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Policy Uncertainty and Asymmetric Volatility in Indonesia's Financial Sector: EGARCH Evidence

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ABSTRACT

Purpose – This study examines the effects of domestic and global economic policy uncertainty on Indonesia's financial sector volatility, given its dominant market position and sensitivity to regulatory and capital flow shocks.
Design/methodology/approach – Monthly IDX Financial Index (JKFINA/IDXFINANCE) returns from January 2011 to December 2025 are analyzed using an EGARCH (1,1) model, with the World Uncertainty Index (WUI) for Indonesia, US EPU, and VIX entered jointly into the variance equation. Because default analytic standard errors proved unreliable in finite samples, inference relies on residual bootstrap, supported by distributional, subsample, and structural-break robustness checks.
Finding/Results – A leverage effect is confirmed and robust to bootstrap-based inference, with negative shocks raising conditional volatility more than equivalent positive shocks. None of the three uncertainty proxies (WUI, EPU, VIX) is robust under this inference, and neither structural break test finds evidence of a break around COVID-19.
Originality/Value – This study demonstrates, through multi-start optimization, residual bootstrap, and structural break testing, that default analytic standard errors from EGARCH-X estimation can be materially unreliable in finite monthly samples. Although this evidence comes from a single application, the underlying mechanism plausibly extends to similarly specified models; a bootstrap-based inferential remedy is proposed. It is also among the first studies to jointly incorporate the WUI for Indonesia, US EPU, and VIX into a single EGARCH variance equation for Indonesia's financial sector.

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1. Introduction

Financial sector stability is a fundamental prerequisite for sustainable economic growth. As the primary intermediary between capital surplus and investment demand, the financial sector plays a central role in monetary policy transmission, capital allocation, and systemic risk management (Abaidoo & Agyapong, 2023). In Indonesia, the strategic importance of this sector is underscored by the fact that the IDX Financial Index (IDXFINANCE, formerly JKFINA) accounts for 26.30% of the total market capitalization of the Indonesia Stock Exchange (IDX) as of May 2026 (IDX, 2026), making it the largest sectoral component of the domestic capital market. Yet despite its strategic position, the financial sector remains among the most vulnerable to uncertainty shocks originating from both domestic policy developments and global financial dynamics.

The severity of this vulnerability is starkly illustrated by the behavior of JKFINA over the study period. At the onset of the COVID-19 pandemic in early 2020, JKFINA declined by 30.03% between December 2019 and April 2020 (authors' calculation based on the JKFINA price data1), reflecting an unprecedented wave of investor panic. This episode coincided with the CBOE Volatility Index (VIX) surging to 82.69 on March 16, 2020, the highest level ever recorded, surpassing the previous peak during the 2008 global financial crisis (CNBC, 2020). Such extreme volatility did not emerge in isolation; it reflected a simultaneous surge in policy uncertainty at both domestic and global levels, spanning unpredictable lockdown measures, unresolved fiscal policy responses, and disjointed global monetary coordination.

Economic policy uncertainty, broadly defined as the inability of economic agents to anticipate the future trajectory of fiscal, monetary, and regulatory policies (Baker et al., 2016), has long been recognized as a key determinant of financial market volatility. The theoretical transmission mechanism operates through elevated investor risk aversion during periods of heightened uncertainty, triggering capital reallocation from risky to safe assets, widening bid-ask spreads, and ultimately amplifying asset price volatility (Bloom, 2009). The consequences extend beyond financial markets: Bloom (2009) demonstrates that uncertainty shocks cause firms to temporarily halt investment and hiring, producing sharp output contractions followed by sluggish recoveries.

In Indonesia, policy uncertainty operates through multiple, often simultaneous, channels. On the domestic front, the Financial Services Authority (OJK) mandated a minimum core capital requirement of IDR 3 trillion for commercial banks under POJK No. 12/POJK.03/2020, creating substantial uncertainty for banks operating below this threshold. Concurrently, Bank Indonesia's aggressive monetary tightening, most recently exemplified by a 50 basis point rate increase to 5.25% in May 2026 amid the rupiah's continued depreciation past IDR 17,700 per USD (Bank Indonesia, 2026), has compounded uncertainty for market participants. On the global front, foreign institutional investors hold 43.85% of listed equity assets recorded in the IDX central settlement system (KSEI, 2025), rendering the Indonesian financial sector highly susceptible to changes in global investor risk appetite.

Despite a growing body of research on the relationship between policy uncertainty and stock market volatility, this literature leaves three gaps unaddressed: a near-exclusive reliance on aggregate market indices such as the Jakarta Composite Index (JCI) rather than sector-specific analysis (Hashmi et al., 2021; Ma'ruf & Setyowati, 2025), a predominance of standard GARCH or ARDL specifications unable to capture the asymmetric leverage effect documented by Black (1976) and Christie (1982), and the absence of any study jointly incorporating the World

Uncertainty Index (WUI), the US EPU index, and the VIX into a single EGARCH variance equation for the Indonesian financial sector.

This study addresses these gaps by employing the EGARCH(1,1) model introduced by Nelson (1991). The three uncertainty proxies are incorporated directly into the EGARCH variance equation, enabling simultaneous MLE estimation and eliminating bias from sequential estimation. The study employs monthly JKFINA/IDXFINANCE return data from January 2011 to December 2025, encompassing the Taper Tantrum (2013), the US-China trade war (2018-2019), the COVID-19 pandemic (2020), and the global monetary tightening cycle (2022-2023).

This study contributes in three respects. First, it provides robust evidence of an asymmetric (leverage) volatility response in the Indonesian financial sector using EGARCH(1,1), a specification largely absent from sector-level Indonesian studies that continue to rely on symmetric GARCH or ARDL frameworks. Second, it shows that standard analytic standard errors for EGARCH-X estimation, the approach most commonly used to incorporate external uncertainty proxies into a GARCH-family variance equation, can be materially unreliable in finite monthly samples, with preliminary diagnostics revealing implausibly large test statistics and a weakly identified likelihood surface. This is a property of the specification itself, not an artifact of this particular dataset, so the risk plausibly extends to other EGARCH-X studies combining a limited monthly sample with multiple external regressors. Our evidence for this, however, comes from a single application; standard errors are, in any case, rarely interrogated beyond default package output in the sector-level literature reviewed here. We propose residual bootstrap as a remedy, and recommend it as a diagnostic step for similar applications. Third, it applies the WUI for Indonesia alongside US EPU and VIX within a single EGARCH variance equation, a sector-specific specification not previously applied to Indonesia's financial sector to our knowledge; the estimated proxy effects are statistically fragile under this same bootstrap-based inference, a fragility we interpret as a methodological finding in its own right. The remainder of this paper is organized as follows. Section 2 presents the literature review. Section 3 describes the data and methodology. Section 4 reports and discusses the estimation results. Section 5 concludes with recommendations.

2. Literature Review & Hypothesis Development

2.1. Theoretical Framework

The theoretical foundation of this study rests on three pillars: the theory of asymmetric conditional volatility, the theory of economic policy uncertainty, and the transmission mechanisms through which uncertainty propagates into financial markets.

The concept of conditional volatility was introduced by Engle (1982) through the ARCH model and subsequently generalized by Bollerslev (1986) into the GARCH framework. While GARCH effectively captures volatility clustering, it carries two fundamental limitations: it imposes non-negativity constraints on parameters and assumes a symmetric volatility response to positive and negative shocks. The latter assumption is empirically untenable. Black (1976) and Christie (1982) documented that stock price declines consistently generate larger subsequent volatility than price increases of equivalent magnitude, a phenomenon known as the leverage effect. Nelson (1991) addressed both limitations simultaneously through the EGARCH model.

The theory of economic policy uncertainty originates with Baker et al. (2016), who define EPU as the condition in which economic agents cannot reliably anticipate the future direction of fiscal, monetary, and regulatory policies. Bloom (2009) establishes the transmission mechanism: as uncertainty rises, firms defer investment and hiring, producing sharp output contractions followed by slow recoveries. Ahir et al. (2022) developed the World Uncertainty Index (WUI), which quantifies uncertainty based on the frequency of the word "uncertainty" in Economist Intelligence Unit (EIU) country reports, enabling consistent cross-country comparisons. The CBOE Volatility Index (VIX) serves as a widely used proxy for global market risk sentiment.

Given that commercial banks, led by BBCA, BBRI, and BMRI, together account for over half of IDXFINANCE's market capitalization weight (IDX, 2026), the financial sector's sensitivity to uncertainty operates through channels that are structurally distinct from those affecting the aggregate market index. First, under heightened policy uncertainty, banks tend to hoard liquidity, reallocating assets toward liquid instruments and scaling back lending and off-balance-sheet exposures as a precautionary response (Berger et al., 2022), a behavioral channel with no direct analogue in non-financial sectors. Second, financial institutions operate under binding regulatory capital constraints (in Indonesia, OJK's minimum core capital requirements), and the degree to which pre-crisis capital buffers are sufficient shapes institutional resilience during periods of stress in ways that do not apply to unregulated sectors (Berger & Bouwman, 2013). Third, as credit intermediaries, banks are directly exposed to borrower default risk: policy uncertainty has been shown to raise non-performing loan ratios and loan concentration, feeding back into asset quality and equity valuations (Chi & Li, 2017). Fourth, financial stocks are among the most liquid, heavily weighted components accessible to foreign portfolios, and given their substantial foreign ownership share (KSEI, 2025), the sector is disproportionately exposed to global risk-driven capital flow reversals, which the literature identifies as predominantly driven by global rather than domestic factors (Forbes & Warnock, 2012). These four channels, liquidity hoarding, capital adequacy constraints, credit risk transmission, and foreign flow sensitivity, jointly imply that uncertainty shocks propagate into financial sector volatility through a more direct and sector-specific mechanism than through the aggregate index, which pools sectors with heterogeneous and partially offsetting exposures.

2.2. Empirical Literature

Research on EPU and stock market volatility has expanded substantially since Baker et al. (2016). At the global level, Yu et al. (2021) employ a GARCH-MIDAS model to show that GEPU significantly impacts stock market volatility across nine emerging economies including Indonesia. Karanasos et al. (2022) demonstrate that EPU, VIX, and credit market conditions jointly influence emerging market stock volatility, underscoring the importance of multiple uncertainty proxies.

At the sectoral level, Yu (2023) provides evidence that the WUI carries significant predictive power for sector-level stock market volatility on the Shanghai Stock Exchange, with the strongest predictive contribution observed during high-volatility regimes. Msomi & Kunjal (2024) apply a GARCH-MIDAS approach to South African sectoral indices and find EPU exhibits a negative relationship with financial sector volatility. Khan et al. (2023) employ a quantile connectedness approach and demonstrate that VIX is the most dominant source of cross-sectoral spillovers across 28 emerging markets.

For the Indonesian context, Hashmi et al. (2021) document a time-varying negative correlation between GEPU and Indonesian stock returns. Adam et al. (2022) find VIX exerts a significant negative effect on Indonesian Islamic stock returns, particularly during crisis periods. Rahmi et al. (2025) find the exchange rate is the dominant determinant for Indonesian green stocks, while EPU is insignificant in the long run. Ma'ruf & Setyowati (2025) show GEPU and the Global Financial Stress Index significantly elevate JCI volatility. Suriani et al. (2026) find Indonesian financial stocks display the highest volatility persistence among indices examined. On the methodological side, Habiba et al. (2019) apply extended EGARCH to Asian emerging markets including Indonesia and confirm significant leverage effects. Akkaya (2021) employs EGARCH to analyze volatility transmission from advanced to emerging markets including Indonesia, validating the leverage effect. Karim et al. (2022) demonstrate that EGARCH with Student-t distribution produces more accurate estimates than normality assumption for emerging markets.

2.3. Research Positioning and Identified Gaps

The foregoing review reveals three gaps this study directly addresses. First, existing Indonesian studies consistently employ aggregate market indices (Hashmi et al., 2021; Ma'ruf & Setyowati, 2025; Suriani et al., 2026), leaving sector-specific volatility dynamics poorly documented. Second, the predominance of standard GARCH and ARDL specifications means the asymmetric effects of uncertainty on Indonesian financial sector volatility have not been formally tested using EGARCH, despite well-documented leverage effects in Asian emerging markets (Habiba et al., 2019; Akkaya, 2021). Third, no existing study jointly incorporates the WUI, US EPU, and VIX within a single EGARCH variance equation for the Indonesian financial sector; this study addresses that gap.

Table 1. Summary of Selected Empirical Studies

Author(s) (Year)	**Country/Object**	**Method**	**Uncertainty Proxy**	**Key Finding**
Hashmi et al. (2021)	Indonesia (JCI)	DCC-ARDL	GEPU	GEPU negatively correlated with Indonesian stock returns
Yu et al. (2021)	9 Emerging markets	GARCH-MIDAS	GEPU	GEPU significantly impacts stock volatility
Adam et al. (2022)	Indonesia (Islamic)	Wavelet	GEPU, VIX	VIX significantly negative for Indonesian stocks during crises
Akkaya (2021)	Indonesia, Turkey	EGARCH	Spillover	Leverage effect confirmed; bidirectional spillover
Habiba et al. (2019)	6 Asian markets	Ext. EGARCH	Spillover	Significant leverage effects across all markets
Yu (2023)	China (10 sectors)	AR-WUI	WUI	WUI significantly predicts sectoral volatility
Khan et al. (2023)	28 Emerging markets	Quantile VAR	VIX, OVX	VIX strongest source of connectedness
Msomi & Kunjal (2024)	South Africa	GARCH-MIDAS	EPU	EPU negatively related to financial sector volatility
Rahmi et al. (2025)	Indonesia (SRI)	ARDL	US EPU	Exchange rate dominant; EPU insignificant long run

Author(s) (Year)	Country/Object	Method	Uncertainty Proxy	Key Finding
Ma'ruf & Setyowati (2025)	Indonesia (JCI)	GARCH-ARDL	GEPU, GFSI	GEPU and GFSI amplify JCI volatility
Suriani et al. (2026)	Indonesia (JCI, JII)	ARDL-GARCH	GEPU	Financial stocks show highest volatility persistence
This study	Indonesia (JKFINA)	EGARCH bootstrap inference	WUI, US EPU, VIX	Asymmetry and leverage effect; domestic vs global; pre/post-COVID

3. Methodology

3.1. Data and Sources

This study employs monthly data spanning January 2011 to December 2025, yielding 179 observations after transformation. The sample period encompasses multiple distinct uncertainty episodes, including the Taper Tantrum (2013), the US-China trade war (2018-2019), the COVID-19 pandemic (2020), and the global monetary tightening cycle (2022-2023), providing sufficient variation to examine the uncertainty-volatility relationship across diverse market conditions.

The dependent variable is the monthly return of the Indonesia Stock Exchange Financial Index (JKFINA/IDXFINANCE), computed as the log return R_t = ln(P_t / P_(t-1)) x 100, where P_t denotes the closing index value at the end of month t. Price data are sourced from Yahoo Finance using the ticker ^JKFINA. Following the introduction of the IDX Industrial Classification (IDX-IC) in January 2021, the financial sector index was relabeled IDXFINANCE; however, the underlying price series remains continuous and is used consistently throughout the analysis.

Three exogenous variables are incorporated into the variance equation as uncertainty proxies. First, the World Uncertainty Index (WUI) for Indonesia, obtained from worlduncertaintyindex.com (Ahir et al., 2022), serves as the proxy for domestic policy uncertainty. Since WUI may take a value of zero in certain periods, the transformation Δln(WUI+1) is applied. Second, the US Economic Policy Uncertainty (EPU) index, obtained from policyuncertainty.com (Baker et al., 2016), is transformed as Δln(EPU). Third, the CBOE Volatility Index (VIX), sourced from FRED, is transformed as Δln(VIX). All three variance-equation regressors are additionally rescaled by a factor of 100, consistent with the scaling already applied to the dependent variable and to Δln(ER) in the mean equation; this rescaling improves the numerical conditioning of the maximum likelihood optimizer. Two control variables are included in the mean equation: the change in the BI Rate (ΔIR) and the log return of the Rupiah-US Dollar exchange rate, both obtained from Bank Indonesia.

Table 2. Variable Description

Variable	Notation	Role in Model	Source	Transformation
JKFINA Return	R_t	Dependent	Yahoo Finance	ln(P_t / P_(t-1)) x 100

Variable	Notation	Role in Model	Source	Transformation
WUI Indonesia	Δln(WUI+1)	Exogenous (variance)	worlduncertaintyindex.com	First diff. log x 100
US EPU	Δln(EPU)	Exogenous (variance)	policyuncertainty.com	First diff. log x 100
VIX	Δln(VIX)	Exogenous (variance)	FRED	First diff. log x 100
BI Rate	ΔIR	Control (mean)	Bank Indonesia	First difference
Exchange Rate	Δln(ER) x 100	Control (mean)	Bank Indonesia	Log return x 100

3.2. Model Specification

This study employs the EGARCH (1,1) model introduced by Nelson (1991), consisting of two equations estimated simultaneously via Maximum Likelihood Estimation (MLE) under a student-t distributional assumption to accommodate fat-tailed return distributions.

Mean Equation:

$$R\_t = \mu + \delta 1 \times \Delta IR\_t + \delta 2 \times \Delta \ln(ER\_t) \times 100 + \varepsilon\_t$$

Variance Equation:

$$\ln(h\_t) = \omega + \alpha[|z\_(t-1)| - E|z\_(t-1)|] + \gamma z\_(t-1) + \beta \ln(h\_(t-1)) + \lambda 1 \Delta \ln \text{ WUI}\_t + 1) \times 100 + \lambda 2 \Delta \ln\ (\text{EPU}\_t) \times 100 + \lambda 3 \Delta \ln\ (\text{VIX}\_t) \times 100$$

where α measures the magnitude of the volatility response to shocks, γ is the asymmetry parameter capturing the leverage effect, β measures persistence of conditional variance, and λ_1, λ_2, λ_3 measure the effects of WUI, US EPU, and VIX (each rescaled by 100, per Table 2) on conditional variance.

Table 3. Parameter Interpretation

Parameter	Interpretation	Expected Sign
ω	Baseline (constant) level of log conditional variance, net of the shock, leverage, and persistence terms	No sign restriction
α	Magnitude of volatility response to shocks	$\alpha > 0$
γ	Leverage effect: bad news amplifies volatility more than good news if $\gamma < 0$	$\gamma < 0$
β	Conditional variance persistence: closer to 1 implies slower mean reversion	$0 < \beta < 1$
λ_1	Effect of WUI Indonesia on conditional variance	$\lambda_1 > 0$
λ_2	Effect of US EPU on conditional variance	$\lambda_2 > 0$
λ_3	Effect of VIX on conditional variance	$\lambda_3 > 0$

3.3. Research Hypotheses

H1: The WUI for Indonesia exerts a positive and significant effect on JKFINA conditional variance ($\lambda_1 > 0$).

H2: The US EPU exerts a positive and significant effect on JKFINA conditional variance ($\lambda_2 > 0$).

H3: The VIX exerts a positive and significant effect on JKFINA conditional variance ($\lambda_3 > 0$).

H4: A significant leverage effect exists in JKFINA volatility ($\gamma < 0$).

H1 through H4 are tested using bootstrap-based inference.

3.4. Estimation Procedure and Diagnostic Tests

The estimation follows four sequential steps. First, descriptive statistics and the Jarque-Bera normality test are computed to justify the Student-t distributional assumption. Second, stationarity is assessed using the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and KPSS tests. Third, the ARCH-LM test (Engle, 1982) and the Ljung-Box test on squared OLS residuals detect ARCH effects, providing the primary statistical justification for the EGARCH specification. Fourth, the EGARCH(1,1) model is estimated via MLE using the rugarch package in R (Ghalanos, 2022), with WUI, EPU, and VIX first-differenced log-changes rescaled by a factor of 100 for numerical consistency with the other regressors in the specification.

Preliminary estimation using default analytic standard errors produced implausibly large t-statistics (in excess of 10,000 for a sample of 179 observations) for nearly all parameters. Given that such magnitudes are inconsistent with standard asymptotic theory at this sample size, four diagnostic procedures were conducted before any parameter was interpreted as significant. First, convergence codes and the condition number of the estimated Hessian were inspected for each fitted model. Second, multi-start optimization (eight restarts with randomized initial values) was conducted to test whether the log-likelihood surface admits a unique, well-identified optimum; this revealed a delta-AIC below 0.05 across restarts despite meaningful variation in individual coefficient estimates, indicating a weakly identified likelihood surface rather than a genuine unique solution. Third, both default and robust (sandwich/QMLE) standard errors were computed and compared; both proved similarly unreliable, indicating that the issue originates in the curvature of the likelihood surface itself rather than in a specific covariance estimator. Fourth, given that both diagnostics rely on local curvature, all inferential statistics reported in Section 4 are instead based on residual bootstrap (Pascual et al., 2006), implemented via the ugarchboot function (method = “Full”) with 1,500 replications, which resamples standardized residuals and refits the full EGARCH recursion, and does not depend on the Hessian. For each parameter, the 1,500 bootstrap replicate estimates form an empirical distribution from which we compute: (i) the bootstrap standard error (Boot-SE), the standard deviation of the replicate estimates; (ii) the percentile-based 95% confidence interval (CI95), the 2.5th and 97.5th percentiles of the replicate distribution; and (iii) the bootstrap significance measure, p_boot = 2 x min(p+, p-), where p+ and p- are the proportions of replicates with positive and negative sign, respectively. This last measure is a nonparametric analogue of a two-sided p-value: it approaches 0 when replicate estimates are overwhelmingly one-signed (strong evidence the true effect is nonzero and of that sign) and approaches 1 when the sign is roughly evenly split across replicates (no reliable evidence of direction). We report CI95 and p_boot, rather than Boot-SE, as the primary basis for inference throughout this study, since Boot-SE can be inflated by a small number of outlier replicates even when the percentile interval itself is well-behaved.

Two robustness checks are conducted, each with bootstrap-based inference and full tabulated results: re-estimation under Normal, Student-t, and GED distributional assumptions; and subsample estimation for pre-COVID (January 2011 to December 2019) and post-COVID

(January 2020 to December 2025) periods. WUI, EPU, and VIX are also re-estimated individually rather than jointly, to test whether joint inclusion suppresses individual significance. In addition, two formal structural break tests are conducted to assess whether COVID-19 constitutes a genuine break in the variance process: a likelihood-ratio test comparing the restricted (full-sample) against the unrestricted (separate pre- and post-COVID) specifications, and a Bai-Perron multiple-breakpoint test (Bai & Perron, 2003) applied to squared returns as a model-free proxy for conditional variance. Model adequacy is additionally evaluated through the Ljung-Box test on standardized residuals and squared standardized residuals, and the Sign Bias Test of Engle & Ng (1993).

4. Result and Discussion

4.1. Descriptive Statistics

Table 4 presents the descriptive statistics for monthly JKFINA returns. The mean return of 0.7268% per month reflects the long-run upward trend of the Indonesian financial sector, though the higher median (1.1750%) signals a left-skewed distribution, confirmed by a skewness coefficient of -0.9800. The kurtosis of 5.5513 substantially exceeds the normal distribution benchmark of 3.0, indicating fat-tailed return behavior. The minimum return of -23.2999% captures the sharp drawdown during the COVID-19 pandemic. The Jarque-Bera test (77.1971, p=0.000) decisively rejects normality, justifying the Student-t distributional assumption in the EGARCH estimation.

Table 4. Descriptive Statistics of JKFINA Returns

Statistic	Value
Mean (%)	0.7268
Median (%)	1.1750
Std. Deviation (%)	5.0993
Minimum (%)	-23.2999
Maximum (%)	11.0423
Skewness	-0.9800
Kurtosis	5.5513
Jarque-Bera	77.1971

*Note: *** significant at the 1% level.*

4.2. Stationarity Tests

Table 5 presents the stationarity test results. All variables are confirmed to be stationary at level I(0) based on simultaneous confirmation from the ADF, PP, and KPSS tests, ensuring the absence of spurious regression concerns in the EGARCH estimation.

Table 5. Stationarity Test Results

Variable	ADF (p-value)	PP (p-value)	KPSS (p-value)	Conclusion
JKFINA Return	0.010	0.010	0.100	I(0)
ΔIR	0.018	0.010	0.100	I(0)
Δln(ER)	0.010	0.010	0.100	I(0)
Δln(WUI+1)	0.010	0.010	0.100	I(0)

Variable	ADF (p-value)	PP (p-value)	KPSS (p-value)	Conclusion
Δln(EPU)	0.010	0.010	0.100	I(0)
Δln(VIX)	0.010	0.010	0.100	I(0)

Note: ADF and PP test H0: unit root exists; KPSS tests H0: series is stationary. Reported p-values of 0.010 and 0.100 represent the lower and upper bounds as reported by the tseries and urca packages in R.

4.3. ARCH Effect Tests

The ARCH-LM test at lag 12 yields a p-value of 0.0947, marginally significant at the 10% level. The Ljung-Box test on squared residuals produces a p-value of 0.0243, significant at the 5% level, confirming autocorrelation in squared residuals and the presence of conditional heteroskedasticity. Taken together, these results indicate the presence of ARCH effects in JKFINA returns, albeit of moderate intensity, providing statistical justification for the EGARCH specification.

4.4. EGARCH (1,1) Estimation Results

Table 6 reports the final EGARCH (1,1) specification, estimated with WUI, US EPU, and VIX included jointly in the variance equation, with inference based on residual bootstrap (1,500 replications; Section 3.4). The model converged (convergence code 0) with AIC = 5.8195, BIC = 6.0154, and log-likelihood = -509.8492.

Table 6. EGARCH (1,1) Estimation Results with Bootstrap-Based Inference (Student-t, Full Sample, N=179)

Parameter	Notation	Estimate	Boot-SE	CI95 (2.5%, 97.5%)	p_boot
Constant	μ	1.266	0.333	[0.633, 2.011]	0.001
ΔIR	δ_1	-5.020	2.270	[-4.961, 2.862][a]	0.527
Δln(ER) x 100	δ_2	-0.901	0.347	[-0.882, 0.307][a]	0.439
Constant	ω	0.071	0.084	[0.021, 0.326]	0.015
ARCH magnitude	α	0.067	0.075	[0.008, 0.325]	0.043
Asymmetry	γ	-0.156	0.082	[-0.439, -0.079]	0.011
Persistence	β	0.976	0.027	[0.879, 0.988]	0.000
Δln(WUI+1) x 100	λ_1	-0.020	0.421[b]	[-0.036, 0.037]	0.992
Δln(EPU) x 100	λ_2	0.010	1.533[b]	[-0.013, 0.010]	0.755
Δln(VIX) x 100	λ_3	0.010	1.237[b]	[-0.013, 0.015]	0.684
Shape (df)	ν	12.938	15.942[b]	[5.705, 77.621]	0.000

Note: Inference based on residual bootstrap (ugarchboot, method = "Full", 1,500 replications, Pascual et al., 2006); p_boot denotes the bootstrap-based two-sided significance measure . [a] See Section 4.4.1 for discussion. [b] Boot-SE inflated by outlier replications; CI95 is used for inference throughout.

4.4.1. Mean Equation

Both mean-equation controls carry negative point estimates: ΔIR (δ_1 = -5.020) and Δln(ER) (δ_2 = -0.901), directionally consistent with the expectation that monetary tightening and Rupiah depreciation depress financial sector returns through higher funding costs and foreign currency balance sheet pressure, respectively. However, neither is robust under bootstrap-based inference (p_boot = 0.527 and 0.439), with both CI95 intervals spanning zero.

4.4.2. Variance Equation - GARCH Parameters

The constant term (ω = 0.071) is positive and robust under bootstrap-based inference (CI95 [0.021, 0.326], p_boot = 0.015), representing the baseline level of log conditional variance net of the shock, leverage, and persistence terms. The ARCH magnitude parameter (α = 0.067) is small, and only marginally robust under bootstrap (p_boot = 0.043), indicating that JKFINA volatility responds modestly to new shocks in a given period. The persistence parameter (β =

0.976) is close to unity and robust (p_boot < 0.001), indicating high volatility persistence consistent with the long-memory dynamics commonly observed in emerging market financial assets.

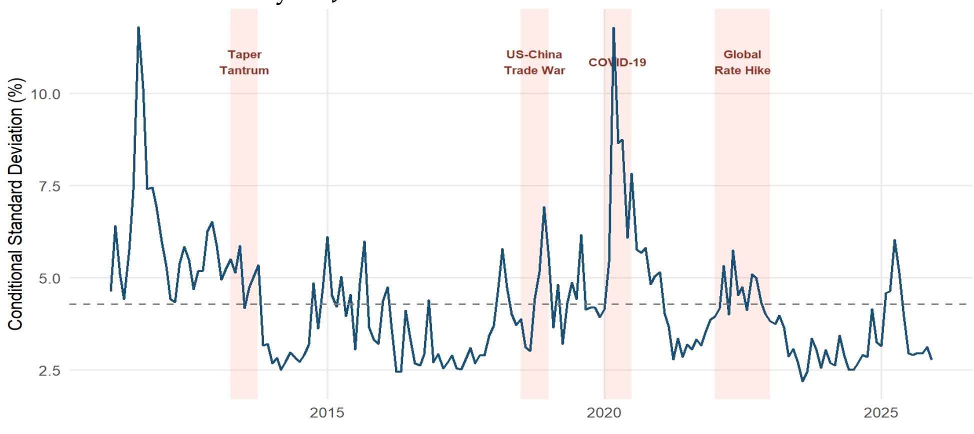
4.4.3. Variance Equation - Uncertainty Effects

None of the three uncertainty proxies is robust to bootstrap-based inference. The WUI for Indonesia (λ_1 = -0.020, p_boot = 0.992) is statistically indistinguishable from a coin flip in sign, providing no support for H1. The US EPU (λ_2 = 0.010, p_boot = 0.755) and the VIX (λ_3 = 0.010, p_boot = 0.684) similarly fail to achieve robust significance, providing no support for H2 or H3.

Several, potentially complementary, explanations may account for this fragility. First, monthly frequency combined with a 179-observation sample may simply provide insufficient statistical power to detect proxy effects on conditional variance, particularly relative to the 11 parameters estimated jointly in the full specification; this is consistent with the weakly identified likelihood surface documented via multi-start optimization. Second, we explicitly tested whether the three proxies compete for shared explanatory power: pairwise correlations among WUI, EPU, and VIX are low to moderate (r = -0.002 for WUI-EPU, 0.055 for WUI-VIX, 0.377 for EPU-VIX), and univariate re-estimation of each proxy individually does not alter this conclusion. This rules out simple collinearity as the primary explanation, particularly for WUI, which is nearly orthogonal to the other regressors yet remains the least robust of the three. Third, the transformation and scaling choices applied here (first-differenced log changes, rescaled by 100 for numerical stability) are standard but not the only defensible choice; alternative transformations, such as level-based or threshold-based specifications, might interact differently with the EGARCH variance recursion. Fourth, aggregation to the sector level may dilute proxy effects that are more pronounced for individual institutions with differing uncertainty exposure. Fifth, and perhaps most fundamentally, uncertainty may transmit to the Indonesian financial sector through channels other than the conditional variance of returns directly, for instance through returns themselves, through liquidity and trading volume, through the exchange rate, or through regime-dependent nonlinearities not captured by a single-regime EGARCH specification.

Figure 1 displays the estimated conditional volatility of JKFINA over the full sample period, revealing pronounced volatility clustering. The highest volatility spike occurs in April 2020, coinciding with the peak of COVID-19 market panic, substantially exceeding prior episodes including the Taper Tantrum (2013) and the US-China trade war (2018-2019), consistent with the near-unity beta estimate.

Figure 1. Conditional Volatility of JKFINA Returns



4.4.4. Variance Equation - Leverage Effect (H4)

The asymmetry parameter (γ = -0.156) is negative and robust under bootstrap-based inference (CI95 [-0.439, -0.079], p_boot = 0.011), supporting H4: negative shocks generate disproportionately larger volatility than positive shocks of equal magnitude, consistent with the leverage effect documented by Black (1976) and Christie (1982). This result is corroborated across all three error distributions and by the formal structural break tests below. This asymmetry is visualized through the News Impact Curve presented in Figure 2, which shows that the conditional variance on the left side (bad news, $z < 0$) consistently exceeds the baseline, while that on the right side (good news, $z > 0$) falls below it. These results corroborate Habiba et al. (2019) and Akkaya (2021).

Figure 2. News Impact Curve of JKFINA Returns

Note: Curve normalized so relative variance = 1 at z = 0 Bootstrap CI95 for gamma: [-0.439, -0.079]

4.5. Diagnostic Tests

Table 7 presents the post-estimation diagnostic results computed from the standardized residuals of the final model. The Ljung-Box test on standardized residuals (Q=16.8933, p=0.1537) and squared standardized residuals (Q^2=10.8894, p=0.5384) both fail to reject their respective null hypotheses, confirming adequate specification of the mean and variance equations. The Sign Bias Test of Engle & Ng (1993) is insignificant across all components (Joint Effect p=0.5767), indicating that the EGARCH model has adequately accommodated the asymmetric volatility dynamics.

Table 7. Post-Estimation Diagnostic Test Results

Test	Statistic	p-value	Conclusion
Ljung-Box Q (z_t, lag=12)	16.8933	0.1537	No autocorrelation
Ljung-Box Q^2 (z^2_t, lag=12)	10.8894	0.5384	No remaining ARCH effects
Sign Bias Test	0.7421	0.4591	Insignificant
Negative Sign Bias	1.4038	0.1622	Insignificant
Positive Sign Bias	0.0471	0.9625	Insignificant
Joint Effect	1.9793	0.5767	Insignificant

4.6. Robustness Checks

4.6.1. Distributional Sensitivity

Table 8 reports re-estimation results under three alternative distributional assumptions, with inference based on 1,500 residual bootstrap replications per distribution. Each distribution is estimated independently rather than reusing Table 6's coefficients; minor variation in the student-t row's γ estimate relative to Table 6 is expected given the near-flat likelihood surface characterized via multi-start optimization and does not affect the qualitative conclusion. The direction of the leverage coefficient (γ) is negative across all three distributions, and its magnitude is broadly comparable (-0.162 to -0.209), in contrast to the sign reversal previously reported under analytic estimation. Under bootstrap-based inference, γ is robust (CI95 excludes zero) for the Normal and Student-t specifications, while the GED specification yields a marginally wider interval that includes zero, reflecting lower estimation precision rather than a genuine reversal in direction. WUI, EPU, and VIX remain statistically fragile across all three distributions. ΔAIC across the three distributions is under 0.02; the Student-t specification is retained as the primary model given the a priori distributional evidence from the Jarque-Bera test and its consistently robust bootstrap inference for the leverage parameter.

Table 8. Robustness Check - Distributional Sensitivity (Bootstrap-Based, 1,500 Replications Each)

Distribution	AIC	BIC	γ: Estimate, CI95, p_boot	λ_1 (WUI) p_boot	λ_2 (EPU) p_boot	λ_3 (VIX) p_boot
Normal	5.8021	5.9802	-0.184, [-0.340, -0.023], 0.035	0.992	0.755	0.669
Student-t (main)	5.8152	6.0111	-0.209, [-0.365, -0.033], 0.028	0.965	0.629	0.679
GED	5.8065	6.0024	-0.182, [-0.341, 0.043], 0.087	0.985	0.597	0.707

Note: p_boot as defined in Table 6. [a] Table 6 remains the single canonical specification referenced throughout this manuscript; see body text above for discussion of this row's independent estimation.

4.6.2. Subsample Analysis: Pre- vs Post-COVID

Table 9 presents subsample estimates alongside the full-sample results, with bootstrap-based inference throughout. The leverage coefficient is not robust in the pre-COVID subsample (CI95 spans zero, p_boot = 0.196), plausibly reflecting limited statistical power on n=107 combined with a shape parameter estimate at the boundary of its search space, rather than the genuine absence of a leverage effect prior to 2020. WUI, EPU, and VIX remain fragile in both subsamples, mirroring the full-sample pattern.

Table 9. Robustness Check - Full-Sample vs. Pre- and Post-COVID Subsamples (Bootstrap-Based)

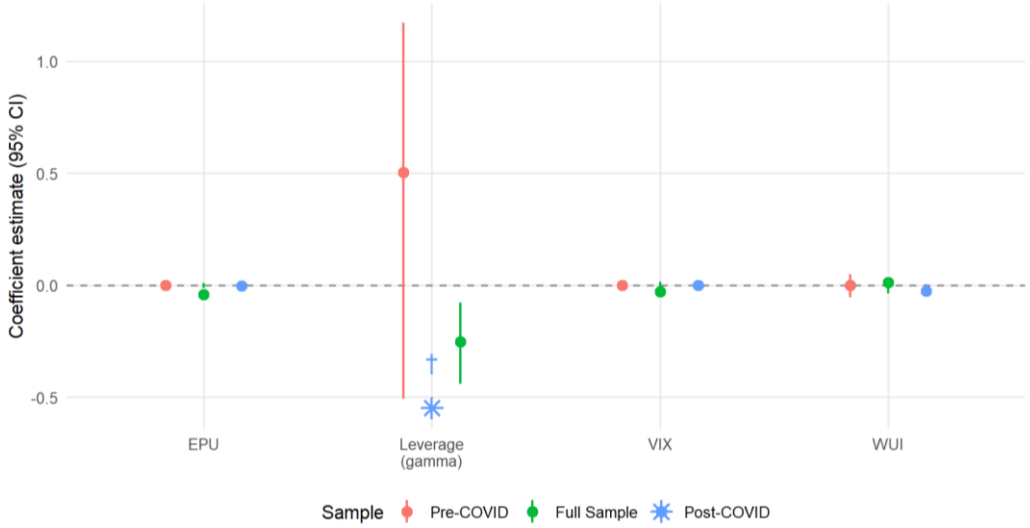
Parameter	Full Sample (N=179)	Pre-COVID (n=107)	Post-COVID (n=72)
γ (asymmetry)	-0.156, CI[-0.439,-0.079], p=0.011	0.586, CI[-0.507,1.172], p=0.196	-0.567, CI[-0.555,-0.516][c], p=0.004[c]
λ_1 (WUI)	-0.020, p=0.992	0.019, p=0.993	-0.058, p=0.077
λ_2 (EPU)	0.010, p=0.755	0.006, p=0.971	0.018, p=0.397
λ_3 (VIX)	0.010, p=0.684	0.005, p=0.976	0.011, p=0.759

Note: p denotes p_boot, as defined in Table 6. [c] The post-COVID bootstrap distribution shows anomalous clustering (82% of 1,500 replications within 0.001 of the median), consistent with degenerate resampling behavior driven by a near-zero ARCH parameter in this subsample rather than genuine sampling precision; this interval should be read as indicative only, and is not treated as confirmatory evidence.

4.6.3. Formal Structural Break Test

To assess whether the subsample differences reported above reflect a genuine structural break rather than sampling variation, two independent formal tests were conducted. A likelihood-ratio test comparing the restricted (single full-sample) model against the unrestricted (separate pre- and post-COVID) models yielded LR = 11.42, df = 11, p = 0.409, failing to reject the restricted specification. A Bai-Perron multiple-breakpoint test applied to squared returns, a model-free proxy for conditional variance that does not depend on the EGARCH specification, selected zero breakpoints by Bayesian Information Criterion. Both tests concur that there is no formal evidence of a structural break in the variance process around COVID-19. Table 6's full-sample estimates therefore remain the primary basis for inference, with Table 9's subsample estimates serving as a supplementary check constrained by the smaller sample sizes involved, as visualized in Figure 3.

Figure 3. Bootstrap 95% Confidence Intervals by Sample



† Post-COVID leverage CI reflects anomalous bootstrap clustering and should not be read as high precision

Figure 3 presents bootstrap 95% confidence intervals for the leverage (gamma), WUI, EPU, and VIX coefficients across the full sample and the pre- and post-COVID subsamples. Consistent with the formal tests reported immediately above, the wide and overlapping intervals across subsamples do not support an interpretation of structural change; the narrow post-COVID interval for the leverage coefficient should be read with the caveat noted in Table 9, given the anomalous bootstrap clustering identified for that subsample.

4.7. Implications for EGARCH-X Inference

Two distinct failure modes surface in this analysis. Analytic standard errors proved unreliable not because a particular covariance estimator was misspecified, but because the underlying likelihood surface is weakly identified once a limited monthly sample is combined with multiple external regressors in the variance equation. This class of problem has an established basis in the formal econometric literature on GARCH-X models. Pedersen & Rahbek (2019) show that testing whether exogenous covariates belong in the GARCH-X variance equation is a non-standard problem precisely because nuisance parameters may be weakly identified or lie on the boundary of the parameter space under the null, and Nielsen et al. (2025) develop bootstrap theory for this same class of model, demonstrating that bootstrap-based inference can remain valid even when standard asymptotic theory breaks down under these conditions. Separately, the bootstrap procedure adopted here as a remedy is itself not universally robust: it showed degenerate replicate clustering when a variance parameter sat near its estimation boundary in the smallest subsample tested. Taken together, these findings suggest a general lesson for applied EGARCH-X work: convergence and a plausible point estimate are not sufficient grounds for trusting reported significance, and by the same logic, a non-significant bootstrap result is not sufficient grounds for concluding that an effect is genuinely absent when the underlying likelihood surface is weakly identified. The diagnostic protocol used throughout this study, checking convergence codes, running multi-start optimization, comparing default and robust standard errors, and inspecting the shape of the bootstrap replicate distribution, offers a practical way to detect both failure modes before results are reported.

5. Conclusion and Suggestion

This study examines the effects of domestic and global policy uncertainty on Indonesian financial sector volatility using an EGARCH(1,1) model estimated on monthly JKFINA/IDXFINANCE return data from January 2011 to December 2025. Three uncertainty proxies are employed simultaneously: the WUI for Indonesia, the US EPU index, and the VIX, all incorporated directly into the EGARCH variance equation to enable simultaneous estimation and avoid the bias of sequential approaches. All inferential claims in this study are based on residual bootstrap, which we recommend as standard practice for EGARCH-X specifications on comparably limited samples.

The results provide robust evidence of a significant leverage effect: negative shocks generate disproportionately larger volatility than positive shocks of equal magnitude, a finding that holds across the full sample, across all three error distributions tested, and is corroborated by two independent formal structural break tests showing no evidence that this relationship shifted around COVID-19. By contrast, none of the three uncertainty proxies, WUI, EPU, or VIX, is robust to bootstrap-based inference. Because the same weak identification affecting standard errors throughout this analysis also limits the study's power to detect proxy effects, this null result is best treated as inconclusive rather than as confirmation that no such effect exists.

These findings carry direct implications for multiple stakeholders. For investors and portfolio managers, risk management strategies should account for the asymmetric downside exposure documented here, which is the most statistically dependable finding in this study. For researchers applying EGARCH-X specifications to sector-level or emerging-market data with limited monthly observations, both failure modes documented in this study warrant attention: convergence and a plausible estimate do not guarantee reliable standard errors, and a non-significant bootstrap result does not guarantee a genuine null. Multi-start optimization and inspection of the bootstrap replicate distribution are recommended as standard diagnostic steps, not optional robustness checks. For policymakers and regulators, the absence of a robust link between the tested uncertainty proxies and sector volatility should not be read as evidence that uncertainty is irrelevant to financial stability, but rather as a call for higher-frequency data and longer time series before such a relationship can be confirmed or ruled out.

6. Limitations and Future Research

This study acknowledges several limitations that open directions for future research. First, this study cannot rule out that the WUI, EPU, and VIX effects would emerge more clearly at a finer sampling frequency than the monthly data available here; future research using higher-frequency data, where uncertainty proxies of sufficient granularity exist, would allow more powerful tests of these hypotheses. Second, the domestic uncertainty proxy relies solely on the WUI, which is constructed from periodic EIU country reports rather than real-time market data and may therefore exhibit a temporal lag relative to actual financial market conditions; future research could incorporate a news-based EPU index specific to Indonesia once such a measure becomes publicly available. Third, the residual bootstrap procedure used throughout this study was not benchmarked against alternative resampling schemes for EGARCH-X; block bootstrap was tested during model development and rejected because it distorted the sequential EGARCH structure and produced spurious sign reversals in the leverage parameter, but a systematic comparison across resampling methods, such as wild or stationary bootstrap variants, remains outside this study's scope and is left for future methodological work. Fourth, bootstrap inference itself showed degenerate behavior in the smallest subsample tested (post-COVID, n=72), where a near-zero ARCH parameter appears to dampen the influence of resampled innovations; this suggests bootstrap-based inference should be interpreted cautiously, and ideally corroborated with alternative resampling schemes, when applied to short subsamples. Fifth, the analysis is conducted at the index level, which may obscure heterogeneity in uncertainty responses across individual institutions and sub-sectors and cannot adjudicate between the liquidity hoarding, capital adequacy, credit risk, and foreign flow channels that motivate treating the financial sector separately from the aggregate market. Extending the framework to banking, insurance, and multifinance separately, ideally with institution-level data, would provide more granular evidence, including on which of these channels is empirically dominant.

Declaration of AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Claude (Anthropic) in order to assist with language refinement, academic phrasing, and structural editing. After using this tool, the authors reviewed and edited all content as needed and take full responsibility for the content of the publication.

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