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Inflation Uncertainty in Indonesia: ARIMA–ARCH Evidence from an Islamic Economics Perspective

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Abstract

This study examines the persistence and conditional uncertainty of Indonesian monthly inflation using an ARIMA(2,0,0)-ARCH(1) model and frames the evidence within Islamic economics, maqashid al-sharia, and sharia-compliant risk management. Monthly inflation data from January 2006 to December 2025 are used, with 2006-2024 as the estimation sample and 2025 as the out-of-sample evaluation period. The Augmented Dickey-Fuller test confirms level stationarity. Among six non-seasonal specifications, ARIMA(2,0,0) is selected because both autoregressive coefficients are significant, the inverse roots are stable, and the AIC is the lowest. ARCH-LM confirms conditional heteroskedasticity, while ARCH(1) removes the remaining first-order ARCH effect. A Student-t distribution improves information criteria and captures fat-tailed price shocks. The 2025 evaluation reports RMSE=0,663449, MAE=0,489019, and Theil U2=0,600060, indicating that the model outperforms a naive benchmark. The Islamic economic contribution lies in interpreting inflation volatility as a risk to hifz al-mal, the real value of contracts, basic consumption, halal business continuity, Islamic banking risk, and zakat-waqf planning. Thus, the model is not merely a forecasting device, but an early-warning instrument for maslahah-oriented price stabilization.

Keywords: *ARCH, ARIMA, Inflation, Islamic Economics, Sharia Risk Management*

INTRODUCTION

Price stability is a prerequisite for sustainable economic growth because consumption, production, investment, and financial contracting decisions are shaped by expectations about the future purchasing power of money. Low but unstable inflation can impose non-trivial economic costs: households face uncertainty in their spending, firms find it difficult to set prices and wages, and the government faces pressure on subsidy spending and social protection. Within the monetary policy framework, the quality of inflation projections also determines the accuracy of interest-rate

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responses and policy communication. Inflation research therefore cannot merely explain the direction of the mean; it must also identify how uncertainty changes after a shock occurs (Tjahjono et al., 2012; Juhro & Iyke, 2019; Binder et al., 2024).

This need is even more relevant for Indonesian monthly data. Monthly inflation records the rapid response of prices to supply disruptions, administered-price adjustments, changes in distribution costs, food and energy shocks, and shifts in expectations. The monthly frequency provides more responsive information than annual data, but at the same time presents more complex statistical characteristics such as spikes, outliers, changing variance, and possible serial correlation. A model that focuses only on a constant mean risks producing inadequate standard errors and prediction intervals when calm periods alternate with turbulent ones (Engle, 1982; Francq & Zakoïan, 2019; Enow, 2023).

From a development standpoint, inflation uncertainty also has a distributional dimension. Low-income households allocate a larger share of their spending to food and basic needs and are therefore more vulnerable to sudden price changes. For businesses, especially micro and small enterprises, volatility in input prices can compress margins and increase working-capital needs. Analysis that can separate mean persistence from variance dynamics therefore adds value to the design of stabilization policy, regional price control, and expectation management.

From an Islamic economics perspective, inflation must be understood not only as an aggregate price increase but as a change in real value that can undermine the fulfillment of maqashid al-sharia. The erosion of purchasing power touches the protection of wealth (hifz al-mal), the protection of life through access to basic needs (hifz al-nafs), and distributional justice. Its impact is not neutral: poor households, fixed-income workers, micro-entrepreneurs, mustahik, and small-scale productive-financing customers find it harder to adjust their incomes than groups that hold real assets, occupy strong market positions, or can pass cost increases on to consumers.

Islamic economics does not treat every price increase as an ethical problem. Price increases arising from genuine scarcity, seasonality, distribution costs, or rising demand can be a legitimate market mechanism. However, increases amplified by hoarding (ihtikar), deception (tadlis), informational gharar, market manipulation (najasy), distribution rents, and speculation that harms the public contradict the principles of al-adl, amanah, and the prohibition against consuming others' wealth unlawfully. Inflation uncertainty is therefore not merely a statistical issue but a matter of Islamic market governance related to consumer protection, contractual justice, the continuity of halal business, and the appropriateness of socio-economic intervention.

The urgency of monthly forecasting is also evident from recent inflation developments. Statistics Indonesia recorded Indonesia's annual inflation in December 2025 at 2.92 percent. This figure remains within the 2025 inflation target range of 2.5±1 percent, yet monthly changes still display spikes that are uneven across periods. This situation underscores that annual inflation stability does not remove the need to identify short-run persistence and changing monthly uncertainty (Badan Pusat Statistik, 2026; Bank Indonesia, 2024).

Although multivariate and machine-learning models have advanced rapidly, univariate models are still needed as a transparent benchmark. ARIMA can summarize persistence and adjustment patterns from the historical information of the series itself. Its advantages are simplicity, ease of replication, and economy in data requirements. However, standard ARIMA focuses on the mean equation and often assumes a constant error variance. This assumption weakens when large residuals tend to be followed by large residuals and small residuals by small ones, a pattern known as volatility clustering. Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity model to capture the dependence of the variance on past squared shocks.

Inflation uncertainty is not solely a statistical concern. Tjahjono et al. (2012) show that inflation expectations affect actual inflation dynamics, while Afin (2023) finds links among inflation, inflation uncertainty, growth, and growth uncertainty in ASEAN-5. Modeling conditional variance can therefore enrich policy information: two periods may share the same mean projection but differ in their level of uncertainty and deviation risk. For policy communication, prediction intervals and the volatility response to shocks are as important as the point forecast.

The inflation-forecasting literature has evolved from simple autoregressive models toward large-scale structural models, forecast combinations, and machine-learning approaches. Yet international evidence shows that model complexity does not always guarantee out-of-sample superiority. Regime changes, data revisions, external shocks, and parameter instability keep inflation hard to forecast, especially at short horizons when information moves quickly (Stock & Watson, 2007; Faust & Wright, 2013; Groen et al., 2013). Transparent univariate models therefore remain important as benchmarks that can be replicated and evaluated objectively. Attention to inflation uncertainty has also grown in recent literature; Pfarrhofer (2022) emphasizes modeling uncertainty and the tail risk of inflation as an important part of contemporary inflation analysis. This recent evidence underscores that the value added of variance modeling lies in its ability to capture uncertainty, not merely in adding complexity.

In the Indonesian context, prior research has examined the roles of expectations, global uncertainty, commodity prices, and various macroeconomic predictors of inflation (Tjahjono et al., 2012; Setiastuti, 2017; Sharma, 2019; Rizvi & Sahminan, 2020). Although they enrich causal understanding, these studies do not always place conditional-variance diagnostics at the core of the forecasting design. Conversely, ARIMA-ARCH/GARCH-based studies often focus on in-sample fit, while the separation of estimation and evaluation samples, the comparison of error distributions, and the explanation of residual limitations are not always carried out consistently.

The gap addressed by this study lies on two fronts. On the econometric side, the study integrates mean-model selection, testing for ARCH effects, evaluation of ARCH(1) sufficiency, the Student-t distribution, and out-of-sample evaluation within a single transparent procedure. On the Islamic economics side, inflation studies generally still separate forecasting technique from discussions of maqashid, market ethics, and the risk management of Islamic institutions. This article connects the two: econometrically measured inflation volatility is translated into purchasing-power risk, contractual risk, halal-business risk, financing risk, and risk to the effectiveness of zakat-waqf.

Recent empirical literature in Indonesia also shows that no single specification is always dominant (Rifai & Zhahirulhaq, 2024). Saifudin et al. (2026) use an ARIMA-GARCH combination for Indonesian inflation data and stress the importance of volatility modeling; another ARIMA-GARCH study for Indonesian monthly inflation likewise concludes that heteroskedasticity in the ARIMA residuals needs to be modeled (Anisa et al., 2025; Mutiara et al., 2024). On the other hand, ARCH theory holds that a simpler model remains adequate when the variance parameter is significant and post-estimation diagnostics no longer detect any remaining ARCH effect. The relevant empirical question is therefore not whether GARCH is always better, but whether ARCH(1) is already sufficient to explain the residual-variance pattern of the chosen mean equation.

The novelty of the study is both empirical-methodological and substantive. Methodologically, the study extends the data through December 2025, distinguishes the conditional-mean problem from the conditional-variance problem, evaluates the robustness of the Student-t distribution, and tests out-of-sample performance for 2025. Substantively, the study offers a bridge between inflation-volatility modeling and Islamic economic concepts: hifz al-mal, hifz al-nafs, maslahah, al-adl, hisbah, price ethics, Islamic business continuity, Islamic banking risk, and zakat-waqf governance. The article therefore answers not only whether inflation can be forecast, but also why inflation uncertainty should be managed as a socio-economic risk within the Islamic economics and business domain.

This study positions itself as providing a simple, transparent, and easily replicable benchmark for analyzing Indonesian inflation within an Islamic economics framework. The ARIMA-ARCH model is positioned as an early-warning instrument that helps authorities, Islamic financial institutions, halal-business actors, takaful, and zakat-waqf managers read when price risk is rising. This position aligns with the fields of Islamic Economics, Islamic Business, Islamic banking, Islamic wealth management, zakat and waqf, Islamic business ethics, and sharia-compliant risk management, because its focus is on measuring price risk, protecting purchasing power, contractual stability, and designing maslahah-based responses.

Based on this background, the research questions address six issues: the stationarity of monthly inflation, the selection of the best relative ARIMA model, the presence of ARCH effects, the sufficiency of ARCH(1), out-of-sample forecast performance, and the implications for Islamic economics. These questions ensure that every model decision has a statistical basis and that every econometric finding can be read as risk information for the protection of purchasing power, Islamic business, Islamic finance, and zakat-waqf.

The objectives of the study are to: (1) test the stationarity of Indonesian monthly inflation; (2) determine the most appropriate autoregressive order among the non-seasonal candidates; (3) identify ARCH effects in the residuals; (4) assess whether ARCH(1) adequately captures conditional heteroskedasticity; (5) evaluate forecast accuracy for 2025; and (6) construct monthly inflation projections for 2026. The econometric hypothesis tested is that the mean-equation residuals contain ARCH effects before variance modeling, but that these effects are no longer significant after ARCH(1) estimation.

LITERATURE REVIEW

Inflation, Persistence, and Expectations

Theoretically, inflation can be driven by aggregate-demand pressure, rising production costs, expectations, price rigidity, the exchange rate, and commodity-price shocks. At the monthly frequency, these mechanisms cannot always be observed directly through a single variable. Their traces, however, are reflected in the persistence, reversal, outliers, and changing variance of the inflation series. Persistence indicates that past information remains relevant to current inflation, while reversal indicates a correction after a shock. Adaptive expectations and price-setting mechanisms can prolong the impact of a surprise, but policy responses and supply normalization can accelerate its dissipation (Tjahjono et al., 2012; Sharma, 2019; Boukas & Panagiotidis, 2025).

In univariate research, the linkage among variables is replaced by the linkage across periods. This does not mean that fundamental factors are ignored; rather, they are summarized in the observed stochastic process. A univariate model is more appropriately positioned as a predictive and benchmark model than as a causal one. Coefficient interpretation is therefore directed at statistical persistence and adjustment dynamics, while economic implications are discussed while acknowledging that the exchange rate, food and energy prices, fiscal policy, and expectations are not included explicitly.

Inflation from an Islamic Economics Perspective

In the Islamic economics literature, inflation can be read through four layers. The first is macroeconomic: inflation as a general price increase that reduces the purchasing power of money. The second is distributional: the shifting of real burdens across groups because their capacity to adjust incomes and prices is unequal. The third is contractual: changes in real value that can affect contractual justice, payment obligations, business margins, and financing quality. The fourth is normative-institutional: inflation as a risk to maqashid, market ethics, and the effectiveness of Islamic social institutions. Price stability is thus not merely a condition for efficiency but part of the protection of wealth (hifz al-mal), the protection of basic consumption (hifz al-nafs), and the strengthening of public maslahah (Chapra, 1992; Chapra, 2008; Dusuki & Abdullah, 2007; Ismail, 2025).

Some Muslim economists view money purely as a medium of exchange and unit of account that must not become an object of trade, whereas others stress the linkage of money to real assets and commodities such as gold and silver as a store of value (Iqbal & Mirakhor, 2011; Kahf, 2003; Ubaidillah & Anshor, 2025). This debate touches on the legal status of paper money, the relationship between money and riba, and the relevance of the al-thaman al-adl principle in setting a just price. Al-Maqrizi, for instance, linked inflation to deficit financing and currency debasement. Recent literature connects this idea to irresponsible liquidity expansion and weak monetary-governance integrity: using a VECM on Indonesian quarterly data for 2000–2024, Rusnaena et al. (2026) find that a 1 percent increase in broad money raises inflation by about 0,28 percent within three quarters, a 1 percent real exchange-rate depreciation raises inflation by about 0,19 percent, and a one-point decline in the corruption-perception index raises inflation by about ,12 percent within two quarters.

In Islamic economics, money should ideally function as a unit of account, a medium of exchange, and a store of value that supports transactional justice, rather than as a rent-bearing object traded for gains detached from the real sector. High or uncertain inflation weakens these functions because the real value of money changes without certainty. As a result, wages, savings, receivables, installment obligations, the nisab and the benefit value of zakat, the operating costs of halal MSMEs, and productive-waqf investment plans can all undergo shifts in real value. Inflation is therefore directly relevant to Islamic wealth management, social-finance planning, and the prudence of Islamic financial institutions (Iqbal & Mirakhor, 2011; Siddiqi, 2004; Ubaidillah & Anshor, 2025).

Islamic economics also distinguishes inflation arising from real factors from inflation aggravated by unethical market behavior. Price increases due to genuine scarcity, seasonal change, logistics costs, or rising demand can be understood as market signals. In contrast, increases amplified by hoarding (ihtikar), misleading information (tadlis), excessive ambiguity (gharar), demand manipulation (najasy), and control of distribution that harms society are inconsistent with the principle of justice. Hisbah, in the Islamic economic tradition, refers to the market-supervision institution operated by the muhtasib to uphold honesty in transactions, prevent fraud in measures and weights, and maintain orderly prices for the public good. Under this understanding, the hisbah tradition provides a normative basis for market supervision when freedom of transaction turns into public harm, and its idea is now reinterpreted in the modern Islamic economy. Umam (2026) shows that the classical function of hisbah remains relevant and can be adapted to technology-based sharia supervision, including in the era of blockchain and artificial intelligence, so that the principles of transactional honesty and price order can be enforced with contemporary instruments (Ibn Taymiyyah, 1976; Chapra, 1992; Umam, 2026; Nurhadi, 2023).

On this basis, ARIMA-ARCH modeling can be positioned as part of sharia-compliant risk management. ARIMA reads the direction and persistence of mean inflation, while ARCH reads when uncertainty rises after a shock. This separation matters because two months may have similar mean inflation projections yet differ in deviation risk and social impact. In the language of sharia policy, conditional-variance information helps distinguish normal conditions, alert conditions, and conditions requiring proportionate intervention to prevent wider harm.

The link between the econometric results and Islamic economics lies in the early-warning function and the design of institutional responses. When the model detects that a large shock raises the following month's variance, this information can be used to accelerate price transparency, keep distribution flowing, prevent ihtikar, construct financing stress tests, adjust programs protecting mustahik, and direct zakat, infak, sadaqah, and productive waqf to the most affected groups. Forecast accuracy is thus positioned as a means, while the ultimate goal is the protection of maslahah and economic justice.

This article sits at the intersection of macroeconomics, Islamic economics, and risk management. Inflation is chosen as the variable because price stability determines purchasing power, the real value of contracts, financing health, the continuity of halal business, and Islamic social-finance planning. By modeling inflation uncertainty, this article contributes to the study of Islamic Economics and sharia-compliant risk management, not merely to time-series forecasting technique.

Its relevance to Islamic Business is seen in the impact of price volatility on input costs, inventory strategy, business margins, and pricing ethics. Its relevance to Islamic banking and Islamic corporate finance arises because inflation can affect customers' repayment capacity, asset quality, margin expectations, financing stress tests, and the need for risk provisioning. Its relevance to zakat and awqaf arises because inflation changes the real needs of mustahik, the benefit value of social funds, and the priorities of programs protecting basic consumption. The study's results are therefore directed at reading inflation risk as a socio-economic risk that must be managed in a sharia-compliant and measurable way.

The ARIMA Model and the Box–Jenkins Principles

The Box–Jenkins framework emphasizes a cycle of identification, estimation, diagnostics, and forecasting. Initial identification proceeds through stationarity, the ACF, and the PACF; estimation then compares several candidates; diagnostics ensure that predictable patterns have been absorbed by the model; and forecasts are evaluated using data not used in estimation (Box et al., 2015; Hyndman & Athanasopoulos, 2021). This principle rejects model selection based on a single indicator. A model with a low AIC but insignificant parameters or correlated residuals is still considered inadequate.

Conditional Heteroskedasticity and the ARCH Model

The constant-variance assumption is often inappropriate for high-frequency macroeconomic data. A period with a large shock can be followed by another period with large errors, while stable times are marked by small errors. This phenomenon is called volatility clustering. Engle (1982) formalized this process through ARCH, in which the current variance depends on past squared innovations. This model allows the conditional mean to continue to follow ARIMA while the conditional variance moves according to the latest information.

ARCH(1) is chosen as the starting point because it is parsimonious and easy to interpret. A positive and significant α coefficient indicates that a large shock in the previous month raises the current month's uncertainty. An α below one indicates that the effect is not explosive. GARCH adds a lag of the conditional variance, but the additional complexity is justified only if the new coefficient is significant and the diagnostics improve (Bollerslev, 1986; Francq & Zakoïan, 2019; Enow, 2023). The parsimony principle thus remains the basis for selecting the variance equation.

The ARCH model separates the mean equation from the variance equation. In ARCH(1), the conditional variance is specified as $h_t = \omega + \alpha\varepsilon^2_{(t-1)}$, with $\omega > 0$ and $\alpha \geq 0$. The coefficient α measures how strongly the previous period's shock affects the current period's uncertainty. If $0 < \alpha < 1$, the shock effect is not explosive and gradually dies out. More complex models such as GARCH add a lag of the conditional variance, but this addition is unnecessary if ARCH(1) already removes the remaining ARCH effect (Engle, 1982; Bollerslev, 1986; Francq & Zakoïan, 2019).

Forecast Evaluation and Analytical Framework

Out-of-sample evaluation distinguishes the ability to explain historical data from the ability to predict new observations. A highly flexible model can achieve a high in-sample fit yet fail when applied to the next period. The study therefore uses 2025 as the test sample. RMSE and MAE are the main measures because inflation data can approach zero or turn negative, making percentage measures such as MAPE unstable (Hodson, 2022). Theil U2 is used to compare the model with a naive benchmark; a value below one indicates improvement relative to the benchmark.

Good forecasting must be evaluated out of sample (Makridakis et al., 2018). RMSE penalizes extreme errors more heavily, MAE measures the average magnitude of absolute errors, and Theil U2 compares the model's performance with a naive benchmark. A Theil U2 below one means the model outperforms the naive benchmark. MAPE is used cautiously because its denominator can approach zero or turn negative for monthly inflation data (Hyndman & Athanasopoulos, 2021; Hodson, 2022). International literature shows that the performance of inflation models changes over time and often weakens when the inflation process undergoes structural change or large shocks (Stock & Watson, 2007; Groen et al., 2013; Faust & Wright, 2013).

Hypotheses and Conceptual Framework

Based on the theoretical review and prior empirical evidence, this study formulates econometric hypotheses that are procedural and directly testable from the data. The hypotheses address two issues at the core of the design: the behavior of the conditional mean and the behavior of the conditional variance of monthly inflation.

Conceptually, the research framework treats monthly inflation as a stochastic process read through two channels. The first channel is the conditional mean, which captures short-run persistence and correction through ARIMA. The second channel is the conditional variance, which captures the clustering of uncertainty through ARCH. These two channels are then interpreted within an Islamic economics frame: the persistence and volatility of inflation can be interpreted as risk signals for the protection of wealth (hifz al-mal), the fulfillment of basic needs (hifz al-nafs), contractual justice, the continuity of halal business, and the effectiveness of zakat-waqf instruments. The econometric results are thus positioned as the empirical basis, while the sharia interpretation is positioned as a normative layer that is theoretical rather than causal proof.

METHOD

Data, Operational Definition, and Sample Split

The main variable is monthly inflation in percent. This definition is chosen because it captures month-to-month price changes directly and suits the needs of short-run forecasting. Using a single variable is consistent with the univariate character of the model, provided the theoretical rationale and econometric procedure are explained. The data are checked to ensure a consistent time order, no duplicate periods, and that all observations share the same monthly frequency.

The period 2006M01–2025M12 provides 240 observations, sufficient to estimate a parsimonious autoregressive model and to conduct a 12-month holdout evaluation. Splitting 2006M01–2024M12 as the estimation sample and 2025M01–2025M12 as the test sample prevents future information from entering the estimation process. After the model is selected and evaluated, the final estimation is re-run on the full data through 2025M12 to use the most recent information in the 2026 forecast.

Model Specification

The candidate mean equations include ARIMA(1,0,0), ARIMA(2,0,0), ARIMA(0,0,1), ARIMA(0,0,2), ARIMA(1,0,1), and ARIMA(2,0,1). Selection uses a combination of parameter significance, AIC, SIC, convergence, stability, and parsimony. The ARIMA(2,0,0) model can be written as $y_t = c + \varphi_1 y_{(t-1)} + \varphi_2 y_{(t-2)} + \varepsilon_t$. After an ARCH effect is detected, the conditional variance is specified as $h_t = \omega + \alpha\varepsilon^2_{(t-1)}$.

ARIMA estimation uses maximum likelihood as implemented in EViews 13. The ARCH model is also estimated by maximum likelihood with backcasting-based pre-sample variance. The Normal distribution is used as the main specification so that results can be compared directly with the base model, while the Student-t is used as a robustness test against outliers and fat tails. All models are retained only if estimation converges and the key parameters have plausible signs.

Estimation and Testing Procedure

The ADF test uses a constant and automatic lag length based on the Schwarz Information Criterion(Dickey & Fuller, 1979; Schwarz, 1978) with a maximum of 12 lags. The correlogram is examined up to lag 36. In residual diagnostics, the Ljung–Box test examines cumulative autocorrelation(Ljung & Box, 1978), while ARCH-LM tests whether squared residuals depend on past squared residuals.

Diagnostics after ARCH(1) are applied to the weighted or standardized residuals. The post-estimation ARCH-LM test assesses whether any ARCH effect remains; a probability above 0,05 indicates that the variance equation has absorbed the conditional-heteroskedasticity pattern. Normality is checked via Jarque–Bera, but a failure of normality does not automatically invalidate the model if the Student-t distribution provides a more suitable specification. In this context, the error distribution is treated as part of the robustness analysis.

The analytical stages comprise graphical inspection, the ADF test, comparison of ARIMA candidates, ARCH-LM testing, ARCH(1) estimation, the Student-t robustness test, the 2025 out-of-sample evaluation, and the reading of results within an Islamic economics framework. Decision criteria use a 5 percent significance level and the parsimony principle.

Selection Criteria and Inference Limits

The model decision is not based on adjusted R-squared alone, because that measure is not a primary criterion in time-series models. AIC emphasizes predictive ability and tends to favor a slightly more flexible model, while SIC imposes a stronger complexity penalty (Akaike, 1974; Schwarz, 1978). When AIC and SIC give different signals, parameter significance, residual diagnostics, and out-of-sample performance serve as additional deciding factors.

The study distinguishes three levels of conclusion. First, “best relative model” means the strongest among the tested candidates, not an absolutely correct model. Second, “adequate variance equation” means the post-estimation ARCH-LM is insignificant, but does not automatically guarantee that the mean residuals are white noise. Third, “forecast better than the benchmark” refers to a Theil U2 below one, and does not mean the forecast error is small in absolute terms. This distinction is needed so that interpretation does not exceed the empirical evidence.

Decision criteria use a 5 percent significance level. For the ADF test, the null of a unit root is rejected when p-value < 0,05. For Ljung–Box, the null of no autocorrelation is rejected when p-value < 0,05. For ARCH-LM, the null of no ARCH effect is rejected when Prob. Chi-Square < 0,05. The ARCH model is deemed adequate when ω and α are positive, α is significant and less than one, estimation converges, and the post-estimation ARCH-LM is insignificant.

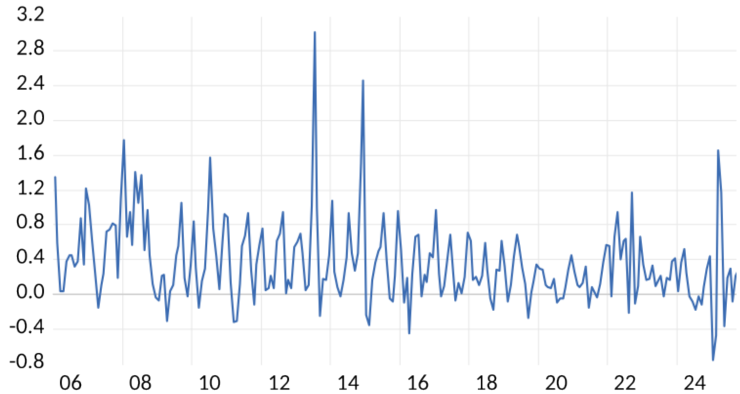
The study uses Indonesian monthly inflation data, measured in percent, covering the period from January 2006 to December 2025, yielding a total of 240 observations. The sample is divided into an estimation period from January 2006 to December 2024 and an out-of-sample evaluation period from January to December 2025. The analysis is conducted using EViews 13. The conditional mean is modeled using ARIMA(2,0,0), while an ARCH(1) specification is employed to capture conditional variance. The Normal distribution is used as the baseline specification, with the Student-t distribution applied as a robustness test to account for potential fat-tailed innovations.

RESULTS AND DISCUSSION

Preliminary Analysis and Stationarity Test

Visually at figure 1, the series exhibits several volatility regimes. Most periods show relatively limited price changes, but there are large spikes at certain points. This pattern gives an initial indication that the mean may be stable while the variance changes over time. The chart also shows no deterministic trend that steadily rises or falls. These visual findings support a formal test of stationarity at level and motivate an examination of ARCH effects after the mean equation is estimated.

Figure 1
Indonesian monthly inflation, 2006M01–2025M12



Source: authors' calculations (2026)

Outliers are not removed because they may contain relevant economic information, such as energy-price adjustments, food disruptions, or distribution shocks. Removing outliers without institutional justification can shrink the variance and produce an overly optimistic model. Instead, the study retains extreme observations and accommodates them through the variance model and a fat-tailed error distribution.

Stationarity Test Results and Implications

The d=0 decision is also consistent with the nature of inflation as the rate of change of the price index rather than the level of the price index itself. Economically, the level of the price index is usually non-stationary, whereas the inflation rate can revert to a medium-term mean. Using ARIMA(p,0,q) therefore has mutually reinforcing statistical and economic bases.

Table 2 shows that the ADF test at level yields a statistic of −11,12770 with a probability of 0,000, This value is more negative than the 1, 5, and 10 percent critical values. The null of a unit root is rejected, so inflation is stationary at level. The order of integration is therefore set at d=0 and differencing is unnecessary. The decision not to difference also avoids the risk of over-differencing, which can add noise and remove short-run dynamic information. The Augmented Dickey–Fuller (ADF) test confirms that Indonesian monthly inflation is stationary at level. The ADF test statistic of −11.12770, with a probability of 0,0000, leads to the rejection of the null hypothesis of a unit root at the 5% significance level. Using an automatically selected lag of 1 based on the Schwarz Information Criterion (SIC), the series is therefore classified as I(0), indicating that no differencing is required. Accordingly, the subsequent ARIMA specification is estimated with d = 0.

Model Selection

Identification Logic and the Parsimony Principle

A prominent PACF at the first two lags gives an initial indication of an AR(2) model, but visual identification is not treated as final. The sample ACF and PACF can be affected by outliers, sample size, and changing volatility. Six candidates are therefore estimated to see whether the theoretical pattern is supported by coefficient significance and information criteria. This comparative approach reduces the risk of choosing a model merely because a single correlogram bar appears prominent.

The parsimony principle favors the simplest model (Enders, 2015) that can summarize the essential information. Adding insignificant parameters can increase estimation uncertainty and reduce forecast performance. This is seen in ARIMA(0,0,2), ARIMA(1,0,1), and ARIMA(2,0,1), which contain insignificant parameters. These models are therefore not selected, even though some have fit measures close to the main candidate.

Comparison Results

ARIMA(0,0,1) has a slightly lower SIC than ARIMA(2,0,0), but ARIMA(2,0,0) has a smaller AIC and both AR coefficients are significant. This difference reflects a trade-off between the complexity penalty and the ability to capture two-month dynamics. In this study, ARIMA(2,0,0) is chosen as the best relative base model because of PACF support, parameter significance, the minimum AIC, root stability, and richer economic interpretation. However, this decision remains conditional on the residual diagnostics.

An adjusted R-squared of 0,182526 is not interpreted as a major weakness, because the goal of a time-series model is to produce unpredictable residuals and competitive forecasts, not to maximize explained variation. A low value can occur in monthly data containing large shocks and a random component. The next focus is therefore to test whether the model has absorbed autocorrelation and whether the residual variance is constant.

Table 1 shows ARIMA(2,0,0) yields an AIC of 1,050137, the lowest among the base candidates. AR(1) and AR(2) are significant, the model converges, and the autoregressive roots are stable. This model is therefore selected as the best relative base model, even though the SIC of ARIMA(0,0,1) is slightly lower.

Table 1
Comparison of Non-Seasonal Candidate ARIMA Models

Model	Sig.	AIC	SIC	Decision
ARIMA(1,0,0)	AR(1)	1,086	1,131	No
ARIMA(2,0,0)	AR(1), AR(2)	1,050	1,110	Selected
ARIMA(0,0,1)	MA(1)	1,058	1,103	Alternative
ARIMA(0,0,2)	MA(1)	1,060	1,121	No
ARIMA(1,0,1)	MA(1)	1,063	1,123	No
ARIMA(2,0,1)	Not strong	1,058	1,134	No

Source: authors' calculations (2026).

Estimation Results

Estimation of the ARIMA(2,0,0) Mean Equation

Table 2
Estimation of ARIMA(2,0,0) on The 2006M01–2024M12 Sample

Parameter	Coefficient	Prob.	Interpretation
C	0,371072	0,0000	Positive conditional mean
AR(1)	0,480921	0,0000	Positive one-month persistence

AR(2)	-0,211090	0,0006	Negative correction in the second month
SIGMASQ	0,161382	0,0000	Residual variance
AIC / SIC	1,050137 / 1,110301	-	Best relative information criterion

Source: authors' calculations (2026).

The estimated equation at table 2 shows two response phases. In the first month, about 0,481 of a shock is passed through to current-month inflation. In the second month, the negative coefficient of −0,211 indicates a correction that restrains the shock's persistence. Based on the AR(2) recursion, the response to a one-unit innovation falls from 1 at the moment of the shock to about 0,481 in the first month, about 0,020 in the second month, and near zero after a few months. This pattern describes a damped oscillation: inflation has short-run memory, but mean shocks do not persist permanently (Castelnuovo, 2023).

Economically, these dynamics are consistent with a transmission process that is rapid and then followed by normalization. A price increase can immediately affect expectations and price-setting in the next month, but supply responses, demand adjustments, or stabilization policy can produce a correction in the second month. Because the model is univariate, the specific mechanism cannot be identified causally; this interpretation should be understood as an explanation consistent with the statistical pattern.

The model yields an AIC of 1,050137, an SIC of 1,110301, a log-likelihood of −115,7156, and a Durbin–Watson of 2,005831. A Durbin–Watson near two is an initial indication but does not replace the Ljung–Box test. The inverse roots of 0,24±0,39i lie inside the unit circle, so the mean process is stable and the effect of shocks does not grow without bound.

Table 3
ARCH-LM(1) Results for ARIMA(2,0,0) Residuals

Statistic	Value	Prob.	Decision
F-statistic	12,39495	0,0005	ARCH effect present
Obs*R-squared	11,85221	0,0006	Rejects H0 of conditional homoskedasticity
RESID2(-1)	0,227604	0,0005	Squared residual at lag 1 is significant

Source: authors' calculations (2026).

Table 3 shows that the ARCH-LM test is applied to the ARIMA(2,0,0) residuals, so the result assesses variance dynamics not yet explained by the mean equation. The $RESID^2(-1)$ coefficient of 0,227604 and probability of 0,0005 indicate that the squared error of the previous month has predictive power for the current squared error. In other words, the magnitude of uncertainty does not spread randomly but clusters over time.

This finding matters because homoskedastic standard errors can understate risk in turbulent periods and overstate it in calm periods. ARCH(1) is therefore chosen to form prediction intervals that depend on the latest information. This step is not intended to "correct" the autocorrelation of the mean equation but to model the conditional variance separately.

The Obs*R-squared probability of 0,0006 is smaller than 0,05. The null of no ARCH effect is therefore rejected. The current period's residual variance is influenced by the previous period's squared residual. This result provides a statistical basis for estimating ARCH(1); variance modeling is not merely a methodological add-on but a response to the violation of the conditional-homoskedasticity assumption.

Estimation of ARIMA(2,0,0)-ARCH(1)

Table 4
Estimation of ARIMA(2,0,0)-ARCH(1), Normal Distribution

Component	Parameter	Coefficient	Prob.	Meaning
Mean	C	0,342603	0,0000	Conditional mean
Mean	AR(1)	0,636979	0,0000	Inflation persistence
Mean	AR(2)	-0,183538	0,0073	Second-lag correction
Variance	omega	0,088957	0,0000	Positive baseline variance
Variance	alpha	0,436432	0,0000	Shocks raise the variance

Source: authors' calculations (2026).

Table 4 shows equation parameters remain significant after the conditional variance is modeled. The AR(1) coefficient rises to 0,636979, while AR(2) remains negative at −0,183538. This shows that ignoring conditional heteroskedasticity can affect the magnitude of the estimated persistence, even though the direction of the relationship stays the same.

The ARCH(1)-Normal model yields an AIC of 0,846694, an SIC of 0,922370, a log-likelihood of −90,67642, and converges after 13 iterations. The decline in information criteria relative to the mean model shows that the variance dynamics carry relevant information, although information criteria across methods should be interpreted together with the residual diagnostics.

Table 5
Comparison of Error Distributions for The ARCH(1) Model

Indicator	ARCH(1)-Normal	ARCH(1)-Student-t	Implikasi
AIC	0,846694	0,786317	Student-t is lower
SIC	0,922370	0,877128	Student-t is lower
log-likelihood	−90,67642	−82,85386	Student-t is higher
ARCH coefficient	0,436432 (p=0,0000)	0,317073 (p=0,0423)	Remains positive and significant
Degrees of freedom	–	3,698478 (p=0,0040)	Fat distribution tail

Source: authors' calculations (2026).

Table 5 shows that the normal distribution assumes a relatively small probability of extreme events, whereas the inflation data show higher skewness and kurtosis. The Student-t places greater probability in the distribution's tails and is therefore more robust to outliers. Degrees of freedom around 3.70 indicate tails far fatter than the Normal. Because AIC and SIC decline, the robustness test supports the conclusion that a fat-tailed error specification is more suitable for inference and risk intervals.

Although the Student-t provides a better fit, the main model is discussed consistently as ARIMA(2,0,0)-ARCH(1). The choice of distribution does not change the mean and variance structure but affects the likelihood, standard errors, and the width of the prediction interval. In a journal article, the Student-t result should be retained as a robustness test, or even as the final model if its re-forecasting and diagnostics are also better.

The Student-t specification gives lower AIC and SIC and a higher log-likelihood. The significant degrees of freedom of 3.698478 indicate that the innovation distribution has fatter tails than the Normal. This finding is consistent with the data chart, which shows several extreme shocks. The Student-t is therefore stronger as a distributional robustness test. However, the available 2026 projection output comes from the ARCH(1)-Normal estimation on the full sample; this distinction is stated explicitly so that the results can be replicated and output sources are not mixed.

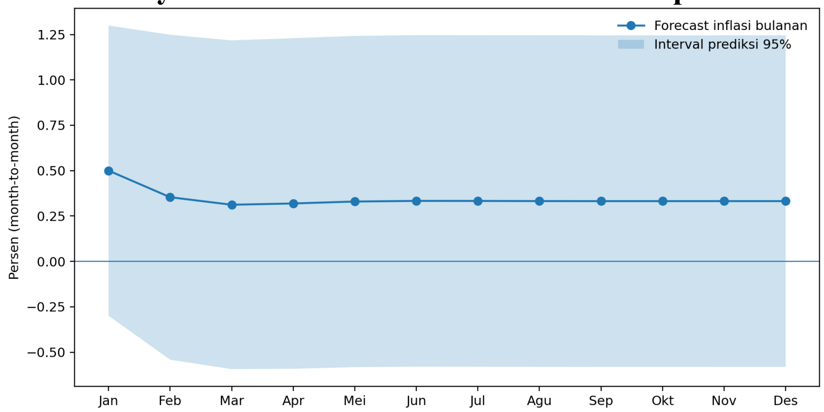
Table 6
Evaluation of The 2025 Inflation Forecast

Measure	Value	Interpretation
RMSE	0,663449	Root mean squared error; sensitive to large errors
MAE	0,489019	Mean absolute error
MAPE	111,1874	Unstable when actual values approach zero/negative
SMAPE	106,1778	Symmetric percentage; still sensitive to small values
Theil U1	0,672306	Closer to zero is better
Theil U2	0,600060	Below one; outperforms the naive benchmark

Source: authors' calculations (2026).

The 2025 evaluation is important because all test observations lie outside the estimation sample. Table 6 shows that the theil U2 of 0,600060, it shows that the model outperforms the naive benchmark, while RMSE and MAE still remind us that accuracy is not perfect. However, an RMSE of 0,663449 and MAE of 0,489019 still indicate room for improvement. MAPE is not used as the main basis because monthly inflation can be very small or negative. This evaluation supports using the model as a benchmark but does not justify a claim of high absolute accuracy. The corresponding forecast is presented in Figure 2.

Figure 2
Indonesian monthly inflation forecast for 2026 and 95% prediction interval



Source: authors' calculations (2026).

Diagnostic Tests

Correlogram of the Mean-Equation Residuals

Table 7
Ljung–Box Diagnostics for ARIMA(2,0,0) Residuals

Lag	Prob. Q-statistic	Decision
3	0,565	No cumulative autocorrelation
4	0,818	No cumulative autocorrelation
5	0,216	No cumulative autocorrelation
6	0,024	Autocorrelation becomes significant
12	0,000	Significant autocorrelation
24	0,000	Significant autocorrelation
36	0,000	Significant autocorrelation

Source: authors' calculations (2026).

The Ljung–Box test at table 7 examines the joint hypothesis that all autocorrelations up to a given lag are zero. Because it is cumulative, small probabilities at lags 12, 24, and 36 mean there is serial information still remaining in the residuals. A Durbin–Watson near two is not sufficient to conclude the absence of autocorrelation, because that statistic is mainly sensitive to first-order autocorrelation and does not replace the correlogram.

This is the most important limitation. Residual autocorrelation that becomes significant at lag 6 and strengthens at lags 12, 24, and 36 indicates a dynamic structure not yet fully captured by ARIMA(2,0,0). For monthly inflation over 2006–2025, this pattern very likely arises from a seasonal component or structural breaks, for example due to administered-price adjustments or food and energy shocks. The model is therefore positioned as the best relative non-seasonal benchmark among the tested candidates, not as a perfect conditional-mean specification. This limitation provides the basis for extending the model in future research, for example through a seasonal component (SARIMA), structural-break testing, the addition of interventions, or exogenous variables.

Variance Diagnostics After ARCH(1)

Table 8
ARCH-LM After ARCH(1) Estimation

Statistic	Value	Probability	Conclusion
F-statistic	1,587749	0,2090	No remaining ARCH effect
Obs*R-squared	1,590664	0,2072	Fails to reject H0
WGT_RESID²(−1)	0,084126	0,2090	Not significant

Source: authors' calculations (2026).

As shown in Table 8, the post-estimation test uses WGT_RESID² at table 8, the squared residual weighted by the conditional variance. The lag coefficient of 0,084126 is insignificant, indicating no remaining first-order ARCH dependence after estimation. The comparison before and after estimation from a p-value of 0,0006 to 0,2072 is the main evidence that ARCH(1) successfully absorbed the conditional heteroskedasticity at the tested order.

The conclusion that "ARCH(1) is sufficient" is limited to first-order variance diagnostics. That is, there is no pressing empirical reason to add GARCH merely for complexity. However, a final journal decision should ideally also consider the correlogram of standardized squared residuals across lags, the stability of results under the Student-t distribution, and relative forecast performance.

The Chi-Square probability of 0,2072 is greater than 0,05. The null of no remaining ARCH effect is not rejected. ARCH(1) therefore successfully captures the first-order variance dependence that was previously significant. This evidence is the main basis for concluding that ARCH(1) is sufficient in the tested specification and that extension to GARCH is not mandatory.

Discussion

A positive AR(1) coefficient indicates short-run inflation momentum, while a negative AR(2) indicates a correction in the second month. From an Islamic economics perspective, this correction lag matters because the purchasing power of vulnerable groups can be squeezed before prices return to normal.

This result is consistent with the character of Indonesian inflation, which is influenced by temporary shocks to food, energy, distribution, and administered prices. Because the data are univariate, the finding is read as a stochastic pattern and an early-warning benchmark, not as a causal identification of inflation sources.

The first finding is very short-run inflation persistence followed by correction. This means price stabilization must be responsive in the early months after a shock so that risks to hifz al-mal and basic consumption do not grow.

The ARCH effect shows that inflation uncertainty has memory: large shocks tend to raise risk in the following period. This information is relevant to sharia-compliant risk management because it helps Islamic financial institutions, halal MSMEs, and zakat-waqf institutions anticipate price pressure.

A moderate α below one indicates that variance shocks dissipate relatively quickly, unlike a highly persistent volatility process. This finding explains why ARCH(1) can suffice in a limited specification: the main information comes from the previous month's squared error, while additional variance lags are not shown to be necessary based on the available output. This principle is consistent with parsimony and avoids overparameterization.

The second finding is strong conditional heteroskedasticity before variance modeling. An ARCH-LM of 0,0006 shows that error magnitude is not random over time but is influenced by the previous month's squared error. The ARCH coefficient of 0,436432 shows a meaningful but not highly persistent transmission of uncertainty. After one month, the effect of a squared shock is still about 43,6 percent; after two months it is about 19 percent. This result carries the policy message that price-shock episodes must be monitored promptly, because uncertainty is greatest at the near horizon rather than spreading without bound.

The Sufficiency of ARCH(1) and Methodological Implications

The change in the ARCH-LM p-value from 0,0006 before estimation to 0,2072 after estimation is a key diagnostic result. This evidence is more important than a mere decline in AIC because it shows that the pattern motivating the use of ARCH has been successfully captured. The choice of ARCH(1) is therefore not a normative decision but one based on a diagnosis–estimation–re-diagnosis sequence.

Even so, the model cannot be claimed to be perfect. Autocorrelation in the standardized residuals shows that the conditional mean still leaves a pattern. This underscores the importance of distinguishing the success of the variance equation from the adequacy of the overall model. Many applied studies fail to make this distinction and conclude that a model is "good" merely because ARCH-LM is insignificant after estimation. This study explicitly retains that limitation in its conclusion.

The third finding is the sufficiency of ARCH(1) in the chosen specification. The post-estimation ARCH-LM yields a probability of 0,2072. Additional variance lags as in GARCH are therefore unnecessary merely to make the model more complex. This result differs from Saifudin et al. (2026), who selected an ARIMA-GARCH structure for a different period and specification; conversely, Anisa et al. (2025) obtained a GARCH(0,1) variance structure that contains no conditional-variance lag and is therefore practically consistent with the ARCH(1) sufficiency found here. These differences need not be seen as a contradiction; the order of the conditional variance is data-dependent and is influenced by the definition of inflation, the sample range, the mean equation, the error distribution, and the testing design. The contribution of this study is to show that a more parsimonious model can be adequate when its success is demonstrated through post-estimation diagnostics.

The superiority of the Student-t shows that large inflation shocks are not events that can be ignored. A fat-tailed distribution is more realistic when there are administered-price changes, supply disruptions, or policy episodes that produce extreme observations. In inference, using the Student-t can prevent the model from understating the probability of extreme events and can provide more appropriate standard errors.

This result is also consistent with the volatility literature, which recommends a non-Normal distribution when residual kurtosis is high (Tsay, 2010; Francq & Zakoïan, 2019), and aligns with the recent literature's emphasis on measuring uncertainty and the tail risk of inflation. Pfarrhofer (2022), tracing the quantiles of the inflation distribution in the United States, the United Kingdom, and the euro area through an unobserved-component quantile regression model, finds that the predictive distribution of inflation is sometimes skewed and occasionally fat-tailed, so that models accounting for conditional volatility perform better, especially for higher-order and tail forecasts. That finding reinforces the choice of the Student-t distribution in this study as an anticipation of extreme events that the Normal assumption tends to understate. However, distributional comparison should not stop at AIC and SIC; further research should produce Student-t forecasts on the same evaluation sample to assess whether the likelihood fit truly translates into improved forecast accuracy.

The fourth finding is the presence of fat tails. The Student-t distribution yields lower AIC and SIC and degrees of freedom around 3.70. This indicates that the probability of extreme shocks is greater than the Normal distribution assumes. Economically, fat tails are relevant for Indonesian inflation because changes in tariffs, energy prices, weather, distribution disruptions, and food volatility can create extreme observations. Rizvi and Sahminan (2020) show the importance of global commodity prices for the inflation dynamics of developing countries, while Setiastuti (2017) shows that global uncertainty can alter the response of Indonesian macro variables. Risk scenarios should therefore not be built from Normal deviations alone.

Forecast Performance and Comparison with the Literature

Out-of-sample performance conveys two messages. First, a Theil U2 below one proves that the model has predictive value relative to the naive benchmark. Second, the errors that still arise require using the model as a benchmark rather than the sole basis for policy.

In the Indonesian context, more complex models can be used to enrich the analysis, but a simple benchmark is still needed so that the performance of more advanced models can be compared objectively. Comparison with recent studies clarifies this position. Anisa et al. (2025), using Indonesian monthly inflation data for March 2007–October 2023, obtained a final ARIMA(2,0,2)-GARCH(0,1) model with a MAPE of 17.78 percent, classified as accurate; interestingly, the best variance structure they selected, GARCH(0,1), is practically equivalent to ARCH(1) because it contains no conditional-variance lag. Saifudin et al. (2026) also chose an ARIMA-GARCH structure for a different sample range. A parallel line of Indonesian work compares volatility models with machine-learning alternatives (Mutiara et al., 2024), reporting that nonlinear methods can lower point-forecast error while variance models remain valuable for reading uncertainty; this reinforces the role of the present model as a transparent benchmark rather than a rival to richer specifications. This study, with a different period and mean equation, shows that ARCH(1) is already adequate in the tested specification. This difference underscores that the order of the conditional variance is data-dependent, not a contradiction. Herein lies the value of ARIMA-ARCH as a benchmark: transparent, replicable, and easily linked to inflation-risk signals.

The fifth finding concerns forecast quality. A Theil U2 of 0,600060 indicates an improvement relative to the naive benchmark, but autocorrelation in the mean residuals limits any claim that the specification is fully final.

In the context of the inflation target, monthly projections should be understood as an indication of direction and risk rather than a numerical certainty. The width of the prediction interval underscores the importance of policy scenarios for handling possible price spikes.

The study's substantive contribution lies in the traceability of its econometric decisions and their integration with Islamic economics. The model signals when price risk rises and when maslahah-based intervention should be strengthened.

Integrating the Econometric Findings with Islamic Economics and Sharia Risk Management

The ARIMA-ARCH findings show that Indonesian monthly inflation contains two problems relevant to Islamic economics: short-run persistence and conditional uncertainty. AR(1) persistence shows that a one-month price increase can carry over to the next month, while a negative AR(2) shows a correction. From a maqashid perspective, this pattern can be interpreted as an important issue because household income, social assistance, the benefit value of zakat, and micro-enterprise revenues do not always adjust as quickly as prices. Such adjustment delays can potentially reduce purchasing power and weaken hifz al-mal and access to basic consumption. This interpretation is theoretical and is not empirically proven by the univariate model used.

A significant ARCH effect before variance modeling shows that large price shocks do not stand alone but raise the uncertainty risk of the following period. From a sharia standpoint, this condition can potentially increase harm because vulnerable households, halal MSMEs, microfinance customers, and Islamic social institutions must make consumption, production, payment, and aid-distribution decisions under changing price information. ARCH(1) is therefore read not only as a variance model but as an indicator of when price risk should be addressed through market coordination, consumer protection, anti-ihtikar supervision, and Islamic social instruments.

The Student-t outperforming the Normal reinforces the argument that extreme events must enter policy design. In Islamic economics, stabilization policy cannot merely pursue a low average inflation; it must also anticipate fat-tail risk, namely rare price spikes with large impacts on the poor. Relevant instruments include price transparency, modern hisbah supervision, smooth logistics, food aid, prudent emergency microfinance, social takaful, and the optimization of zakat-waqf to protect basic consumption.

The results can therefore be interpreted as initial support for a sharia-grounded approach to price stability, although this linkage still needs to be tested directly. ARIMA(2,0,0) helps read inflation momentum and correction, while ARCH(1) helps read uncertainty risk after a shock. This combination can be positioned as an early-warning system for authorities, Islamic financial institutions, halal business, takaful, and Islamic social institutions. However, because the model is univariate, a sharia assessment of inflation sources still requires additional data on food, energy, the exchange rate, distribution, market behavior, expectations, and government policy.

Table 9

Links Between The ARIMA-ARCH Results and The Islamic Economics and Business Domains

Empirical result	Risk meaning	Islamic-economics linkage	Research domain
Inflation stationary at level	Monthly inflation fluctuates around its mean but still contains shocks	Price stability is read as part of maslahah and the protection of purchasing power	Islamic Economics
Positive AR(1) and negative AR(2)	One-month persistence followed by correction	Delayed correction can pressure the hifz al-mal of vulnerable households and small businesses	Islamic Business; Islamic wealth management
ARCH-LM significant and ARCH(1) adequate	Large shocks raise uncertainty in the following period	Conditional variance signals risk for price intervention, microfinance, and social assistance	Sharia-compliant risk management; Islamic banking; takaful

Student-t outperforms Normal	The probability of extreme events is higher than the Normal assumption implies	Policy should anticipate extreme price spikes through anti-ihtikar measures, logistics, zakat, and productive waqf	Zakat and waqf; Islamic business ethics
Theil U2 below one	The model has predictive value relative to the naive benchmark	Forecasts can serve as an early-warning aid, not a substitute for policy ijtihad and sectoral data	Islamic Economics; risk management

Source: authors' calculations (2026)

Policy and Practical Implications

Authorities should monitor the conditional variance after a price shock, because the greatest uncertainty effect appears in the following one to two months. Point forecasts should always be accompanied by prediction intervals. A stable mean projection is not identical to low risk.

ARIMA-ARCH can be used as a quick benchmark for comparing the results of structural models, expectation surveys, and policy considerations. A fat-tailed distribution supports the use of stress scenarios for food, energy, administered prices, and distribution disruptions. Because a univariate model is not a causal model, operational policy decisions must combine information on the exchange rate, commodity prices, expectations, interest rates, and fiscal conditions.

From an Islamic economics perspective, price-stabilization policy should be directed at five levels. First, the market level, through price transparency, anti-ihtikar supervision, improved distribution, prevention of information asymmetry, and enforcement of Islamic business ethics. Second, the household level, through protecting the purchasing power of vulnerable groups when inflation variance rises. Third, the Islamic business level, through pricing-ethics guidelines, inventory management, halal supply-chain efficiency, and safeguarding MSME continuity. Fourth, the Islamic financial-institution level, through financing stress tests, mapping of repayment-capacity risk, and risk-reserve planning consistent with prudential principles. Fifth, the Islamic social-finance level, through sharpening the targeting of zakat, infak, sadaqah, and productive waqf during high-volatility periods.

Zakat institutions, waqf managers, Islamic financial institutions, takaful, and local governments can use inflation-volatility information as a basis for timing interventions. When the model shows rising uncertainty, food-aid programs, emergency microfinance, social takaful, productive food waqf, well-targeted distribution subsidies, and transparent price education can be prioritized. Forecast results therefore do not end as statistical output but become inputs to maslahah governance that is measurable, auditable, and relevant to the scope of Islamic economics and business.

CONCLUSION

This study separates the mean and variance dynamics of Indonesian monthly inflation through a staged time-series procedure. In brief, inflation is shown to be stationary at level; the best relative mean specification among the tested non-seasonal candidates shows short-run persistence followed by correction; and its residuals contain conditional heteroskedasticity that is successfully absorbed by a first-order variance equation. The robustness test shows that a fat-tailed distribution is more suitable for describing extreme events, while the out-of-sample evaluation shows performance superior to the naive benchmark.

The synthesis of these findings points to one main message: in monitoring inflation, the uncertainty that changes over time is as important as the direction of the mean. Price shocks tend to raise risk in the nearest period, so point forecasts must always be read together with their intervals. The ARIMA-ARCH model is positioned as a parsimonious, transparent, and easily replicable early-warning instrument, not as a causal model or a perfect specification.

From an Islamic economics perspective, these results can be interpreted as risk signals for the protection of wealth (hifz al-mal), the fulfillment of basic needs (hifz al-nafs), contractual justice, the continuity of halal business, and the effectiveness of zakat-waqf instruments. This interpretation is theoretical because the study uses only the inflation variable; it guides, rather than replaces, further empirical study of inflation sources. When uncertainty rises, maslahah-oriented policies such as price transparency, anti-ihtikar supervision, smooth distribution, consumer protection, and the strengthening of zakat and waqf can potentially reduce harm to vulnerable groups.

This study has several limitations. The model is univariate and therefore does not explain inflation sources causally; the mean residuals are not entirely free of autocorrelation at some horizons, leaving open the possibility of an unaccommodated seasonal component or structural change; and the evaluation uses only a single holdout year. The further agenda includes adding exogenous variables, testing for a seasonal component and structural breaks, comparing error distributions on the same evaluation sample, and more formal forecast testing. Within this framework, the evidence on inflation volatility can be developed into a price-stabilization agenda aligned with maqashid and the scope of Islamic economics and business.

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