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BITCOIN SENTIMENT AND FINANCIAL ASSET CONNECTEDNESS: EVIDENCE FROM GLOBAL MARKETS USING FEVD

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ABSTRACT

This study examines the influence of investor psychology on asset pricing within financial markets, with a focus on Bitcoin as a distinctive investment opportunity. It aims to quantify the interdependence of the constructed Bitcoin sentiment index with various financial assets, including stocks, bonds, the USDX, crude oil, and gold. The research also investigates the main transmitter and receiver of shocks in the financial market. This study employs the OLS regression model and the Forecast Error Variance Decomposition method by Diebold and Yilmaz (2012) to analyse daily data from January 1, 2014, to May 30, 2023. The findings suggest that the Bitcoin Sentiment has shown significant interconnectedness with other financial assets. However, Crude oil mainly transmits shocks, while the USDX is the primary shock receiver in various countries. However, Bitcoin sentiment is the primary transmitter in India, Argentina, the Philippines, China, and Pakistan, and the stock market is the leading receiver of the shocks in these countries. Moreover, the crude oil market has a significant influence on other sample financial markets. These findings are crucial for investors, policymakers, and portfolio managers in developing effective short- and long-term diversification strategies.

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INTRODUCTION

In the world of finance, investors' behaviour plays a vital role. Investors' behaviour creates future investment opportunities. According to Behavioural Finance, these emotions of investors, commonly known as investor sentiments, are the main component that affects the investment decision. Such investor sentiments are used as an effective proxy to explore the financial markets, like stock market returns, volatility, and trade volume, real estate price, and Bitcoin[1] price, etc. These are the proxies that are part of Behavioural Finance. The integral components of behavioural finance are prospect theory, noise trading theory, and herding behaviour, which explain how psychological factors affect decision-making. Among them, Prospect theory is an important idea in behavioral finance. It questions the traditional belief that people always make rational choices in their financial decisions. Instead, it shows that people often make irrational choices because of psychological biases. Moreover, understanding how sentiment-induced shocks spread across asset classes has become crucial for risk management, portfolio diversification, and evaluating financial stability as the world's financial markets become increasingly interconnected. Robust econometric approaches that can capture the volume and direction of asset spillovers over time are necessary to measure such interconnection.

There are still significant gaps in the rapidly growing body of research on Bitcoin, investor sentiment, and financial market spillovers. First, rather than analysing the system-wide connectivity between Bitcoin and various asset classes, most current research focuses on the effect of sentiment on returns or volatility in isolation. Second, there is still a dearth of empirical data on directional spillovers, or which assets function as net transmitters or receivers of sentiment-driven shocks, especially in multi-national contexts. Third, although previous studies have used a variety of sentiment proxies, there aren't many thorough investigations that combine a formal connectivity framework based on Forecast Error Variance Decomposition (FEVD) with a created Bitcoin Sentiment Index. Furthermore, despite significant regional variations in Bitcoin usage and market dynamics, cross-country studies including industrialised, emerging, and underdeveloped countries remain understudied.

As a result, the literature currently available insufficiently informs investors and policymakers about the origins and pathways of sentiment-driven financial risk, even though it does not offer enough insights into how Bitcoin sentiment contributes to overall and directed connectedness across financial assets globally.

The existing literature on Bitcoin and its influence on different financial markets has grown significantly. However, there is a lack of detailed studies examining how sentiment-driven changes in Bitcoin prices affect its correlation with traditional asset classes across various countries. Understanding this dynamic is essential, as it can provide important insights for investors, portfolio managers, and policymakers regarding risk management and diversification strategies.

[1] Bitcoin is a peer-to-peer (p2p) payment cash system and an unregulated digital currency that was created in 2008 but has no legal tender status (Krause and Pham, 2017).

Bitcoin and other cryptocurrencies are gaining popularity, but there are currently no reliable text-based tools for measuring investor sentiment. Market analysis relies heavily on understanding sentiment, particularly during times of volatility. To understand the phenomenon of mispricing, it is essential to evaluate it through investor sentiment analysis with the help of a textual data index. Secondly, to identify new financial crises and monitor ongoing market disruptions, it is crucial to assess the interdependence of financial assets. To fill these deficiencies, this work initially constructs a sentiment index and further explores asset connectivity for better financial monitoring and crisis prediction.

The Bitcoin Sentiment Index (BSI), one of the constructed indices for 28 different countries, measures investor attitudes toward Bitcoin by analysing various data sources, including news articles. Positive sentiment often correlates with rising Bitcoin prices, while negative sentiment may signal downturns. The interconnectedness of Bitcoin with traditional asset classes (like stocks and bonds) varies, influenced by market sentiment and global economic conditions. This correlation can vary by country, depending on market maturity, regulation, and investor behaviour. Advanced statistical methods, such as VAR and FEVD models, are used for data analysis.

This study examines the role of Bitcoin as a financial asset and its impact on global financial markets, focusing on interconnectedness and spillover effects. The study's primary objective is to address a significant research gap by thoroughly examining the connectedness/spillover effect is through individual BSI(i) among each country's asset classes, i.e., Stock, Bonds, Gold, Crude Oil, and foreign exchange. Secondly, the directional spillover of BSI(i) with other assets is analysed. With the help of the OLS regression model and the Forecast Error Variance Decomposition method, all these objectives were assessed.

The study encompasses various countries from around the world. This study includes a list of the top 28 countries (Table 1) selected based on Bitcoin mining Volume on online exchanges (Mohsin et al., 2023). These countries are selected based on their awareness and ownership of Bitcoin. Secondly, these countries have more than 50% of Google's Share of Search traffic worldwide. The study period spans from January 1, 2014, to May 30, 2023, on a daily data basis. Moreover, Table 1 also categorises countries by continent or region worldwide on the basis of their economic development.

Table 1. Bitcoin mining volume and google share of search traffic from all continents.

Sr. No	Continents	Countries	Bitcoin Mining Volume on online exchanges in various countries worldwide in 2020 in a million US dollars	Google's share of Search traffic worldwide	Group
1	Asia 38%	China	198.26	5.03%	Developed
		India	63.72	95.45%	Emerging
		Philippines	30.77	95.31%	Emerging
		Malaysia	17.04	98.32%	Emerging
		Pakistan	12.4	98.39%	Emerging
		Vietnam	12.12	93.15%	Emerging
		Singapore	10.64	96.19%	Emerging
		Indonesia	8.84	98.19%	Emerging
		Saudi Arabia	20.09	91.12%	Emerging
		Hong Kong	27.23	99.33%	Developed
		Thailand	91.96	98.10%	Emerging
2	Africa 14%	Kenya	400.08	98.81%	Emerging
		Nigeria	87	95.44%	Emerging
		South Africa	8.28	97.85%	Emerging
		Morocco	421.38	48.78%	Under-Developed
3	Europe 14%	Russia	193	85.70%	Developed
		United Kingdom	18.02	93.63%	Developed
		Ukraine	23.38	90%	Emerging
		Sweden	1523.6	88.83%	Developed
4	North America 10%	USA	23.47	96.44%	Developed
		Mexico	65.56	88.38%	Emerging
		Canada	25.22	92.58%	Developed
5	South America 17%	Brazil	147.49	64.47%	Under-Developed
		Colombia	47.85	97.62%	Emerging
		Argentina	23.81	92.65%	Emerging
		Chile	44.69	97.09%	Emerging
		Peru	9.92	94.77%	Emerging
6	Australia/Oceania 7%	New Zealand	54.78	90.23%	Developed
		Australia	54.78	90.23%	Developed

Note: The table represents the list of all selected countries (i) as of 30/05/2021. The sources of data for the third column are https://www.statista.com/statistics/1195753/bitcoin-trading-selected-countries/, and for the Google search column, it is https://www.statista.com/statistics/220534/googles-share-of-search-market-in-selected-countries/. Encompassing developed, developing, and underdeveloped countries across six continents. Source: Created by Authors.

This study offers valuable insights into market participants' perceptions of Bitcoin, which can impact investment decisions, risk management, and trading strategies. Such an investigation into the interconnections between Bitcoin and other asset classes helps investors understand the broader implications of Bitcoin's price fluctuations on global markets.

Theoretical Background and Literature Review

The field of behavioural science explores how psychological factors influence investment decisions, highlighting that investors may not always make rational choices. Richard Thaler has given tremendous contributions (Zhang and Sussman, 2017; Kahneman et al., 2019; Lee et al., 1991; Qiu and Welch, 2011; Thaler, 2019; Thaler and Johnson, 1990) in the field of Investor sentiment and Behavioural Finance. Similarly, Barberis and Huang (2001), in their article Prospect Theory and Asset Prices, defined investor sentiments as preferences made by market participants irrationally. According to the definition given by Long, Summers, and Waldmann (1990), when expectations of noise traders' (individual investors') asset value systematically deviate, such a phenomenon is called investor sentiment. Moreover, these noise traders are excellent sources of mispricing.[2] Likewise, Lee et al. (1991) say that investor sentiments are part of investor assets' future return. The fundamentals are insufficient to explain the extent to which deviations in their future prices, without any apparent reason, are caused by investor sentiment.

Likewise, systemic risk is essentially linked to behavioural responses, common exposures, and financial linkages among investors. When assets and markets are interconnected, adverse shocks tend to spread through a goal-oriented mechanism, which ultimately increase chance of spillovers. However, financial asset connectedness takes the direction and degree of shock transmission among markets, institutions, and assets. Such a phenomenon reflects how volatility, returns, or risks in one market influence others over time. Such connectedness emerges due to behavioral and sentiment effects, portfolio rebalancing, or information transmission.

Consumer confidence indices, investor surveys, and media sentiment are the indicators of sentiments according to recent studies(Mao et al., 2011; Qiu and Welch, 2011; Garcia et al., 2015), which can provide insights into stock market movements. Just as sentiment can impact stock prices, it is important to recognize that positive sentiment has the potential to drive prices higher, while negative sentiment can result in declines (Takeda and Wakao, 2014; Klemola et al., 2016; Burggraf et al., 2021; Clarke, 2021). Furthermore, identifying mispricing based on sentiment can lead to short-term opportunities to generate higher returns. During a period of heightened market sentiment, stocks can become overpriced, potentially leading to market corrections. Conversely, when sentiment is low, there may be opportunities to purchase undervalued stocks.

Over the last decade, analysing the co-movement between Bitcoin and other asset classes has been a topic of interest in the literature. The dynamic relationship between the bitcoin market and conventional asset classes, specifically the stock market, government bonds, and Indian currency in the US and UK, was explored by Chung et al. (2012).

There has to be an investigation into the sentiment of potential Bitcoin investors and how that sentiment-based behaviour could affect other asset classes. Such an impact of investor sentiment on Bitcoin returns, volatility, and trade volume (D'Alfonso et al., 2016; Shen et al., 2019; Wołk, 2020) and its use in predicting Bitcoin's future price (Karalevicius et al., 2018; Prajapati, 2020) have all been the subject of prior research. A text-based sentiment analysis approach for potential Bitcoin investors has yet to be explored. Another broad area of financial assets concerns asset connectedness and spillover. Where the connectedness of different financial assets is used to evaluate potential crises and monitor ongoing ones.

Financial asset prices can be considered to be influenced by investor sentiment, which then leads to a deviation from the fundamentally supported equilibrium level. Bitcoin behaves more like an asset than a currency, and such changes in Bitcoin prices occur due to fluctuations in the Bitcoin system itself (Cretarola et al., 2017). Monitoring connectedness among asset classes and financial markets worldwide has felt necessary after the global financial crisis of 2007 to 2009. Such a crisis and other global crises of the same nature have created an aspect of Systemic risk[3], which creates adverse shocks throughout the whole system. Such systemic risk has been evaluated in academic literature in recent years.

Exploring these assets based on the sentiments of Bitcoin investors, which is the most volatile asset, is vital for the future benefit of diversifying risk and enhancing returns, given the dynamism of these assets and their co-movement with each other.

METHODOLOGY

The Overview

This article explores the dynamic relationship between Bitcoin and other financial assets. Here, research follows the methodology used by Da et al. (2015) and Rajput et al. (2020) to construct the Bitcoin sentiment index for each country from the sample frame. While analysing asset connectedness and spillover with Bitcoin using the Bitcoin Sentiment Index, a model proposed by Diebold and Yilmaz (2012), Baruník and Krehlík (2018), and Zeng et al. (2020) is integrated. Sample Size and Selection Criteria of the Sample.

The main objective of the study is to provide evidence of the interconnectedness of Bitcoin with other financial assets from worldwide data. Therefore, the sample of this study is selected from all developed, emerging, and underdeveloped countries worldwide. The sample selection criteria are derived from the study of crypto trade volume by Mohsin et al. (2023). The study sample is selected from the top Bitcoin-mining countries, with a top priority on Google search usage (Table 1). These 28 sample nations provide this research project with a wide-ranging and international perspective.

Sources of Data

This research is based on secondary data like price data for Bitcoin, the Stock markets of each sample country, Bond markets, foreign exchange market data, Crude oil data, and gold rates for each country throughout the sample period of Jan 01, 2014 to May 30, 2023, are collected on a daily basis from Yahoo Finance, investing.com and Data Stream Portal. Here, BSI(i) is the independent variable, and the Stock market index, Bond market index, foreign exchange rates, Crude Oil prices, and gold prices are the dependent variables of this study.

Data Analysis Strategies

The constructed Bitcoin Sentiment Indices are taken from Soomro et al. (2026). A summary table of all models is provided in Table 2 below, which covers all BSI indices.

[2] Mispricing is the difference between the securities' market value and its fundamental value.

[3] It is the risk of collapse of an entire financial system or entire market.

Table 2. Bitcoin sentiment index details.

Sr. No	Country	Bitcoin Sentiment Index Symbol	Model-BSI	OLS t-stat Value	Stock Market
1	China	BSI-CN	NM30	-7.36	Price Hang Seng CSI
2	India	BSI-IN	M30	8.65	Price BSE
3	Philippines	BSI-PH	M30	9.47	PHS ALL
4	Malaysia	BSI-MY	M30	8.81	Price KLCI
5	Pakistan	BSI-PK	NM30	-8.45	Price KSE-100
6	Vietnam	BSI-VN	NM30	-7.84	FTSE All
7	Singapore	BSI-SG	M30	6.91	FTSE Singapore
8	Indonesia	BSI-IO	NM30	-7.2	Price Jakarta
9	Hong Kong	BSI-HK	M25	7.7	HKG
10	Thailand	BSI-TH	NM30	-9.46	Price FTSE set
11	Kenya	BSI-KE	NM25	-8.1	Price Nairobi
12	Nigeria	BSI-NG	NM30	-7.85	NGX-All share
13	South Africa	BSI-ZA	M30	9.42	Price S.AF
14	Morocco	BSI-MA	M30	4.77	Price Moroccan All share
15	Russia	BSI-RU	M30	9.38	Price MOEX
16	United Kingdom	BSI-GB	NM25	-9.7	Price FTSE UK
17	Ukraine	BSI-UA	M25	7.58	PFTS stock index
18	Sweden	BSI-SE	M30	8.96	Price OMX
19	USA	BSI-US	M25	10.14	S&P 500
20	Mexico	BSI-MX	NM30	-7.33	S&P/BMV IPC
21	Canada	BSI-CA	M30	9.73	Price TSX
22	Brazil	BSI-BR	NM30	-7.71	Price Bovespa
23	Colombia	BSI-CO	NM30	-8.01	Price COLCAP
24	Argentina	BSI-AR	M30	8.85	PriceBYMA
25	Chile	BSI-CL	NM30	-6.83	Price CLX IPSA
26	Peru	BSI-FE	M25	6.92	Price PSEi
27	New Zealand	BSI-NZ	M30	8.05	Price NZX
28	Australia	BSI-AU	M30	10.19	Price ASX

Note: The Table represents the list of all sample countries (i) as of 30/05/2021. This list denotes essential symbols and stock markets from which data is collected. The second-to-last column presents the t-statistic value of each BSI model, calculated using OLS. The source of stock market return data is https://www.investing.com/; Source: Soomro et al. (2026).

The connectedness among financial assets reflects the transmission of information across markets, aiding in portfolio construction and risk reduction (Choi, 2021). Directional volatility connectedness examines how exogenous shocks to certain variables explain the forecast error variance of each variable. The study also aims to determine this connectedness using the FEVD method. According to one definition, variance decomposition is the proportion of information in each variable in the study that contributes to the other variable in the auto-regression.

$$\theta_{ij}^{g}(\mathrm{H}) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1}\left(\acute{e}_i \mathrm{A}_h \Sigma \mathrm{e}_j\right)^2}{\sum_{h=0}^{H-1}\left(\acute{e}_i \mathrm{A}_h \Sigma \acute{A}_h \mathrm{e}_j\right)} \tag{2}$$

Where;

$\theta_{ij}^{g}(\mathrm{H})$= H step ahead of FEVD,

g =generalised form of VAR

σ_{ii} = standard deviation of the error term

Σe_j, and e_j is a selection vector with jth element unity and zeros

A_h is the coefficient matrix multiplying the h-lagged shock vector in the infinite moving–average representation of the non-orthogonalized VAR, and Σ is the covariance matrix of the shock vector in the non-orthogonalized VAR.

In this study, cross variance shares or spillover are calculated using Equation 03, which forecasts error variances for assets (e.g., real estate, commodities, futures, financial derivatives, and cryptocurrencies) affected by shocks from the Bitcoin sentiment index (*j*) where *i*, *j* = 1, 2…. N such that *i* ≠ *j.* The cross variance shares or spillover is explained in a few steps by Diebold and Yilmaz (2012). Refer to Equation 3 and Equation 4.

$$\tilde{\theta}_{ij}^{g}(\mathrm{H}) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{3}$$

In Equation 3 Variance decomposition matrix is denoted by $\tilde{\theta}_{ij}^{g}(\mathrm{H})$. Where the variance decomposition is denoted by $\theta_{ij}^{g}(H)$ and $\sum_{j=1}^{N} \theta_{ij}^{g}(H)$ denotes the sum of elements of each row of the variance decomposition.

$$S^{g}(\mathrm{H}) = \frac{\sum_{\substack{i,j=1,\\ i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1,}^{N} \tilde{\theta}_{ij}^{g}(H)}\, 100 \tag{4}$$

The total spillover is calculated through Equation 4, denoted by $S^{g}(\mathrm{H})$. It is constructed through volatility contributions from variance decompositions.

Moreover, the directional volatility spillover is determined through the time-varying parameter vector autoregression model and Generalized Forecast Error Variance Decomposition (GFEVD). The models are given in the study (Diebold and Yilmaz, 2012; Baruník and Křehlík, 2018). The directional volatility spillovers received by all asset classes "*i*" from Bitcoin markets through Bitcoin Sentiment Index BSI(i) "*j"* are given in Equation 5 when the Bitcoin market is the independent variable.

$$S_{i}^{g}(\mathrm{H}) = \frac{\sum_{\substack{j=1,\\ j\neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{j=1,}^{N} \tilde{\theta}_{ij}^{g}(H)}\, 100 \tag{5}$$

Whereas, the directional volatility spillovers are transmitted by the asset's classes to the Bitcoin market when "*j"* is the dependent variable given in Equation 6.

$$S_j^g(\mathrm{H}) = \frac{\sum_{j=1,\, j\neq i}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{j=1,}^{N} \tilde{\theta}_{ji}^{g}(H)}\ 100 \qquad (6)$$

RESULTS AND DISCUSSION

This study uses daily average return data to track the performance of the sample country's stock market index. Additional variables include the 10-year US Treasury bond (TB) for the country-specific bond market and the US dollar index (USDX), which represents the trade-weighted value of the US dollar against key currencies in the foreign exchange market. Here, crude oil returns are based on West Texas Intermediate prices in dollars per barrel, and gold futures prices are quoted in dollars per ounce.

Table 3(A&B) provides descriptive information about all six variables and their unit root test for each sample country. The unit root tests for all variables indicate that they are stationary, confirming the appropriateness of using the vector autoregressive model for analysis. The summary statistics indicate that all variables exhibit positive average daily rerun volatility. At the same time, Crude oil has the highest unconditional volatility among all variables. However, it is the lowest for stock market returns after the US dollar index.

Table 3A. Summary statistics and unit root tests.

Summary Statistics	Obs.	Mean	Median	SD	Min	Max	PP	ADF
STv-CN	1747	0.000	0.000	0.000	0.000	0.003	-71.28***	-4.55***
BSI_CN	1747	0.026	0.025	0.004	0.017	0.060	-389.2***	-9.52***
Bond-CN	1747	0.000	0.000	0.000	0.000	0.001	-169.6***	-6.67***
STv-IN	1747	0.000	0.000	0.000	0.000	0.005	-116.7***	-6.93***
BSI_IN	1747	0.029	0.027	0.005	0.014	0.066	-447.0***	-9.08***
Bond-IN	1747	0.000	0.000	0.000	0.000	0.000	-38.97***	-4.05***
STv-PH	1747	0.000	0.000	0.000	0.000	0.003	-410.5***	-8.16***
BSI_PH	1747	0.027	0.026	0.005	0.021	0.061	-532.0***	-9.09***
Bond-PH	1747	0.001	0.000	0.002	0.000	0.012	-80.26***	-4.98***
STv-MY	1747	0.000	0.000	0.000	0.000	0.001	-56.24***	-5.68***
BSI_MY	1747	0.030	0.029	0.003	0.026	0.049	-631.3***	-10.1***
Bond-MY	1747	0.000	0.000	0.000	0.000	0.001	-85.66***	-4.51***
STv-PK	1747	0.0001	0.0001	0.0002	0.000	0.0029	-297.4***	-7.82***
BSI_PK	1747	0.0312	0.0298	0.0046	0.023	0.0698	-708.7***	-11.6***
Bond-PK	1747	0.0002	0.0001	0.0004	0.000	0.0041	-45.69***	-4.05***
STv-VN	1747	0.000	0.000	0.000	0.000	0.001	-76.4***	-5.86***
BSI_VN	1747	0.039	0.039	0.005	0.027	0.053	-49.35***	-4.81***
Bond-VN	1747	0.000	0.000	0.001	0.000	0.007	-61.65***	-5.48***
STv-SG	1747	0.000	0.000	0.000	0.000	0.002	-53.73***	-8.07***
BSI_SG	1747	0.037	0.033	0.014	0.025	0.221	-868.6***	-11.2***
Bond-SG	1747	0.000	0.000	0.001	0.000	0.007	-37.92***	-5.49***
STv-IO	1747	0.000	0.000	0.000	0.000	0.002	-275***	-7.74***
BSI_IO	1747	0.044	0.041	0.008	0.037	0.094	-1277***	-11.0***
Bond-IO	1747	0.000	0.000	0.000	0.000	0.007	-581***	-10.1***
STv-HK	1747	0.000	0.000	0.000	0.000	0.001	-53.75***	-5.27***
BSI_HK	1747	0.040	0.040	0.002	0.027	0.058	-2741***	-12.2***
Bond-HK	1747	0.001	0.001	0.001	0.000	0.008	-17.76***	-3.43***
STv-TH	1747	0.000	0.000	0.001	0.000	0.029	-1016.5***	-9.03***
BSI_TH	1747	0.031	0.026	0.010	0.022	0.061	-5.340***	-1.59***
Bond-TH	1747	0.000	0.000	0.001	0.000	0.016	-165.1***	-7.38***
STv-KE	1747	0.001	0.000	0.017	0.000	0.557	-679.4***	-11.3***
BSI_KE	1747	0.031	0.029	0.004	0.024	0.086	-534.7***	-9.92***
Bond-KE	1747	0.000	0.000	0.000	0.000	0.002	-180.0***	-8.72***
STv-NG	1747	0.000	0.000	0.000	0.000	0.001	-314.7***	-8.07***
BSI_NG	1747	0.027	0.025	0.004	0.022	0.050	-682.1***	-10.8***
Bond-NG	1747	0.000	0.000	0.000	0.000	0.003	-38.05***	-5.01***
STv-ZA	1747	0.000	0.000	0.000	0.000	0.002	-54.81***	-6.85***
BSI_ZA	1747	0.028	0.027	0.005	0.022	0.051	-652.4***	-10.2***
Bond-ZA	1747	0.000	0.000	0.000	0.000	0.001	-244.3***	-7.62***
STv-MA	1747	0.000	0.000	0.0001	0.000	0.0024	-275.4***	-7.74***
BSI_MA	1747	0.0275	0.0269	0.0021	0.02	0.0401	-1277***	-11.0***
Bond-MA	1747	0.0198	0.0196	0.0013	0.0077	0.0452	-580.9***	-10.1***
Crude Oil	1747	6.759	2.007	33.644	0.426	607.850	-138.6***	-7.55***
Gold	1747	0.001	0.001	0.000	0.000	0.005	-53.86***	-5.66***
USDX	1747	0.000	0.000	0.000	0.000	0.000	-32.63***	-4.02***

Note: The table summarises the summary statistics and Unit root test data of 14 sample countries. The asterisk *** shows the stationarity of data at a 1% significance level; Source(s): Estimated by Authors.

Table 3B. Summary statistics and unit root.

Summary Statistics	Obs.	Mean	Median	SD	Min	Max	PP	ADF
STv-RU	1747	0.000	0.000	0.000	0.000	0.002	-147.3***	-7.50***
BSI_RU	1747	0.027	0.025	0.005	0.020	0.054	-533.6***	-11.1***
Bond-RU	1747	0.000	0.000	0.000	0.000	0.000	-241.1***	-23.7***
STv-GB	1747	0.000	0.000	0.000	0.000	0.003	-106.4***	-6.78***
BSI_GB	1747	0.034	0.033	0.004	0.028	0.062	-616.8***	-10.1***
Bond-GB	1747	0.004	0.001	0.007	0.000	0.047	-57.62***	-5.53***
STv-UA	1747	0.003	0.0002	0.0365	0.000	1.363	-1410***	-11.3***
BSI_UA	1747	0.045	0.0441	0.0103	0.0226	0.0918	-63.53***	-4.79***
Bond-UA	1747	0.023	0.0022	0.0782	0.0001	0.8064	4.642***	-3.32***
STv-SE	1747	1E-04	0.0001	0.0002	0.000	0.0018	-61.56***	-5.80***
BSI_SE	1747	0.033	0.0321	0.005	0.0272	0.0888	-597.5***	-10.0***
Bond-SE	1747	4E-04	0.0002	0.0007	0.0001	0.0065	-37.92***	-5.49***
STv-US	1747	0.000	0.000	0.000	0.000	0.006	-89.52***	-6.91***
BSI_US	1747	0.033	0.032	0.005	0.024	0.075	-1048.6***	-9.70***
Bond-US	1747	0.001	0.000	0.003	0.000	0.032	-46.59***	-5.38***
STv-MX	1747	0.000	0.000	0.000	0.000	0.001	-62.12***	-6.18***
BSI_MX	1747	0.035	0.0345	0.0035	0.0228	0.0466	-3477***	-12.5***
Bond-MX	1747	1E-04	0.0001	0.0002	0.000	0.0023	-73.32***	-6.23***
STv-CA	1747	0.000	0.000	0.000	0.000	0.008	-117.6***	-8.05***
BSI_CA	1747	0.031	0.030	0.005	0.025	0.055	-453.4***	-9.14***
Bond-CA	1747	0.001	0.001	0.002	0.000	0.022	-42.83***	-4.70***
STv-BR	1747	3E-04	0.0002	0.0004	0.0001	0.0055	-72.38***	-6.89***
BSI_BR	1747	0.038	0.0356	0.0083	0.0287	0.0915	-884.4***	-10.2***
Bond-BR	1747	2E-04	0.0001	0.0006	0.0001	0.0089	-145.0***	-7.87***
STv-CO	1747	0.000	0.000	0.000	0.000	0.006	-117.2***	-8.45***
BSI_CO	1747	0.027	0.026	0.004	0.022	0.058	-734.6***	-12.0***
Bond-CO	1747	0.086	0.007	1.651	0.001	38.340	-746.7***	-11.0***
STv-AR	1747	0.001	0.001	0.003	0.000	0.042	-170.5***	-7.21***
BSI_AR	1747	0.029	0.027	0.004	0.024	0.082	-743.5***	-11.1***
Bond-AR	1747	0.000	0.000	0.001	0.000	0.009	-145.0***	-7.87***
STv-CL	1747	1E-04	0.0001	0.0004	0.000	0.0056	-98.35***	-7.55***
BSI_CL	1747	0.032	0.0309	0.0033	0.0271	0.0476	-559***	-10.4***
Bond-CL	1747	2E-04	0.000	0.0006	0.000	0.0121	-186.6***	-7.35***
STv-FE	1747	1E-04	0.0001	0.0002	0.0001	0.003	-292.4***	-7.52***
BSI_FE	1747	0.038	0.0385	0.0012	0.0189	0.04	-317.9***	-9.45***
Bond-FE	1747	5E-04	0.0003	0.001	0.0001	0.021	-342.3***	-8.48***
STv-NZ	1747	0.000	0.000	0.000	0.000	0.001	-90.47***	-6.25***
BSI_NZ	1747	0.026	0.0259	0.0023	0.0119	0.0362	-2841***	-12.1***
Bond-NZ	1747	8E-04	0.0002	0.0018	0.0001	0.0187	-38.53***	-4.41***
STv-AU	1747	0.000	6 E-05	0.000	0.000	0.003	-63.98***	-7.29***
BSI_AU	1747	0.029	0.028	0.005	0.022	0.064	-479.2***	-9.94***
Bond-AU	1747	0.001	0.000	0.002	0.000	0.019	-28.57***	-4.06***
Crude Oil	1747	6.759	2.007	33.644	0.426	607.850	-138.6***	-7.55***
Gold	1747	0.001	0.001	0.000	0.000	0.005	-53.86***	-5.66***
USDX	1747	0.000	0.000	0.000	0.000	0.000	-32.63***	-4.02***

Note(s): The table summarises the summary statistics and Unit root test data of 14 sample countries. The asterisk *** shows the stationarity of data at a 1% significance level; Source(s): Estimated by Authors.

Moreover, Table 4 for each country details the interconnectedness among assets, including Total and Directional volatility, among variables. The model for total connectedness among financial assets is represented by Equations 2, 3, and 4. However, the data on directional connectedness is calculated using the forecast error variance decomposition (FEVD), based on equations (5) and (6). The "Net Receiver" (Net Transmitter) column displays the total spillover received (transmitted) by one market from (to) all other markets. However, the "Total" value represents the overall level of spillover. In Table 4, the empirical results show that the total volatility connectedness among the financial markets of each sample country ranges from a low percentage (Colombia, 16.8%) to a high percentage (Kenya, 64.74%) of total connectedness. In comparison, USDX is the net recipient of shocks in 22 of the 28 sample countries' financial markets. However, the four countries, including Kenya, India, Pakistan, and Argentina, are the primary shock receivers from their respective stock market. At the same time, Vietnam and Sweden receive shocks from their respective Bond markets. Likewise, Crude oil is the net transmitter of the shock among 23 sample countries. However, in Kenya, India, the Philippines, Pakistan, and Argentina, BSI-KE, BSI-IN, BSI-PH, BSI-PK, and BSI-AR, respectively, are the primary transmitters of the shocks. However, in Sweden, the Swedish stock market serves as the primary channel for transmitting shocks. Such a trend of Bitcoin sending shocks in different countries reveals high potential markets for Bitcoin in Kenya, India, Phillipines. Pakistan and Argentina. Similarly, as Crude oil is a strong commodity worldwide, it has a significant impact on the global financial markets. Likewise, USDX, being an international currency, receives uneven shocks from all other financial markets. These mixed results are consistent with those of Antonakakis et al. (2020) and Yoon et al. (2019).

Table 4. Total and directional volatility connectedness/spillover.

Country	Total	Net Receiver	Net Transmitter
China	28.4	USDX 4.07	Crude Oil 5.71
India	36.6	STv-IN 9.74	BSI-IN 10.44
Philippines	32.8	USDX 4.71	BSI-PH 6.46
Malaysia	20.2	USDX 4.19	Crude Oil 5.29
Pakistan	33.4	STv-PK 6.54	BSI-PK 9.28
Vietnam	37.5	Bond 6.49	Crude Oil 4.84
Singapore	27.9	USDX 5.54	Crude Oil 4.92
Indonesia	22.2	USDX 4.92	Crude Oil 3.84
Hong kong	20.64	USDX 4.24	Crude Oil 3.58
Thailand	21.2	USDX 4.24	Crude Oil 5.07
Kenya	64.74	STv-KE 15.57	BSI-KE 16.52
Nigeria	21.5	USDX 4.24	Crude Oil 4.85
South Africa	20.1	USDX 4.3	Crude Oil 5.13
Morocco	23.8	USDX 5.1	Crude Oil 5.01
Russia	21.3	USDX 3.69	Crude Oil 5.15
UK	24.1	USDX 3.77	Crude Oil 4.8
Ukraine	20.5	USDX 3.77	Crude Oil 5.07
Sweden	44.4	Bond 8.86	STv-SE 6.52
USA	25.5	USDX 3.8	Crude Oil 4.97
Mexico	21.5	USDX 4.99	Crude Oil 4.94
Canada	25.6	USDX 4.32	Crude Oil 5.05
Brazil	23.5	USDX 4.24	Crude Oil 3.46
Colombia	16.8	USDX 3.82	Crude Oil 4.89
Argentina	40.2	STv-AR 9.59	BSI-AR 9.41
Chile	21.5	USDX 3.76	Crude Oil 4.94
Peru	19.94	USDX 3.65	Crude Oil 5.07
New Zealand	17.5	USDX 3.97	Crude Oil 5.16
Australia	20.08	USDX 3.78	Crude Oil 4.78

Note: The table exhibits the volatility, connectedness/spillover among financial assets of 28 sample countries; Source(s): Estimated by the authors.

CONCLUSIONS

Bitcoin has been recognised as a valuable tool for diversifying investments, providing protection against fluctuations in various commodities, stocks, bonds, and the US dollar. This indicates its potential as a safeguard against conventional financial assets (Hoang et al., 2020). This study innovatively analyses the total and directional connectedness/spillover effects based on the methods of Diebold & Yilmaz (2012) and Baruník and Křehlík (2018). In addition, this study is based on sentiments associated with potential Bitcoin investors to determine the involvement and connectedness of digital assets with other financial and commodity markets, as influenced by human sentiments. The main empirical findings indicate that digital assets are among the leading financial assets for portfolio construction. Overall, among the sample, five countries, Kenya, India, Pakistan, the Philippines, and Argentina, significantly impact stock returns mainly through BSI. Specifically, the results for Kenya show a strong correlation among variables, with a correlation coefficient of 64.74%. Another significant outcome is that the spillover effect is significantly greater in the crude oil and USDX markets. Hence, a significant connectedness between Bitcoin and other financial assets, i.e., equities, bonds, currencies, and commodities, was found from 2014 to 2023 with the help of BSI(i), as expected from the analysis results. These findings are opposite to the existing literature that points out the detached feature of Bitcoin from other financial markets (Kang et al., 2019; Koutmos, 2020).

Based on the above analysis, it is suggested that investors optimise their investment decisions based on the findings. Secondly, for each sample country, policymakers should give more attention to human sentiments/nature to increase portfolio return and achieve optimum output. Finally, due to Bitcoin's volatile nature, countries must implement policies and provide regular updates about it. Investors should focus on indicators such as foreign exchange rates and crude oil prices before making trade decisions.

Research Implications

This study contributes to the risk and management of Bitcoin and other financial assets. Moreover, the significant results may help investors consider Bitcoin as a diversifying financial asset. Likewise, consistent patterns emerge across continents. Crude oil serves as a significant global transmitter, maintaining its status as the primary source of volatility transmission in both developed and emerging economies. These findings can inspire the design of artificial intelligence and machine learning-based portfolio management platforms that integrate Bitcoin sentiment and real-time spillover monitoring. Consequently, FinTech firms can utilise these insights to create risk dashboards that track asset interdependence and alert investors and managers about emerging shocks. Moreover, policymakers and the country's governments are advised to address the legal formalities regarding the usage of Bitcoin and other cryptocurrencies. The effects of spillover on the system are strongly correlated with the stability of the economic environment and international situations. Hence, it is imperative for policymakers to closely monitor the global crisis in real-time and develop a strategy to prevent and mitigate risks.

Future Research and Limitations

This article may inspire research. Additionally, crude oil, gold, and money were priced internationally. We can also use local currency rates for precision. Bitcoin is famous, but sentiment indexes can also include other cryptocurrencies. An alternate study idea may focus on recent global uncertainty indicators. Separately analyzing developed and impoverished countries is possible. For further accuracy, the connection should be analyzed using a sentiment index and simple Bitcoin price/returns, then compared. Ensuring research quality is crucial. Researchers confront limits in all research. Stock markets and other financial asset classes had data only five days a week, or approximately 260 days a year, but Bitcoin had data 365 days a year. A regression study was conducted on a 365-day time series that incorporated data from the stock market, financial assets, and Bitcoin. The data were transformed into 260 trading days using Stata for analysis. The study was limited by the availability of financial data on a single platform. Result fluctuations may arise. The primary limitation of this study was the time constraint. Structure breaks can be added to this study in the future.

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