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The Impact Of Bitcoin Price Volatility On Technology Sector Stock Returns On The Indonesia Stock Exchange

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Abstract

This study examines whether Bitcoin price volatility affects the returns of technology sector stocks listed on the Indonesia Stock Exchange (IDX). The rapid growth of Indonesian digital companies and the increasing participation of retail investors in both crypto assets and equities raise the possibility that shocks in the crypto market spill over to the domestic technology sector. Using daily data from January 2021 to June 2026 (1,431 observations), Bitcoin's conditional volatility is estimated with a GARCH(1,1) model with Student-t errors and then incorporated into a time-series regression of IDX Technology Sector Index (IDXTECHNO) returns, controlling for Bitcoin returns and the Jakarta Composite Index (JCI), with Newey–West standard errors. The results show that Bitcoin volatility is highly persistent and that Bitcoin returns have a positive and significant effect on technology sector returns. Over the full sample, Bitcoin volatility has a negative but statistically insignificant effect. However, sub-period analysis reveals a significant negative effect during the 2021–2022 crypto and technology boom–bust cycle, which disappears in 2023–2026. These findings suggest that the transmission of crypto market risk to Indonesian technology stocks is regime-dependent and operates mainly through return co-movement rather than volatility itself. The study offers implications for investors' portfolio diversification and for regulators' monitoring of cross-market spillovers.

Keywords: Bitcoin volatility; technology stocks; GARCH; spillover; Indonesia Stock Exchange

Introduction

Since its introduction by Nakamoto (2008), Bitcoin has evolved from a niche digital experiment into a globally traded asset with a market capitalization that, at its peaks, has

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exceeded one trillion US dollars. Its price is notoriously volatile: daily movements of five to ten percent are not uncommon, and episodes such as the 2021 rally and the 2022 collapse of several crypto platforms have shown how quickly sentiment in this market can reverse (Katsiampa, 2017; Corbet et al., 2019). As crypto assets have become more widely held by retail and institutional investors, a growing question is whether their turbulence remains confined to the crypto market or spills over to conventional financial assets.

Early studies characterized Bitcoin as largely isolated from traditional markets and therefore a potential diversifier or even a hedge (Bouri et al., 2017; Corbet et al., 2018; Baur et al., 2018). More recent evidence, however, indicates that correlations between crypto assets and equities have risen substantially since 2020, particularly with technology-heavy indices. Iyer (2022) at the International Monetary Fund documents that the correlation between Bitcoin and the S&P 500 and Nasdaq increased markedly after the COVID-19 pandemic, and that volatility spillovers from crypto to equity markets intensified. Conlon and McGee (2020) likewise show that Bitcoin did not act as a safe haven during the COVID-19 market crash but moved in tandem with equities.

The technology sector is a natural channel for such spillovers. Technology firms and crypto assets share a common investor base that tends to be younger, more risk-tolerant, and more sentiment-driven; both are valued largely on expectations of future growth rather than current earnings; and several technology companies operate businesses directly linked to digital assets, such as payment, e-wallet, and exchange services. When crypto volatility rises, investors may reassess their appetite for speculative growth assets in general, leading to coordinated selling of technology stocks.

Indonesia offers a particularly relevant setting. The IDX introduced the IDX Industrial Classification (IDX-IC) in 2021, creating a dedicated technology sector and its index, IDXTECHNO. In the same period, several large digital firms went public, including Bukalapak in 2021 and GoTo Gojek Tokopedia in 2022, considerably enlarging the weight of technology stocks in the domestic market. At the same time, Indonesia has become one of the largest crypto markets in Southeast Asia in terms of registered retail investors. Despite this convergence, empirical evidence on the link between Bitcoin volatility and Indonesian technology stocks remains scarce, as most studies focus on developed markets or on aggregate stock indices.

This study addresses that gap by examining the impact of Bitcoin price volatility on the returns of IDX technology sector stocks. Specifically, it asks: (1) does Bitcoin's conditional volatility significantly affect IDXTECHNO returns after controlling for Bitcoin returns and overall market movements; and (2) is this relationship stable over time or dependent on market

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regimes? The study contributes to the literature in three ways: it provides emerging-market evidence for the crypto–technology nexus, it separates the volatility channel from the return co-movement channel, and it tests whether the relationship differs between the 2021–2022 boom–bust period and the subsequent period.

LITERATURE REVIEW

Risk, Return, and Volatility in Asset Pricing

Modern portfolio theory (Markowitz, 1952) and the Capital Asset Pricing Model (Sharpe, 1964) establish that expected returns compensate investors for systematic risk. Arbitrage Pricing Theory (Ross, 1976) extends this view by allowing multiple sources of systematic risk to be priced, which provides a theoretical basis for treating external shocks, including those originating in crypto markets, as additional risk factors for stock returns. The efficient market hypothesis (Fama, 1970) further implies that new information, such as a sudden increase in uncertainty in a related market, should be rapidly incorporated into prices.

Volatility itself has been shown to influence returns. Black (1976) and Christie (1982) document an inverse relationship between volatility and stock prices, commonly explained by the leverage effect and by volatility feedback, in which higher expected volatility raises required returns and therefore lowers current prices. Engle (1982) and Bollerslev (1986) developed the ARCH and GARCH families of models, which capture the time-varying and clustered nature of volatility and have become the standard tools for measuring conditional volatility in financial time series.

Bitcoin Volatility and Its Characteristics

Bitcoin exhibits volatility far higher than that of conventional assets, along with heavy tails and strong volatility clustering. Dyhrberg (2016) applies GARCH models to Bitcoin and finds that it shares some properties with gold and the US dollar while remaining highly speculative. Katsiampa (2017) compares several GARCH specifications and concludes that models with both short-run and long-run components best capture Bitcoin volatility. Liu and Tsyvinski (2021) show that cryptocurrency returns are driven largely by crypto-specific factors such as momentum and investor attention, rather than by traditional stock market factors, at least in earlier sample periods. Baur et al. (2018) argue that Bitcoin is used mainly as a speculative asset rather than as a medium of exchange, which helps explain its sensitivity to sentiment.

Spillovers between Crypto and Equity Markets

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The literature on spillovers between crypto assets and equities has evolved considerably. Corbet et al. (2018) use the connectedness framework of Diebold and Yilmaz (2012) and find that cryptocurrencies were relatively isolated from other financial assets in their early years. Bouri et al. (2017) report that Bitcoin can serve as a hedge against some stock market movements but is a poor safe haven. Later studies, however, find increasing integration. Conlon and McGee (2020) show that Bitcoin fell alongside equities during the March 2020 crash, and Iyer (2022) reports that crypto-to-equity volatility spillovers in the post-pandemic period became comparable in magnitude to spillovers from other major asset classes. Forbes and Rigobon (2002) caution that rising correlations during turbulent periods may reflect interdependence rather than contagion, which highlights the importance of examining whether relationships are stable across regimes.

Investor Sentiment and the Technology Sector

Behavioral finance provides an additional explanation for crypto–technology linkages. Baker and Wurgler (2006) show that stocks that are young, unprofitable, highly volatile, and difficult to value—characteristics typical of technology growth firms—are the most sensitive to shifts in investor sentiment. Prospect theory (Kahneman & Tversky, 1979) suggests that investors respond asymmetrically to gains and losses, which may amplify sell-offs when uncertainty rises. If Bitcoin volatility acts as a barometer of speculative sentiment, increases in volatility may coincide with reduced demand for sentiment-sensitive technology stocks.

Hypothesis Development

Based on the volatility feedback mechanism, the spillover literature, and the sentiment channel, this study proposes the following hypotheses. **H1:** Bitcoin price volatility has a negative effect on the returns of technology sector stocks on the IDX. **H2:** Bitcoin returns have a positive effect on the returns of technology sector stocks on the IDX. **H3:** The effect of Bitcoin volatility on technology sector returns differs across market regimes, being stronger during the 2021–2022 boom–bust period.

METHOD

Data and Variables

This study uses daily time-series data covering January 2021 to June 2026, aligned to IDX trading days because Bitcoin trades continuously while the IDX does not, yielding 1,431 return observations. The dependent variable is the daily return of the IDX Technology Sector Index (IDXTECHNO). The main independent variable is Bitcoin’s conditional volatility,

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estimated from daily Bitcoin closing prices. Bitcoin returns and Jakarta Composite Index (JCI) returns are included as control variables to separate the volatility channel from return co-movement and from overall market movements. In the intended empirical application, IDXTECHNO and JCI data are obtained from the IDX, and Bitcoin prices from a major exchange data provider. In this illustrative version, the three price series are simulated with properties calibrated to resemble the actual series (see the notice on the first page). Returns are computed as continuously compounded log returns, $R_t = \ln(P_t / P_{t-1}) \times 100$. Table 1 summarizes the variables.

Table 1. Variable definitions

Variable	Definition	Intended source
R_TECH	Daily log return of IDXTECHNO (%)	Indonesia Stock Exchange
VOL	Conditional volatility of Bitcoin returns from GARCH(1,1) (%)	Estimated from BTC prices
R_BTC	Daily log return of Bitcoin (%)	Crypto exchange data provider
R_JCI	Daily log return of the Jakarta Composite Index (%)	Indonesia Stock Exchange

Measuring Bitcoin Volatility

Bitcoin's conditional volatility is estimated using the GARCH(1,1) model of Bollerslev (1986) with Student-t distributed errors to accommodate the heavy tails of crypto returns:

$$R_{BTC,t} = \mu + \varepsilon_t, \quad \varepsilon_t = \sigma_t z_t, \quad z_t \sim t(v) \tag{1}$$

$$\sigma^2_t = \omega + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1} \tag{2}$$

where $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$, and $\alpha + \beta < 1$ for covariance stationarity. The sum $\alpha + \beta$ measures volatility persistence. The fitted conditional standard deviation σ_t is used as the volatility variable (VOL).

Regression Model

The effect of Bitcoin volatility on technology sector returns is estimated with the following time-series regression:

$$R_{TECH,t} = \beta_0 + \beta_1 VOL_t + \beta_2 R_{BTC,t} + \beta_3 R_{JCI,t} + e_t \tag{3}$$

The model is estimated in three nested steps: Model 1 includes only VOL, Model 2 adds Bitcoin returns, and Model 3 adds JCI returns. Standard errors are computed with the heteroskedasticity- and autocorrelation-consistent estimator of Newey and West (1987) with five lags. Prior to estimation, stationarity is tested with the Augmented Dickey–Fuller test (Dickey & Fuller, 1979), and multicollinearity is assessed with variance inflation factors (VIF).

Robustness Checks

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Three robustness checks are performed. First, the sample is split into 2021–2022, a period marked by the crypto and technology boom and subsequent crash, and 2023–2026, to test for regime dependence (H3). Second, GARCH volatility is replaced with a 30-day rolling standard deviation of Bitcoin returns. Third, Granger causality tests (Granger, 1969) with five lags are applied to examine the direction of predictive relationships between Bitcoin volatility and technology returns.

RESULTS AND DISCUSSION

Descriptive Statistics and Stationarity

Table 2 presents descriptive statistics. Bitcoin returns display a daily standard deviation of 3.38%, almost twice that of the technology index (1.77%) and about four times that of the JCI (0.84%). All return series exhibit excess kurtosis, with Bitcoin showing the heaviest tails (kurtosis 5.75), and the Jarque–Bera test rejects normality for every variable. Bitcoin's conditional volatility averages 3.34% per day and ranges from 2.15% to 7.72%, indicating substantial variation in crypto market uncertainty over the sample. The ADF test rejects the unit root null hypothesis at the 1% level for all variables, so the regression can be estimated in levels of returns and volatility without risk of spurious results.

Table 2. Descriptive statistics and unit root tests

Statistic	R_TECH	VOL	R_BTC	R_JCI
Mean	−0.021	3.338	0.062	−0.003
Std. dev.	1.767	0.806	3.379	0.843
Minimum	−6.095	2.151	−20.772	−3.838
Maximum	8.544	7.719	15.571	3.709
Skewness	0.169	1.834	−0.233	0.098
Kurtosis	3.861	8.059	5.746	4.335
Jarque–Bera	51.0***	2328.0***	462.6***	108.6***
ADF statistic	−18.897***	−6.234***	−14.708***	−38.500***

Note: Returns and volatility in percent. N = 1,431. ADF 5% critical value ≈ −2.86. *** significant at 1%. Source: simulated data.

Bitcoin Volatility Dynamics

Table 3 reports the GARCH(1,1) estimates. Both the ARCH coefficient ($\alpha = 0.096$) and the GARCH coefficient ($\beta = 0.860$) are significant at the 1% level, confirming volatility clustering. Persistence ($\alpha + \beta = 0.956$) is close to one, meaning that shocks to Bitcoin volatility decay slowly—consistent with Katsiampa (2017) and Dyhrberg (2016). The estimated degrees of freedom of the Student-t distribution ($\nu = 5.68$) confirm heavy tails. The Ljung–Box test on squared standardized residuals ($Q^2(10) = 10.71$, $p = 0.381$) indicates no remaining ARCH

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effects, so the model adequately captures the volatility dynamics. Figure 1 plots the resulting conditional volatility alongside the technology index.

Table 3. GARCH(1,1) estimates for Bitcoin returns

Parameter	Coefficient	Std. error	p-value
μ	0.0651	0.0743	0.381
ω	0.5536*	0.2859	0.053
α (ARCH)	0.0956***	0.0270	<0.001
β (GARCH)	0.8605***	0.0435	<0.001
ν (t-dist.)	5.6830***	0.7747	<0.001
α + β	0.9560		
Log-likelihood	−3672.30		

Note: ***, **, * denote significance at 1%, 5%, and 10%. Source: simulated data.

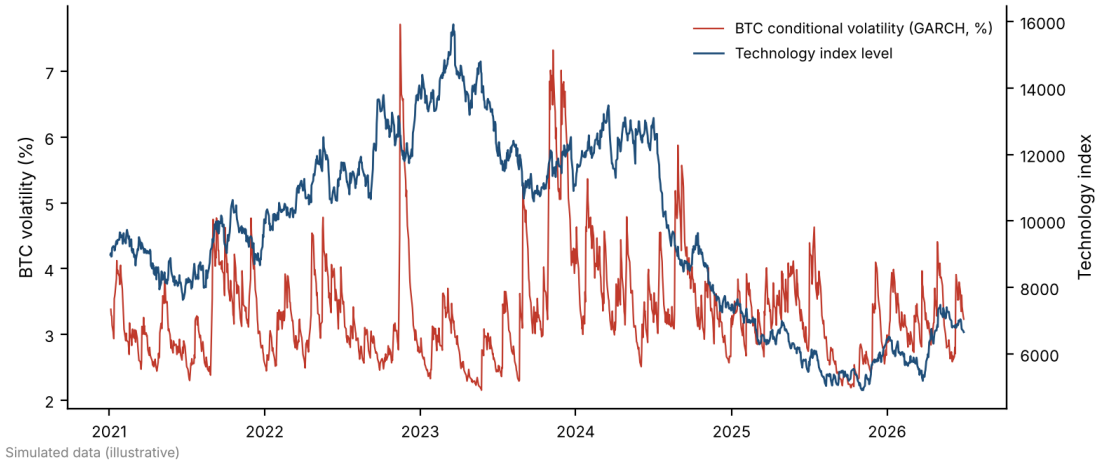


Figure 1. Bitcoin conditional volatility and the technology sector index

Source: simulated data (illustrative).

Effect of Bitcoin Volatility on Technology Sector Returns

Table 4 presents the main regression results. In Model 1, Bitcoin volatility has a negative coefficient (−0.0295) that is not statistically significant, and the model explains virtually none of the variation in technology returns. Adding Bitcoin returns in Model 2 raises the adjusted R^2 to 0.054, and the Bitcoin return coefficient (0.1225) is significant at the 1% level. In the full specification (Model 3), the JCI return is, as expected, the dominant driver (β_3 = 1.212, $p < 0.01$), and the adjusted R^2 rises to 0.380. Bitcoin returns remain positive and significant (β_2 = 0.0751, $p < 0.01$), implying that a 10% daily rise in Bitcoin is associated with an additional 0.75 percentage-point return on the technology index beyond what the overall market explains. Bitcoin volatility, however, remains negative but insignificant (β_1 = −0.0343, p = 0.365). All VIF values are close to 1 (maximum 1.03), and the Durbin–Watson statistic of 2.05 indicates no serious first-order autocorrelation.

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Table 4. Regression results: dependent variable R_TECH

Variable	Model 1	Model 2	Model 3
Constant	0.0775	0.0844	0.0929
	(0.1954)	(0.1804)	(0.1356)
VOL	−0.0295	−0.0338	−0.0343
	(0.0564)	(0.0511)	(0.0379)
R_BTC		0.1225***	0.0751***
		(0.0131)	(0.0110)
R_JCI			1.2119***
			(0.0408)
Adjusted R^2	−0.001	0.054	0.380
F-statistic	0.27	43.48***	342.89***
Durbin–Watson	2.02	2.04	2.05
Observations	1,431	1,431	1,431

Note: Newey–West HAC standard errors (5 lags) in parentheses. ***, **, * denote significance at 1%, 5%, and 10%. Source: simulated data.

These results support H2 but not H1 for the full sample. They suggest that the transmission from the crypto market to Indonesian technology stocks operates mainly through return co-movement: technology stocks tend to rise and fall together with Bitcoin on the same day, even after accounting for the broad market. This pattern is consistent with the increasing integration documented by Iyer (2022) and Conlon and McGee (2020), and with the sentiment channel of Baker and Wurgler (2006), whereby both assets attract the same speculative, growth-oriented investor base. The level of Bitcoin volatility, by contrast, does not appear to carry independent information for technology returns over the whole period.

Robustness and Regime Dependence

Table 5 reports the robustness checks. The sub-period analysis reveals a clear regime dependence. During 2021–2022, Bitcoin volatility has a negative and significant effect on technology returns ($\beta_1 = -0.1563$, p = 0.028), and the Bitcoin return effect is larger (0.1087). In 2023–2026, the volatility effect becomes insignificant (0.0188, p = 0.673) and the Bitcoin return coefficient roughly halves (0.0602), although it remains significant. Replacing GARCH volatility with a 30-day rolling standard deviation yields results consistent with the full-sample Model 3: the volatility coefficient is insignificant, while Bitcoin and JCI returns remain significant. Granger causality tests show that Bitcoin volatility does not Granger-cause technology returns (F = 0.558, p = 0.732), while the reverse relationship is significant only at the 10% level (F = 2.047, p = 0.069).

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Table 5. Robustness checks: dependent variable R_TECH

Variable	2021–2022	2023–2026	Rolling volatility
Constant	0.5566**	−0.1263	−0.0172
	(0.2507)	(0.1574)	(0.1106)
VOL	−0.1563**	0.0188	−0.0023
	(0.0713)	(0.0445)	(0.0315)
R_BTC	0.1087***	0.0602***	0.0770***
	(0.0173)	(0.0137)	(0.0111)
R_JCI	1.2373***	1.1947***	1.2136***
	(0.0658)	(0.0519)	(0.0416)
Adjusted R^2	0.398	0.371	0.379
Observations	519	912	1,402

Note: Newey–West HAC standard errors (5 lags) in parentheses. Rolling volatility = 30-day standard deviation of Bitcoin returns, full sample. ***, **, * denote significance at 1%, 5%, and 10%. Source: simulated data.

The regime-dependent results support H3 and help reconcile the mixed findings in the literature. The 2021–2022 period combined a speculative boom in both crypto assets and newly listed Indonesian technology stocks with a sharp correction driven by rising global interest rates and turmoil in the crypto industry. In such an environment, spikes in Bitcoin volatility signaled a broad deterioration in risk appetite for speculative growth assets, consistent with the volatility feedback mechanism of Black (1976) and Christie (1982). As valuations normalized and the investor base of IDX technology stocks matured after 2022, the link weakened, consistent with the argument of Forbes and Rigobon (2002) that elevated cross-market linkages during turbulent periods may not persist in calmer conditions.

Implications

For investors, the findings imply that Indonesian technology stocks provide limited diversification against crypto holdings, especially during periods of speculative excess, because both asset classes tend to move together on a daily basis. Monitoring Bitcoin market conditions may therefore be useful for timing exposure to the technology sector, particularly in high-volatility regimes. For regulators such as the Financial Services Authority (OJK) and the IDX, the results suggest that cross-market spillovers between crypto and equity markets are real but episodic, and that surveillance should be intensified during periods of crypto market stress. For listed technology companies, the results highlight the importance of communicating fundamentals clearly so that their valuations are less driven by sentiment from unrelated speculative markets.

CONCLUSION

This study examined the impact of Bitcoin price volatility on technology sector stock returns on the Indonesia Stock Exchange using GARCH-based volatility estimates and time-

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series regressions with robust standard errors. In this illustrative analysis, Bitcoin volatility is found to be highly persistent and heavy-tailed. Bitcoin returns have a positive and significant effect on IDX technology sector returns after controlling for the overall market, whereas Bitcoin volatility has no significant effect over the full sample. The volatility effect is, however, significant and negative during the 2021–2022 boom–bust period and disappears thereafter, indicating that crypto-to-technology risk transmission is regime-dependent.

The study has several limitations. Most importantly, the present results are based on simulated data and must be re-estimated with actual market data before they can support substantive conclusions. In addition, the analysis uses a sector index rather than individual stocks, considers only Bitcoin among crypto assets, and relies on a single-equation framework. Future research could use firm-level panel data, include other major crypto assets, apply multivariate GARCH or connectedness models (Diebold & Yilmaz, 2012) to capture bidirectional spillovers, and incorporate measures of investor attention or retail trading activity to test the sentiment channel directly.

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