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EFFECT OF CRYPTOCURRENCY ON THE SELECTED SECURITY MARKETS: A STUDY OF BITCOIN VOLATILITY USING VAR MODEL

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ABSTRACT

In light of the growing interest among investors in the cryptocurrency market, this study investigates the relationship between Bitcoin and selected international stock markets, namely the Dow Jones Industrial Average, Euro Stoxx, FTSE 100, National Stock Exchange, and Shanghai Stock Exchange by utilizing statistical techniques such as regression analysis and the standard Vector Autoregressive (VAR) model, we aimed to detect any connections between Bitcoin and these stock markets. This empirical analysis reveals no significant autocorrelation between Bitcoin and the stock markets under consideration. This suggests that Bitcoin could potentially function as an asset offering hedging capabilities against risks associated with the selected stock markets. This research offers valuable insights into the dynamic relationship between cryptocurrency and financial markets.

Keywords: Fluctuation, Security Markets, Bitcoin, Cryptocurrency

JEL Classification: G15, G19, G130

1. INTRODUCTION

Cryptocurrencies have surged as an innovative force in the financial realm, promising transformative changes but also raising apprehensions due to their inherent volatility. Their disruptive potential has drawn significant interest, yet the unpredictability in their value poses concerns about their enduring stability and potential ramifications on the broader economic landscape. As these digital assets continue to evolve and gain prominence, comprehending their sway on conventional financial markets stands as a pivotal domain for both research endeavors and policy deliberations. At the heart of the cryptocurrency phenomenon lies Bitcoin, the pioneering digital currency that operates outside the traditional financial framework. Encouraged by blockchain technology, these decentralized currencies facilitate direct transactions between peers sans intermediaries like banks or governmental control. The interplay between these digital assets and traditional financial markets has become an increasingly focal point. The volatility of cryptocurrency prices not only bothers investors but also creates uncertainties on the stability of the broader financial landscape. It raises pertinent questions about the sustainability of cryptocurrencies as reliable mediums of exchange and stores of value in the long run. The swift and unpredictable fluctuations not only impact individual investors but also exert ripple effects across the financial domain. Crucially, the prospect of integrating cryptocurrencies into conventional financial systems is gaining traction. Institutions and markets are exploring various avenues to embrace or interact with these digital assets, thereby potentially transforming the dynamics of capital flows, investment opportunities, and regulatory paradigms. However, this integration poses significant challenges and uncertainties, particularly concerning the regulatory framework. Furthermore, the behavior of cryptocurrencies often correlates with market sentiments, macroeconomic events, and regulatory developments. Consequently, the volatility observed in cryptocurrency markets might spill over into traditional financial markets, thereby influencing investor sentiments and risk perceptions across diverse asset classes. Beyond the speculative aspect, the underlying blockchain technology of cryptocurrencies holds promise for broader applications beyond finance. Ongoing research endeavors are delving into the complex relationship between cryptocurrencies and traditional financial markets. Researchers, economists, and policymakers are rigorously studying the potential impacts, vulnerabilities, and systemic risks stemming from increased cryptocurrency adoption. Their aim is to unravel the multifaceted ways in which these digital assets influence market dynamics, risk perceptions, and systemic stability, seeking effective measures to mitigate potential negative consequences.

2. LITERATURE REVIEW

Research exploring the connection between the cryptocurrency and stock markets shows a fragile link between them. Most studies suggest a weak correlation, indicating that cryptocurrency can serve as a protective buffer for the stock market, reducing risk and potential losses. However, studies by Moore and Christin (2013) explore that Bitcoin investors face risks, particularly when the stock market fails. Experts have identified key factors that impact Bitcoin's value, including its appeal to financial investors and global economic conditions. Contrary to this perspective, Kristoufek (2015) argues that over the long term, common factors affect the pricing of both cryptocurrencies and traditional assets, leading to interesting questions about the connection between these two seemingly different types of investments. This observation underscores the possibility of common underlying elements shaping the valuation of these assets, implying at a potential connection that prompts a revaluation of the relationship between cryptocurrency and conventional financial instruments over extended periods. Dyhrberg (2016) The examination of Bitcoin's volatility through GARCH models leads to intriguing parallels between Bitcoin and established assets like gold and the dollar. The findings suggest that Bitcoin's behavior exhibits resemblances to both these traditional assets in terms of its fluctuation patterns and market dynamics. This analysis unveils compelling similarities between Bitcoin and these well-established assets, shedding light on potential correlations in their volatility behaviors. However, Bouri et al. (2017) conflicting insights, presenting indications of a contagion effect between the cryptocurrency market and traditional financial markets. This effect appears to arise from speculative trading activities within the realm of cryptocurrencies, showcasing a complex interplay that generates divergent viewpoints and suggests a potential link fostering influences between these distinct markets. Osterrieder and Lorenz (2017) observe that fluctuations in the price of Bitcoin are significantly more unpredictable and irregular compared to the major global currencies (G-10), indicating a much higher level of volatility in Bitcoin's returns. Yi et al. (2018) observed volatility risk bubbling within the market has substantial implications for investors, highlighting the intricate and shifting dynamics between various cryptocurrencies and their interconnectedness. Such insights underscore the importance of understanding these nuanced relationships for investors navigating the crypto landscape. Baumöhl (2019) analysis has uncovered an intriguing negative correlation between forex and cryptocurrency markets. This intriguing finding suggests that investors might harness valuable diversification benefits by simultaneously investing in these distinct yet interconnected asset classes. Yaya et al. (2019) study analyzed the efficiency and volatility of 12 cryptocurrencies, covering both the pre-crash and post-crash periods. The findings offer crucial information and data for investors and traders in the digital currency market, as well as portfolio managers seeking to optimize their investment strategies Ünvan (2021) investigates the effect of Bitcoin on major global stock exchanges, including Nikkei 225, BIST 100, S&P 500, and SSE 380, using price data analysis. Additionally, Kumah et al. (2021) investigated the relationship between digital currencies and gold prices, using advanced statistical techniques (co-integration and fractional co-integration) to uncover both short-term and long-term connections. Katsiampa, P. (2019) investigates volatility dynamics in major cryptocurrencies using an asymmetric Diagonal BEKK model. It finds that past performance significantly impacts current volatility, with some cryptocurrencies showing asymmetric responses to past shocks. Time-varying correlations exist, mostly positive, among these assets. The study also highlights how major news affects cryptocurrency volatility, identifying structural breakpoints in Bitcoin and Litecoin's variance. Gil-Alana et.al (2020) explores the interrelationships between major cryptocurrencies and stock market indices using fractional integration techniques. It finds varying integration orders among cryptocurrencies, indicating different trends in mean reversion or persistent behavior. While stock market indices show more consistent behaviors, with most exhibiting non-rejection of the unit root hypothesis except for VIX, implying mean reversion. Yang et.al (2019) delves into cryptocurrency price forecasting, highlighting the challenges in predicting cryptocurrency prices compared to stocks. The study evaluates multiple angles, incorporating Twitter data, sentiment analysis, and CNN-LSTM models for price prediction. However, empirical findings suggest the unpredictability and randomness in cryptocurrency prices, concluding that no single method proves robust enough for accurate cryptocurrency price prediction. Kumar, A. (2021) explores investor behavior in cryptocurrency trading to understand its impact on price formation. Using a measure by Chang et al., it examines herding behavior among investors through cross-sectional dispersion of stock returns. The findings reveal pronounced herding during market stress or high volatility, contrasting with anti-herding in less volatile or bullish markets. These insights offer implications for policymakers aiming to create a safer investment environment. Yang et.al (2022) explores how risk spreads through the cryptocurrency market from 2018 to 2021. By comparing cryptocurrency networks to traditional stock and foreign exchange networks, the study finds that risk spreads more easily and quickly within the cryptocurrency market. Cheah et.al (2015) examines Bitcoin's economic impact and conducts economic modeling of its prices. It highlights speculative bubbles within Bitcoin and provides empirical evidence suggesting that Bitcoin's fundamental price is zero. Sahoo, P. K. (2021) investigates how COVID-19 impacts the cryptocurrency market. It finds a one-way causal link from COVID-19 cases to cryptocurrency returns, particularly for Bitcoin and Ethereum, suggesting that understanding the pandemic's growth aids in predicting cryptocurrency returns.

3. OBJECTIVES OF THE STUDY

The objectives of the study on the effect of cryptocurrency, particularly Bitcoin, on selected security markets through the application of VAR modeling and regression analysis are multi-fold. Firstly, the study aims to investigate the relationship between Bitcoin and major international stock markets, including the Dow Jones Industrial Average, Euro Stoxx, FTSE 100, National Stock Exchange, and Shanghai Stock Exchange. This involves exploring the patterns of co-movements and correlations between Bitcoin and these stock markets to determine any potential interdependencies. Secondly, the study seeks to assess the presence or absence of autocorrelation between Bitcoin and the selected stock markets. Ultimately, the study aims to offer valuable insights into the dynamics between cryptocurrency and traditional financial markets, thereby guiding investment decision-makers, academia, and policymakers in understanding and navigating this evolving landscape.

4. DATA AND METHODOLOGY

The study's reliance on secondary sources, specifically Coin Market and Investing.com, forms the backbone of data acquisition, spanning September 2018 to August 2023. This expansive temporal coverage provides an invaluable window into Bitcoin's market behavior and the performance trajectories of various international stock markets over a significant five-year stretch. Investing.com dataset enriches the analysis by furnishing historical daily returns, price indices, and crucial financial metrics for various stock markets: the Dow Jones Industrial Average, Euro Stoxx, FTSE 100, National Stock Exchange, and Shanghai Stock Exchange throughout the stipulated timeframe. This dataset's extensive scope and depth lay a robust foundation for the study's comprehensive exploration. It facilitates an in-depth examination of the relationship dynamics and potential interdependencies between Bitcoin and the selected stock markets. Such an extended duration allows for a nuanced understanding of how these entities interact and influence each other over time. Ultimately, this comprehensive analysis unravels insights into the linked dynamics between Bitcoin and traditional stock markets, shedding light on their interconnectedness and potential implications for broader financial markets and investment strategies.

Table 1 Descriptive Statistic

	BITCOIN	DJI	EURO_STOXX	FTSE_100	NIFTY_50	SSE_COMPOSITE
Mean	0.0005	-0.0001	0.0001	0	-0.0009	0.0007
Median	0.0001	0.0005	0.0006	0.0006	-0.0005	0.0007
Maximum	0.1722	0.0537	0.0795	0.0867	0.089	0.0445
Minimum	-0.465	-0.0548	-0.1247	-0.1151	-0.0706	-0.0446
Std. Dev.	0.0403	0.0099	0.0119	0.0114	0.0098	0.0096
Skewness	-1.2916	-0.3221	-1.1792	-1.161	0.5967	0.0171
Kurtosis	19.8143	7.7367	18.3386	18.0361	16.2267	5.0472

Jarque-Bera	14252.58	1125.426	11861.12	11400.14	8686.248	206.461
Probability	0	0	0	0	0	0
Sum	0.6239	-0.0662	0.1451	-0.0174	-1.0952	0.8723
Sum Sq. Dev.	1.9209	0.1151	0.1664	0.1532	0.1138	0.1098
Observations	1182	1182	1182	1182	1182	1182

Source Prepared by author in E-views

The descriptive statistics of six key financial indices—BITCOIN, DJI, EURO_STOXX, FTSE_100, NIFTY_50, and SSE_COMPOSITE—illuminate distinct price behaviors that define their market dynamics. BITCOIN emerges as the most volatile, characterized by a notably low mean (-0.0005) and an exceptionally high maximum value (0.1722), showcasing significant price fluctuations. In contrast, DJI exhibits a relatively stable pattern with a slightly negative mean (-0.0001) and a moderate maximum value of 0.0537. EURO_STOXX and FTSE_100 display positively skewed distributions, their kurtosis values surpassing 3, indicating heavier tails and a tendency toward higher values. Conversely, NIFTY_50 leans slightly toward negative skewness, while SSE_COMPOSITE reflects stability, evident from its skewness close to zero. The Jarque-Bera test unequivocally rejects the assumption of normality across all indices, underscoring their non-normal distribution shapes.

Table 2 Correlation

	BITCOIN	DJI	EURO_STOXX	FTSE_100	NIFTY_50	SSE_COMPOSITE
BITCOIN	1					
DJI	0.2768	1				
EURO_STOXX	0.2745	0.3957	1			
FTSE_100	0.2336	0.3579	0.8467	1		
NIFTY_50	0.1079	0.0996	0.3537	0.3573	1	
SSE_COMPOSITE	0.0003	-0.0009	0.0506	0.0265	0.0158	1

Source Prepared by author in E-views

The correlation analysis between Bitcoin and key stock indices—DJI, EURO_STOXX, FTSE_100, NIFTY_50, SSE_COMPOSITE—unveils a predominantly weak positive relationship. Bitcoin showcases correlations spanning from 0.2768 with DJI to an almost negligible 0.000289 with SSE_COMPOSITE, indicating a tendency for mild alignment in price movements but inconsistent synchronization. EURO_STOXX (0.2745) and FTSE_100 (0.2336) reveal similar faint positive associations, while NIFTY_50 exhibits a notably weaker link at 0.1079. These findings imply that although Bitcoin occasionally moves in parallel with these indices, its behavior lacks consistent co-movements. The varying strengths of correlation underscore distinct levels of interdependence between Bitcoin and each index, carrying substantial implications for investment strategies. The mild positive correlations of Bitcoin hint at its potential as a diversification tool within conventional portfolios, potentially alleviating overall risk due to its imperfect correlation. The diversity in correlation strengths across indices suggests regional and sectoral influences on Bitcoin, shaped by specific regulations, investor sentiments, and economic dynamics. These weak correlations emphasize Bitcoin's resilience against purely market-driven forces, highlighting the significant impact of cryptocurrency-specific factors on its price dynamics—factors encompassing technological advancements and regulatory shifts. This analysis underscores the intricate relationship between Bitcoin and traditional stock markets, indicating that while irregular movements align, the overall dynamics remain detached.

Table 3 Unit Root Test

Augmented Dickey-Fuller test statistic		
	t-Statistic	**Prob.**
BITCOIN	-35.9803	0.0000
DJI	-21.7165	0.0000
EURO_STOXX	-21.2215	0.0000
FTSE_100	-34.9552	0.0000
NIFTY_50	-16.2698	0.0000

SSE_COMPOSITE	-35.6377	0.0000

Source Prepared by author in E-views

The Augmented Dickey-Fuller test serves as a key scale for the stationarity of time series data, aiming to discern if a variable possesses a unit root, signifying a non-stationary process. The table 3 presents test statistics and their associated probabilities for Bitcoin, DJI, EURO_STOXX, FTSE_100, NIFTY_50, and SSE_COMPOSITE. Lower t-statistics, especially further from zero, coupled with smaller probabilities, stand as compelling indicators against the existence of a unit root, signaling stronger support for stationarity. Remarkably substantial negative t-statistics, such as Bitcoin's -35.9803, strongly refute the null hypothesis of a unit root, suggesting a high likelihood that these series are stationary. The consistently minuscule probabilities (all 0.0000) support this evidence, underlining a significant level of statistical significance. Thus, predicated on the Augmented Dickey-Fuller test outcomes, it appears that these financial indices—Bitcoin, DJI, EURO_STOXX, FTSE_100, NIFTY_50, and SSE_COMPOSITE show traits indicative of stationarity.

Bitcoin = β_0 + β_1 * DJI + β_2 * EURO_STOXX + β_3 * FTSE_100 + β_4 * NIFTY_50 + β_5 * SSE_COMPOSITE (1)

Where:

β_0 is the intercept

β_1, β_2, β_3, β_4, and β_5 are the regression coefficients

DJI, EURO_STOXX, FTSE_100, NIFTY_50, and SSE_COMPOSITE are the independent variables

The equation presented represents a multiple linear regression model intending to estimate the valuation of Bitcoin. Bitcoin's value (the dependent variable) is determined by the values of five different stock market indices: DJI (Dow Jones Industrial Average), EURO_STOXX, FTSE_100, NIFTY_50, and SSE_COMPOSITE (the independent variables). Each β coefficient (β_1 to β_5) represents the influence and magnitude that the respective stock market index holds over Bitcoin's valuation when all other variables remain constant.

Table 4 Multiple regression

1. **Variable**	2. **Coefficient**	3. **Std. Error**	4. **t-Statistic**	5. **Prob.**
6. **BITCOIN**	**7. 0.0006**	**8. 0.0011**	**9. 0.5406**	**10. 0.5889**
11. **DJI**	**12. 0.8198**	**13. 0.1227**	**14. 6.6796**	**15. 0.0000**
16. **EURO_STOXX**	**17. 0.6871**	**18. 0.1802**	**19. 3.8129**	**20. 0.0001**
21. **FTSE_100**	**22. -0.0615**	**23. 0.1847**	**24. -0.3330**	**25. 0.7392**
26. **NIFTY_50**	**27. 0.0933**	**28. 0.1219**	**29. 0.7659**	**30. 0.4439**
31. **SSE_COMPOSITE**	**32. -0.0404**	**33. 0.1153**	**34. -0.3507**	**35. 0.7259**

Source Prepared by author in E-views

The regression analysis delves into the intricate interplay between Bitcoin and five prominent indices—DJI, EURO_STOXX, FTSE_100, NIFTY_50, and SSE_COMPOSITE—exposing a diverse spectrum of relationships. Unexpectedly, alterations in Bitcoin, with a coefficient of 0.0006 and a non-significant p-value of 0.5889, do not significantly influence the other indices. However, the impact of these indices on Bitcoin is notably distinct. DJI exhibits a robust and statistically significant association, mirrored in its coefficient of 0.8198 (p-value = 0), suggesting that a one-unit change in DJI corresponds to an average 0.82 unit change in Bitcoin. EURO_STOXX similarly displays a significant impact, with a coefficient of 0.6871 (p-value = 0.0001), indicating that a 1-unit shift in EURO_STOXX aligns with an average 0.69 unit change in Bitcoin. In contrast, the coefficients of FTSE_100, NIFTY_50, and SSE_COMPOSITE lack statistical significance, signaling no substantial influence on Bitcoin's fluctuations. This analysis underscores Bitcoin's stronger connections with the US and European stock markets (DJI and EURO_STOXX) compared to the Indian, UK, or Chinese markets (NIFTY_50, FTSE_100, SSE_COMPOSITE), shedding light on distinctive regional relationships shaping Bitcoin's behavior within diverse global financial landscapes. The robust impact of DJI and EURO_STOXX on Bitcoin underscores their pivotal roles in influencing its price dynamics, potentially serving as leading indicators or closely tied assets. However, the absence of significant associations with other indices suggests a decoupling of Bitcoin from these particular global markets, hinting at the presence of unique drivers or localized factors impacting Bitcoin's movements within distinct geographical spheres.

$$\text{Bitcoin} = \beta_1 * \text{BITCOIN} + \beta_2 * \text{DJI\_RETURNS} + \beta_3 * \text{EURO\_STOXX} + \beta_4 * \text{FTSE\_100} + \beta_5 * \text{NIFTY\_50} + \beta_6 * \text{SSE\_COMPOSITE} + \beta_7 * \text{RESID(-1)} + \beta_8 * \text{RESID(-2)} + \varepsilon \quad (2)$$

$\beta 1, \beta 2, \beta 3, \beta 4, \beta 5, \beta 6, \beta 7, \beta 8$ are the coefficients associated with the respective variables. BITCOIN, DJI_RETURNS, EURO_STOXX, FTSE_100, NIFTY_50, SSE_COMPOSITE, RESID(-1), and RESID(-2) represent the variables. ε represents the error term, indicating the variability in Bitcoin returns that isn't explained by the included variables in the model.

Table 4 Breusch-Godfrey Serial Correlation LM Test

F-statistic	**0.8917**	**Prob. F(2,1174)**	**0.4102**	**Column1**
Obs*R-squared	1.7928	**Prob. Chi-Square(2)**	0.408	
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
BITCOIN	0	0.0011	-0.0083	0.9934
DJI_RETURNS	-0.0079	0.1229	-0.0641	0.9489
EURO_STOXX	0.022	0.181	0.1215	0.9033
FTSE_100	-0.0152	0.1851	-0.0821	0.9346
NIFTY_50	-0.0068	0.1221	-0.0557	0.9556
SSE_COMPOSITE	-0.0004	0.1156	-0.0032	0.9975
RESID(-1)	-0.0374	0.0293	-1.2738	0.203
RESID(-2)	-0.0131	0.0293	-0.4484	0.6539

Source Prepared by author in E-views

The F-test, evaluating the collective significance of all explanatory variables, presents an F-statistic of 0.8917 with a p-value of 0.4102, indicating an inability to reject the null hypothesis. This suggests that the included variables possess coefficients of zero, signifying the regression model's incapability to significantly clarify variations in the dependent variable. The adjusted R-squared value, a mere 1.79%, combined with a p-value of 0.4080, highlights the model's extremely weak explanatory power, elucidating only a fraction of the dependent variable's variance by the independent variables. Notably, the coefficients of BITCOIN, DJI_RETURNS, EURO_STOXX, FTSE_100, NIFTY_50, SSE_COMPOSITE, and lagged residuals (RESID(-1) and RESID(-2)) lack statistical significance. BITCOIN's coefficient, specifically at 0.0000, accompanied by a t-statistic of -0.0083 and a p-value of 0.9934, indicates an insignificant impact on the dependent variable. This insignificance extends across all variables, implying that none have a substantial effect on the dependent variable. This collective insignificance points to a lack of meaningful explanatory power within the model. It signifies an absence of significant relationships between the studied variables and the inability to capture any substantial autoregressive structures within the dataset. Consequently, the model inadequately explains the variance in the dependent variable, emphasizing the absence of statistically significant impacts or meaningful relationships among the variables studied.

Table 5 Heteroskedasticity Test

36. **Variable**	37. **Coefficient**	38. **Std. Error**	39. **t-Statistic**	40. **Prob.**
41. **BITCOIN**	**42. 0.0015**	**43. 0.0001**	**44. 11.6334**	**45. 0.0000**
46. **DJI_RETURNS**	**47. -0.0220**	**48. 0.0140**	**49. -1.5734**	**50. 0.1159**
51. **EURO_STOXX**	**52. -0.0630**	**53. 0.0205**	**54. -3.0671**	**55. 0.0022**
56. **FTSE_100**	**57. -0.0345**	**58. 0.0210**	**59. -1.6412**	**60. 0.1010**
61. **NIFTY_50**	**62. -0.0071**	**63. 0.0139**	**64. -0.5094**	**65. 0.6106**
66. **SSE_COMPOSITE**	**67. -0.0493**	**68. 0.0131**	**69. -3.7546**	**70. 0.0002**

Source Prepared by author in E-views

The regression analysis delves into BITCOIN returns' correlation with five major stock indices: DJI, EURO_STOXX, FTSE_100, NIFTY_50, and SSE_COMPOSITE. The coefficient for BITCOIN stands at 0.0015, boasting statistical significance (p-value = 0), indicating strong evidence that BITCOIN returns significantly impact the dependent variable. A one-unit change in BITCOIN returns coincides with an average 0.0015 unit change in the dependent variable. Conversely, DJI_RETURNS, FTSE_100, and NIFTY_50 exhibit coefficients lacking statistical significance (p-values > 0.05), suggesting no statistically significant impacts on the dependent variable. EURO_STOXX and SSE_COMPOSITE, however, display statistically significant impacts. EURO_STOXX's coefficient of -0.0630 (p-value = 0.0022) signifies a significant negative impact; a one-unit change in EURO_STOXX corresponds to an average -0.0630 change in the dependent variable. Similarly, SSE_COMPOSITE's coefficient of -0.0494 (p-value = 0.0002) indicates a significant negative impact; a one-unit change in SSE_COMPOSITE leads to an average -0.0490 change in the dependent variable. In summary, the analysis suggests BITCOIN returns significantly and positively affect the dependent variable. However, EURO_STOXX and SSE_COMPOSITE exhibit significant negative impacts. Conversely, DJI_RETURNS, FTSE_100, and NIFTY_50 do not demonstrate significant impacts on the dependent variable. These findings highlight distinct correlations between BITCOIN returns and various stock indices, emphasizing both positive and negative associations that underscore the intricate relationships within the financial landscape.

$$BITCOIN(t)=a\cdot BITCOIN(t-1)+b\cdot BITCOIN(t-2)+c\cdot BITCOIN(t-3)+d\cdot DJI(t-1)+e\cdot DJI(t-2)+f\cdot DJI(t-3)+g\cdot EURO\_STOXX(t-1)+h\cdot EURO\_STOXX(t-2)+i\cdot EURO\_STOXX(t-3)+j\cdot FTSE\_100(t-1)+k\cdot FTSE\_100(t-2)+l\cdot FTSE\_100(t-3)+m\cdot NIFTY\_50(t-1)+n\cdot NIFTY\_50(t-2)+o\cdot NIFTY\_50(t-3)+p\cdot SSE\_COMPOSITE(t-1)+q\cdot SSE\_COMPOSITE(t-2)+r\cdot SSE\_COMPOSITE(t-3)+s\cdot BITCOIN+intercept \quad (3)$$

This equation encapsulates a Vector Autoregression (VAR) model, a powerful tool depicting the interdependencies among financial indices and Bitcoin's value across multiple time periods. At its core, this equation unveils the current value of each financial index (at time 't') as a composite outcome of its own prior values (at times 't-1', 't-2', 't-3') and the preceding values of other indices. The coefficients (a-s) delineate the specific impact of each index's historical values on Bitcoin's present value, while the intercept term embodies the constant or unexplained variation in this intricate relationship. Deciphering this equation requires an insight into how previous index values shape the current valuation of Bitcoin. For instance, coefficients (a, b, c) associated with Bitcoin's lagged values (BITCOIN(t-1), BITCOIN(t-2), BITCOIN(t-3)) quantify the extent to which Bitcoin's past performances contribute to its current value. Simultaneously, coefficients corresponding to other indices—DJI, EURO_STOXX, FTSE_100, NIFTY_50, and SSE_COMPOSITE—signify their individual influences on Bitcoin's prevailing value.

Table 6 Standard Vector Auto-regression Estimates

	BITCOIN	**DJI**	**EURO_STOXX**	**FTSE_100**	**NIFTY_50**	**SSE_COMPOSITE**
BITCOIN(-1)	-0.0302	-0.0022	0.0137	0.0003	-0.0123	-0.0039
	[-0.98049]	[-0.29943]	[1.53288]	[0.03952]	[-1.66917]	[-0.52522]
BITCOIN(-2)	-0.006	-0.0046	0.0122	0.0082	0.0062	0.0138
	[-0.19454]	[-0.61695]	[1.35564]	[0.96086]	[0.83153]	[1.85466]
BITCOIN(-3)	0.0414	0.0036	-0.0053	-0.0097	0.0046	-0.0038
	[1.34581]	[0.49096]	[-0.59189]	[-1.14673]	[0.62971]	[-0.51738]
DJI(-1)	0.0908	-0.0682	0.1878	0.2437	-0.0123	0.0145
	[0.67573]	[-2.11528]	[4.80740]	[6.57424]	[-0.38178]	[0.44609]
DJI(-2)	0.09	-0.0208	0.0919	0.0128	-0.0669	0.0246
	[0.65888]	[-0.63417]	[2.31380]	[0.34057]	[-2.04357]	[0.74379]
DJI(-3)	-0.3417	-0.1576	-0.0949	-0.1303	-0.1455	0.0499
	[-2.51537]	[-4.83598]	[-2.40168]	[-3.47741]	[-4.46932]	[1.52194]
EURO_STOXX(-1)	-0.3416	0.0807	-0.0132	-0.0072	0.0089	0.017
	[-1.76703]	[1.73933]	[-0.23550]	[-0.13428]	[0.19166]	[0.36373]
EURO_STOXX(-2)	0.2323	0.1012	0.1535	0.1564	0.1334	0.0085
	[1.21031]	[2.19826]	[2.75071]	[2.95434]	[2.90108]	[0.18292]
EURO_STOXX(-3)	0.0872	0.0306	0.0342	0.1052	0.1364	0.0051
	[0.45535]	[0.66619]	[0.61517]	[1.99196]	[2.97319]	[0.11082]
FTSE_100(-1)	0.3216	-0.0601	-0.0372	-0.0545	-0.0131	0.0265
	[1.62508]	[-1.26606]	[-0.64747]	[-0.99865]	[-0.27551]	[0.55495]
FTSE_100(-2)	0.265	0.092	-0.0519	-0.0472	0.0068	-0.0605

	[1.34066]	[1.93937]	[-0.90338]	[-0.86523]	[0.14441]	[-1.26613]
FTSE_100(-3)	-0.0616	-0.0751	-0.084	-0.1561	-0.0677	0.0112
	[-0.31656]	[-1.60928]	[-1.48496]	[-2.91071]	[-1.45381]	[0.23754]
NIFTY_50(-1)	-0.3471	-0.0214	-0.0689	-0.1149	-0.0805	-0.0794
	[-2.65505]	[-0.68331]	[-1.81181]	[-3.18644]	[-2.56897]	[-2.51417]
NIFTY_50(-2)	-0.1259	0.0318	-0.0407	-0.0599	-0.1995	0.0376
	[-0.96994]	[1.01983]	[-1.07804]	[-1.67344]	[-6.41630]	[1.19922]
NIFTY_50(-3)	-0.1022	0.0656	-0.0333	0.0135	-0.0791	-0.0039
	[-0.77922]	[2.08610]	[-0.87352]	[0.37401]	[-2.51737]	[-0.12418]
SSE_COMPOSITE(-1)	0.1367	-0.0192	-0.0021	0.0004	-0.0585	-0.0327
	[1.12507]	[-0.65799]	[-0.05833]	[0.01150]	[-2.00889]	[-1.11467]
SSE_COMPOSITE(-2)	-0.1155	0.0299	-0.0206	0.0315	0.0325	0.0122
	[-0.94965]	[1.02253]	[-0.58331]	[0.93901]	[1.11521]	[0.41510]
SSE_COMPOSITE(-3)	0.0226	-0.0291	0.0227	0.0381	-0.0098	0.03
	[0.18623]	[-0.99746]	[0.64338]	[1.13770]	[-0.33595]	[1.02325]
BITCOIN	0.0001	0	0	-0.0002	-0.0013	0.0007
	[0.04614]	[-0.06605]	[-0.02819]	[-0.67721]	[-4.46122]	[2.40922]

Source Prepared by author in E-views

Understanding the relationship between Bitcoin and traditional stock indices, such as DJI, EURO STOXX, FTSE 100, NIFTY 50, and SSE COMPOSITE, across various lag periods (-1, -2, -3) is a multifaceted endeavor marked by intricate fluctuations and nuanced dynamics. Delving into the intricate web of correlations reveals a landscape of predominantly weak associations between Bitcoin and these indices. The interplay is characterized by modest and often close-to-zero correlations, suggesting a lack of consistent directional coherence between Bitcoin and the more conventional stock indices examined.

At first glance, the correlations between Bitcoin and these indices tend to hover around zero or slightly below it, indicative of an absence of a linear relationship. These findings suggest that movements in Bitcoin prices are not inherently mirrored or linearly linked with the movements observed in the traditional stock indices under consideration. Rather, they imply a degree of independence or lack of systematic correlation between these markets. Although sporadic instances of notable correlations emerge—such as the positive correlation between Bitcoin and EURO STOXX at lag -2 or the negative correlation with FTSE 100 at lag -1—their magnitudes remain modest within the spectrum of potential correlation values. These infrequent instances might indicate transient or short-lived relationships, possibly anomalies, rather than sustained or dependable correlations substantial enough to inform investment decisions. The statistical significance of these correlations, as indicated by the accompanying p-values, highlights varying degrees of significance across different lag periods and indices. While some correlations, like EURO STOXX at lag -2, exhibit statistical significance, their practical significance might not be robust enough to establish a reliable predictive or investment relationship between Bitcoin and the examined stock indices. This nuanced analysis underscores the complexity and variability inherent in Bitcoin's associations with traditional stock indices, signaling the inadequacy of solely relying on historical correlations to predict or explain Bitcoin's movements concerning these indices. Indeed, this intricate relationship underscores the necessity for a more nuanced and comprehensive approach in comprehending the interplay between cryptocurrencies and traditional financial markets. Relying solely on historical correlations might prove insufficient in decoding or forecasting Bitcoin's movements concerning conventional stock indices. Instead, it emphasizes the imperative need for incorporating additional factors and employing more sophisticated modeling techniques to effectively capture and elucidate their dynamic relationships. In essence, the exploration of correlations between Bitcoin and traditional stock indices at different lag periods unveils a landscape marked by predominantly weak associations and sporadic, modest correlations. This intricate web of interactions underscores the intricate and multifaceted nature of Bitcoin's relationship with traditional financial markets, advocating for a deeper and more nuanced approach to cracking their complex dynamics

5. CONCLUSION

This comprehensive study delved into the intricate relationship between Bitcoin and major international stock markets over the period from September 2018 to August 2023, revealing a significant insights into their interactions. Through detailed analysis encompassing descriptive statistics, correlation examinations, unit root tests, and regression models, distinct patterns emerged. Bitcoin stood out as a volatile asset, showcasing significant price fluctuations compared to more stable traditional indices like the Dow Jones Industrial Average (DJI). Correlation analyses unveiled mild positive relationships between Bitcoin and select stock indices, suggesting potential diversification benefits within investment portfolios. However, regression analyses, including multiple linear regression and vector auto-regression models, highlighted complex and dynamic relationships. Surprisingly, while Bitcoin's changes displayed limited influence on other indices, the DJI and EURO STOXX exhibited significant impacts on Bitcoin's fluctuations, while the FTSE 100, NIFTY 50, and SSE COMPOSITE demonstrated minimal influence on its valuation. Yet, serial correlation and Heteroskedasticity tests indicated model inadequacies in explaining the dependent variable's variations. Overall, this study underscores the complexity of Bitcoin's interactions with traditional stock markets, emphasizing its occasional alignment with certain indices while maintaining substantial independence. These findings have implications for portfolio diversification strategies and underscore the need for nuanced models and further research to comprehend the evolving relationships between cryptocurrencies and traditional financial systems comprehensively.

6. LIMITATIONS OF THE STUDY

1) The study only examines Bitcoin, leaving out other prominent cryptocurrencies like Ethereum, Litecoin, etc.
2) The study only explores the relationships between Bitcoin and five major stock markets, potentially overlooking other significant markets or regional exchanges.
3) The findings might not generalize to other periods, market conditions, or economic contexts.
4) The study might not fully capture market inefficiencies, such as information asymmetry or market sentiment

CONFLICT OF INTERESTS

None.

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