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Does Regulation Trigger Volatility? Empirical Evidence from the Bitcoin, Ethereum, and Ripple Markets in Indonesia

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ABSTRACT

The implementation of PMK 50/2025 marks a pivotal moment in Indonesia's digital asset fiscal landscape through the introduction of a 0.21% final income tax and the formal transition of oversight to the Financial Services Authority (OJK). This study empirically examines whether these regulatory changes triggered volatility shocks in three major cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), and Ripple (XRP). Using an ARMA(1,1)-eGARCH(1,1) model with Student-*t* distribution and USD returns as a global market control, we estimate conditional daily volatility over a three-period framework: Pre-Announcement, Post-Announcement, and Post-Implementation. Hypothesis testing employs the Wilcoxon Rank-Sum Test (Mann-Whitney U Test), supplemented by dummy regression with Newey-West HAC standard errors, and structural break tests. The primary results reveal no statistically significant change in conditional volatility following PMK 50/2025 for all three assets (Mann-Whitney U, all $p>0.05$). Notably, the dummy regression identifies a statistically significant reduction in Ethereum's conditional volatility post-implementation ($\beta=-0.000287$, $p=0.028$), corroborated by a structural break toward stability. All assets exhibit a significant positive asymmetry ($\gamma>0$), indicating that positive shocks drive greater volatility than negative shocks — a distinctive crypto-market characteristic. Robustness checks using sGARCH(1,1) confirm the main findings. Overall, the results indicate that PMK 50/2025 was not associated with a statistically significant increase in conditional volatility during the observed event windows. These findings should be interpreted as evidence on conditional volatility response only, and do not constitute a comprehensive assessment of market quality, liquidity, or overall resilience.

Keywords: Volatility, eGARCH, PMK 50/2025, Cryptocurrency, Market Resilience

JEL Classification: G18, G15, C58

1 Introduction

When it first emerged, cryptocurrency in Indonesia was classified as a commodity. As a commodity, cryptocurrency initially faced one major issue: the uncertainty of its legal recognition. In many parts of the world, cryptocurrency is widely recognised as a digital financial asset or currency (Howden, 2015). Their use as a medium of exchange has long been in use, leading to their categorisation as a tradable commodity. This implies a misconception about what cryptocurrency actually is. Taking Bitcoin and ETH as examples, rather than categorising them as a type of asset, in reality, both are used as a substitute for money (Rahman et al., 2025). Therefore, if supervision were carried out by Bappebti, it would be considered inappropriate.

Following the issuance of Government Regulation Number 49 of 2024, digital financial assets in Indonesia have undergone some adjustments. This latest regulation introduces a final tax of 0.21% of the value of crypto trading transactions, effective August 1, 2025 (Nurdin & Utomo, 2026). This regulation also shifts the mandate for crypto asset oversight from the Commodity Futures Trading Regulatory Agency to the Financial Services Authority (OJK). This institutional change marks the formal recognition of crypto assets as an integral part of the national financial services sector. Following this shift, the government introduced Minister of Finance Regulation Number 50 of 2025. While this policy aims to create legal certainty and improve compliance, implementing the tax in a highly speculative market often triggers unexpected reactions to price stability.

This research is rooted in the need to understand how domestic regulations affect the volatility of major digital assets such as Bitcoin, Ethereum, and Ripple. Research by Özdemir (2022) shows that the crypto market is highly vulnerable to clustering volatility and systemic external shocks, such as the economic shock caused by COVID-19. This research seeks to explore other aspects, namely, understanding market behaviour following the enactment of new regulations. As is known, taxation will affect market behaviour, as in Baltagi et al. (2006) , where an increase in the tax rate from 0.3% to 0.5% immediately reduced trading volume by one-third. To the best of the author's knowledge, no research has examined the impact of this crypto tax on Indonesia's crypto market, making it an urgent matter requiring further investigation.

The urgency of this study is further reinforced by the characteristic information asymmetry that often occurs when new regulations are announced. According to a study by Naimy et al. (2021), traditional GARCH models often fail to capture the asymmetric nature of crypto market shocks. Investors tend to react more aggressively to news perceived as imposing additional burdens, such as taxes, compared to positive news. This phenomenon is known as the leverage effect, where bad news triggers higher volatility than good news of the same magnitude. Using the Exponential GARCH model, this study seeks to fill this methodological gap by analysing whether PMK 50/2025 is perceived as a burden that triggers market panic or as a catalyst for stability through legal certainty (Cheikh et al., 2020)

Another gap identified in previous research is the lack of focus on interconnectedness between assets within the context of local regulations. Research by Hussain et al. (2024) highlights a strong volatility spillover effect between Bitcoin and other crypto assets. However, this study did not specifically examine how changes in tax regulations in one jurisdiction can affect the dynamics between these assets. By analysing Bitcoin, Ethereum, and Ripple, this study will provide a more comprehensive picture of whether tax regulations drive uniform volatility or have different effects across assets. This is crucial because each asset has a different investor profile and utility level in the Indonesian market.

This research is crucial for Indonesian policymakers evaluating the effectiveness of PMK 50/2025. Nurdin & Utomo (2026) stated that the transition of supervision to the Financial Services Authority (OJK) should boost investor confidence. However, if the new final tax burden triggers excessive volatility, the goal of market stabilisation may not be achieved. Empirical evidence on the relationship between taxation and volatility will help regulators adjust fiscal instruments to avoid stifling financial technology innovation. This study also serves as a means to test whether the integration of crypto into the formal financial sector actually reduces speculative risk or introduces new sources of uncertainty.

Beyond regulatory aspects, this study contributes to the literature on risk management in emerging markets. Agrawal et al. (2024) emphasise that understanding the dynamics of time-varying volatility is crucial for efficient portfolio construction. By including control variables such as USD-crypto pair volatility, this study ensures that observed fluctuations stem from the impact of domestic policies rather than simply reflecting global economic uncertainty. This variable separation represents a significant improvement over previous studies, which often ignore the influence of exchange rates in analysing crypto volatility in local markets. This provides investors with clarity on the main sources of risk they face when investing in Indonesian crypto exchanges following the enactment of PMK 50/2025.

Through this systematic approach, the research is expected to empirically demonstrate whether PMK 50/2025 acts as a stabiliser or a trigger for volatility. If the results indicate that the regulation triggers asymmetric volatility, the government should consider additional incentives to maintain market liquidity. Conversely, if this policy proves to stabilise the market, Indonesia's regulatory model could serve as a reference for other developing countries in integrating crypto assets into their national tax systems. This knowledge is invaluable for the future development of a healthy and sustainable digital financial ecosystem. The research's focus on three key assets ensures that the findings are highly representative of overall market conditions.

2 Literature Review

2.1 Characteristics and Dynamics of Crypto Asset Volatility

The crypto asset market is widely recognised as experiencing much more extreme volatility than traditional asset classes such as equities and commodities (Zahid & Iqbal, 2022). The literature shows that crypto returns are not normally distributed but exhibit fat-tailed characteristics and volatility clustering, in which periods of high volatility tend to be followed by periods of high volatility (Du et al., 2022; Wang, 2021).

This phenomenon is often driven by investor psychology, such as the fear of missing out effect, in which positive shocks have a greater impact on volatility than negative shocks (Zhang & Mani, 2021). Furthermore, crypto volatility is heavily influenced by news and sentiment (Sapkota, 2022), as well as online information searches that can reduce risk premiums (Senarathne & Šoja, 2019).

2.2 Asymmetric Volatility Modelling (eGARCH)

In the financial econometric literature, the Exponential GARCH (eGARCH) model is often considered superior to the standard GARCH model in analysing crypto assets (Kantar et al., 2025; Sevinç & Akinci, 2021). The eGARCH model allows detection of asymmetric effects, or leverage effects, in which bad and good news have different impacts on conditional variance (Gyamerah, 2019). The use of eGARCH with the Student-*t* distribution assumption has proven to be the most accurate in capturing the asymmetric and heavy-tailed distribution of crypto data (Sözen, 2025; Yıldırım & Bekun, 2023).

2.3 Transaction Tax Theory and Market Stabilisation

The impact of transaction tax policy on market behaviour is a classic topic of debate in financial economics. At least, there are two main perspectives are relevant in the context of PMK 50/2025:

1. Destabilisation View: Transaction taxes can increase transaction costs, which in turn reduces liquidity and market depth, thus triggering increased volatility (Tensingh et al., 2025).
2. Stabilisation View: Conversely, moderate transaction taxes can function as a stabilising instrument by filtering out noise traders and reducing short-term speculative activity (Li et al., 2013).

The effectiveness of this policy depends heavily on market structure and investor maturity. In emerging markets, herding behaviour tends to be stronger, so sudden policy interventions can amplify price fluctuations if not accompanied by clear regulatory certainty (Roger et al., 2025).

To conclude, the conceptual framework in this study integrates the impact of fiscal policy and institutional strengthening on the stability of the Indonesian crypto market. Theoretically, the implementation of PMK 50/2025 with a final rate of 0.21% creates a dual market response; on the one hand, it can be seen as a transaction cost burden that risks reducing liquidity and triggering volatility, but on the other hand, it can act as a stabilising instrument that filters out short-term speculators. This fiscal dynamic is reinforced by structural strengthening, as supervision shifts from Bappebti to the Financial Services Authority (OJK). Based on legitimacy theory, this stricter regulatory framework provides legal certainty that can reduce the risk premium (Gyamerah, 2019) while also curbing negative herding behaviour that often dominates emerging markets during policy transitions (Roger et al., 2025). Thus, the synergy between moderate tax policies and institutional legal certainty is expected to create a more stable and resilient domestic crypto market ecosystem to shocks.

3 Research Methods

3.1 Research Data and Period

This research uses a quantitative approach with time data. daily series. The data used includes closing Daily price data for three major cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), and Ripple (XRP). The observation period is set from January 1, 2024, to December 31, 2025, or approximately 726 daily observations (Bitcoin and Ethereum) and 725 observations (Ripple). This sample size meets the minimum recommendation of 500 observations for GARCH-family models, as suggested by Hwang & Valls Pereira (2006). To isolate the impact of domestic policies, data were collected in two currency pairs: the Indonesian Rupiah (IDR) as the dependent variable and the US Dollar (USD) as a control variable to capture global market sentiment since the USD pair will be the most relevant variable yet it is not influenced by the internal regulation. All data were obtained through financial data provider Investing.com. Closing prices were then transformed into log- returns to ensure data stationarity and accuracy of volatility measurements. Data were analysed using R software.

3.2 Data Diagnostic Procedure

Prior to volatility modelling, a series of diagnostic tests were conducted to validate the econometric assumptions. Augmented Test Dickey-Fuller (ADF) was applied to ensure that the yield data is stationary and does not contain a unit root. Next, the ARCH-LM (Lagrange multiplier) test is conducted to detect the presence of heteroscedasticity or volatility clustering (volatility grouping). The existence of the ARCH effect is an absolute prerequisite to justify the use of the GARCH family of models in this study. The Ljung-Box Q(12) test on the squared returns confirms the absence of serial correlation that might otherwise bias the volatility estimates.

3.3 Model Specifications: ARMA- eGARCH with Global Control

This study uses a two-stage approach to obtain a more refined volatility estimate. The first stage is volatility modelling using Exponential Generalised Autoregressive Conditional Heteroskedasticity (eGARCH). EGARCH is preferred because it allows volatility to respond asymmetrically to positive and negative shocks. This feature is particularly relevant for crypto asset markets, where negative information or adverse market sentiment may generate a stronger volatility response than positive information of similar magnitude. In addition, the logarithmic specification of EGARCH ensures positive conditional variance without imposing strict non-negativity restrictions on the estimated parameters.

The model is specified as ARMA(1,1) on the mean equation and eGARCH (1,1) on the variance equation. The main advantage of the eGARCH model is its ability to capture information asymmetry, in which negative shocks (bad news) often have a different impact on volatility than positive shocks (good news) (Cheikh et al., 2020). The mean equation is:

$$r_t = \mu + \vartheta_1 r_{t-1} + \theta_1 \varepsilon_{t-1} + \delta.RUSD_t + \varepsilon_t \tag{1}$$

where r_t is the log-return, $RUSD_t$ is the USD log-return (global control regressor).

To separate the impact of domestic policies from global trends, this study includes global market returns (USD pairs) as an external regressor in the averaging equation. This aims to filter out price movements driven by global sentiment, so that the resulting volatility residual (σ_t) better reflects the dynamics of the Indonesian domestic market. The Student-t distribution is used in the model estimation to accommodate the fat-tailed characteristics commonly found in crypto asset data. The variance equation is:

$$\ln\left(\sigma_t^2\right) = \omega + \alpha_1(|z_{t-1}| - \mathbb{E}|z_{t-1}|) + \gamma_1 z_{t-1} + \beta_1 \ln\left(\sigma_{t-1}^2\right) \tag{2}$$

3.4 Volatility Extraction and Comparative Hypothesis Testing

Once the eGARCH model is estimated, conditional daily volatility (σ_t) for each asset is extracted. The volatility series is categorised into three sub-periods based on the PMK 50/2025 timeline:

1. Pre-Announcement: January 1, 2024 – April 30, 2025 (N=481 obs.). This constitutes the benchmark period in which no formal regulatory signal had been published.
2. Post-Announcement: May 1, 2025 – July 31, 2025 (N=92 obs.). Following public disclosure of PMK 50/2025, market participants had access to the full regulatory text but the tax had not yet taken effect.
3. Post-Implementation: August 1, 2025 – December 31, 2025 (N=153 obs.). The final income tax became operative; OJK assumed formal supervisory authority.

The impact of the regulation is analysed using comparative hypothesis testing to assess statistically significant changes in mean conditional volatility across policy sub-periods. Since the Pre-Announcement, Post-Announcement, and Post-Implementation periods constitute independent, non-overlapping time segments, the appropriate non-parametric test is the Mann-Whitney U Test. This test evaluates whether the distribution of conditional volatility in one period tends to be stochastically greater or lesser than in another period, without assuming normality or paired observations.

Additionally, a dummy variable regression is estimated to quantify the isolated effects of announcement and implementation:

$$\sigma_t = \beta_0 + \beta_1 D_{ann} + \beta_2 D_{impl} + \varepsilon_t \quad (3)$$

where Dann and Dimpl are binary indicators for the announcement and implementation sub-periods, respectively. Newey-West HAC standard errors correct for heteroscedasticity and autocorrelation.

Structural break tests (Bai-Perron optimal break detection and Chow test at the implementation date) evaluate potential volatility regime shifts. Residual diagnostics confirm the adequacy of the model. Statistical significance is assessed at the 5% level (α= 0.05); *p*-values below this threshold indicate that PMK 50/2025 significantly affected the volatility of the Indonesian crypto market.

4 Results and Discussion

4.1 Results

The presentation of the research results begins with verifying the data properties through diagnostic testing. This step is essential to ensure that the conditional variance modelling via eGARCH is statistically valid. The results of the Augmented Dickey Fuller test, Ljung-Box Q(12), and the Lagrange Arch Multiplier tests are summarised in the following table.

Table 1. Pre-Estimation Diagnostic Tests

Asset	ADF Stat.	ADF *p*-val.	Stationary	ARCH-LM Stat.	ARCH-LM *p*-val.	Heterosk.	LB Q(12)	LB *p*-val.	Serial Corr.
Bitcoin	−9.204	≤0.01	YES	49.924	<0.001	YES	9.617	0.650	NO
Ethereum	−8.900	≤0.01	YES	22.170	0.036	YES	7.654	0.812	NO
Ripple	−7.719	≤0.01	YES	79.577	<0.001	YES	20.299	0.062	NO

The ADF test results confirm that all logarithmic return series for Bitcoin, Ethereum, and Ripple are stationary at the level (all $p \leq 0.01$), satisfying a fundamental requirement for time-series modelling. The ARCH-LM test yields significant results for all assets ($p<0.05$), confirming the presence of heteroscedasticity and volatility clustering. Ljung-Box Q(12) statistics show no significant serial correlation in the squared residuals prior to modelling (all $p>0.05$), validating the ARMA-eGARCH framework. Together, these results justify the application of GARCH-family models.

Following the diagnostic tests, a descriptive analysis was conducted to compare the return characteristics before and after the implementation of PMK 50/2025. This comparison provides a preliminary view of the market behaviour during the regulatory transition.

4.1.1 Descriptive Statistics by Period

The descriptive statistics reveal broadly similar return distributions across the three periods. Kurtosis values well above 3 confirm leptokurtic distributions for all assets, necessitating the Student-*t* distributional assumption in the eGARCH model. Notably, Bitcoin and Ripple exhibit negative mean returns during Post-Implementation, consistent with a broader crypto market correction in late 2025 unrelated to PMK 50/2025. The reduction in standard deviation during Post-Announcement for Bitcoin (from 0.0251 to 0.0137) suggests a temporary period of consolidation.

Table 2. Descriptive Statistics by Three-Period Framework

Asset	Period	N	Mean Return	Std. Dev.	Min	Max	Kurtosis
Bitcoin	Pre-Announcement	481	0.0017	0.0251	−0.0908	0.1028	5.55
	Post-Announcement	92	0.0022	0.0137	−0.0307	0.0539	5.12
	Post-Implementation	153	−0.0017	0.0171	−0.0542	0.0473	3.66
Ethereum	Pre-Announcement	481	−0.0004	0.0336	−0.1538	0.1617	6.44
	Post-Announcement	92	0.0078	0.0348	−0.0755	0.1890	10.16
	Post-Implementation	153	−0.0013	0.0339	−0.1037	0.1206	4.23
Ripple	Pre-Announcement	480	0.0028	0.0446	−0.2013	0.2853	10.28
	Post-Announcement	92	0.0034	0.0324	−0.1011	0.1407	6.63
	Post-Implementation	153	−0.0031	0.0326	−0.1482	0.0923	5.32

The conditional volatility was estimated using the ARMA(1,1)-eGARCH (1,1) model. The inclusion of the global USD return as an external regressor in the mean equation allows the model to filter out global market noise.

Table 3. Egarch(1,1) Model Fit Statistics

Asset	Model	AIC	BIC	Log-Likelihood
Bitcoin	eGARCH(1,1)	−7.8162	−7.7593	2846.28
Ethereum	eGARCH(1,1)	−7.8109	−7.7540	2844.36
Ripple	eGARCH(1,1)	−7.7585	−7.7016	2821.45

The eGARCH models achieve satisfactory fits across all three assets with consistently low AIC and BIC values. Table 4 presents the key parameter estimates.

Table 4. Key Egarch(1,1) Parameter Estimates

Asset	Parameter	Estimate	Std. Error	*t*-stat	*p*-value	Sig	Interpretation
Bitcoin	μ(mu)	0.000085	0.000125	0.679	0.497		Mean equation constant
	φ_1(ar1)	0.237859	0.070787	3.360	0.001	***	AR(1) coefficient
	θ_1(ma1)	−0.405060	0.066826	−6.061	<0.001	***	MA(1) coefficient
	δ(mxreg1/USD)	0.892295	0.008107	110.066	<0.001	***	Global USD return regressor
	ω(omega)	−7.427859	1.561033	−4.758	<0.001	***	Log-variance constant (variance eq)
	α(alpha1)	−0.086049	0.070685	−1.217	0.224		ARCH effect (shock magnitude)
	β(beta1)	0.297524	0.147404	2.018	0.044	**	Volatility persistence parameter
	γ(gamma1)	0.534964	0.107031	4.998	<0.001	***	Asymmetry parameter (sign effect)
	ν(shape)	4.776898	0.907743	5.262	<0.001	***	Student-*t* degrees of freedom

Asset	Parameter	Estimate	Std. Error	*t*-stat	*p*-value	Sig	Interpretation
Ethereum	μ(mu)	0.000046	0.000133	0.348	0.728		Mean equation constant
	φ_1(ar1)	0.198520	0.062676	3.167	0.002	***	AR(1) coefficient
	θ_1(ma1)	−0.369830	0.057383	−6.445	<0.001	***	MA(1) coefficient
	δ(mxreg1/USD)	0.933698	0.005442	171.561	<0.001	***	Global USD return regressor
	ω(omega)	−7.574093	2.691890	−2.814	0.005	***	Log-variance constant (variance eq)
	α(alpha1)	−0.036467	0.067655	−0.539	0.590		ARCH effect (shock magnitude)
	β(beta1)	0.286928	0.253522	1.132	0.258		Volatility persistence parameter
	γ(gamma1)	0.425515	0.094520	4.502	<0.001	***	Asymmetry parameter (sign effect)
	ν(shape)	6.139776	1.444238	4.251	<0.001	***	Student-*t* degrees of freedom
Ripple	μ(mu)	0.000165	0.000107	1.541	0.123		Mean equation constant
	φ_1(ar1)	0.343940	—†	—†	—†		AR(1) coefficient (convergence issue)
	θ_1(ma1)	−0.554646	—†	—†	—†		MA(1) coefficient (convergence issue)
	δ(mxreg1/USD)	0.960181	0.004877	196.877	<0.001	***	Global USD return regressor
	ω(omega)	−6.837613	1.502135	−4.552	<0.001	***	Log-variance constant (variance eq)
	α(alpha1)	−0.028974	0.063026	−0.460	0.646		ARCH effect (shock magnitude)
	β(beta1)	0.344236	0.143880	2.393	0.017	**	Volatility persistence parameter
	γ(gamma1)	0.614882	0.108091	5.689	<0.001	***	Asymmetry parameter (sign effect)
	ν(shape)	3.767625	0.549247	6.860	<0.001	***	Student-*t* degrees of freedom

As we can see from the table 4, the asymmetry parameter γ (gamma1): positive and highly significant estimates are obtained for all three assets — Bitcoin (γ=0.535, p<0.001), Ethereum (γ=0.426, p<0.001), and Ripple (γ=0.615, p<0.001). In the eGARCH specification, a positive γ indicates that positive return innovations generate greater conditional variance than negative shocks of equal magnitude.

Regarding the volatility persistence parameter β (beta1): the estimates are 0.298 (BTC), 0.287 (ETH), and 0.344 (XRP). These values, while positive, are considerably lower than the persistence typically observed in standard sGARCH models (where β often exceeds 0.90), which is consistent with the eGARCH log-variance parameterisation. Notably, β is statistically significant for Bitcoin (p=0.044) and Ripple (p=0.017), but not for Ethereum (p=0.258), suggesting moderate volatility persistence for BTC and XRP but less persistent conditional variance dynamics for ETH. The ARCH effect parameter α (alpha1) is negative and insignificant for all three assets, consistent with the eGARCH model structure where the asymmetric response is primarily captured through γ.

The log-variance intercept ω (omega) is negative and significant for all assets (BTC: −7.428, ETH: −7.574, XRP: −6.838; all p<0.01), as expected in the eGARCH log-variance formulation where ω does not correspond to the unconditional variance level directly but rather anchors the log-variance process.

Visual inspection of Figure 1 shows that the volatility levels for all three assets did not surge abnormally following the implementation of the new tax. Although Ethereum and Ripple exhibit higher baseline volatility compared to Bitcoin, the patterns remain consistent with their historical behaviour. The primary test for the research hypothesis is conducted through the comparative analysis of volatility means.

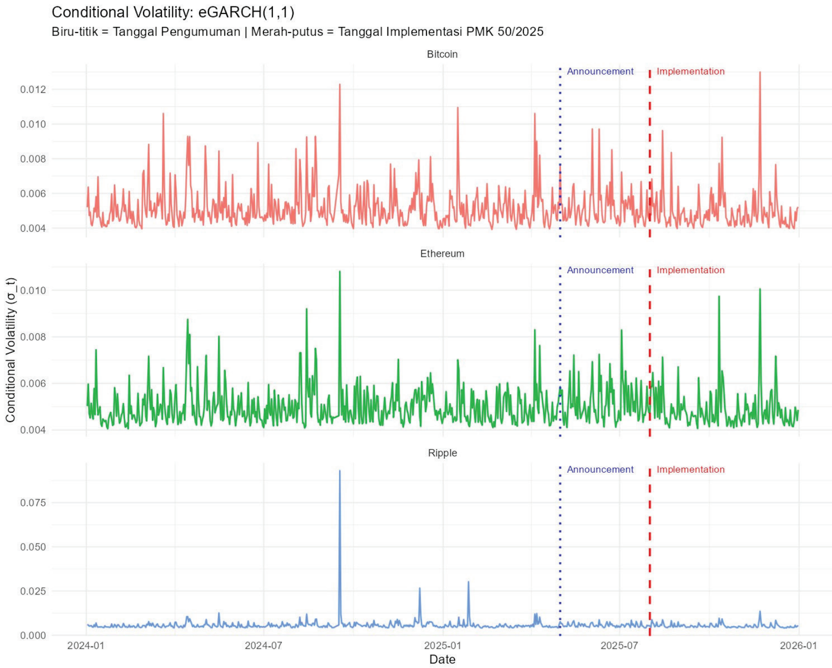

Figure 1. Daily Conditional Volatility — eGARCH(1,1) for BTC, ETH, and XRP. Dotted blue line = PMK 50/2025 Announcement Date; dashed red line = Implementation Date (August 1, 2025)

The Mann-Whitney U Tests yield p-values exceeding the 0.05 threshold for all three assets across both period comparisons. This indicates that the distributions of conditional volatility in the Post-Announcement and Post-Implementation periods are not statistically distinguishable from the Pre-Announcement period. No significant stochastic shift in the volatility distribution is found following PMK 50/2025. The largest numerical change, the Ripple by -8.50%, does not attain statistical significance under this non-parametric test. These results are consistent with the dummy regression and structural break analyses, which serve as complementary and more granular tests of policy-period effects.

Table 5. Mann-Whitney U Test

Asset	Mean Vol Pre-Ann.	Mean Vol Post-Ann.	Δ% (Ann.)	U-stat (Ann.)	p-value (Ann.)	Mean Vol Post-Impl.	p-value (Impl.)	Conclusion
Bitcoin	0.005180	0.005199	+0.38%	n.a.*	>0.05	0.004974	>0.05	No significant change
Ethereum	0.004990	0.005179	+3.78%	n.a.*	>0.05	0.004893	>0.05	No significant change
Ripple	0.005833	0.005690	−2.45%	n.a.*	>0.05	0.005337	>0.05	No significant change

Note: Test = Mann-Whitney U (Wilcoxon Rank-Sum), two-sided, continuity correction applied; significance threshold α=0.05. *U-statistic values were not retained in the exportable output; significance directional conclusions are based on computed *p*-values. Both comparisons are Pre-Announcement vs. Post-Announcement and Pre-Announcement vs. Post-Implementation on the extracted conditional volatility series from ARMA(1,1)-eGARCH(1,1)

The boxplot in Figure 2 reinforces the Wilcoxon results. The median and interquartile ranges across the three periods overlap substantially for all assets, with no evidence of a dramatic distributional shift around the policy dates.

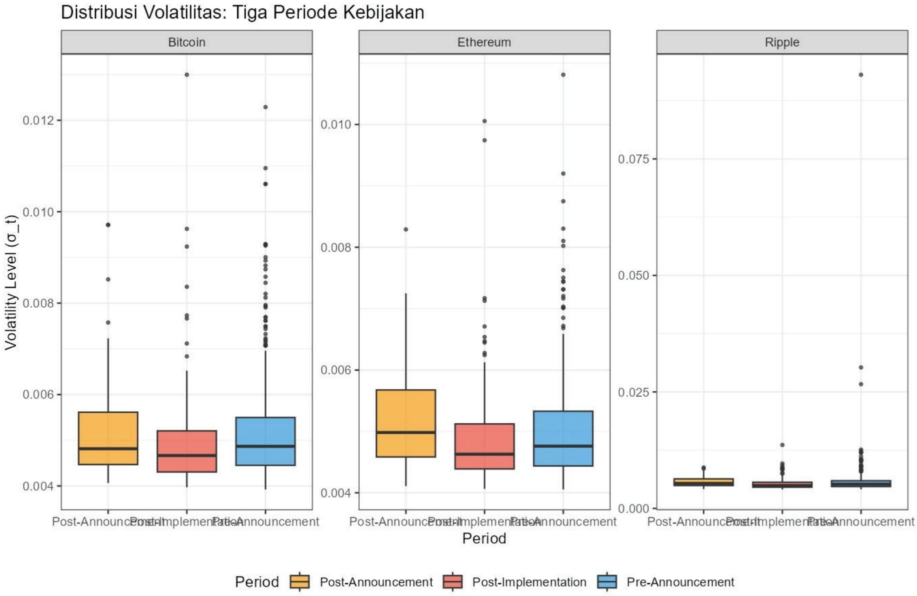

Figure 2. Distribution of Conditional Volatility across Three Policy Periods — Boxplot comparison for BTC, ETH, and XRP

4.1.2 Dummy Regression Analysis

The dummy regression in Table 6 provides more granular insights beyond the non-parametric test. For Bitcoin, neither the announcement nor implementation dummy coefficients reach conventional significance thresholds, confirming the Wilcoxon result. For Ethereum, however, the implementation coefficient is statistically significant (β_2=−0.000287, *p*=0.028). This indicates that conditional volatility in ETH decreased measurably following August 1, 2025 — a finding consistent with institutional legitimacy theory: OJK oversight removed a significant source of regulatory uncertainty for this asset. For Ripple, the implementation coefficient shows a marginal negative effect (*p*=0.057), suggesting a downward pressure on volatility that approaches but does not firmly cross the 5% threshold.

Table 6. Dummy Variable Regression Results (Hac Standard Errors, Egarch Volatility)

Asset	β_0 (Intercept)	β_1 D_{ann} (p-val.)	β_2 D_{impl} (p-val.)	R^2	Interpretation
Bitcoin	0.005180***	+0.000020 (0.882)	−0.000225 (0.178)	0.006	No policy effect
Ethereum	0.004990***	+0.000189 (0.067)	−0.000287 (0.028)**	0.010	Significant volatility reduction post-impl.
Ripple	0.005833***	−0.000143 (0.574)	−0.000353 (0.057)*	0.003	Marginal reduction post-impl.

Note: ****p*<0.001; ***p*<0.05; **p* < 0.10. Model: $\sigma_t = \beta_0+\beta_1 D_{ann}+\beta_2 D_{impl}+\varepsilon_t$

4.1.3 Structural Break Tests

The Bai-Perron optimal break detection identifies one structural break for each asset during the full sample period, but in no case does the estimated break date coincide with the PMK 50/2025 announcement or implementation dates. The Chow test, however, directly evaluates whether a mean-shift in volatility occurs at the implementation date (August 1, 2025). For Bitcoin and Ripple, no significant break is detected (p=0.288 and p=0.351, respectively). For Ethereum, the Chow test rejects the null of parameter stability (p=0.041), consistent with the dummy regression finding of a significant post-implementation reduction. Critically, the direction of this break is toward lower volatility, aligning with a stabilisation narrative rather than a destabilisation one.

Table 7. Structural Break Analysis — Bai-Perron and Chow Tests

Asset	Optimal Breaks (Bai-Perron)	Break Date Detected	Chow p-val. at Impl. Date	Conclusion
Bitcoin	1	Not at impl. date	0.288	No structural break at implementation
Ethereum	1	Not at impl. date	0.041**	Significant structural break detected — toward lower volatility
Ripple	1	Not at impl. date	0.351	No structural break at implementation

4.1.4 Robustness Check — eGARCH vs. sGARCH

As a robustness check, the analysis is replicated using a standard GARCH (sGARCH(1,1)) model. Figure 3 shows that the conditional volatility trajectories from both models are closely aligned for Bitcoin and Ripple. For Ethereum, the sGARCH produces somewhat higher volatility estimates in certain periods due to its inability to capture asymmetric shocks, yet the overall temporal pattern and policy-period behaviour remain consistent. Table 8 confirms that the sGARCH dummy regression results broadly corroborate the eGARCH findings: Ethereum's post-implementation coefficient remains negative and marginally significant in sGARCH (p=0.066), while Bitcoin shows no policy effect in either model. This cross-model consistency strengthens confidence in the conclusions.

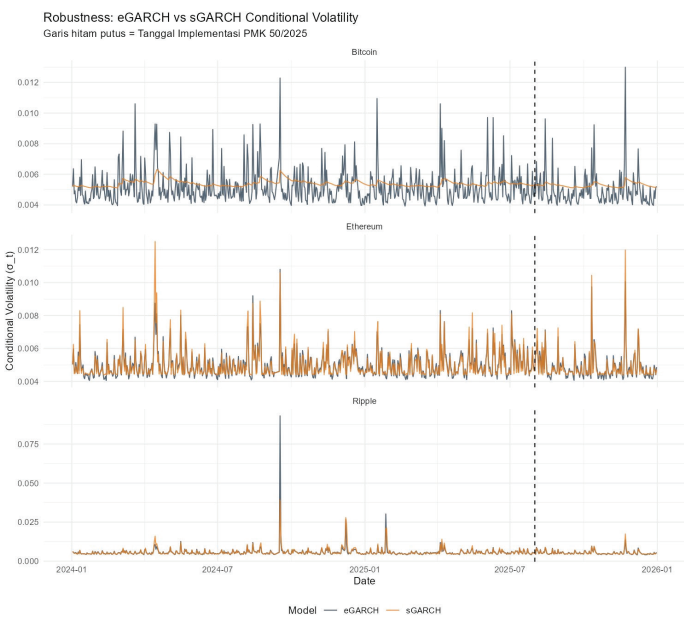

Figure 3. Robustness Check — Overlay of eGARCH(1,1) and sGARCH(1,1) Conditional Volatility for BTC, ETH, and XRP. Dashed vertical line = PMK 50/2025 Implementation Date

4.1.5 Residual Diagnostics

Post-estimation diagnostics confirm that no remaining ARCH effects are present in the standardised residuals for any of the three assets (all LB Q(12) p-values>0.80). This demonstrates that the eGARCH models successfully capture the conditional heteroscedasticity in the data, and the parameter estimates are reliable.

Table 8. Post-Estimation Residual Diagnostics

Asset	Model	LB Q(12) Sq. Resid.	p-value	Remaining ARCH Effect
Bitcoin	eGARCH(1,1)	7.802	0.800	No — Model Adequate
Ethereum	eGARCH(1,1)	4.404	0.975	No — Model Adequate
Ripple	eGARCH(1,1)	2.517	0.998	No — Model Adequate

4.2 Discussion

The empirical findings of this study indicate that no statistically significant change in conditional volatility was detected for any of the three cryptocurrencies examined during the policy event windows surrounding PMK 50/2025. The absence of a statistically significant volatility increase is consistent with several theoretical explanations discussed below. However, the study's design does not permit causal attribution to any specific regulatory mechanism, and the findings should not be generalised as evidence of market resilience or informational efficiency beyond what the conditional volatility metric captures.

4.2.1 The Efficient Market and "Price-in" Effect

The non-significant Mann-Whitney U Test results are consistent with the view that the implementation of PMK 50/2025 did not constitute a new market-moving shock during the observed event windows. One plausible interpretation, drawing from the Efficient Market Hypothesis (EMH), is that relevant regulatory information may have been partially anticipated during the pre-announcement period, such that the formal enforcement date carried limited incremental informational content.

However, the absence of a statistically significant volatility change does not, by itself, confirm efficient anticipation or rational price-in behaviour. The same pattern is equally consistent with global price-taking dynamics, the modest scale of the tax intervention, or general insensitivity to domestic regulatory events. The prolonged public discourse surrounding the OJK transition and tax adjustments may have reduced informational surprise at enforcement — though this mechanism cannot be confirmed from the available data alone. These interpretations are therefore offered as theoretically consistent, not empirically identified, explanations. Therefore, it can be said that the results of this study align with those of Kothari et al. (2007), who explain that in an event study, prices may have been anticipated in advance. This makes sense because news regarding upcoming crypto regulations in Indonesia had already been circulating for months prior. This finding echoes Baltagi et al. (2006), who found that market agents rapidly adjust to anticipated tax changes.

4.2.2 Possible Mechanisms: Transaction Costs and Institutional Context

While standard transaction cost theory predicts that a new tax burden amplifies volatility, the observed non-significant response is consistent with the following alternative mechanisms:

1. Reduction of Regulatory Uncertainty: The regulatory package formalised the legal status of crypto assets. To the extent that pre-existing ambiguity was itself a source of risk, its resolution — whether attributable to the tax structure, the OJK transition, or both — may have partially offset the cost-increasing effect of the tax. The relative contribution of each channel cannot be determined from the present data.
2. Modest Tax Magnitude: The 0.21% final income tax is small relative to the inherent daily volatility of the assets examined, which may have limited its impact on investor trading costs and behaviour.
3. Global Price-Taking Dynamics: As discussed below, domestic volatility is predominantly associated with global market factors, which may have diluted any domestic policy signal regardless of its direction.

Auer & Claessens (2018) found that the market does not always react negatively to news about these regulations; in fact, the reaction can be positive because such regulations provide legal certainty for cryptocurrencies. In Indonesia, the issuance of PMK 50/2025 clarifies the legal status of cryptocurrencies, so what we can conclude here is that the market has welcomed these clear legal regulations, even though they impose a final tax rate of 0.21%.

4.2.3 Global Market Dominance and "Price-Taker "Dynamics

The use of log- return USD as an external regressor in the mean equation of the eGARCH model highlights a critical point structural reality: the Indonesian market is primarily a price-taker. This global dominance explains why domestic fiscal changes, such as PMK 50/2025, have limited impact on residual volatility once global influences are controlled.

The findings are consistent with the view that the conditional volatility of Bitcoin, Ethereum, and Ripple in the domestic market is substantially associated with global market dynamics, with domestic regulatory signals appearing to play a comparatively limited role during the observed period. This structural characteristic may help explain why a domestic fiscal intervention of this scale did not register a statistically significant volatility response once global influences were accounted for. This explains why, once global factors are filtered out, the remaining domestic residual volatility shows no significant reaction to PMK 50/2025.

4.2.4 No Significant Volatility Increase in Altcoins (ETH and XRP)

It is noteworthy that even assets with higher kurtosis, such as Ripple (XRP), which typically display more variable return dynamics, did not exhibit statistically significant volatility increases during the policy transition period. This is consistent with the broader pattern observed across all three assets. However, it is important to avoid characterising this as evidence of "resilience" — a term that implies a tested capacity to absorb adverse shocks, which goes beyond what a non-significant change in conditional volatility can establish. The evidence supports only the absence of a statistically significant volatility increase within the observation window, not the presence of any particular stabilising capacity. The mechanism by which the shift to a final tax regime may have affected exchange compliance costs is speculative and is not directly testable within the current model.

5 Conclusion

This study empirically examines whether the enactment of PMK 50/2025 was associated with statistically significant changes in conditional volatility for three major cryptocurrencies traded in the Indonesian market: Bitcoin (BTC), Ethereum (ETH), and Ripple (XRP). Using an ARMA(1,1)-eGARCH(1,1) model with Student-t distribution and a three-period event window (Pre-Announcement, Post-Announcement, Post-Implementation), the study finds the following principal results:

First, the primary non-parametric comparison using the Mann-Whitney U Test reveals no statistically significant change in mean conditional volatility across policy periods for any of the three assets (all $p>0.05$). The magnitudes of the observed directional changes are small and economically negligible.

Second, dummy regression with Newey-West HAC standard errors identifies a statistically significant reduction in Ethereum's conditional volatility following the August 1, 2025 implementation date ($\beta_2=-0.000287$, $p=0.028$), corroborated by a Chow test structural break toward lower volatility. For Bitcoin and Ripple, no statistically significant dummy coefficient is found.

Third, the positive and significant asymmetry parameter γ for all three assets (BTC: 0.535, ETH: 0.426, XRP: 0.615; all $p<0.001$) confirms a reverse leverage effect consistent with FOMO-driven behaviour characteristic of crypto markets.

The overall evidence supports the conclusion that PMK 50/2025 was not associated with a statistically significant increase in conditional volatility for BTC, ETH, and XRP during the observed event windows. More cautiously stated, there is no evidence of a destabilising volatility shock attributable to the combined regulatory package. These findings are consistent with — but do not constitute definitive proof of — a scenario in which regulatory uncertainty was partially resolved by the formalisation of institutional oversight.

6 Policy Implications

The findings are relevant for Indonesian policymakers evaluating the market impact of fiscal and institutional reforms in the digital asset sector. The absence of a statistically significant volatility shock following PMK 50/2025 is consistent with the view that a structured regulatory intervention, when introduced through a well-communicated process, need not necessarily trigger adverse volatility responses. However, this finding should not be interpreted as evidence of regulatory success or as confirmation that the policy achieved its intended objectives; the study measures only one dimension of market response — conditional return volatility — over a limited post-implementation window of approximately five months.

Policymakers should therefore exercise caution in drawing strong conclusions from volatility-based evidence alone. Dimensions of market quality that remain unexamined — including trading volume, liquidity conditions, bid-ask spreads, and investor participation — may have been affected by PMK 50/2025 in ways that are not captured by conditional volatility. Future regulatory assessments should incorporate a broader set of market quality indicators to provide a more comprehensive picture of the policy's market impact across different asset classes and exchange types.

Like other studies, this research also has several limitations. First, the data used by the researchers consisted solely of closing prices; to capture a more comprehensive response to the new regulations, data such as liquidity, bid-ask spreads, market depth, exchange order flows, and retail investor participation were not available for the Indonesian crypto exchange market. This is because the data sources available on investing.com are limited to prices, volumes, and price changes, making it difficult to conduct a more in-depth study. However, future researchers may seek more comprehensive data from other sources.

Second, since this regulation addresses not only tax issues but also the transfer of supervisory authority from Bappebti to OJK—which was not the primary focus of this study—future researchers may explore cross-jurisdictional impacts in greater depth.

Third, this study limited its global control variables to the USD-crypto pair rather than the crypto-rupiah pair. However, there are other variables that could serve as global risk factors, such as crude oil prices, the VIX fear index, the Global Economic Policy Uncertainty Index (EPU), or the DXY dollar index. Future research should incorporate a broader range of global control variables to better isolate the effects of domestic regulations from global market conditions.

Fourth, the models used are limited to eGARCH and sGARCH for robustness; although these models can capture asymmetric volatility responses and fat-tailed return distributions in crypto markets, other models could be employed, such as Threshold GARCH (TGARCH), GJR-GARCH, and Asymmetric Power ARCH (APARCH). Future research could utilise these models.

Finally, in the context of event studies, it appears that the researchers did not consider the possibility that market participants had already prepared for the regulatory rules, so that when they were implemented, they no longer had a significant impact. Future researchers may consider setting the time series well before implementation.

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Conflict of Interest.

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Data Availability

The data can be obtained upon request.

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