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Inflation Dynamics and Stock Market Volatility in Indonesia: ARMA–GARCH Evidence

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Abstract : *This study aims to identify adequate models for monthly Indonesian consumer price inflation and for the volatility of Jakarta Composite Index (JCI) returns, and uses them to evaluate forecasting performance and the inflation–return relationship. Monthly prices for January 2000–September 2025 yield 308 observations of inflation and returns (February 2000–September 2025). Inflation shows no ARCH effects; among five pre-specified ARMA candidates, ARIMA(0,0,1) is selected as a parsimonious baseline, while a seasonal extension removes remaining residual autocorrelation and forecasts better without changing the substantive conclusions. For JCI returns, AIC selects an AR(1)–GARCH(1,1) model with Student-t errors, whereas BIC marginally prefers a constant mean with nearly identical variance dynamics. Estimated volatility persistence is high ($\alpha + \beta = 0.985$), but its 95% confidence interval includes one, and a sup-LR test detects a downward shift in the volatility level around 2010–2013 that lowers persistence substantially, so the implied half-life is imprecise. Training-sample model selection yields the same specifications. In one-step-ahead forecasts (August 2020–September 2025), the ARIMA(0,0,1) model is significantly more accurate than the training-sample mean but not than random-walk or AR(1) benchmarks, while the GARCH model outperforms a constant-variance benchmark and performs on par with EWMA and rolling-variance benchmarks. Correlation, Granger causality, cross-correlation, threshold and GARCH-X tests find no significant association between monthly inflation and JCI returns or volatility. The results indicate that MA(1) is a useful parsimonious baseline for monthly inflation, while a GARCH model with Student-t errors captures the volatility clustering and fat tails of JCI returns better than a constant-variance model.*

Keywords: inflation, stock market volatility, ARMA–GARCH, volatility persistence, Indonesia

JEL Classification Codes: C22, E31, G12

1. INTRODUCTION

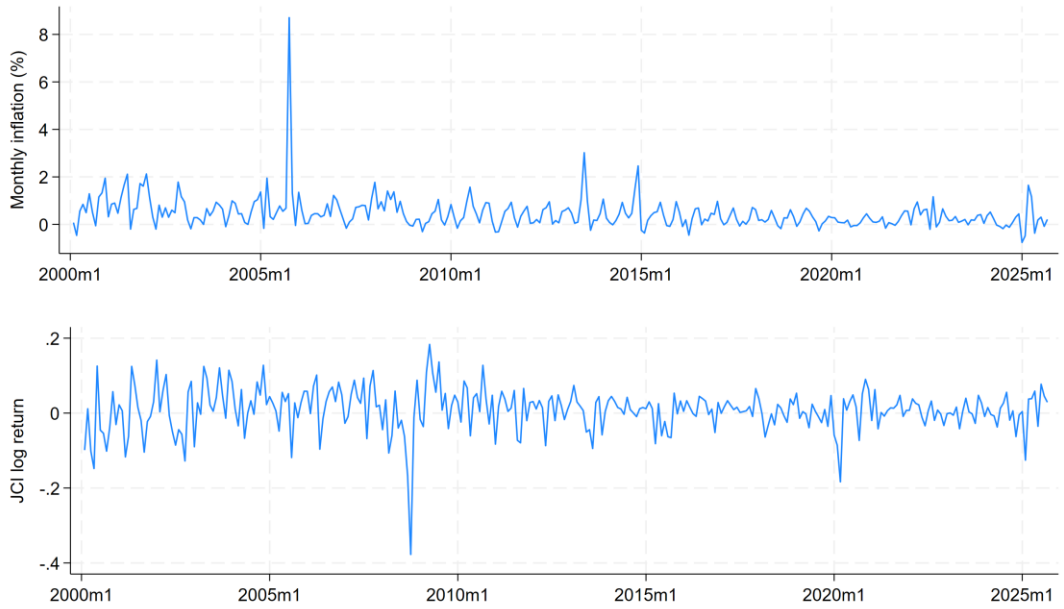
Inflation is a key indicator of macroeconomic stability. It is widely argued to be a significant determinant of a country's economic growth (Mayasari & Mahinshapuri, 2022), and Simanungkalit (2020) similarly identifies inflation as one of the primary benchmarks for assessing a country's economic stability. From an economic perspective, inflation is fundamentally a monetary phenomenon: fluctuations in the inflation rate tend to be associated with broader economic turbulence.

On the capital-market side, the Jakarta Composite Index (JCI, known domestically as IHSG) is the principal barometer of Indonesian equity performance, combining all stocks listed on the Indonesia Stock Exchange (Samsul, 2015). Movements in Indonesian stock indices have been linked to macroeconomic variables — including the BI policy rate, inflation and the exchange rate (Adisetiawan, 2012; Rustyaningsih & Purwohandoko, 2018) — as well as to global financial conditions and international capital flows (Bekaert & Harvey, 1997). As an emerging market, Indonesia exhibits comparatively high volatility in both inflation and equity returns.

Between 2000 and 2025, Indonesia experienced at least five major crisis episodes with significant macroeconomic consequences: the 2005 fuel-price crisis, in which gasoline prices rose 87.5% and kerosene prices nearly tripled, triggering mass protests (BBC News, 2005); the 2008

Global Financial Crisis, during which the JCI fell 59%, a steeper contraction than in many peer markets (Modjo et al., 2025); the 2013 Taper Tantrum, which raised capital-market and exchange-rate volatility following foreign capital outflows (Eichengreen & Gupta, 2015) and coincided with a domestic fuel-price increase; the 2020 COVID-19 pandemic, which severely pressured corporate profitability and the financial sector (The Jakarta Post, 2020); and the 2022 global inflation wave, which pushed inflation above Bank Indonesia's target through energy and food price pressures (ING Think, 2022). In this study, these episodes are used to describe how the two series behaved around documented shocks and to test whether pre-defined crisis windows shift the conditional mean or variance of JCI returns; they are not modelled as separate regimes.

Figure 1. Monthly Indonesian Inflation and JCI Returns, February 2000–September 2025



Source: FAO (2026), FAOSTAT Consumer Price Indices, Indonesia, general index, 2015 = 100 (inflation computed by the author); Investing.com (2026), Jakarta Stock Exchange Composite Index, monthly close (JCI log return computed by the author). Figure generated in Stata by the replication do-file.

There is, however, no theoretical or empirical consensus on the sign of the inflation–stock return relationship: the Fisher hypothesis implies that nominal stock returns move with expected inflation (Fisher, 1930), whereas the proxy-effect hypothesis predicts a negative association because inflation proxies for expected real activity (Fama, 1981), and evidence from both developed and developing markets has failed to resolve the conflict (Hondroyiannis & Papapetrou, 2006). Studies on Indonesia are similarly mixed: Krisna and Wirawati (2013) report a positive and significant effect of inflation on the JCI, whereas Kewal (2012), Hismendi et al. (2013), Wijaya (2013), and Yunita and Robiyanto (2018) find no significant effect of inflation on the JCI or on financial-sector index returns.

This study contributes to that literature in four respects. First, it uses a long monthly sample — 308 observations from February 2000 to September 2025 — that spans five documented shock episodes, compared with shorter windows in earlier Indonesian studies such as Adisetiawan (2012), and it documents the data sources and transformations so that every result can be replicated from the supplementary data and Stata code. Second, it reports the complete model-selection evidence: all candidate ARMA and GARCH specifications, their information criteria, and post-estimation diagnostics, including a seasonal robustness check for the inflation model. Third, rather than taking the estimated volatility persistence at face value, it reports its sampling uncertainty, tests it against a unit-persistence null, and checks its sensitivity to a shift in the volatility level and to crisis windows.

Fourth, it evaluates one-step-ahead out-of-sample forecasts against explicit benchmarks, using loss functions that remain valid when volatility is latent.

Based on this background, the study addresses four research questions: (1) which parsimonious univariate specifications, among pre-specified candidates, represent monthly Indonesian inflation and the conditional volatility of JCI returns, and how well they pass post-estimation diagnostics; (2) how persistent JCI volatility is, and how robust that persistence is to a shift in the volatility level and to five documented crisis episodes; (3) whether monthly inflation is statistically associated with JCI returns or their volatility; and (4) whether the selected models forecast more accurately than simple benchmarks out of sample. The first question is the primary objective of the study; questions (2) and (4) examine the properties and forecasting performance of the selected models, and question (3) uses them to test the inflation–return relationship. Section 2 reviews the literature, Section 3 describes the data and methods, Section 4 presents and discusses the results, and Section 5 concludes.

2. LITERATURE REVIEW

Inflation and Stock Returns: Theory

The classical starting point is the Fisher (1930) hypothesis, under which nominal asset returns incorporate expected inflation so that real returns are unaffected by it. Because equities are claims on real assets, a strict version implies that nominal stock returns should rise one-for-one with expected inflation. Early tests for the United States rejected this prediction: Fama and Schwert (1977) found that common stock returns were negatively related to both expected and unexpected inflation. Fama (1981) explained the anomaly through the proxy-effect hypothesis: higher inflation signals lower expected real activity, and because stock prices anticipate real activity, the negative inflation–return correlation proxies for the positive relation between stock returns and future output. Geske and Roll (1983) added a fiscal–monetary channel in which falling real activity reduces tax revenue, raises the deficit and leads to monetisation, so that stock prices and subsequent inflation move in opposite directions. Over long horizons, however, Boudoukh and Richardson (1993) find a positive relation between nominal stock returns and inflation, consistent with a long-run Fisher effect.

A further strand explains the negative short-run association through valuation errors and monetary conditions rather than real activity. Modigliani and Cohn (1979) argue that investors suffer from inflation illusion: they discount real cash flows at nominal interest rates, so that equities are undervalued when inflation is high and overvalued when it is low. Campbell and Vuolteenaho (2004) find that the component of the U.S. dividend yield that is not explained by rational expectations of future dividend growth moves closely with inflation, which is consistent with this mispricing view. Kaul (1987) shows that the stock return–inflation relation is shaped by the monetary sector: the negative relation arises from the response of money demand and money supply to real activity, and its strength differs across monetary policy regimes. Together, these explanations imply that the inflation–return relation is not a structural constant but depends on how inflation is generated, how investors perceive it and how the central bank responds to it, which is one reason why empirical results differ across countries and periods.

These theories distinguish between expected and unexpected inflation and between short and long horizons. The present study uses realised month-on-month headline inflation, not a decomposition into expected and unexpected components, and focuses on the monthly horizon. Its empirical specification therefore tests the statistical association between realised inflation and JCI returns and volatility — that is, the information content of monthly inflation for equity risk — rather than providing a structural test of the Fisher or proxy-effect hypotheses. Under the proxy-effect view, monthly headline inflation is informative about returns only to the extent that it carries news about real activity; under a short-horizon Fisher view, anticipated inflation is already priced and should not predict returns. A weak association at the monthly frequency is therefore theoretically plausible, and

the absence of a relationship has to be interpreted as a property of this specification rather than as evidence against either theory.

Empirical Evidence on Inflation and Stock Markets

International evidence remains mixed and appears to depend on the regime. Hondroyiannis and Papapetrou (2006), using a Markov-switching framework for Greece, show that the inflation–return relation varies across regimes, which helps explain why linear full-sample estimates often yield conflicting conclusions. Schwert (1989) shows that U.S. stock-market volatility is only weakly related to the volatility of macroeconomic variables such as inflation and output growth, whereas it rises markedly during recessions and financial crises. For emerging markets, Bekaert and Harvey (1997) document that equity volatility is high, differs across countries and over time, and is shaped by the degree of integration with world capital markets, which suggests that global factors may dominate domestic macroeconomic news.

A related literature asks whether macroeconomic conditions affect the level of volatility at lower frequencies rather than month-to-month returns. Officer (1973) showed early that the variability of the U.S. market factor moves with the variability of industrial production. Using a spline-GARCH model for a large panel of countries, Engle and Rangel (2008) find that the slowly moving component of equity volatility is higher when inflation is higher and output growth is slower or more volatile, and that it is higher in emerging markets. Engle et al. (2013), with a GARCH-MIDAS specification, similarly find that inflation and industrial production growth help to explain the long-run component of U.S. stock market volatility, while short-run fluctuations remain dominated by GARCH-type dynamics. This evidence suggests that, if inflation matters for equity risk, its influence is more likely to appear in the low-frequency level of volatility than in monthly returns or in the short-run conditional variance — a distinction that is relevant for interpreting the results of the present study.

Indonesian evidence mirrors this ambiguity. Krisna and Wirawati (2013) report a positive and significant partial effect of inflation on the JCI, whereas Kewal (2012), Hismendi et al. (2013), and Wijaya (2013) find no significant effect of inflation on the JCI. Rustyaningsih and Purwohandoko (2018) examine GDP, inflation, the exchange rate, world oil and gold prices and the Nikkei 225 as determinants of the mining-sector index, Adisetiawan (2012) studies causality among the BI rate, inflation and the composite index over 1995–2012, and Yunita and Robiyanto (2018), using a GARCH specification for 2011–2017, find that exchange-rate changes, but neither inflation nor the BI rate, significantly affect financial-sector index returns. These studies differ in sample period, data frequency, the inflation measure (monthly or annual), and whether stock prices or returns are modelled, which makes their results difficult to compare directly and motivates a transparent, fully documented specification such as the one used here.

Modelling Inflation Dynamics

Univariate Box–Jenkins models remain a standard benchmark for short-horizon inflation forecasting (Box et al., 2015). Applied work on Indonesia has used ARIMA–GARCH specifications for monthly inflation (Anisa et al., 2025) and multivariate or semiparametric approaches for inflation and related macroeconomic series (Lu'lu'a et al., 2024), and Likassa et al. (2026) illustrate the use of multivariate GARCH models for inflation data in another developing economy. An issue that matters for monthly data is seasonality. Monthly consumer prices are subject to recurrent calendar effects, such as religious holidays and the timing of administered-price adjustments, which can generate autocorrelation at the twelve-month lag. A non-seasonal model that ignores this structure may appear adequate on short-lag diagnostics while leaving systematic autocorrelation at seasonal lags. This study therefore checks residual autocorrelation at both short and seasonal horizons (Ljung & Box, 1978) and re-estimates the selected model with a seasonal term as a robustness check.

Forecasting inflation is also notoriously difficult. Atkeson and Ohanian (2001) show that, for the United States since the mid-1980s, a naive forecast that sets expected inflation equal to its average over the previous year is at least as accurate as forecasts from Phillips-curve models, and Stock and

Watson (2007) document that inflation has become harder to forecast relative to simple univariate benchmarks because its predictable component has declined. These findings motivate the use of a random walk and a historical mean as benchmarks in the out-of-sample evaluation, and they caution against expecting large gains from univariate ARMA models over naive forecasts at the monthly horizon.

Modelling Stock Market Volatility

Financial returns display volatility clustering and fat tails (Mandelbrot, 1963). The ARCH model of Engle (1982) and its generalisation, GARCH (Bollerslev, 1986), capture clustering by letting the conditional variance depend on past squared shocks and past variances, and Bollerslev (1987) showed that Student-t innovations accommodate the excess kurtosis that remains after conditioning. Asymmetric extensions allow negative shocks to raise volatility more than positive shocks of the same size, either through a threshold term (Glosten et al., 1993) or through a log-variance specification (Nelson, 1991), and Engle and Ng (1993) provide diagnostics for such news-impact asymmetries. In Indonesia, hybrid ARIMA–GARCH models have been applied to forecast LQ45 stock prices (Kaito et al., 2025), and the impact of global crises on the domestic financial sector has been documented by Modjo et al. (2025).

Surveys of this literature emphasise that a GARCH(1,1) specification, often with fat-tailed errors, captures the main stylised facts of financial returns parsimoniously and is sufficient for many applications (Bollerslev et al., 1992). In forecasting, the evidence is more mixed: reviewing 93 studies, Poon and Granger (2003) conclude that no single class of models dominates, that option-implied volatility tends to forecast best where it is available, and that simple historical-volatility estimators often perform about as well as GARCH models. Because no option-implied volatility series covering the sample period is available for the JCI, this study compares GARCH forecasts with historical-volatility benchmarks.

A key quantity in GARCH models is persistence, the sum $\alpha + \beta$, which governs how quickly the conditional variance reverts to its long-run level. Estimated persistence is often close to one in long samples. Lamoureux and Lastrapes (1990) show that unmodelled shifts in the unconditional variance bias GARCH persistence upward, so a near-unit estimate may reflect changes in the volatility level rather than genuinely long memory, and Hamilton and Susmel (1994) make a related point with regime-switching ARCH models. This literature implies that persistence and half-life estimates should be reported with their sampling uncertainty and checked for stability before economic conclusions are drawn from them.

Emerging markets are particularly prone to such shifts. Applying the iterated cumulative sums of squares (ICSS) algorithm of Inclán and Tiao (1994), which detects discrete changes in the unconditional variance, Aggarwal et al. (1999) find that sudden changes in the volatility of emerging stock markets are mostly associated with local political and economic events, with the October 1987 crash as the main global event, and that allowing for these changes reduces the estimated persistence of GARCH models. Since Indonesia experienced several large shocks after 2000, it is important to check whether the estimated persistence survives once a shift in the volatility level is allowed for.

Evaluating Forecasts

Forecast accuracy is meaningful only relative to a benchmark. Diebold and Mariano (1995) propose a test of equal predictive accuracy based on the loss differential between two forecasts, and Harvey et al. (1997) provide a small-sample correction. Evaluating volatility forecasts is more delicate because volatility is latent. Andersen and Bollerslev (1998) show that noisy proxies such as squared returns make even correctly specified GARCH models appear to forecast poorly, and Patton (2011) shows that only certain loss functions — notably the mean squared error and the QLIKE loss defined on the variance — rank competing forecasts consistently when an unbiased but noisy proxy is used. Hansen and Lunde (2005) find that, for exchange-rate data, no model clearly outperforms a simple GARCH(1,1), whereas for stock returns only models with a leverage effect do better; simple

specifications, including exponentially weighted moving averages and rolling variances, are therefore demanding benchmarks.

Research Gap and Hypotheses

The literature leaves three gaps that this study addresses for Indonesia: the absence of fully reported model-selection and diagnostic evidence for monthly inflation and JCI volatility over a long sample; limited attention to the uncertainty and stability of volatility persistence; and the lack of benchmarked, replicable out-of-sample evaluation. The study tests the following null hypotheses: H1, monthly inflation has no ARCH effects, whereas JCI returns do; H2, JCI volatility persistence equals one (integrated GARCH); H3, monthly inflation is not associated with JCI returns or their conditional variance; H4, pre-defined crisis windows do not shift the conditional mean or variance of JCI returns beyond what the GARCH dynamics capture; and H5, the selected models are not more accurate than simple benchmarks out of sample.

3. RESEARCH METHOD

Data

The study uses monthly data on Indonesian consumer prices and the JCI. Consumer prices are measured by the general consumer price index for Indonesia (Consumer Prices, General Indices, 2015 = 100, monthly) from the Consumer Price Indices domain of FAOSTAT, the statistical database of the Food and Agriculture Organization of the United Nations, downloaded on 8 March 2026 (FAO, 2026). FAOSTAT compiles the general CPI series primarily from IMF data, supplemented by other international and national sources, and rebases each series to 2015 = 100 by dividing it by the geometric mean of its 2015 monthly values (FAO, n.d.). Because rebasing multiplies the whole series by a constant, it does not affect month-on-month percentage changes; no additional splicing or rebasing was performed by the author. Monthly inflation is computed as $\pi_t = 100 \times (CPI_t/CPI_{t-1} - 1)$. Equity data are the monthly closing values of the Jakarta Stock Exchange Composite Index (symbol JKSE) from Investing.com, downloaded on 9 March 2026 (Investing.com, 2026). The monthly value is the close of the last trading day of each month, so non-trading days do not create gaps. The JCI return is computed as the log return $r_t = \ln(JCI_t/JCI_{t-1})$.

Index levels cover January 2000–September 2025 (309 months). Because both variables are first differences of the levels, January 2000 is lost, leaving 308 observations from February 2000 to September 2025 for both series, with no missing values. Specifications that include one lag of the JCI return use 307 observations (March 2000–September 2025); to keep information criteria comparable, all GARCH candidates are estimated on this common sample. The raw level data, the transformed series and the Stata do-file that reproduces every table are provided as supplementary files.

Unit Root Testing

Stationarity is assessed prior to model estimation because non-stationary series can produce spurious regression results (Granger & Newbold, 1974; Gujarati & Porter, 2009). A series is stationary if it contains no unit root; otherwise it follows a random-walk process (Enders, 2015). Stationarity is tested using the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979) with a constant and four lagged differences:

$$\Delta Y_t = \alpha + \gamma Y_{t-1} + \Sigma \delta_i \Delta Y_{t-i} + \varepsilon_t$$

with the null hypothesis H_0: $\gamma = 0$ (unit root / non-stationary) tested against H_1: $\gamma < 0$ (stationary), evaluated with MacKinnon (1996) approximate p-values (Dickey & Fuller, 1979; Fuller, 1976). A specification that adds a linear trend is reported as a robustness check. As a further check, the non-parametric Phillips-Perron (PP) test, which corrects for heteroskedasticity and autocorrelation with a Newey–West long-run variance (bandwidth of four lags) instead of adding lagged difference terms, is also applied (Phillips & Perron, 1988; Perron, 1989). Because unit-root tests assume a stable

deterministic component, a large one-off shock such as the October 2005 fuel-price increase can affect their power (Perron, 1989; Maddala & Kim, 1998).

ARMA Framework for Inflation

The Box-Jenkins ARMA framework (Box et al., 2015) combines an autoregressive component, in which the current value depends on past values, and a moving-average component, in which the current value depends on past shocks. The ARMA(p,q) model is written in backshift-operator form as $\varphi(B)Y_t = \theta(B)\varepsilon_t$, where B is the backshift operator ($BY_t = Y_{t-1}$) and $\varphi(B)$ and $\theta(B)$ are lag polynomials of orders p and q. Because economic and financial series are often non-stationary, the model is extended to ARIMA(p,d,q) via differencing of order d: $\varphi(B)(1-B)^d Y_t = \theta(B)\varepsilon_t$ (Box et al., 2015; Gujarati & Porter, 2009). Since both series are stationary in levels (Section 4), d = 0 throughout. As a robustness check for calendar effects in monthly prices, the selected model is also extended with a multiplicative seasonal AR term at lag 12, SARIMA(p,0,q)(1,0,0)$_{12}$:

$$(1 - \Phi B^{12})(1 - \varphi_1 B)(\pi_t - \mu) = (1 + \theta_1 B)\varepsilon_t, \quad \varepsilon_t \sim \text{i.i.d.}(0, \sigma^2)$$

where μ is the unconditional mean of monthly inflation, φ_1 and θ_1 are the non-seasonal AR and MA coefficients, and Φ is the seasonal AR coefficient at lag 12. Five candidates, specified before estimation, are estimated by exact maximum likelihood on the full sample (N = 308): ARIMA(1,0,0), (0,0,1), (1,0,1), (2,0,1) and (1,0,2). The candidate that minimises the Akaike and Bayesian information criteria (AIC, BIC) is used as the parsimonious baseline model; it is not presumed to be the final, fully adequate specification, and its adequacy is assessed with Ljung–Box tests on the residuals at 10, 12, 20 and 24 lags (Ljung & Box, 1978), Ljung–Box tests on squared residuals (McLeod & Li, 1983), ARCH-LM tests (Engle, 1982), and the Jarque–Bera normality test (Jarque & Bera, 1980). Two robustness checks are reported but are not part of the candidate set: the selected model with a seasonal AR term at lag 12, and the selected model with an intervention dummy for October 2005, an extreme outlier (8.71%) associated with the fuel-price increase.

ARCH/GARCH Framework for JCI Returns

Financial asset volatility is characterized by clustering — periods of large price movements followed by periods of relative calm (Engle, 1982; Mandelbrot, 1963). The presence of this pattern is tested with the ARCH-LM test (Engle, 1982), based on the auxiliary regression $\varepsilon_t^2 = \alpha_0 + \Sigma\alpha_i\varepsilon_{t-i}^2 + v_t$, with test statistic $LM = n \times R^2$ distributed $\chi^2(q)$ under H_0 of no ARCH effects. Where ARCH effects are present, the GARCH(1,1) model of Bollerslev (1986) with an AR(1) mean equation and standardized Student-t innovations (Bollerslev, 1987) is estimated:

$$\text{Mean: } r_t = c + \varphi r_{t-1} + \varepsilon_t, \quad \varepsilon_t = \sigma_t z_t, \quad z_t \sim \text{standardized Student-t}(\nu)$$

$$\text{Variance: } \sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

where α captures the short-run impact of news/shocks and β captures volatility persistence. Total persistence is $P = \alpha + \beta$, and the half-life of a volatility shock — the time required for its impact to decay by half — is Half-life = $\ln(0.5)/\ln(P)$ (Bollerslev, 1986; Tsay, 2010; Enders, 2015). Because the half-life is a non-linear function of P that tends to infinity as P approaches one, its standard error is obtained by the delta method and a Wald test of H_0: $\alpha + \beta = 1$ is reported. Because unmodelled shifts in the volatility level bias persistence towards one (Lamoureux & Lastrapes, 1990), robustness is assessed by letting the intercept of the variance equation shift at a pre-specified date that splits the sample into two halves, $\sigma_t^2 = \exp(\lambda_0 + \lambda_s S_t) + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$ with $S_t = 1$ from January 2013 onwards, by repeating this with January 2010 as the shift date, and by re-estimating the model on the January 2013–September 2025 sub-sample. These pre-specified dates are sensitivity analyses. The date of the shift is also estimated formally: the LR statistic for a shift is computed for every candidate month in the central 70% of the sample (15% trimming; January 2004–November 2021), and its maximum (sup-LR) is compared with the asymptotic critical values of Andrews (1993). Each candidate model is estimated from two sets of starting values and the higher likelihood is kept. The first half of the

sample is not estimated separately because unrestricted maximum likelihood on that sub-sample converges to inadmissible values (negative ω and α).

Ten candidate volatility models are compared on the common sample of 307 observations: GARCH(1,1) with a constant mean and normal errors; AR(1)–GARCH(1,1) with normal errors; AR(1)–GARCH(1,1) with Student-t errors; AR(1) models with two ARCH lags or two GARCH lags; AR(1)–TGARCH(1,1) and AR(1)–EGARCH(1,1) with normal errors (Glosten et al., 1993; Nelson, 1991); and the constant-mean GARCH(1,1), AR(1)–TGARCH(1,1) and AR(1)–EGARCH(1,1) with Student-t errors. The AR(1) term enters the mean equation as the regressor r_{t-1}. All models are estimated by maximum likelihood with the Stata arch command and its default settings: presample values of ε_t^2 and σ_t^2 equal to the mean squared residual, outer-product-of-gradients standard errors, and no non-negativity restrictions, so that inadmissible estimates (for example, negative ARCH coefficients) are visible and flagged rather than imposed away. The model with the lowest AIC among admissible candidates is used as the baseline, and any disagreement between AIC and BIC is reported and discussed rather than resolved by assumption. Adequacy is assessed on the standardized residuals $z_t = \hat{\varepsilon}_t/\hat{\sigma}_t$ with Ljung–Box tests on z_t and z_t^2, ARCH-LM tests and the Jarque–Bera test. Whether Student-t errors improve on normal errors is assessed by a likelihood-ratio (LR) test; because normality lies on the boundary $1/\nu = 0$, its p-value is taken from a 50:50 mixture of $\chi^2(0)$ and $\chi^2(1)$.

Tests of the Inflation–Return Relationship

Five complementary tests are used. (i) Pearson and Spearman correlations between π_t and r_t. (ii) Granger (1969) causality tests in a bivariate VAR, with the lag length chosen by the AIC, Schwarz (SBIC) and Hannan–Quinn criteria up to 12 lags and, for robustness, with four lags; each direction is tested by an F-test that the lags of the other variable are jointly zero. (iii) Cross-correlations $\text{corr}(r_t, \pi_{t+k})$ for $k = -12, \ldots, 12$, compared with the approximate 95% band $\pm 1.96/\sqrt{N} = \pm 0.112$. (iv) Threshold regressions $r_t = a + b \cdot 1(\pi_t > 1\%) + u_t$, with contemporaneous and one-month-lagged indicators and Newey–West (1987) standard errors with four lags; 36 months exceed the 1% threshold, whereas only two months exceed 3% (October 2005 and July 2013), so a 3% threshold cannot be estimated meaningfully and is not used. (v) GARCH-X models that add inflation to the selected AR(1)–GARCH(1,1)-t model, either lagged in the mean equation, $r_t = c + \varphi r_{t-1} + \delta \pi_{t-1} + \varepsilon_t$, or in the variance equation, $\sigma_t^2 = \exp(\lambda_0 + \lambda_1 x_t) + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$, with $x_t = \pi_{t-1}$ (predetermined) or $x_t = \pi_t$ (contemporaneous). In the variance specification inflation enters multiplicatively through the intercept, which keeps the variance positive. Significance is assessed by z-tests and by LR tests against the selected model. Failure to reject these null hypotheses is interpreted as an absence of evidence of association in the tested specifications, not as proof of statistical independence.

Crisis-Window Design

Five episodes are dated ex ante by the calendar month of a documented trigger event (t_0): the fuel-price increase of 1 October 2005 (t_0 = October 2005; BBC News, 2005); the collapse of Lehman Brothers on 15 September 2008 (t_0 = September 2008; Modjo et al., 2025); the U.S. Federal Reserve's tapering signal of 22 May 2013 (t_0 = May 2013; Eichengreen & Gupta, 2015); the onset of the COVID-19 pandemic in Indonesia (t_0 = March 2020; Modjo et al., 2025); and the domestic fuel-price adjustment of September 2022 during the global inflation wave (t_0 = September 2022; ING Think, 2022). Identical windows are used for every episode: pre-crisis ($t_0 - 6$ to $t_0 - 1$), crisis (t_0 to $t_0 + 5$) and post-crisis ($t_0 + 6$ to $t_0 + 11$). For each window the study reports mean and maximum inflation, the cumulative and minimum JCI log return, and the mean conditional standard deviation from the selected GARCH model; these numerical measures replace qualitative impact labels. To test formally whether the crisis windows matter beyond the GARCH dynamics, a dummy D_t equal to one in the 30 crisis-window months is added to both equations of the selected model, $r_t = c + \varphi r_{t-1} + \kappa D_t + \varepsilon_t$ and $\sigma_t^2 = \exp(\lambda_0 + \lambda D D_t) + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2$, and the joint restriction $\kappa = \lambda D = 0$ is tested by LR. Because a single pooled dummy can mask differences between episodes, the model is also re-estimated with five episode-specific dummies in the mean equation; episode-specific terms in the variance equation cannot be estimated reliably with six observations per window.

Out-of-Sample Forecast Design

The sample is split into a training period of February 2000–July 2020 (246 observations, 80%) and a test period of August 2020–September 2025 (62 observations, 20%). Model parameters are estimated once on the training period and held fixed; the one-step-ahead forecast for each test month uses only information available at the end of the previous month (a fixed-parameter, expanding-information scheme). The inflation models use all 246 training observations; the AR(1)–GARCH models use 245 (March 2000–July 2020) because the lagged return is not available for February 2000. To rule out look-ahead bias at the model-selection stage, the full selection exercise — all ARMA candidates, the seasonal model and all ten GARCH-family candidates — is repeated on the training sample alone (reported in Section 4), so that the specifications evaluated out of sample are those that would have been chosen with information available in July 2020. Inflation forecasts from the selected ARIMA(0,0,1) model are compared with three benchmarks — an AR(1), a random walk (π_{t-1}) and the training-sample mean — and with the seasonal robustness model. Accuracy is measured by the mean absolute error (MAE), the root mean squared error (RMSE) and Theil's U relative to the random walk. The mean absolute percentage error (MAPE) is not used because nine of the 62 test-period inflation values lie within ±0.05 percentage points of zero, which makes percentage errors unbounded.

Because conditional volatility is latent, the evaluation target is the squared one-step return forecast error $\hat{\varepsilon}^2_t$, an unbiased but noisy proxy for σ^2_t (Andersen & Bollerslev, 1998). Forecasts $\hat{\sigma}^2_{t|t-1}$ from the selected AR(1)–GARCH(1,1)-t model are compared with three benchmarks: an exponentially weighted moving average, $h_t = 0.94h_{t-1} + 0.06\hat{\varepsilon}^2_{t-1}$ (EWMA); the mean of the previous 12 squared errors (rolling variance); and the constant training-sample variance. The loss functions are MSE = mean$[(\hat{\varepsilon}^2_t - \hat{\sigma}^2_t)^2]$ and QLIKE = mean$[\hat{\varepsilon}^2_t/\hat{\sigma}^2_t - \ln(\hat{\varepsilon}^2_t/\hat{\sigma}^2_t) - 1]$, both of which rank forecasts consistently under a noisy proxy (Patton, 2011). MAE and RMSE between $\hat{\sigma}_t$ and $|\hat{\varepsilon}_t|$ are also reported for comparability with earlier studies. Equal predictive accuracy is tested with the Diebold and Mariano (1995) statistic with the Harvey et al. (1997) small-sample correction.

Analysis Stages

1. Data exploration: descriptive statistics and the Jarque-Bera normality test.

2. Stationarity testing using the ADF and PP unit root tests.

3. Ljung–Box tests on the raw series and ARCH-LM tests on the residuals of an AR(4) regression.

4. Selection of the inflation model among five pre-specified ARIMA candidates on the basis of AIC/BIC, followed by residual diagnostics and seasonal and outlier robustness checks.

5. Selection of the JCI volatility model among ten GARCH-family candidates estimated on a common sample, followed by diagnostics on standardized residuals and an assessment of the uncertainty and stability of volatility persistence.

6. Testing the inflation–return relationship via correlation, Granger causality, cross-correlation, threshold regressions and GARCH-X models.

7. Descriptive comparison of pre-crisis, crisis and post-crisis windows for five episodes, and an LR test of crisis-window dummies in the selected GARCH model.

8. One-step-ahead out-of-sample evaluation (training February 2000–July 2020; test August 2020–September 2025) against explicit benchmarks, using MAE, RMSE and Theil's U for inflation and MSE and QLIKE for volatility, with Diebold–Mariano tests.

4. RESULTS AND DISCUSSION

Descriptive Statistics

Table 1. Descriptive Statistics: Inflation and JCI Returns

Statistic	Inflation (%)	JCI return (log)
Observations	308	308
Mean	0.4634	0.0082
Std. deviation	0.6966	0.0581
Minimum	−0.7584 (Jan 2025)	−0.3772 (Oct 2008)
Maximum	8.7067 (Oct 2005)	0.1834 (Apr 2009)
Skewness	5.8670	−1.1580
Kurtosis	65.7561	9.2562
Jarque–Bera	52,308.81***	571.13***

*Note: Jarque–Bera = $(N/6)[S^2 + (K - 3)^2/4] \sim \chi^2(2)$, where S is skewness and K is kurtosis; *** significant at the 1% level. Excluding October 2005, the standard deviation of inflation is 0.5139, its skewness 1.3085 and its kurtosis 5.9373. Source: author's calculation.*

Average monthly inflation is 0.46% (standard deviation 0.70 percentage points), and the average JCI log return is 0.82% per month. Neither variable is normally distributed ($p < 0.01$). Inflation is strongly right-skewed and leptokurtic, but this is driven largely by a single observation, the 8.71% increase in October 2005, when administered fuel prices were raised; excluding that month reduces skewness from 5.87 to 1.31 and kurtosis from 65.8 to 5.9. JCI returns are negatively skewed and fat-tailed (kurtosis 9.26), with the largest monthly fall in October 2008 (−0.377 in log terms, a 31.4% decline in the index).

Figure 1 shows that the largest inflation spikes are concentrated in a few months that follow adjustments of administered energy prices: March 2005 (1.95%) and October 2005 (8.71%), after the two fuel-price increases of that year; July 2013 (3.02%), after the fuel-price increase of June 2013; and December 2014 (2.46%), after the fuel-price increase of November 2014. Conversely, the largest deflation in the sample occurs in January and February 2025 (−0.76% and −0.48%), when a temporary government discount on household electricity tariffs was in effect, followed by a rebound in March 2025 (1.65%) when it ended. The largest falls in the JCI — October 2008 (−0.377), March 2020 (−0.183) and September 2008 (−0.167) — do not coincide with any of these inflation episodes. This separation between the timing of inflation spikes and equity sell-offs foreshadows the formal results reported below.

Stationarity and Autocorrelation

Table 2. Unit Root Test Results

Variable	ADF, constant	PP Z(t), constant	ADF, constant + trend	Conclusion
Inflation	−6.588 (<0.001)	−13.448 (<0.001)	−8.234 (<0.001)	Stationary, I(0)
JCI return	−7.153 (<0.001)	−14.390 (<0.001)	−7.191 (<0.001)	Stationary, I(0)

Note: Test statistics with MacKinnon (1996) approximate p-values in parentheses. The ADF regressions include four lagged differences; the PP test uses a Newey–West bandwidth of four lags. Critical values (constant only, Stata): −3.456 (1%), −2.878 (5%), −2.570 (10%). Source: author's calculation.

Both series are stationary in levels under all specifications, so no differencing is required (d = 0).

Table 3. Ljung-Box Q-Tests on the Raw Series

Variable	Q(1)	Q(10)	Q(12)	Q(20)
Inflation	19.95 (<0.001)	38.80 (<0.001)	60.25 (<0.001)	69.37 (<0.001)
JCI return	12.37 (<0.001)	22.51 (0.013)	23.06 (0.027)	26.08 (0.163)

Note: Ljung–Box Q statistics with p-values in parentheses. First-order autocorrelation: inflation 0.253; JCI return 0.199. Source: author's calculation.

Inflation displays strong autocorrelation at short and seasonal lags (Q(12) = 60.25), which motivates ARMA modelling and a check of the residuals at seasonal lags. JCI returns are also significantly autocorrelated at short lags: the first-order autocorrelation is 0.199 (Q(1) = 12.37, $p < 0.001$) and Q(10) = 22.51 ($p = 0.013$), although Q(20) is not significant ($p = 0.163$). This supports including an AR(1) term in the mean equation of the volatility model. Positive first-order autocorrelation in index returns is commonly attributed, at least in part, to non-synchronous trading of index constituents (Lo & MacKinlay, 1990); the result is therefore reported as evidence of linear dependence at the tested lags, not as a test of market efficiency.

ARCH Effect Test

Table 4. ARCH-LM Test Results

Lag	Inflation	JCI return
1	$\chi^2 = 0.140$ ($p = 0.709$)	$\chi^2 = 7.478$ ($p = 0.006$)***
2	$\chi^2 = 0.161$ ($p = 0.923$)	$\chi^2 = 7.442$ ($p = 0.024$)**
3	$\chi^2 = 0.167$ ($p = 0.983$)	$\chi^2 = 7.476$ ($p = 0.058$)*
4	$\chi^2 = 0.182$ ($p = 0.996$)	$\chi^2 = 7.655$ ($p = 0.105$)
12	$\chi^2 = 0.514$ ($p = 1.000$)	$\chi^2 = 20.410$ ($p = 0.060$)*

*Note: LM = $T \cdot R^2$ from the regression of the squared residuals of an AR(4) model on their own lags, distributed $\chi^2(q)$ under H_0 of no ARCH effects. *** p<0.01, ** p<0.05, * p<0.1. Source: author's calculation.*

Inflation shows no ARCH effect at any lag (all $p > 0.70$), so its error variance can be treated as constant and a GARCH model is not required. JCI returns show significant ARCH effects at lags 1 and 2 and marginal effects at lags 3 and 12, confirming the need for GARCH modeling (H1 is supported).

ARIMA Model for Inflation

Table 5. Comparison of ARIMA Candidate Models for Inflation

Model	Log-L	AIC	BIC	Key coefficients	Q(10) p	Q(20) p
ARIMA(1,0,0)	−314.99	635.98	647.17	AR1 0.253***	0.090	0.009
ARIMA(0,0,1)	**−314.11**	**634.22**	**645.41**	**MA1 0.276*** **	**0.143**	**0.016**
ARIMA(1,0,1)	−314.08	636.16	651.08	AR1 −0.054; MA1 0.327	0.141	0.015
ARIMA(2,0,1)	−312.83	635.65	654.30	AR1 −0.702***; AR2 0.215***; MA1 0.977***	0.197	0.020
ARIMA(1,0,2)	−312.60	635.21	653.86	AR1 −0.945***; MA1 1.225***; MA2 0.241***	0.216	0.023
Robustness: $SARIMA(0,0,1)(1,0,0)_{12}$	−308.94	625.88	640.80	MA1 0.259***; SAR12 0.186***	0.173	0.367

*Note: Exact maximum likelihood, N = 308; all models include a constant (estimated mean ≈ 0.463, p < 0.01) and all converged. The first five rows are the pre-specified candidates; the selected model is in bold. The last row is a robustness check that adds a seasonal AR term at lag 12 to the selected model. Q(10) p and Q(20) p are Ljung–Box p-values for the residuals. ARIMA(2,0,1) and ARIMA(1,0,2) have nearly cancelling AR and MA roots (moduli 1.07/1.02 and 1.06/1.02), indicating over-parameterisation. *** p<0.01. Source: author's calculation.*

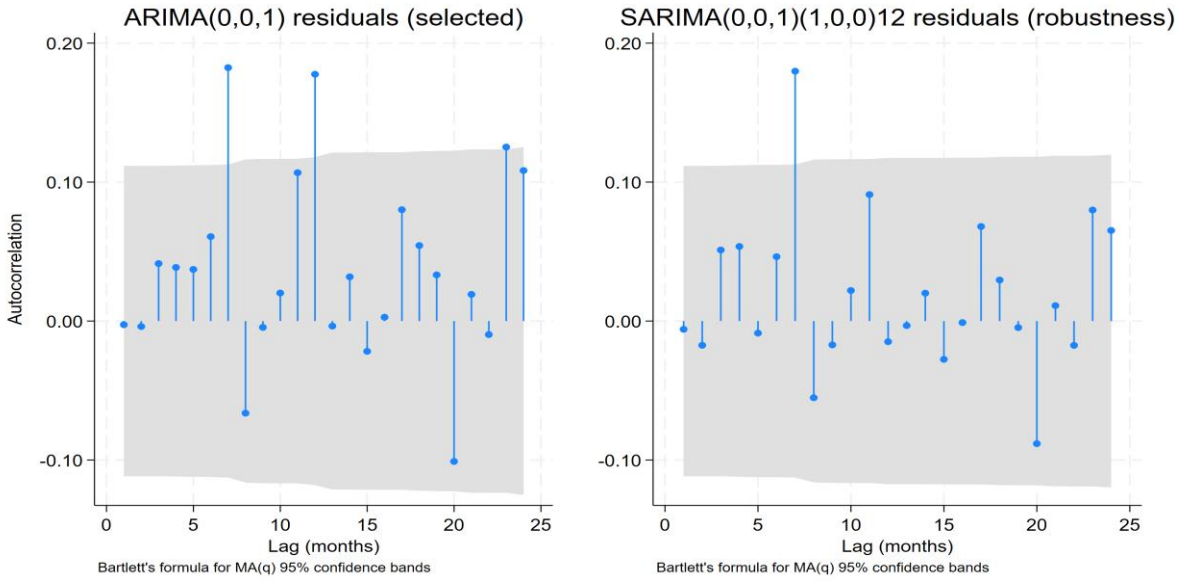
Baseline model: ARIMA(0,0,1) / MA(1)

$\pi_t = 0.4631 + \varepsilon_t + 0.2762\varepsilon_{t-1}$, with standard errors (0.075)*** and (0.037)*** respectively.

ARIMA(0,0,1) has the lowest AIC and BIC among the five pre-specified candidates (Table 5) and is used as the parsimonious baseline; ARIMA(2,0,1) and ARIMA(1,0,2) have nearly cancelling AR and MA roots, a sign of over-parameterisation. The unconditional mean of monthly inflation is 0.46% per month. The MA(1) coefficient implies that a one-percentage-point inflation shock raises inflation in the following month by about 0.28 percentage points; its direct effect then ends, because an MA(1) process has a memory of one period.

The residual diagnostics (Table 7) show no ARCH effects and no autocorrelation at short horizons (Q(10) = 14.70, p = 0.143), but significant autocorrelation at seasonal horizons (Q(12) = 28.54, p = 0.005; Q(20) = 35.85, p = 0.016), with residual autocorrelations of 0.178 at lag 12 and 0.182 at lag 7 (Figure 2). The lag-7 autocorrelation appears to be related to the two administered fuel-price increases of March and October 2005, which are seven months apart, although this attribution has not been established by a formal intervention or outlier analysis. To assess whether the lag-12 pattern affects the conclusions, the selected model was re-estimated with a seasonal AR term at lag 12. The seasonal term is significant ($\Phi = 0.186$, $p < 0.01$) and removes the residual autocorrelation (Q(20) p = 0.367), but it leaves the unconditional mean (0.463) and the MA coefficient (0.259 versus 0.276) almost unchanged and does not introduce ARCH effects. Because its residuals are not white noise at seasonal lags, the ARIMA(0,0,1) model is not presented as a fully adequate final model. It is retained as a parsimonious baseline: it is the preferred member of the pre-specified candidate set, and the substantive conclusions drawn from it — short memory, a constant conditional variance and no association with JCI returns — are the same under the better-specified seasonal model. The seasonal model is statistically preferable, with lower AIC and BIC in both the full sample (Table 5) and the training sample (see Additional Robustness Checks), and is the better choice when the aim is forecasting (Table 10). Re-estimating the selected model with an intervention dummy for October 2005 raises the MA coefficient to 0.353 (standard error 0.042) but strengthens the residual autocorrelation, indicating that the outlier dampens rather than creates the estimated dynamics.

Figure 2. Residual Autocorrelations of the Selected ARIMA(0,0,1) Model and the Seasonal Robustness Model, Lags 1–24



Source: author's calculation (Stata). Shaded area: 95% confidence bands based on Bartlett's formula.

GARCH Model for JCI Returns

Table 6. Comparison of GARCH-Family Candidate Models for JCI Returns (T = 307)

Model	Log-L	AIC	BIC	ARCH term(s)	GARCH term(s)	Persis-tence	ν	Remark
(1) GARCH(1,1)-N, constant mean	474.76	−941.52	−926.61	0.222***	0.751***	0.973	–	
(2) AR(1)–GARCH(1,1)-N	477.15	−944.29	−925.66	0.199***	0.773***	0.972	–	
(3) AR(1)–GARCH(1,1)-t	**483.54**	**−955.08**	**−932.72**	**0.160*****	**0.825*****	**0.985**	**5.69**	**Min AIC; selected**
(4) AR(1)–ARCH(2)–GARCH(1)-N	479.20	−946.41	−924.05	α_1 0.305***; α_2 −0.214***	0.887***	0.978	–	$\alpha_2 < 0$
(5) AR(1)–ARCH(1)–GARCH(2)-N	479.00	−946.01	−923.65	0.259***	β_1 0.246; β_2 0.453**	0.958	–	
(6) AR(1)–TGARCH(1,1)-N	478.06	−944.12	−921.76	0.237***; γ −0.104	0.784***	0.968[a]	–	
(7) AR(1)–EGARCH(1,1)-N	478.26	−944.53	−922.17	|z| 0.266***; z −0.088**	0.943***	0.943[b]	–	
(8) GARCH(1,1)-t, constant mean	481.76	−953.51	−934.88	0.166***	0.821***	0.986	5.40	Min BIC
(9) AR(1)–TGARCH(1,1)-t	483.54	−953.08	−927.00	0.161***; γ −0.001	0.825***	0.985[a]	5.70	
(10) AR(1)–EGARCH(1,1)-t	483.99	−953.98	−927.89	|z| 0.247***; z −0.041	0.965***	0.965[b]	5.99	

Note: Common estimation sample March 2000–September 2025 (T = 307). Maximum likelihood with Stata defaults (presample values = mean squared residual; OPG standard errors; no non-negativity restrictions). N = normal errors; t = standardized Student-t errors with ν degrees of freedom. Persistence = α + β (sum over lags for models 4 and 5). [a] *TGARCH: Stata's threshold term $\gamma\varepsilon^2_{t-1}\cdot 1(\varepsilon_{t-1} > 0)$, so γ < 0 indicates a larger response to negative shocks; persistence = α + β + γ/2.* [b] *EGARCH: $\ln \sigma^2_t = \omega + \theta z_{t-1} + \gamma(|z_{t-1}| - E|z_{t-1}|) + \beta \ln \sigma^2_{t-1}$; persistence = β. *** p<0.01, ** p<0.05. Source: author's calculation.*

Selected model: AR(1)–GARCH(1,1) with Student-t errors

Mean: $r_t = 0.00799 + 0.1093 r_{t-1} + \varepsilon_t$, standard errors (0.00252)*** and (0.0601)*.

Variance: $\sigma^2_t = 0.0000875 + 0.1601\varepsilon^2_{t-1} + 0.8253\sigma^2_{t-1}$, standard errors (0.0000581), (0.0535)***, (0.0560)***.

Distribution: standardized Student-t with ν = 5.69 degrees of freedom (standard error 2.18).

Volatility persistence: α+β = 0.1601 + 0.8253 = 0.9854 (standard error 0.0355; 95% confidence interval 0.916–1.055); Wald test of α+β = 1: z = −0.41, p = 0.680. Half-life = ln(0.5)/ln(0.9854) ≈ 47 months at the point estimate, ≈ 7.9 months at the lower confidence bound, and undefined (infinite) at the upper bound.

The information criteria do not agree on the conditional mean. AR(1)–GARCH(1,1)-t has the lowest AIC among the ten candidates (Table 6), whereas BIC marginally prefers the constant-mean GARCH(1,1)-t (−934.88 versus −932.72), and the LR test of the AR(1) term is significant only at the 10% level (LR = 3.57, p = 0.059). The AR(1) specification is therefore not presented as unambiguously the best model; it is used as the baseline because the raw returns are significantly autocorrelated (Table 3), and the two models imply almost identical variance dynamics (persistence 0.986 versus 0.985), so the conclusions about volatility do not depend on this choice. Student-t errors improve the fit decisively over normal errors (LR = 12.79, p < 0.001), and none of the asymmetric models improves on the selected model: the threshold term in AR(1)–TGARCH(1,1)-t is essentially zero (γ = −0.001, p = 0.99), and the asymmetry coefficient in AR(1)–EGARCH(1,1)-t is insignificant (p = 0.43). The model with two ARCH lags is inadmissible because its second ARCH coefficient is significantly negative (−0.214), which can produce negative conditional variances.

The estimated α + β of 0.985 indicates that the conditional variance reverts slowly to its unconditional level; it is a decay factor for the conditional variance, not the share of a volatility shock

that is literally carried over from one month to the next. Two qualifications are essential. First, the estimate is imprecise: its 95% confidence interval includes one and the unit-persistence (IGARCH) null cannot be rejected ($p = 0.680$), so the point half-life of about 47 months is surrounded by very wide uncertainty, from roughly eight months to infinity (H2 cannot be rejected). Second, the estimate is sensitive to a shift in the volatility level. In sensitivity analyses with pre-specified dates, allowing the intercept of the variance equation to fall from January 2013 improves the fit substantially (LR = 11.94, $p < 0.001$; the baseline variance after 2013 is about 78% lower, $\exp(-1.526) = 0.22$) and reduces persistence to 0.794 (standard error 0.121), a half-life of about three months. A shift dated January 2010 gives a similar result (persistence 0.858; half-life 4.5 months), and the January 2013–September 2025 sub-sample yields 0.854 (Table 12). A formal test that estimates the date of the shift, reported in the Additional Robustness Checks below, confirms a significant downward shift in the volatility level around 2010–2013. Near-unit persistence in the full sample combined with much lower persistence once the level shift is allowed for is the pattern that Lamoureux and Lastrapes (1990) attribute to shifts in the unconditional variance, and Figure 3 shows that the volatility level was markedly higher in 2000–2009 than after 2013. The four-year half-life should therefore be read as a full-sample summary that partly reflects such level shifts, not as a structural property of JCI volatility.

The degrees-of-freedom estimate ($\nu = 5.69$) indicates tails heavier than those of the normal distribution. The significance of ν itself is not a test of normality, which is why the LR comparison above is reported. To quantify the tail difference with an explicit threshold, the probability that a standardized shock exceeds three standard deviations in absolute value is 1.08% under a standardized t(5.69) distribution and 0.27% under the normal distribution, a ratio of about 4.0; for a four-standard-deviation threshold the ratio is about 46. In the data, 4 of the 307 standardized residuals exceed 3 in absolute value (1.3%), close to the t-implied 1.08% and well above the normal-implied 0.27%.

Post-Estimation Diagnostics

Table 7. Residual Diagnostics of the Selected Models

Test	Inflation: ARIMA(0,0,1) residuals	JCI: AR(1)–GARCH(1,1)-t standardized residuals
Ljung–Box Q(10)	14.70 (0.143)	5.08 (0.886)
Ljung–Box Q(12)	28.54 (0.005)	–
Ljung–Box Q(20)	35.85 (0.016)	9.31 (0.979)
Ljung–Box Q(24)	45.20 (0.006)	–
Ljung–Box Q(10), squared residuals	0.61 (1.000)	6.33 (0.787)
Ljung–Box Q(20), squared residuals	0.75 (1.000)	7.91 (0.992)
ARCH-LM, 1 lag	0.158 (0.691)	1.74 (0.188)
ARCH-LM, 4 lags	0.210 (0.995)	1.96 (0.743)
ARCH-LM, 12 lags	0.597 (1.000)	6.63 (0.881)
Skewness / kurtosis	6.25 / 73.44	−0.81 / 4.37
Jarque–Bera	65,675.14 (<0.001)	57.52 (<0.001)

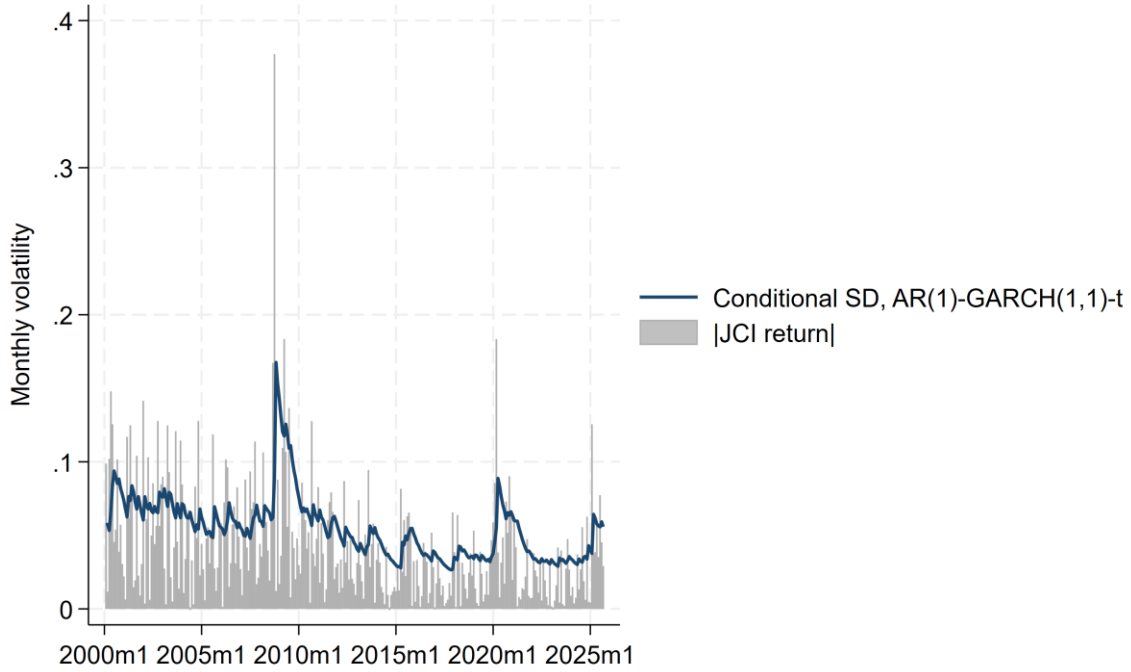
Note: Test statistics with p-values in parentheses. Standardized residuals $z_t = \hat{\varepsilon}_t/\hat{\sigma}_t$. Source: author's calculation.

Table 7 reports the diagnostics of both selected models. For inflation, the ARIMA(0,0,1) residuals show no ARCH effects, which supports the constant-variance specification, and no autocorrelation at 10 lags, but significant autocorrelation at 12, 20 and 24 lags, reflecting the seasonal pattern discussed above. They are also strongly non-normal (Jarque–Bera = 65,675), mainly because of the October 2005 outlier; because the model is estimated by Gaussian (quasi-)maximum likelihood, non-normality affects the efficiency of the estimates and the width of forecast intervals rather than the consistency of the coefficients. For JCI returns, the standardized residuals show no remaining autocorrelation in levels or squares and no remaining ARCH effects at 1, 4 or 12 lags, so the AR(1)–GARCH(1,1)-t model captures the serial dependence and volatility clustering in the data. The rejection of normality by the Jarque–Bera test for these residuals is not in itself a failure of the model, because the innovations are modelled as Student-t rather than normal. The remaining distributional

features are therefore reported descriptively: the standardized residuals are fat-tailed (kurtosis 4.37), which the Student-t distribution allows for, but also negatively skewed (−0.81), which a symmetric Student-t distribution does not capture; a skewed Student-t distribution would be a natural extension.

Behaviour Around Five Crisis Episodes

Figure 3. Conditional Volatility of JCI Returns and Crisis Windows



Source: author's calculation (Stata) from the AR(1)–GARCH(1,1)-t model in Table 6. Bars show absolute monthly JCI log returns.

Table 8 compares the pre-crisis, crisis and post-crisis windows. The episodes differ sharply in which variable was affected. The 2005 fuel-price shock produced the largest inflation spike in the sample (8.71% in October 2005) but no equity sell-off: the JCI rose by a cumulative 0.20 in log terms during the crisis window, and conditional volatility stayed close to its sample mean of 0.055. The 2008 Global Financial Crisis is the mirror image: inflation fell during the window (mean 0.28% per month), while the JCI lost 0.52 in cumulative log terms, recorded its largest monthly fall (−0.377 in October 2008), and conditional volatility more than doubled (mean 0.124, peak 0.168). The 2013 Taper Tantrum combined a moderate equity decline (−0.11) with an inflation spike of 3.02% in July 2013 that followed the domestic fuel-price increase of June 2013, so the inflation and equity shocks in that window had different origins. During the COVID-19 window, the JCI fell by 0.183 in March 2020 and conditional volatility rose to 0.074 on average, while inflation stayed close to zero but positive (0.096% in March 2020; mean 0.04% over the window), so there was no deflation. The 2022 global inflation wave raised domestic inflation (1.17% in September 2022) without visible equity stress: JCI returns and conditional volatility were below their sample averages.

Two observations follow. First, in three of the five episodes (2005, 2013 and 2022) the largest monthly inflation spike coincided with a domestic adjustment of administered fuel prices, whereas the two largest equity shocks (2008 and 2020) originated abroad and were accompanied by low or falling inflation. Second, the formal test is consistent with these descriptive patterns. Adding a crisis-window dummy to the mean and variance equations of the selected model does not improve the fit (LR = 3.63, p = 0.163): the dummy is only marginally significant in the mean ($\kappa = -0.015$, p = 0.090) and

insignificant in the variance (p = 0.82), and persistence is essentially unchanged (0.990; Table 12). This result should be read narrowly: it shows no significant common shift across the pooled, pre-defined crisis windows once the GARCH dynamics are taken into account, not that the individual crises had no effect. Episode-specific dummies, reported in the Additional Robustness Checks, reveal heterogeneity. Mean returns were significantly lower during the 2008 window (−0.081 per month, p = 0.011) and marginally lower during the 2013 window (−0.025, p = 0.048), whereas the 2005, 2020 and 2022 windows show no significant shift; the five dummies are jointly significant by a Wald test ($\chi^2(5) = 12.05$, p = 0.034) but not by the LR test (LR = 9.09, p = 0.106), and persistence is unchanged (0.988). Episode-specific variance terms cannot be estimated reliably with six observations per window. H4 therefore cannot be rejected for the pooled windows, but the evidence points to a significant decline in mean returns during the Global Financial Crisis.

Table 8. Inflation and JCI Returns Before, During and After Five Crisis Episodes

Episode	Window	Mean inflation (%)	Max. inflation (%) (month)	Cumulative JCI log return	Min. JCI log return (month)	Mean conditional SD
2005 fuel-price shock (t_0 = Oct 2005)	Pre	0.51	0.78 (Jul 05)	−0.001	−0.119 (Aug 05)	0.054
	Crisis	1.99	8.71 (Oct 05)	0.204	−0.012 (Oct 05)	0.057
	Post	0.34	0.45 (Jun 06)	0.148	−0.096 (May 06)	0.062
2008 Global Financial Crisis (t_0 = Sep 2008)	Pre	0.98	1.41 (May 08)	−0.228	−0.106 (Mar 08)	0.065
	Crisis	0.28	0.97 (Sep 08)	−0.522	−0.377 (Oct 08)	0.124
	Post	0.18	0.56 (Aug 09)	0.600	0.008 (Aug 09)	0.117
2013 Taper Tantrum (t_0 = May 2013)	Pre	0.41	0.70 (Feb 13)	0.146	−0.017 (Nov 12)	0.042
	Crisis	0.84	3.02 (Jul 13)	−0.110	−0.094 (Aug 13)	0.045
	Post	0.33	1.07 (Jan 14)	0.071	−0.058 (Nov 13)	0.050
2020 COVID-19 (t_0 = Mar 2020)	Pre	0.13	0.34 (Dec 19)	−0.149	−0.086 (Feb 20)	0.036
	Crisis	0.04	0.18 (Jun 20)	−0.040	−0.183 (Mar 20)	0.074
	Post	0.18	0.45 (Dec 20)	0.175	−0.073 (Sep 20)	0.063
2022 global inflation wave (t_0 = Sep 2022)	Pre	0.51	0.95 (Apr 22)	0.041	−0.034 (Jun 22)	0.033
	Crisis	0.38	1.17 (Sep 22)	−0.048	−0.033 (Dec 22)	0.032
	Post	0.15	0.33 (Apr 23)	0.016	−0.042 (May 23)	0.032
Full sample (Feb 2000–Sep 2025)		0.46	8.71 (Oct 05)	–	−0.377 (Oct 08)	0.055

Note: Pre = $t_0 - 6$ to $t_0 - 1$; Crisis = t_0 to $t_0 + 5$; Post = $t_0 + 6$ to $t_0 + 11$ (months). Conditional SD from the AR(1)–GARCH(1,1)-t model (full-sample estimates). Source: author's calculation.

Relationship Between Inflation and JCI Returns

Table 9. Tests of the Inflation–JCI Return Relationship

Test	Specification	Statistic	p-value
Pearson correlation	π_t and r_t, N = 308	r = −0.028	0.621
Spearman rank correlation	π_t and r_t, N = 308	ρ = −0.040	0.479
Granger: inflation → return	1 lag (selected by AIC, SBIC, HQIC)	F(1, 304) = 0.09	0.761
Granger: return → inflation	1 lag	F(1, 304) = 0.15	0.697
Granger: inflation → return	4 lags (robustness)	F(4, 295) = 0.67	0.616
Granger: return → inflation	4 lags (robustness)	F(4, 295) = 1.70	0.149
Cross-correlation, max |r|, k = −12…12	corr(r_t, π_{t+2}); 95% band ±0.112	r = −0.111	0.052
Threshold, contemporaneous	r_t on 1(π_t > 1%); 36 months; Newey–West (4)	b = 0.0139; t = 1.54	0.124
Threshold, lagged	r_t on 1(π_{t-1} > 1%); 36 months; Newey–West (4)	b = −0.0022; t = −0.23	0.821
GARCH-X, mean equation	$\delta\pi_{t-1}$ in AR(1)–GARCH(1,1)-t	δ = 0.0013; z = 0.26; LR = 0.11	0.795
GARCH-X, variance equation	exp($\lambda_0 + \lambda_1\pi_{t-1}$)	λ_1 = 0.398; z = 1.32; LR = 0.43	0.188
GARCH-X, variance equation	exp($\lambda_0 + \lambda_1\pi_t$), contemporaneous	λ_1 = 0.335; z = 0.78; LR = 0.29	0.438

Note: p-values for GARCH-X rows refer to the z-test; LR is the likelihood-ratio statistic against the selected AR(1)–GARCH(1,1)-t model ($\chi^2(1)$). The cross-correlation p-value uses the Fisher z-transformation (N = 306). Source: author's calculation.

None of the tests rejects the null hypothesis of no association between monthly inflation and JCI returns or volatility at the 5% level (H3 cannot be rejected). The contemporaneous correlation is close to zero (r = −0.028); Granger tests are insignificant in both directions at the lag length selected by all three information criteria (one lag) and at four lags; the largest cross-correlation (−0.111, with returns leading inflation by two months) lies just inside the 95% band (±0.112; p = 0.052), and one value of this size among 25 lags examined is to be expected by chance alone; high-inflation months are not associated with different returns; and inflation does not enter the mean or variance equation significantly in the GARCH-X models. These results show that, in the tested linear, lagged, threshold and conditional-variance specifications, there is no evidence of an association. They do not establish that the two series are statistically independent, and they do not exclude relationships through channels that are not modelled here, such as expected inflation, the policy rate or the exchange rate.

Out-of-Sample Forecasting Evaluation

Table 10. One-Step-Ahead Inflation Forecast Accuracy, August 2020–September 2025

Model	MAE	RMSE	Theil's U (vs random walk)	DM vs ARIMA(0,0,1) (p)
ARIMA(0,0,1)	**0.351**	**0.445**	**0.862**	–
AR(1)	0.348	0.446	0.864	−0.17 (0.866)
Random walk (π_{t-1})	0.326	0.516	1.000	−1.16 (0.251)
Training-sample mean	0.408	0.485	0.940	−2.32 (0.024)
Robustness: SARIMA(0,0,1)(1,0,0)$_{12}$	0.325	0.419	0.812	3.67 (<0.001)

Note: Errors in percentage points. Parameters estimated on February 2000–July 2020 (246 observations) and held fixed; 62 one-step-ahead forecasts. DM = Diebold–Mariano statistic for the squared-error loss differential, loss(ARIMA(0,0,1)) minus loss(alternative), with the Harvey et al. (1997) correction; a negative value favours ARIMA(0,0,1), a positive value favours the alternative. Source: author's calculation.

Table 11. One-Step-Ahead Volatility Forecast Accuracy for JCI Returns, August 2020–September 2025

Model	MSE (×10⁻⁶)	QLIKE	MAE (SD)	RMSE (SD)	DM, MSE (p)	DM, QLIKE (p)
AR(1)–GARCH(1,1)-t	**7.53**	**1.9049**	**0.0244**	**0.0299**	–	–
EWMA (λ = 0.94)	7.38	1.9923	0.0232	0.0289	0.36 (0.723)	−0.81 (0.419)
Rolling 12-month variance	7.59	1.9513	0.0214	0.0275	−0.13 (0.900)	−0.33 (0.743)
Constant training variance	12.34	2.2615	0.0381	0.0423	−3.39 (0.001)	−2.62 (0.011)

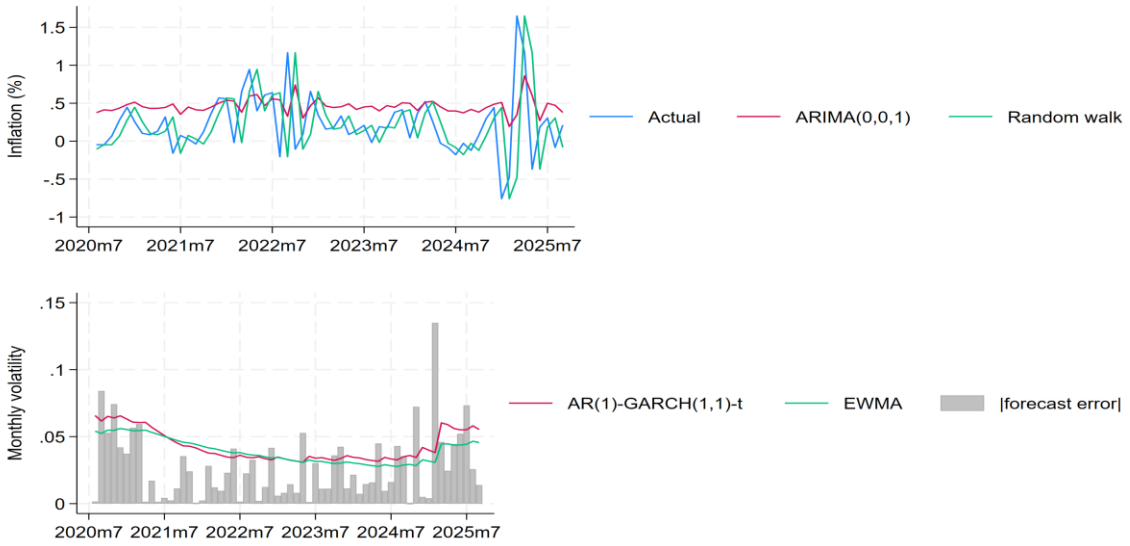
Note: Proxy for the latent variance = squared one-step return forecast error $\hat{\varepsilon}^2_t$. MSE and QLIKE are computed on the variance and are robust to proxy noise (Patton, 2011); MAE (SD) and RMSE (SD) compare $\hat{\sigma}_t$ with $|\hat{\varepsilon}_t|$ and are reported for comparability only. GARCH parameters (training estimates): $\omega = 0.0000746$, $\alpha = 0.1271$, $\beta = 0.8614$, $\nu = 6.04$. DM statistics are for loss(GARCH) minus loss(benchmark); a negative value favours GARCH. Source: author's calculation.

Inflation forecast equation (training estimates): $\hat{\pi}_{t+1|t} = 0.523 + 0.260\hat{\varepsilon}_t$.

Volatility forecast equation (training estimates): $\hat{\sigma}^2_{t+1|t} = 0.0000746 + 0.1271\hat{\varepsilon}^2_t + 0.8614\hat{\sigma}^2_t$.

For inflation, the ARIMA(0,0,1) model is significantly more accurate than the training-sample mean (Diebold–Mariano p = 0.024) and has a 14% lower RMSE than the random walk (Theil's U = 0.86), although this difference is not statistically significant (p = 0.251); it performs on par with an AR(1). The random walk has a slightly lower MAE because it tracks large month-to-month swings with a one-month delay, which is costly under squared-error loss but much less so under absolute-error loss (Figure 4). The seasonal robustness model is significantly more accurate than the ARIMA(0,0,1) (p < 0.001), so the seasonal term matters for forecasting even though it does not change the in-sample conclusions. For volatility, the AR(1)–GARCH(1,1)-t model is significantly more accurate than a constant-variance forecast under both MSE (p = 0.001) and QLIKE (p = 0.011), but its accuracy is statistically indistinguishable from that of the EWMA and rolling-variance benchmarks. H5 is therefore rejected against the naive benchmarks but not against the adaptive ones. This is in line with evidence that simple volatility models are demanding benchmarks (Hansen & Lunde, 2005) and with the low power of comparisons based on a squared-return proxy over 62 months (Andersen & Bollerslev, 1998; Patton, 2011).

Figure 4. One-Step-Ahead Out-of-Sample Forecasts, August 2020–September 2025



Source: author's calculation (Stata). Upper panel: actual inflation, ARIMA(0,0,1) and random-walk forecasts. Lower panel: absolute one-step return forecast errors and forecast conditional standard deviations (AR(1)–GARCH(1,1)-t and EWMA).

Robustness of Volatility Persistence

Table 12 collects the variants of the volatility model used to assess the robustness of the persistence estimate. The constant-mean model and the training-sample estimates reproduce the near-unit persistence of the selected model, and adding crisis-window dummies leaves it unchanged. In contrast, every specification that allows the volatility level to differ between the earlier and the later part of the sample produces much lower persistence (0.79–0.86) and half-lives of three to five months, and both level-shift models are preferred to the selected model by the likelihood-ratio test and by AIC and BIC. Because the shift dates in Table 12 are pre-specified, these models are sensitivity analyses rather than estimates of a structural break; the selected model is retained as the baseline specification

for the remaining analysis, but conclusions about the duration of volatility shocks are based on the full set of results in Table 12.

Table 12. Robustness of the AR(1)–GARCH(1,1)-t Volatility Model

	(1) Selected model	(2) Constant mean	(3) Level shift Jan 2013	(4) Level shift Jan 2010	(5) Crisis dummies	(6) Sub-sample 2013–2025	(7) Training sample
φ (AR1)	0.109* (0.060)	–	0.112* (0.063)	0.097 (0.061)	0.097 (0.061)	0.082 (0.092)	0.138** (0.065)
α (ARCH)	0.160*** (0.053)	0.166*** (0.054)	0.159** (0.068)	0.128** (0.059)	0.172*** (0.057)	0.247* (0.144)	0.127*** (0.048)
β (GARCH)	0.825*** (0.056)	0.821*** (0.056)	0.635*** (0.151)	0.730*** (0.105)	0.817*** (0.057)	0.608*** (0.193)	0.861*** (0.054)
ν (Student-t)	5.69	5.40	6.37	5.95	5.88	4.71	6.04
Shift / crisis terms	–	–	λ_S −1.526*** (0.308)	λ_S −1.593*** (0.348)	κ −0.015* (0.009); λ_D −1.01 (4.50)	–	–
α + β (SE)	0.985 (0.036)	0.986 (0.037)	0.794 (0.121)	0.858 (0.082)	0.990 (0.036)	0.854 (0.149)	0.989 (0.031)
Half-life (months)	47.0	50.8	3.0	4.5	66.6	4.4	59.8
Log-L	483.54	481.76	489.51	489.19	485.36	295.21	364.10
LR vs (1)	–	–	11.94***	11.30***	3.63 (2 df)	–	–
T	307	307	307	307	307	153	245

*Note: Standard errors (OPG) in parentheses. Level-shift models: $\sigma^2_t = exp(\lambda_0 + \lambda_S S_t) + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1}$, with $S_t = 1$ from the shift date. Crisis model: κ is the crisis-window dummy in the mean equation and λ_D its coefficient in the variance intercept. Training sample: March 2000–July 2020. Half-life = ln(0.5)/ln(α + β). *** p<0.01, ** p<0.05, * p<0.1. Source: author's calculation.*

Additional Robustness Checks

Model selection on the training sample. Table 13 repeats the complete selection exercise on February 2000–July 2020 only. Among the five pre-specified ARMA candidates, ARIMA(0,0,1) again has the lowest AIC (541.67) and BIC (552.18); the seasonal extension has lower values still (537.09 and 551.11) and removes the residual autocorrelation at 12 lags (Ljung–Box p = 0.360 versus 0.058). Among the admissible GARCH-family candidates, AIC again selects AR(1)–GARCH(1,1)-t (−716.19), narrowly ahead of AR(1)–EGARCH(1,1)-t (−716.12), and BIC again prefers the constant-mean GARCH(1,1)-t (−696.15 versus −695.18). The model with two ARCH lags has the lowest AIC and BIC but is again inadmissible ($\alpha_2 = -0.323$, $p < 0.001$). The specifications evaluated out of sample are therefore the same as those that would have been chosen with information available in July 2020, and the forecast comparison in Tables 10 and 11 is not affected by look-ahead bias in model selection.

Episode-specific crisis dummies. Panel A of Table 14 reports the episode-specific dummies discussed with Table 8. Only the 2008 window (−0.081, p = 0.011) and, marginally, the 2013 window (−0.025, p = 0.048) show significantly lower mean returns; the five dummies are jointly significant by the Wald test (p = 0.034) but not by the LR test (p = 0.106), and persistence is unchanged (0.988).

Estimated date of the volatility shift. Figure 5 plots the LR statistic for a shift in the intercept of the variance equation at each candidate month between January 2004 and November 2021. Its maximum, sup-LR = 15.55 in October 2011, exceeds the 1% asymptotic critical value of Andrews (1993) (12.35; 8.85 at 5%), so the hypothesis of a constant volatility level is rejected (Table 14, Panel B). The LR profile is flat between 2010 and 2013, however: every candidate month in this interval gives an LR above 11.29, including the pre-specified dates of January 2010 (11.30) and January 2013 (11.94). The timing of the shift is therefore estimated imprecisely, and the pre-specified dates lie within the range supported by the data. At the estimated date, persistence falls to 0.691 (standard error 0.176; half-life about 1.9 months), and across the ten candidate dates with the highest LR it ranges from 0.28 to 0.76. The evidence thus supports a downward shift in the volatility level around 2010–2013 and post-shift persistence well below the full-sample estimate, but not a precise post-shift persistence or half-life. The level-shift results are therefore interpreted as evidence that the full-sample persistence is overstated, not as a precisely dated change of regime.

Table 13. Model Selection on the Training Sample, February 2000–July 2020

Model	Log-L	AIC	BIC	Note
Panel A. ARMA candidates (N = 246)				
ARIMA(1,0,0)	−268.49	542.98	553.50	Q(12) p = 0.031
ARIMA(0,0,1)	**−267.83**	**541.67**	**552.18**	Baseline; Q(12) p = 0.058
ARIMA(1,0,1)	−267.82	543.63	557.65	Q(12) p = 0.059
ARIMA(2,0,1)	−266.74	543.49	561.01	Q(12) p = 0.058
ARIMA(1,0,2)	−266.54	543.07	560.60	Q(12) p = 0.079
Robustness: SARIMA(0,0,1)(1,0,0)$_{12}$	−264.54	537.09	551.11	Q(12) p = 0.360
Panel B. GARCH-family candidates (T = 245)				
1. GARCH(1,1)-N, constant mean	356.96	−705.93	−691.92	[a]
2. AR(1)–GARCH(1,1)-N	359.76	−709.53	−692.02	[a]
3. AR(1)–GARCH(1,1)-t	**364.10**	**−716.19**	**−695.18**	Lowest AIC among admissible models
4. AR(1)–ARCH(2)–GARCH(1)-N	365.29	−718.57	−697.57	Inadmissible: α_2 = −0.323***
5. AR(1)–ARCH(1)–GARCH(2)-N	361.33	−710.66	−689.65	
6. AR(1)–TGARCH(1,1)-N	360.42	−708.84	−687.83	[a]
7. AR(1)–EGARCH(1,1)-N	361.61	−711.22	−690.22	
8. GARCH(1,1)-t, constant mean	361.83	−713.66	−696.15	Lowest BIC among admissible models
9. AR(1)–TGARCH(1,1)-t	364.10	−714.20	−689.69	
10. AR(1)–EGARCH(1,1)-t	365.06	−716.12	−691.62	[b]

*Note: Exact maximum likelihood for the ARMA models; Stata arch defaults for the GARCH-family models (common sample March 2000–July 2020). Q(12) p = Ljung–Box p-value of the residuals at 12 lags. [a] With Stata's default starting values these models stop at a local maximum (log-likelihood 354.53, 355.81 and 357.01); re-estimation from alternative starting values gives the higher maxima reported. [b] Stata does not declare convergence because the likelihood surface is flat; the log-likelihood reached is reported. *** p<0.01. Source: author's calculation.*

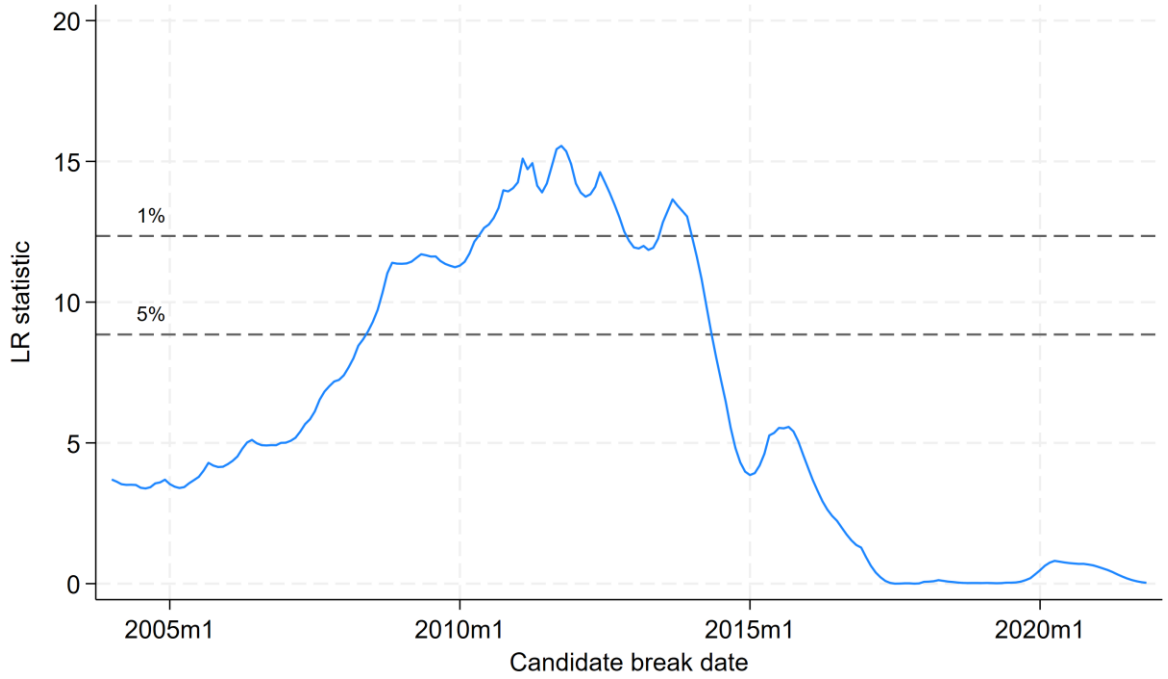
Table 14. Episode-Specific Crisis Dummies and the Estimated Shift in the Volatility Level

	Estimate	Note
Panel A. Episode-specific dummies in the mean equation (T = 307)		
2005 fuel-price shock (Oct 2005–Mar 2006)	0.023 (0.024)	
2008 Global Financial Crisis (Sep 2008–Feb 2009)	−0.081** (0.032)	
2013 Taper Tantrum (May–Oct 2013)	−0.025** (0.013)	
2020 COVID-19 (Mar–Aug 2020)	−0.005 (0.035)	
2022 fuel-price adjustment (Sep 2022–Feb 2023)	−0.017 (0.016)	
Joint test of the five dummies	LR = 9.09; Wald = 12.05	p = 0.106; p = 0.034 (5 df)
α + β with episode dummies	0.988 (0.036)	Selected model: 0.985
Panel B. Estimated shift in the volatility level (sup-LR)		
Candidate dates	Jan 2004–Nov 2021	215 months; 15% trimming
sup-LR statistic	15.55	Critical values 7.17 / 8.85 / 12.35 (10% / 5% / 1%)
Estimated break date	October 2011	LR > 11.29 for every month in 2010–2013
LR at pre-specified dates	11.30 (Jan 2010); 11.94 (Jan 2013)	Table 12, columns (4) and (3)
α + β at the estimated date	0.691 (0.176)	Half-life ≈ 1.9 months
α + β, ten highest-LR dates	0.28–0.76	Imprecise post-shift persistence

Note: Panel A adds one dummy per crisis window (t_0 to t_0 + 5) to the mean equation of the AR(1)–GARCH(1,1)-t model; OPG standard errors in parentheses. Panel B: LR statistic for $\sigma^2_t = \exp(\lambda_0 + \lambda_s S_t) + \alpha\varepsilon^2_{t-1} + \beta\sigma^2_{t-1}$ with S_t = 1 from the candidate month, against the selected model; each candidate is estimated from two sets of starting values and the higher

*likelihood is kept. Critical values from Andrews (1993) for one restriction and 15% trimming. ** p<0.05. Source: author's calculation.*

Figure 5. LR Statistic for a Shift in the Volatility Level by Candidate Break Date



Source: author's calculation (Stata). Dashed lines: asymptotic 5% and 1% critical values of the sup-LR test (Andrews, 1993).

Discussion

The primary aim of the study is to identify adequate models for monthly inflation and JCI volatility, and the selected specifications have a clear economic reading. For inflation, an MA(1) structure means that a shock to monthly inflation affects the following month and then disappears from the conditional mean, so month-to-month inflation in Indonesia behaves as a stable mean plus short-lived disturbances rather than as a persistent process. This is consistent with the importance of one-off price-level adjustments in the series: an administered increase in fuel prices raises the price level once, raises inflation in the month of the change and, possibly through delayed pass-through, in the following month, but does not by itself generate continuing inflation. The two largest observations in the sample, March and October 2005, illustrate this pattern and appear to be related to the lag-7 residual autocorrelation reported in Section 4, although this link has not been established formally. The residual autocorrelation at lag 12 points to a recurring seasonal component that a non-seasonal ARMA model cannot capture; calendar-related demand pressures and price adjustments that recur at similar times each year are plausible sources, although the present design does not identify them. The out-of-sample results fit this interpretation. A model that captures only one month of dependence improves on the historical mean but not significantly on a random walk, in line with the difficulty of beating naive inflation benchmarks documented by Atkeson and Ohanian (2001) and Stock and Watson (2007), whereas adding the seasonal term yields a significant gain. For applied work on Indonesian monthly inflation, this suggests that the forecastable information lies mainly in the seasonal structure rather than in additional non-seasonal ARMA lags.

For JCI volatility, the high full-sample persistence of the selected AR(1)–GARCH(1,1)-t model parallels findings for many equity markets, but the level-shift evidence suggests that it partly reflects a downward shift in the volatility level, from the turbulent early 2000s and the Global Financial Crisis to the calmer period after 2013, rather than shocks that each take years to decay (Lamoureux & Lastrapes, 1990). The sup-LR test supports this interpretation: it detects a significant

shift around 2010–2013 without pinning down its exact month. Once the shift is allowed for, whether at the estimated date or at the pre-specified dates, volatility shocks have half-lives of a few months rather than years, although the exact value is imprecise. This matters for interpretation: a forecaster using the full-sample model would expect elevated volatility to persist much longer than the within-period evidence suggests. The same finding helps explain why the GARCH model does not significantly outperform the EWMA and rolling-variance forecasts out of sample: when the volatility level shifts, simple adaptive estimators with short memory can be as accurate as a GARCH model with near-unit persistence. Finally, the absence of asymmetry once Student-t errors are allowed suggests that, at the monthly frequency, the apparent leverage effect in the normal EGARCH model reflects fat tails rather than a distinct response to negative news (Engle & Ng, 1993).

The choice of error distribution also has practical consequences beyond model fit. Under the selected model, the probability of a standardized monthly shock larger than three standard deviations in absolute value is about four times higher under the fitted Student-t distribution than under the normal distribution, and about 46 times higher at four standard deviations. Over 307 months, the normal distribution implies fewer than one such three-standard-deviation shock ($0.27\% \times 307 \approx 0.8$), whereas the Student-t distribution implies about three ($1.08\% \times 307 \approx 3.3$); the four observed in the data are clearly closer to the latter. A risk measure based on conditional normality would therefore understate the likelihood of extreme monthly moves in the JCI even if the conditional variance were correctly specified. Finally, the disagreement between AIC, which favours the AR(1) mean equation, and BIC, which marginally favours a constant mean, has little practical weight: Table 12 shows that the constant-mean specification yields essentially the same persistence as the selected model, so the conclusions on volatility do not depend on this choice.

The third research question, whether inflation and the JCI are related, yields no evidence of an association in monthly data. This result is consistent with Kewal (2012), Hismendi et al. (2013), Wijaya (2013), and Yunita and Robiyanto (2018), and differs from the positive effect reported by Krisna and Wirawati (2013). Three economic mechanisms can account for the result. First, a large part of the variation in monthly headline inflation reflects administered-price adjustments and food-price movements. Such changes are announced or seasonal and therefore largely anticipated; under a short-horizon Fisher view, anticipated inflation is already reflected in prices and should not generate return surprises. The crisis-window evidence supports this interpretation: the largest inflation spikes (2005, 2013 and 2022) coincided with domestic fuel-price adjustments that left the JCI largely unaffected. Second, the proxy-effect channel of Fama (1981) operates only if inflation carries news about future real activity, and month-on-month headline inflation that is dominated by supply-side price changes is a noisy proxy for such news. Third, as in other emerging markets, JCI risk appears to be driven mainly by global factors and capital flows (Bekaert & Harvey, 1997): the two largest equity shocks in the sample, in 2008 and 2020, originated abroad and coincided with falling inflation, and the 2013 episode was transmitted through capital flows rather than through domestic prices (Eichengreen & Gupta, 2015). Differences from earlier Indonesian studies may also reflect methodological choices — annual versus monthly inflation, price levels versus returns, and shorter samples — so the comparison should be read with caution.

These tests should be read with their precision in mind. With about 300 monthly observations, cross-correlations smaller than about 0.11 in absolute value cannot be distinguished from zero at the 5% level; a correlation of this size would correspond to inflation explaining roughly 1% of the variation in monthly JCI returns. The results therefore indicate that any month-to-month link between headline inflation and the JCI is weak at most, while leaving open the possibility of relationships at longer horizons or through inflation expectations, which the present design does not examine.

The results are also consistent with the low-frequency view of the macro–volatility link. Engle and Rangel (2008) and Engle et al. (2013) associate inflation with the slowly moving level of equity volatility rather than with its month-to-month fluctuations. In the present sample, monthly inflation has no detectable effect on the conditional variance, while the dominant feature of the volatility process is a downward shift in its level: average monthly inflation fell from about 0.69% in

2000–2009 to about 0.30% in 2013–2025, and the mean conditional standard deviation of JCI returns fell from about 0.072 to about 0.041 over the same periods. Whether this joint decline reflects a causal low-frequency link, or common drivers such as improved macroeconomic stability and global financial conditions, cannot be determined with the present design; a component model such as spline-GARCH or GARCH-MIDAS would be the natural way to test it.

5. CONCLUSION

Monthly Indonesian inflation shows no ARCH effects and, among the pre-specified candidates, is summarised by a parsimonious ARIMA(0,0,1) baseline model: a one-percentage-point shock raises inflation in the following month by about 0.28 percentage points, after which its direct effect ends. The residuals retain autocorrelation at seasonal lags; a better-specified seasonal extension removes it and improves forecasts without changing the substantive conclusions. JCI returns exhibit volatility clustering and fat tails and are well captured by an AR(1)–GARCH(1,1) model with Student-t errors, selected by AIC (BIC marginally prefers a constant mean with nearly identical variance dynamics), whose standardized residuals show no remaining autocorrelation or ARCH effects. Repeating model selection on the training sample yields the same specifications. Full-sample volatility persistence is high (0.985), but it is imprecisely estimated, cannot be distinguished statistically from one, and falls well below one once a downward shift in the volatility level, detected by a sup-LR test around 2010–2013, is allowed for, so the four-year half-life implied by the point estimate should not be taken literally.

No evidence of an association between monthly inflation and JCI returns or volatility is found in correlation, Granger causality, cross-correlation, threshold or GARCH-X tests, and a pooled crisis-window dummy adds no significant explanatory power once the GARCH dynamics are modelled, although episode-specific dummies show a significant decline in mean returns during the 2008 window. Descriptively, the five episodes differ in origin: the largest inflation spikes were domestic fuel-price adjustments with little equity-market impact, whereas the largest equity shocks (2008 and 2020) originated abroad and were accompanied by low inflation. Out of sample, the ARIMA(0,0,1) model forecasts inflation more accurately than the training-sample mean and comparably to AR(1) and random-walk forecasts, but less accurately than its seasonal extension, and the GARCH model forecasts volatility more accurately than a constant variance but not significantly better than EWMA or rolling-variance benchmarks.

These results have limited but concrete implications. For investors and risk managers, conditional-variance models with fat-tailed errors describe JCI risk better than constant-variance assumptions, but simple adaptive estimators perform comparably at the monthly horizon, and persistence estimates should be updated as the volatility level changes. Within this sample and specification, month-on-month headline inflation provides little information about subsequent JCI returns or volatility. Because the study uses realised headline inflation in a univariate and bivariate framework, the findings do not measure the effect of monetary policy on the stock market and should not be read as evidence about the effectiveness of particular policy instruments.

Limitations and Suggestions for Future Research

The study has several limitations. First, it uses realised month-on-month headline inflation; it does not separate expected from unexpected inflation or core from administered and volatile-food components, and it does not include other macro-financial variables such as the policy rate, the exchange rate and global risk indicators. Second, the crisis windows are dated by trigger events rather than estimated, and the sup-LR test allows for a single shift in the volatility level only; multiple-break tests (Bai & Perron, 2003), ICSS (Inclán & Tiao, 1994) or Markov-switching ARCH models (Hamilton & Susmel, 1994) could identify several volatility regimes. Third, volatility forecasts are evaluated against a squared-return proxy at the monthly frequency over 62 months, which limits the power of the comparisons; daily data and realised-volatility measures would allow sharper tests. Fourth, the residuals of the main inflation model are non-normal because of the October 2005 outlier and retain autocorrelation at seasonal lags; the seasonal robustness model addresses the latter but was

not part of the pre-specified candidate set, and the standardized GARCH residuals are negatively skewed, which a skewed Student-t distribution could accommodate. Future research could extend the analysis with survey-based inflation expectations, multivariate models such as DCC-GARCH (Engle, 2002), rolling or recursive re-estimation, and comparisons with machine-learning forecasts.

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