.781	0.746	0.883	1.687	0.910	0.623	0.625	0.779
	p value	0.832	0.551	0.963	0.311	0.281	1.000	0.609	0.438	0.920	0.390
	t value	−0.212	0.596	−0.046	−1.014	−1.079	0.000	−0.511	0.776	0.100	0.860
FTSEMIB	Coefficient	0.141	1.782	1.962	−2.018	−1.958	−1.335	−0.386	−0.048	−0.134	0.614
	Standard error	1.096	0.743	0.880	0.988	1.132	1.186	0.942	0.649	0.621	0.812
	p value	0.897	0.016**	0.026*	0.041*	0.084*	0.260	0.682	0.941	0.829	0.449
	t value	0.129	2.399	2.229	−2.041	−1.730	−1.126	−0.410	−0.074	−0.216	0.756
CAC40	Coefficient	−1.852	1.093	1.812	−0.478	−0.526	−38.282	0.045	1.122	0.012	1.259
	Standard error	1.020	0.722	0.889	0.788	0.950	1.050	0.956	0.680	0.704	0.831
	p value	0.069	0.130	0.041*	0.544	0.580	1.000	0.963	0.099*	0.986	0.129
	t value	−1.816	1.514	2.039	−0.607	−0.554	0.000	0.047	1.650	0.018	1.516
DAX	Coefficient	−1.441	1.365	0.433	−0.247	−0.072	0.428	−0.260	−0.186	0.106	−0.716
	Standard error	0.960	0.691	0.888	0.760	0.894	1.007	0.933	0.646	0.615	0.926
	p value	0.133	0.048**	0.626	0.745	0.936	0.670	0.780	0.773	0.864	0.440
	t value	−1.501	1.976	0.488	−0.325	−0.080	0.426	−0.279	−0.288	0.172	−0.773
Vietnam ETF	Coefficient	−0.560	−0.440	−0.250	0.221	0.218	−0.648	1.772	−0.310	−0.138	1.527
	Standard error	0.886	0.568	0.749	0.747	0.867	1.174	0.916	0.647	0.615	0.822
	p value	0.527	0.438	0.738	0.767	0.801	0.581	0.053**	0.631	0.823	0.063*
	t value	−0.632	−0.775	−0.334	0.296	0.252	−0.552	1.934	−0.480	−0.224	1.858
SSE	Coefficient	1.499	−0.399	1.114	−0.343	−0.873	−0.562	−0.883	0.180	−0.870	−0.719
	Standard error	0.924	0.570	0.858	0.781	0.879	1.029	0.866	0.664	0.626	0.817
	p value	0.105	0.485	0.194	0.660	0.321	0.585	0.308	0.787	0.164	0.379
	t value	1.622	−0.699	1.298	−0.440	−0.993	−0.546	−1.020	0.271	−1.391	−0.880

behaviours during different periods of time. Therefore, our findings align with existing literature, reinforcing the robustness of our methods. We further highlight variations in which cryptos act as safe havens for specific markets, emphasizing that co-movements and spillovers are dynamic and time dependent.

We found that the COVID-19 pandemic significantly affects the cryptos' safe haven feature for UK and Chinese stock markets. The number of cryptos that show safe-haven features for UK and Chinese stock markets increased from 12 and 19 to 15 and 23, respectively, during the transition from before the COVID-19 pandemic to during the COVID-19 pandemic, while both numbers reduced to 9 after the COVID-19 pandemic. These indicate that UK and Chinese investors intensively seek cryptos as assets to preserve value during the periods of global economic uncertainty because cryptos are less affected by geopolitical tensions and localised economic policies. Moreover, the number of cryptos that show safe haven features for the US stock market kept decreasing (i.e. from 11 to 4) after the COVID-19 pandemic. This might be because of the growing participation of US institutional investors in moving funds between stock markets and cryptos due to its maturity. Meanwhile, stablecoins such as USDC, DAI, and TUSD demonstrated a safe haven feature for most stock markets most of the time. This might be because their values are pegged to fiat currency such as the US dollar, thus it can provide stability in the volatile crypto market. This also indicates that USDC, DAI, and TUSD are the most reliable stablecoins given their high liquidity and market capitalisation.

Bitcoin persistently shows co-movements with Italian, French, and Chinese stock markets before, during, and after the COVID-19 pandemic. However, it did not show any co-movement with UK stock

Table 9. Correlation: Crypto features and co-movement with stock markets after the Covid-19 pandemic.

Stocks	Parameter	Intercept	PoS	PoW	Limited supply	Stablecoin	Privacy coin	EVM	Defi coin	Means of payment	NFT coin
S&P500	Coefficient	−0.990	−0.522	−0.232	−0.846	−0.444	−0.709	1.683	1.070	2.422	0.353
	Standard error	0.976	0.618	0.849	0.589	0.864	1.009	1.072	0.876	0.767	0.783
	p value	0.310	0.398	0.785	0.151	0.608	0.482	0.117	0.222	0.002***	0.652
	t value	−1.014	−0.845	−0.273	−1.436	−0.513	−0.703	1.569	1.222	3.158	0.451
IBEX35	Coefficient	−1.929	0.806	1.440	0.522	−0.636	−0.456	1.041	0.843	1.810	0.874
	Standard error	0.911	0.583	0.752	0.485	0.771	0.882	1.025	0.855	0.670	0.630
	p value	0.034*	0.167	0.055*	0.282	0.410	0.605	0.310	0.324	0.007**	0.165
	t value	−2.118	1.382	1.916	1.076	−0.824	−0.517	1.015	0.986	2.703	1.389
FTSE100	Coefficient	0.091	0.614	0.461	1.209	−0.644	−1.614	27.319	0.167	0.682	−0.268
	Standard error	0.937	0.553	0.753	0.487	0.824	0.929	1.979	0.848	0.679	0.595
	p value	0.923	0.267	0.541	0.013**	0.434	0.082*	1.000	0.844	0.315	0.652
	t value	0.097	1.111	0.612	2.482	−0.782	−1.738	0.000	0.197	1.005	−0.450
FTSEMIB	Coefficient	−3.162	1.584	2.257	0.897	0.016	0.155	1.008	0.694	0.832	0.541
	Standard error	1.072	0.708	0.859	0.509	0.828	0.944	1.069	0.876	0.667	0.631
	p value	0.003**	0.025**	0.009**	0.078*	0.984	0.870	0.346	0.428	0.212	0.391
	t value	−2.949	2.237	2.627	1.762	0.020	0.164	0.943	0.792	1.248	0.857
CAC40	Coefficient	0.964	−0.844	−1.115	1.020	−0.245	−1.680	27.721	0.149	1.475	0.334
	Standard error	0.977	0.638	0.819	0.518	0.790	0.915	1.897	0.966	0.765	0.621
	p value	0.323	0.186	0.173	0.049**	0.757	0.066*	1.000	0.877	0.054**	0.591
	t value	0.987	−1.323	−1.362	1.970	−0.310	−1.836	0.000	0.154	1.928	0.538
DAX	Coefficient	−0.755	0.125	0.150	0.463	0.201	−0.999	0.018	0.687	1.302	0.872
	Standard error	0.831	0.524	0.700	0.462	0.706	0.831	1.004	0.916	0.640	0.573
	p value	0.364	0.812	0.830	0.316	0.776	0.229	0.986	0.453	0.042**	0.129
	t value	−0.908	0.238	0.215	1.003	0.284	−1.202	0.018	0.750	2.036	1.520
Vietnam ETF	Coefficient	1.627	−0.243	−0.158	0.280	0.173	−1.703	−1.165	0.191	0.774	−0.418
	Standard error	1.009	0.649	0.859	0.556	0.836	0.935	1.024	1.173	0.870	0.686
	p value	0.107	0.708	0.854	0.615	0.836	0.069*	0.255	0.871	0.374	0.542
	t value	1.612	−0.375	−0.184	0.503	0.207	−1.821	−1.138	0.163	0.890	−0.609
SSE	Coefficient	−0.095	−0.868	−0.272	0.830	0.807	0.641	0.309	0.414	0.314	−1.057
	Standard error	0.865	0.551	0.728	0.460	0.746	0.870	1.016	0.875	0.638	0.587
	p value	0.913	0.115	0.709	0.071*	0.280	0.462	0.761	0.636	0.622	0.071*
	t value	−0.110	−1.574	−0.373	1.804	1.081	0.736	0.304	0.473	0.493	−1.803

market before the COVID-19 pandemic, nor with the US, Spanish, German, or Vietnam stock markets during the COVID-19 pandemic. The fact that the Italian, French and Chinese stock markets exhibited stronger integration with Bitcoin might be because some investors sought liquidity and hedges across diverse asset classes during different times. The varying degrees of integration between cryptos and stock markets may also indicate different investment strategies and regulatory responses to the COVID-19 pandemic. This might also be related to increasing number of countries promoting regulations towards Bitcoin and cryptos as these instruments gain popularity amongst the citizens. Meanwhile, Ethereum began to show co-movements with more stock markets after the COVID-19 pandemic due to its adoption of PoS mechanism, increased institutional adoption and market maturation.

6. Conclusion

This study explores the spillovers and co-movements between the top 100 cryptos and eight representative stock markets (i.e. S&P500, IBEX35, FTSE100, FTSEMIB, CAC40, DAX, Vietnam ETF, and SSE) as well as the features of the cryptos that are associated with the spillover and co-movements. We use ordinary least squares regression and cointegration tests to explore whether cryptos can act as a safe haven for stock markets and examine the hedge effectiveness between 100 cryptos on eight representative stock markets. Secondly, we use Granger causality tests to establish if there is any significant co-movement between cryptos and stock markets and investigate the dynamic co-movement between 100 cryptos and

Table 10. Summary of the association between crypto features, hedge effects, and co-movements with stock markets.

Stocks	Parameter		PoS	PoW	Limited supply	Stablecoin	Privacy coin	EVM	Defi coin	Means of payment	NFT coin	Total
S&P500	Hedge effect	Before										
		During										
		After										
		Sub-total										0
	Co-movement	Before										
		During										
		After										
		Sub-total										0
IBEX35	Hedge effect	Before										
		During										
		After							X			1
		Sub-total										1
	Co-movement	Before										
		During										
		After		X						X		2
		Sub-total										2
FTSE100	Hedge effect	Before										
		During										
		After							X			1
		Sub-total										1
	Co-movement	Before										
		During										
		After			X		X					2
		Sub-total										2
FTSEMIB	Hedge effect	Before										
		During										
		After	X									1
		Sub-total										1
	Co-movement	Before										
		During	X	X	X	X						4
		After										
		Sub-total										4
CAC40	Hedge effect	Before										
		During										
		After										
												0
	Co-movement	Before										
		During		X					X			2
		After			X		X			X		3
		Sub-total										5
DAX	Hedge effect	Before	X									1
		During										
		After										
		Sub-total										1
	Co-movement	Before	X									1
		During										
		After								X		1
		Sub-total										2
Vietnam ETF	Hedge effect	Before										
		During										
		After								X		1
		Sub-total										1
	Co-movement	Before										
		During						X			X	2
		After					X					1
		Sub-total										3
SSE	Hedge effect	Before						X				1
		During										
		After										
		Sub-total										1
	Co-movement	Before										
		During										
		After			X						X	2
												2
Summary			PoS	PoW	Limited supply	Stablecoin	Privacy coin	EVM	Defi coin	Means of payment	NFT coin	
Total			4	3	4	1	3	2	3	4	2	26

the eight stock markets. We also use logistic regression models to explore the cryptos' key fundamental and functional features that are associated with their safe haven and co-movements with the selected stock markets.

The number of cryptos showing co-movements with UK, French, German and Vietnam stock markets increased consistently over the periods of the study suggesting the increasing maturity of the cryptos market. There were fewer cryptos showing co-movements with Spanish stock market during the pandemic, indicating that the investor base for cryptos differs from that for stock markets. IBEX35 investors primarily involve traditional financial institutions and retail investors, while cryptos may attract tech enthusiasts and institutional investors. The number of cryptos showing co-movements with the S&P500 kept decreasing, indicating that individual cryptos may develop unique features and functionalities that cause them to decouple from the US stock market.

Acting as a Defi coin appears as a crucial factor for cryptos being a safe haven for IBEX35 and FTSE100 while acting as a means of payment was associated with cryptos being a safe haven for Vietnam ETF after the COVID-19 pandemic. These indicate that decentralised finance can offer users access to various financial services and allow Spanish and UK investors to diversify their portfolios. For investors in Vietnam ETFs, incorporating cryptos as a means of payment can diversify their holdings beyond traditional assets and reduce reliance on local financial systems. Consensus mechanisms, having limited supply, being adopted as privacy coins, and acting as a means of payment were important cryptos features associated with their co-movements with the stock markets, especially during and after the COVID-19 pandemic. Consensus mechanisms contribute to the security and stability of cryptos, PoS can reduce the energy consumption of blockchain validation and can lead to increased adoption and integration with traditional financial systems.

During economic uncertainty, such as the COVID-19 pandemic, investors might turn to assets with limited supply to preserve value, thus causing these cryptos to move in the same direction as traditional stock markets. Privacy coins focus on transaction anonymity. Although they are appealing to investors, they often face regulatory scrutiny. During the COVID-19 pandemic, the increased need for digital transactions might have increased the use of cryptos. Being adopted as a means of payment could lead to higher liquidity of cryptos, making their price movements align more with traditional stock markets.

This study has significant theoretical implications. It contributes to the growing body of literature on cryptos by integrating their unique features into the analysis of hedge effects and co-movements with stock markets. This extends traditional theories of asset valuation by accounting for the distinctive attributes of digital assets, such as consensus mechanisms, supply limitations, and functionality as a means of payment. Moreover, the findings provide evidence that the hedge and safe-haven properties of cryptos are not universal but vary across different markets and time periods. Furthermore, by employing methods such as OLS regression and Granger causality tests, the study provides a methodological framework for exploring how asset features drive co-movement and volatility. This offers a foundation for future research to explore other emerging asset classes.

This study also has significant practical implications. It provides insights into cryptos with weak havens or fails to act as safe-haven assets for specific markets. This helps investors make informed decisions about the choice of cryptos in their portfolios, especially during periods of market volatility. Understanding the dynamic co-movements between different types of cryptos and stock markets allows risk managers to better anticipate spillovers and mitigate risks. This is particularly useful for institutional investors and hedge funds managing cross-asset portfolios.

In addition, this study is useful for policymakers and regulators, as it highlights the need to consider cryptos' unique features and market integration when designing financial regulations, especially in volatile markets. The study also underscores the importance of underlying features like consensus mechanisms and supply limitations for developers. These attributes influence their appeal as hedging instruments and their integration with traditional markets, potentially shaping future innovation.

Although the findings from this study provide significant insights to corporate and individual investors regarding the association of cryptos with market co-movements and their potential to hedge market risks, there are other emerging issues deserving of additional attention. For example, future studies could explore the impacts of individual crypto news sentiment, investment sentiment, and network effects on crypto performance. The findings from such a study could further support the maturity of the cryptos market. The regulatory framework for cryptos and their impacts on the spillover and connectedness of cryptos to other asset class remains under-explored.

Authors' contribution

Ismail Adelopo: Conceptualisation, Data curation, Formal analysis, Validation, Investigation, Methodology, Writing-review & editing

Xiaojun Luo: Writing- original draft, Resources, Software, Methodology, Formal analysis, Writing-review & editing

All authors have read and approved the final work.

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Data availability statement

All data is collected from publicly available databases and can be shared upon reasonable request.

References

Ahmed, M. Y., Sarkodie, S. A., & Leirvik, T. (2023). Mutual coupling between stock market and cryptos. *Heliyon*, *9*(5), Article16179. https://doi.org/10.1016/j.heliyon.2023.e16179

Balcilar, M., Bouri, E., Gupta, R., & Roubaud, D. (2017). Can volume predict Bitcoin returns and volatility? A quantiles-based approach. *Economic Modelling*, *64*, 74–81. https://doi.org/10.1016/j.econmod.2017.03.019

Barberis, N., Shleifer, A., & Wurgler, J. (2005). Comovement. *Journal of Financial Economics*, *75*(2), 283–317. https://doi.org/10.1016/j.jfineco.2004.04.003

Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *Financial Review*, *45*(2), 217–229. https://doi.org/10.1111/j.1540-6288.2010.00244.x

Baur, D. G., & McDermott, T. K. (2010). Is gold a safe haven? International evidence. *Journal of Banking & Finance*, *34*(8), 1886–1898. https://doi.org/10.1016/j.jbankfin.2009.12.008

Będowska-Sójka, B., & Kliber, A. (2021). Is there one safe-haven for various turbulences? The evidence from gold, Bitcoin and ether. *The North American Journal of Economics and Finance*, *56*, 101390. https://doi.org/10.1016/j.najef.2021.101390

Bejaoui, A., Frikha, W., Jeribi, A., & Bariviera, A. F. (2023). Connectedness between emerging stock markets, gold, cryptos, DeFi and NFT: Some new evidence from wavelet analysis. *Physica A: Statistical Mechanics and Its Applications*, *619*, 128720. https://doi.org/10.1016/j.physa.2023.128720

Blandin, A., Cloots, A. S., Hussain, H., Rauchs, M., Saleuddin, R., Allen, J. G., Zhang, B. Z., & Cloud, K. (2019). *Global cryptoasset regulatory landscape study*. University of Cambridge Faculty of Law.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). On the hedge and safe-haven properties of Bitcoin: Is it really more than a diversifier? *Finance Research Letters*, *20*, 192–198. https://doi.org/10.1016/j.frl.2016.09.025

Cao, M., & Celik, B. (2021). Valuation of bitcoin options. *Journal of Futures Markets*, *41*(7), 1007–1026. https://doi.org/10.1002/fut.22214

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366), 427–431. https://doi.org/10.2307/2286348

Diniz-Maganini, N., Diniz, E. H., & Rasheed, A. A. (2021). Bitcoin's price efficiency and safe haven properties during the COVID-19 pandemic: A comparison. *Research in International Business and Finance*, *58*, 101472.https://doi.org/10.1016/j.ribaf.2021.101472

Ederington, L. H. (1979). The hedging performance of the new futures markets. *The Journal of Finance*, *34*(1), 157–170. https://doi.org/10.2307/2327150

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, *37*(3), 424–438. https://doi.org/10.2307/1912791

Grossman, S., & Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *American Economic Review*, *70*, 393–408.

Jang, H., & Sul, W. (2002). The Asian financial crisis and the co-movement of Asian stock markets. *Journal of Asian Economics*, *13*(1), 94–104. https://doi.org/10.1016/S1049-0078(01)00115-4

Jeribi, A., Jena, S. K., & Lahiani, A. (2021). Are cryptocurrencies a backstop for the stock market in a COVID-19-led financial crisis? Evidence from the NARDL approach. *International Journal of Financial Studies*, *9*(3), 33. https://doi.org/10.3390/ijfs9030033

Jiang, Y., Lie, J., Wang, J., & Mu, J. (2021). Revisiting the roles of cryptos in stock markets: A quantile coherency perspective. *Economic Modelling*, *95*, 21–34. https://doi.org/10.1016/j.econmod.2020.12.002

Just, M., & Echaust, K. (2024). Cryptos against stock market risk: New insights into hedging effectiveness. *Research in International Business and Finance*, *67*, 102134. https://doi.org/10.1016/j.ribaf.2023.102134

Kliber, A. (2022). Looking for a safe haven against American stocks during COVID-19 pandemic. *The North American Journal of Economics and Finance*, *63*, 101825. https://doi.org/10.1016/j.najef.2022.101825

Kopyl, K. A., & Lee, J. B. T. (2016). How safe are the safe haven assets? *Financial Markets and Portfolio Management*, *30*(4), 453–482. https://doi.org/10.1007/s11408-016-0277-5

Kumar, A. S., & Padakandla, S. R. (2022). Testing the safe-haven properties of gold and bitcoin in the backdrop of COVID-19: A wavelet quantile correlation approach. *Finance Research Letters*, *47*, 102707. https://doi.org/10.1016/j.frl.2022.102707

Li, X. L., Chang, T., Miller, S. M., Balcilar, M., & Gupta, R. (2015). The co-movement and causality between the US housing and stock markets in the time and frequency domains. *International Review of Economics & Finance*, *38*, 220–233. https://doi.org/10.1016/j.iref.2015.02.028

Li, L., & Miu, P. (2023). Are cryptos a safe haven for stock investors? A regime-switching approach. *Journal of Empirical Finance*, *70*, 367–385. https://doi.org/10.1016/j.jempfin.2022.12.010

Maitra, D., Rehman, M. U., Dash, S. R., & Kang, S. H. (2022). Do cryptos provide better hedging? Evidence from major equity markets during COVID-19 pandemic. *The North American Journal of Economics and Finance*, *62*, 101776. https://doi.org/10.1016/j.najef.2022.101776

Matar, A., Al-Rdaydeh, M., Ghazalat, A., & Eneizan, B. (2021). Co-movement between GCC stock markets and the US stock markets: A wavelet coherence analysis. *Cogent Business & Management*, *8*(1), 1948658. https://doi.org/10.1080/23311975.2021.1948658

Mgadmi, N., Sadraoui, T., Alkaabi, W., & Abidi, A. (2023). The interconnectedness of stock indices and cryptos during the Russia-Ukraine war. *Journal of Economic Criminology*, *2*, 100039. https://doi.org/10.1016/j.jeconc.2023.100039

Nick, T. G., & Campbell, K. M. (2007). Logistic regression. *Methods in Molecular Biology, 404*, 273–301.

Oanh, T. T. K. (2022). The impact of COVID-19 vaccination on stock market: Is there any difference between developed and developing countries? *Heliyon*, *8*(9), e10718. https://doi.org/10.1016/j.heliyon.2022.e10718

Phillips, P. C. B. (1988). Testing for a unit root in time series regression. *Biometrika*, *75*(2), 335–346. https://doi.org/10.2307/2336182

Rubbaniy, G., Khalid, A. A., Syriopoulos, K., & Polyzos, E. (2024). Dynamic returns connectedness: Portfolio hedging implications during the COVID-19 pandemic and the Russia–Ukraine War. *Journal of Futures Markets*, *44*(10), 1613–1639. https://doi.org/10.1002/fut.22539

Shahzad, S. J. H., Bouri, E., Roubaud, D., & Kristoufek, L. (2020). Safe haven, hedge and diversification for G7 stock markets: Gold versus bitcoin. *Economic Modelling*, *87*, 212–224. https://doi.org/10.1016/j.econmod.2019.07.023

Stensås, A., Nygaard, M. F., Kyaw, K., & Treepongkaruna, S. (2019). Can Bitcoin be a diversifier, hedge or safe haven tool? *Cogent Economics & Finance*, *7*(1), Article 1593072. https://doi.org/10.1080/23322039.2019.1593072

Tiwari, A. K., Raheem, I. D., & Kang, S. H. (2019). Time-varying dynamic conditional correlation between stock and crypto markets using the copula-ADCC-EGARCH model. *Physica A: Statistical Mechanics and Its Applications*, *535*, 122295. https://doi.org/10.1016/j.physa.2019.122295

Veldkamp, L. L. (2006a). Media frenzies in markets for financial information. *American Economic Review*, *93*, 577–601.

Veldkamp, L. L. (2006b). Information markets and the comovement of asset prices. *The Review of Economic Studies*, *73*(3), 823–845. https://doi.org/10.1111/j.1467-937X.2006.00397.x

Wadhwani, S. B. (1999). The US stock market and the global economic crisis. *National Institute Economic Review*, *167*, 86–105. https://doi.org/10.1177/002795019916700110

Wang, H., Wang, X., Yin, S., & Ji, H. (2022). The asymmetric contagion effect between stock market and crypto market. *Finance Research Letters*, *46*(Part A)102345. https://doi.org/10.1016/j.frl.2021.102345

Wu, J., Xu, K., Zheng, X., & Chen, J. (2021). Fractional cointegration in bitcoin spot and futures markets. *Journal of Futures Markets*, *41*(9), 1478–1494. https://doi.org/10.1002/fut.22216

Yoo, H. K., Byun, H. G., Caprioli, F., Fumery, M., Peyrin-Biroulet, L., Sreedhar, S., Potter, J., & Jang, M. (2022). Budget impact analysis of the subcutaneous infliximab (CT-P13 SC) for treating inflammatory bowel disease in the Big-5 European countries. *BMC Health Services Research*, *22*(1), 1319. https://doi.org/10.1186/s12913-022-08683-y