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Conditional Volatility and Risk in the Return Series of Coffee Prices in Paraná

Volatilidade condicional e risco na série de retornos dos preços do café no Paraná

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ABSTRACT
This study analyzes the risk associated with fluctuations in the return series of coffee prices in the state of Paraná, using the real price series of unprocessed coffee beans received by producers from July 1994 to December 2025. The prices were initially deflated and subsequently transformed into returns, which were modeled using univariate conditional volatility models from the ARCH family. Among the estimated specifications, the GARCH ((1,1)) and EGARCH ((1,1)) models provided the best fit to the data. The estimated conditional volatility was then used to compute the Value at Risk (VaR), allowing for the measurement of price risk faced by producers. The results indicate a high degree of volatility persistence, suggesting that shocks in coffee prices tend to have long-lasting effects. The EGARCH ((1,1)) model further revealed the presence of asymmetry in volatility, indicating that positive and negative shocks affect variance differently. The VaR estimates obtained from both models were similar, pointing to a significant level of price risk in the coffee market of Paraná. Backtesting results confirmed the strong predictive performance of the models, reinforcing their usefulness as tools to support risk management and decision-making in the coffee sector. These metrics also enable firms to better manage their operations, as knowledge of the estimated maximum potential loss allows rural enterprises to maintain adequate capital reserves to meet financial obligations, such as loan repayments and input purchases.
Keywords: Prices; Returns; Risk.

RESUMO
O artigo analisa o risco associado às oscilações da série de retornos dos preços do café no estado do Paraná, utilizando a série de preços reais do quilo do café em coco recebidos pelos produtores entre julho de 1994 e dezembro de 2025. Os preços foram inicialmente deflacionados e, em seguida, convertidos em retornos, os quais foram modelados por meio de modelos univariados de volatilidade condicional da família ARCH. Entre as especificações estimadas, os modelos GARCH (1,1) e EGARCH (1,1) apresentaram melhor ajuste aos dados. A volatilidade condicional estimada foi empregada no cálculo do Value at Risk (VaR), permitindo mensurar o risco de preço enfrentado pelos produtores. Os resultados indicaram elevada persistência da volatilidade, evidenciando que choques nos preços do café tendem a produzir efeitos duradouros. O modelo EGARCH (1,1) revelou ainda a presença de assimetria na volatilidade, indicando que choques positivos e negativos afetam a variância de forma distinta. As estimativas de VaR obtidas pelos dois modelos foram semelhantes, apontando para um nível significativo de risco de preço no mercado cafeeiro paranaense. Os testes de backtesting confirmaram o bom desempenho preditivo dos modelos, reforçando sua utilidade como ferramentas de

apoio à gestão de risco e à tomada de decisão no setor cafeeiro. Com essas métricas a empresa poderá gerenciar melhor seu negócio. Por exemplo, sabendo-se a perda potencial máxima estimada pelos modelos estudados, a empresa rural poderá manter reservas de capital adequadas para honrar compromissos financeiros, como empréstimos e compra de insumos.

Palavras-chave: Preços, Retorno, Risco.

1INTRODUCTION

Monitoring and evaluating the behavior of agricultural prices plays a fundamental role in the management of rural activities. Understanding price fluctuations enables producers to more accurately estimate production profitability and to identify financial risks associated with adverse movements in both product prices and input costs (Araujo et al., 2012).

According to Campos (2007), analyzing price behavior is essential for business planning and decision-making in agricultural activities, as it directly influences the selection of economic opportunities. Producers' decisions are closely related to profitability expectations and price fluctuations, while the relationship between input prices and final product prices guides the adoption of technologies.

The relevance of studies on international agricultural and energy commodity markets has increased substantially in light of the heightened price volatility observed in recent years. Recent events, such as the COVID-19 pandemic in 2020, Russia's invasion of Ukraine in 2022, and adverse climatic conditions, have intensified fluctuations in agricultural markets.

These developments have disrupted global supply chains, particularly affecting the availability of key inputs such as fertilizers exported by Ukraine and Russia, thereby impacting the production and supply of several agricultural commodities worldwide, including soybeans, corn, wheat, and meat.

In this context of heightened uncertainty, analyzing risk and developing appropriate methods to measure it becomes essential for market participants, as it allows for a more accurate assessment of market conditions and supports more informed economic decision-making.

Thus, by analyzing the conditional volatility and risk arising from fluctuations in the return series of coffee prices in the state of Paraná, this study contributes to a better understanding of price formation and the risks faced by producers in the region, providing relevant insights for public policy formulation, risk management strategies, and decision-making processes within the coffee production chain.

Arêdes (2013) highlighted the application of Value at Risk (VaR) as a tool to support risk management in agricultural commercialization. According to the author, risk management plays a strategic role in the agricultural sector by contributing to the mitigation of financial losses, promoting more efficient use of productive resources, and reducing the exposure of rural enterprises to adverse outcomes.

Within this framework, the research question guiding this study is: what is the behavior of the conditional volatility of the return series of coffee prices in the state of

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Paraná, and what is the level of risk associated with these price fluctuations, as measured by VaR? The hypotheses to be tested are: (i) the volatility of coffee prices in the state of Paraná exhibits persistent and asymmetric behavior, which can be adequately captured by ARCH family models; and (ii) ARCH family models demonstrate satisfactory predictive performance in estimating the VaR of coffee price returns, as evidenced by backtesting results.

Accordingly, the objective of this study is to analyze the conditional volatility of the return series of coffee prices in the state of Paraná over the period from July 1994 to December 2025 and, based on this estimation, to compute the Value at Risk (VaR) metric. To this end, univariate conditional volatility models belonging to the ARCH family are employed. The volatility estimated by these models is used to calculate the VaR of coffee price returns, considering confidence levels of 90%, 95%, and 99%. Subsequently, the adequacy and predictive performance of the VaR estimates are evaluated through backtesting procedures.

2. MATERIALS AND METHODS

2.1. Literature Review

Food price instability is recognized as a global challenge, affecting both developed and developing countries, although its impacts are more severe in more vulnerable economies. In this context, understanding price volatility behavior is essential for policymakers to implement measures at both national and international levels aimed at reducing abrupt fluctuations, monitoring price trends, and protecting populations most exposed to such variations (Hefnawy & Shaker, 2021).

The analysis of volatility in agricultural commodity price returns has largely been conducted through the use of Autoregressive Integrated Moving Average (ARIMA) models, proposed by Box and Jenkins (1976), in conjunction with models from the Autoregressive Conditional Heteroskedasticity (ARCH) family, introduced by Engle (1982), which are widely employed to capture volatility dynamics in time series.

Within this field, Arêdes and Pereira (2008) analyzed the behavior of wheat price series in the state of Paraná from June 1994 to September 2007. Using the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, the authors found that the price series exhibited a high level of volatility and strong persistence of shocks over time.

Lordemann et al. (2021) applied the GARCH model to estimate the conditional volatility of green coffee price returns across three markets: spot, futures, and physical. The results indicated that volatility follows a GARCH (1,1) process and that speculation in the futures market contributes to reducing price volatility.

Hefnawy and Shaker (2021) investigated wheat price volatility in the global commodity market from January 1960 to December 2019 using models from the GARCH family. Among the tested specifications, the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model provided the best fit to the data. The findings revealed the presence of volatility asymmetry, indicating that positive shocks exert a stronger impact on variance than negative shocks. Moreover, these shocks were found to be persistent, influencing volatility over an extended period.

Revista Conhecimento Contábil
DOI:
ISSN: 2447 - 2921

A study conducted by Kacperska et al. (2025) examined the volatility of wheat and corn prices in the European market between December 2021 and May 2024. Using the GARCH model, the authors identified high levels of volatility in these markets. The study aimed to assess whether the Grain Agreement contributed to price stabilization. The results indicated that uncertainty related to international grain trade conditions maintained market instability, generating persistent volatility shocks.

Silva (2020) emphasizes that volatility constitutes a relevant measure of risk for commodities, as it reflects the intensity of price fluctuations over time. According to the author, volatility modeling relies on the use of historical information to anticipate the future behavior of this variable. The author also highlights that financial series may exhibit asymmetric volatility behavior.

Silva et al. (2005) analyzed the volatility of coffee and soybean returns using conditional volatility models from the ARCH family. Silva (2020) examined the conditional volatility of spot price returns for live cattle in the state of São Paulo using ARCH family models. Other studies have also employed such models, including Campos (2007), who analyzed the dynamics of conditional volatility in soybean, coffee, corn, and live cattle prices; Pereira et al. (2010), who analyzed the conditional volatility of returns for coffee, soybean, and live cattle prices and, based on the estimated volatility, calculated the Value at Risk (VaR) for these commodities; and Rodrigues (2020), who investigated the presence of leverage effects and volatility asymmetry in coffee prices in the Brazilian market.

The Value at Risk (VaR) method constitutes one of the most widely used measures for quantifying market risk in the financial domain, being applied to the evaluation of assets such as investments, stocks, derivatives, and commodities. This metric allows for the estimation of the maximum expected loss of an asset or portfolio over a given time horizon, considering a specified confidence level (Jorion, 2003).

According to Hussaina and Precilla (2025), VaR models are important tools for risk assessment in commodity market operations. They enable the estimation of potential losses associated with positions held by investors, such as traders and asset managers. In agricultural commodity futures markets, price fluctuations may lead to substantial gains but also significant losses. Therefore, understanding market conditions is essential for more efficient investment management.

The study by Azmi et al. (2022) analyzed investment risk in three agricultural commodities—wheat, cocoa, and cotton—using Value at Risk (VaR) and Expected Shortfall (ES) measures. Daily price data from 2017 to 2020 were employed, with time series models applied, including ARIMA for the mean equation and GARCH for volatility. The results indicated that risk levels varied across the analyzed commodities. According to VaR, cotton exhibited the lowest risk and cocoa the highest, whereas ES produced different results, identifying cocoa as the least risky asset and cotton as the most risky.

In another study, Conte et al. (2020) analyzed short-term volatility of sugar, coffee, soybean meal, and soybean oil in both Brazilian and global markets. The authors employed GARCH, GJR, and EGARCH models, as well as a Vector Autoregression (VAR) model. The results showed that coffee exhibited the highest volatility in the global market, while in Brazil, sugar was identified as the most volatile commodity with the

Revista Conhecimento Contábil
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ISSN: 2447 - 2921

highest seasonality. Additionally, the Brazilian markets for coffee and soybean meal were found to be influenced by global markets, whereas for sugar, soybean oil, and soybeans, volatility risks were specific to each market.

2.2. Autoregressive and Conditional Volatility Models

Proposed by Box and Jenkins (1976), the Autoregressive Integrated Moving Average model, commonly referred to as ARMA (Autoregressive Moving Average), is employed in the modeling of univariate time series, combining an autoregressive (AR) component with a moving average (MA) component.

According to Gujarati (2011), the ARMA (1,1) model can be expressed as:

$$Y_t = \theta + \alpha_1 Y_{t-1} + \beta_0 u_t + \beta_1 u_{t-1} \quad (1)$$

where (Y_t) denotes the time series under analysis, (\theta) is a constant term, (\alpha_1) represents the autoregressive parameter, (Y_{t-1}) is the lagged value of the series (AR(1) component), (\beta_1) is the moving average parameter, (u_{t-1}) is the lagged error term (MA(1) component), and (\beta_0) corresponds to the parameter associated with the error term (u_t).

In general, the model is expressed as ARMA ((p,q)), where (p) denotes the autoregressive order and (q) represents the moving average order. The model can only be applied to stationary series, that is, series with constant mean and variance and time-invariant covariance. If the series is not stationary, it must be differenced (d) times until stationarity is achieved. When a series becomes stationary after first differencing, it is said to be integrated of order one, (I(1)), and the model is then specified as an Autoregressive Integrated Moving Average process, ARIMA ((p,d,q)) (Gujarati, 2011).

However, if the residuals of the ARIMA model exhibit conditional variance, models from the Autoregressive Conditional Heteroskedasticity (ARCH) family should be employed. In this framework, the conditional variance of the error term is determined by the squared lagged residuals up to order (q), and the model is denoted as ARCH ((q)) (Engle, 1982).

In the case of a model with a single lag of the error term, its ARCH ((1)) representation is given by: $\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2$ (2)

Where (\sigma_t^2) denotes the conditional variance, (\alpha_0) and (\alpha_1) are the parameters associated with the intercept and the lagged error term, respectively, and (\alpha_1) represents the reaction coefficient related to the error term.

Bollerslev (1986) proposed an extension of the ARCH model, known as the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, in which, in addition to (q) lags of squared errors, (p) lags of the conditional variance itself are incorporated. This specification is denoted as GARCH ((q,p)).

The GARCH ((1,1)) model is represented as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (3)$$

Where (\sigma_t^2) denotes the conditional variance, and (\alpha_0), (\alpha_1), and (\beta) are the parameters associated with the intercept, the lagged squared error term, and the lagged conditional variance, respectively. The coefficient (\alpha_1) captures the ARCH effect (reaction coefficient), while (\beta) represents the GARCH

Revista Conhecimento Contábil
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ISSN: 2447 - 2921

effect (volatility persistence). The sum (\alpha_1 + \beta) measures the persistence of shocks on the variance; the closer this sum is to one, the longer it takes for shocks to dissipate.

Zakoian (1994), in turn, proposed the Threshold Autoregressive Conditional Heteroskedasticity (TARCH) model, which is capable of capturing asymmetry and leverage effects in series exhibiting conditional volatility. This approach incorporates a dummy variable into the variance equation to account for the fact that market volatility may respond differently depending on the direction of shocks. The TARCH ((q,p)) model includes (q) lags of squared errors and (p) lags of the conditional variance. The TARCH ((1,1)) model can be expressed as:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 (4)$$

Where (\sigma_t^2) denotes the conditional variance; (\alpha_1) represents the ARCH effect; (\gamma) is the coefficient capturing the asymmetric (or leverage) effect; (\beta) denotes the GARCH effect; and (d_{t-1}) is the dummy variable. The dummy variable is defined as (d_{t-1} = 1) when (\varepsilon_{t-1} < 0), and (d_{t-1} = 0) when (\varepsilon_{t-1} > 0). If (\gamma \neq 0), an asymmetry effect is present, meaning that positive and negative shocks of the same magnitude do not affect volatility in the same way. If (\gamma > 0), a leverage effect occurs, indicating that negative shocks lead to higher volatility than positive shocks.

Another model capable of capturing asymmetry is the model proposed by Nelson (1991), known as the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model, which in its EGARCH ((1,1)) specification can be expressed as:

$$\ln(\sigma_t^2) = \alpha + \beta \ln(\sigma_{t-1}^2) + \alpha_1 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \lambda \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (5)$$

This model captures asymmetry when (\lambda \neq 0), indicating that positive and negative shocks affect volatility differently. When (\lambda < 0), a leverage effect is present, meaning that negative shocks lead to higher volatility than positive shocks. The parameter (\alpha_1) corresponds to the ARCH effect, while (\beta) represents the GARCH effect.

2.3. Value at Risk (VaR) Metric

Value at Risk (VaR) is a metric that quantifies the potential risk of losses in specific assets through a single indicator over a given time horizon and at a specified confidence level (Jorion, 2003).

VaR can be calculated using parametric, historical, or Monte Carlo simulation approaches. According to Pereira et al. (2010), parametric VaR is defined as:

$$VaR = V_0 \, [(\mathrm{c} \times \sigma) + \mu] \qquad (6)$$

where (V) represents the most recent available price, (c) is the critical value obtained from the standard normal distribution (1.65, 1.96, and 2.58) for confidence levels of 90%, 95%, and 99%, respectively, (\sigma) denotes the standard deviation of the return series (in this study, the conditional standard deviation), and (\mu) is the mean return of the series.

Revista Conhecimento Contábil
DOI:
ISSN: 2447 - 2921

Rugani and Silveira (2006), Pereira et al. (2010), Arêdes (2013), and Vasconcellos and Arêdes (2024) estimated the maximum potential loss in terms of invested value. According to Rugani and Silveira (2006), this relationship allows for the assessment of the level of risk absorbed.

The relationship between VaR and the invested value is given by the following equation:

$$PR = \frac{VaR}{I}\ x\ 100 \tag{7}$$

here PRdenotes the percentage of risk assumed, $VaR$is the Value at Risk of the investment, and Irepresents the level of investment. The higher the PR, the greater the exposure to risk.

Under the parametric approach, VaR can be estimated by obtaining the conditional variance from the estimation of an autoregressive and conditional volatility model, such as those belonging to the ARCH family, provided that conditional heteroskedasticity is present in the residual series of the autoregressive model. In this study, the estimation of conditional volatility models was performed using the R software environment (R Core Team, 2026).

2.4. Data Treatment and Source

The price series used in this research corresponds to the price of a kilogram of unprocessed coffee beans in the state of Paraná, obtained from the Institute for Applied Economic Research (IPEADATA, 2025). The coffee price series was adjusted for inflation using the IGP-DI index, with December 2025 as the base period. Subsequently, the price series was transformed into a return series by applying the following equation:

$$r = \frac{(P_t - P_{t-1})}{(P_{t-1})} \tag{8}$$

where $P_t$represents the price of coffee at time t, $P_{t-1}$is the coffee price lagged by one period, and $r_t$denotes the return on coffee prices.

3. RESULTS AND DISCUSSION

Figure 1 presents the monthly average price series of unprocessed coffee beans (per kilogram) received by producers in the state of Paraná over the period from July 1994 to December 2025. The price series exhibits an irregular pattern over time, revealing significant fluctuations, which are also reflected in the return series. The highest recorded price was BRL 38.70 per kilogram in February 2025, while the lowest observed price was BRL 6.34 in June 2003.

At the beginning of the series, between 1994 and 2000, average coffee prices were relatively higher, although they displayed a downward trend throughout the period. Between 2001 and 2020, prices showed more stable behavior, albeit at a lower average level compared to the initial period. From 2021 onward, a pronounced upward trend is observed, driven mainly by the reduction in global inventories, adverse climatic conditions in major producing regions, and increased global demand for the product.

Revista Conhecimento Contábil
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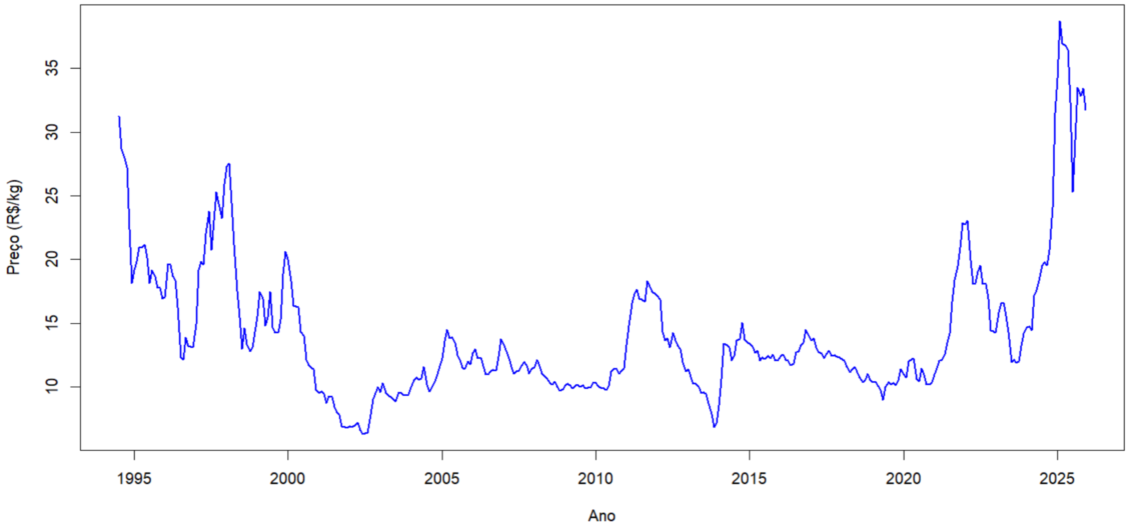
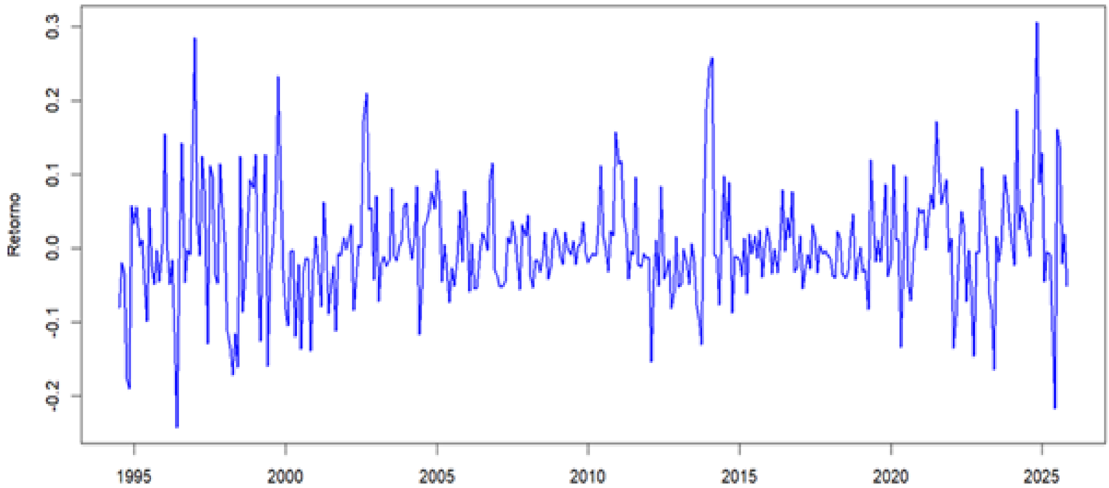
Figure 1: Monthly average price series of unprocessed coffee beans (per kilogram) received by producers in the state of Paraná, from 07/1994 to 12/2025.



Source: Authors' own elaboration.

Figure 2 presents the return series of coffee prices, which is the series modeled using ARCH family models. Return series tend to be stationary and provide more accurate measures of risk; therefore, they are commonly used in financial and commodity time series analysis.

Figure 2: Return series of the average prices of unprocessed coffee beans (per kilogram) received by producers in the state of Paraná, from 07/1994 to 12/2025.



Source: Authors' own elaboration

Regarding the descriptive statistics of the coffee price series, Table 1 indicates that the average price per kilogram of unprocessed coffee beans was BRL 14.17, with a standard deviation of BRL 5.59, suggesting substantial variability over the analyzed period. The skewness and kurtosis coefficients were 1.84 and 6.96, respectively, indicating an asymmetric distribution with heavier tails than the normal distribution.

These results suggest that the price series does not follow a normal distribution, since, theoretically, a normal distribution has zero skewness and kurtosis equal to three.

Revista Conhecimento Contábil
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ISSN: 2447 - 2921

Additionally, the Jarque–Bera (JB) test statistic was 461.44, with an associated probability close to zero (2.2e-16), reinforcing the rejection of the null hypothesis of normality for the price series.

Table 1: Statistical properties of the price series of unprocessed coffee beans (per kilogram) and its return series, from 07/1994 to 12/2025.

Indicator	Coffee Price (BRL)	Coffee Return (%)
Mean	14.17	0.0027
Minimum	6.34	-0.2432
Maximum	38.70	0.3067
Skewness	1.84	0.4952
Kurtosis	6.96	5.0831
Standard Deviation	5.59	0.0742
Jarque–Bera (JB)	461.44	83.576
Probability (JB)	2.2e-16	2.2e-16

Source: Authors' own elaboration

Table 1 also presents the descriptive statistics of the coffee price return series. The average return over the period was 0.0027%, with a standard deviation of 0.0742%, indicating high variability. The skewness and kurtosis coefficients were 0.4952 and 5.0831, respectively, revealing an asymmetric distribution with heavier tails than the normal distribution. The Jarque–Bera (JB) test yielded a statistic of 83.576, with a probability close to zero (2.2e-16), confirming the rejection of the null hypothesis of normality for the return series.

The presence of asymmetry and heavy tails in the return series suggests that extreme events may occur more frequently. This behavior has direct implications for producers' revenues, as it complicates the forecasting of prices and income while increasing the likelihood of significant losses. In this context, producers may adopt risk mitigation strategies, such as hedging through futures or options contracts, in order to reduce their exposure to price risk. Additionally, the use of risk metrics such as Value at Risk (VaR) can support financial planning by enabling the maintenance of capital reserves to withstand potential sharp declines in commodity prices.

The return series does not follow a normal distribution, which is a common result in financial and commodity time series. This characteristic does not invalidate the use of GARCH family models, which are widely employed in the literature to model volatility in series exhibiting such behavior. Other studies have also identified non-normal distributions in commodity price and return series using the Jarque–Bera test and have applied ARCH family models, such as Pereira et al. (2010) for soybean, coffee, and live cattle return series; Silva (2020) for live cattle returns; and Hefnawy and Shaker (2021) for wheat return series.

Prior to estimating the ARCH family models, the Augmented Dickey–Fuller (ADF) unit root test was applied to verify the stationarity of the return series, since only stationary series—i.e., those free of unit roots—are suitable for econometric modeling. The results of the ADF test are presented in Table 2.

Revista Conhecimento Contábil
DOI:
ISSN: 2447 - 2921

Three specifications of the test were estimated: without a constant, with a constant, and with both a constant and a trend. In all cases, the absolute value of the test statistic exceeded the critical values at the 1% and 5% significance levels, leading to the rejection of the null hypothesis of a unit root. Therefore, it is concluded that the return series is stationary, as shown in Table 2.

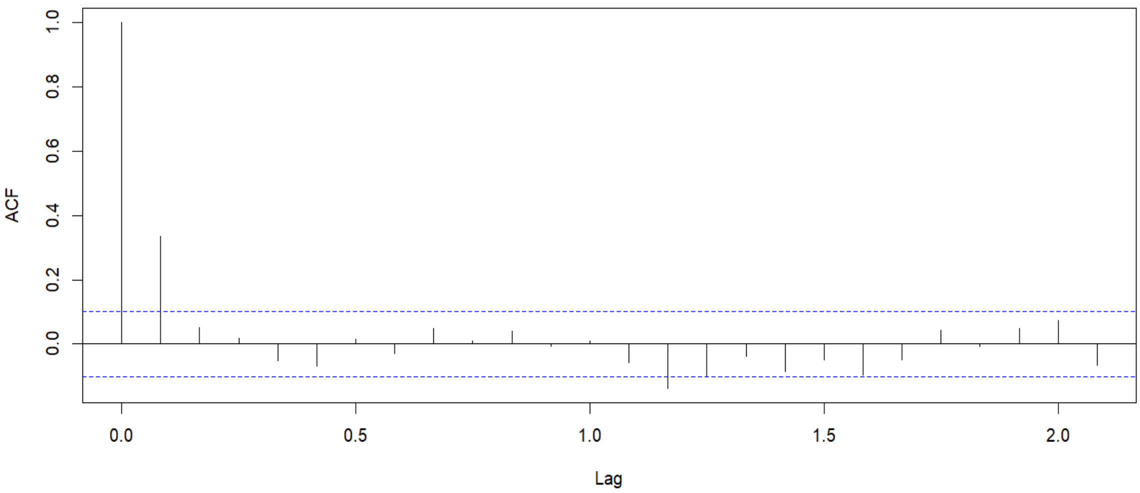
Table 2: Results of the Augmented Dickey–Fuller (ADF) unit root test for the return series of coffee prices, from 07/1994 to 12/2025.

Test Equation	**t-statistic**	**Critical Value (1%)**	**Critical 5%)**
Equation without constant	-11.9251***	-2.58	-1.95
Equation with constant	-11.9288***	-3.44	-2.87
Equation with constant and trend	-12.0247***	-3.98	-3.42

Note: *** Significant at the 1% level.
Source: Research results.

In the subsequent step, the orders of the autoregressive ((p)) and moving average ((q)) components to be incorporated into the ARMA ((p,q)) model were determined. For this purpose, the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) were analyzed. The estimates of these functions for the return series are presented in Figure 3.

Figure 3: Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the return series of coffee prices, from 07/1994 to 12/2025.



Revista Conhecimento Contábil
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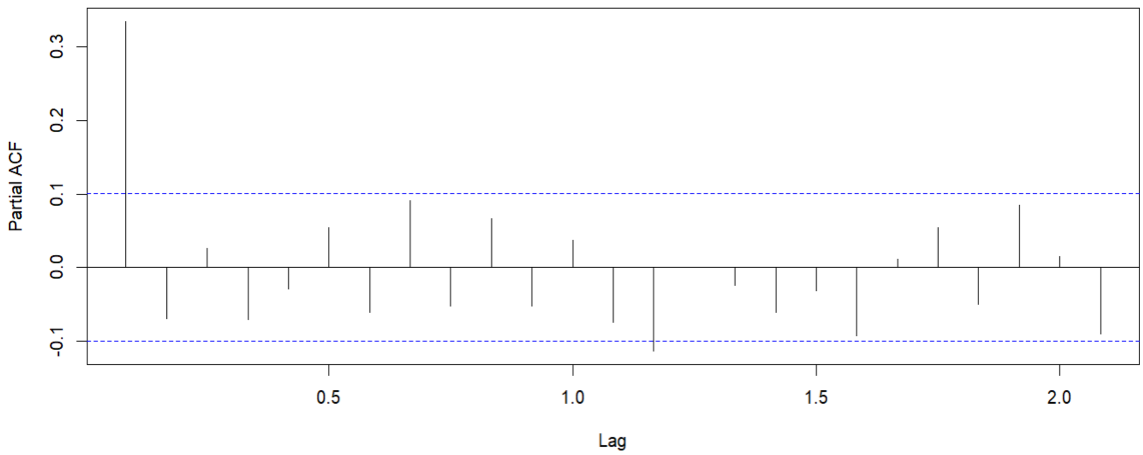

Source: Research results.

Based on the ACF and PACF, an Autoregressive Integrated Moving Average model ARIMA ((1,0,2)) was estimated and deemed appropriate for the modeling, as all coefficients associated with the first- and second-order lags were statistically significant at the 1% level (Table 3).

Table 3: Estimates of the ARIMA ((1,0,2)) model for the return series of coffee prices, from 07/1994 to 12/2025.

Variables	Coefficient	Standard Error	t-statistic	p-value
Intercept	0.0025	0.0024	1.0479	0.2947
AR(1)	0.9613	0.0494	19.4639	2.2e-16
MA(1)	-0.6216	0.0645	-9.6309	2.2e-16
MA(2)	-0.3547	0.0471	-7.5290	5.1e-14

Note 1: AIC: Akaike Information Criterion; SC: Schwarz Criterion; HQ: Hannan–Quinn Criterion. **Source:** Research results.

Table 3 presents the results of the ARIMA ((1,0,2)) model estimated for the return series of coffee prices. The intercept is not statistically significant, suggesting that the mean return of the series does not differ significantly from zero over the analyzed period. In contrast, the autoregressive coefficient AR(1) exhibits a high positive value (0.9613) and is statistically significant at the 1% level, indicating strong temporal persistence in returns; that is, current returns are strongly influenced by returns observed in the previous period. Furthermore, the moving average coefficients MA(1) (-0.6216) and MA(2) (-0.3547) are also statistically significant, indicating that random shocks occurring in the two preceding periods continue to influence current returns, albeit with an inverse effect.

From a practical perspective, these findings suggest that the short-term dynamics of coffee prices exhibit temporal dependence and rapid incorporation of market shocks. Consequently, recent price changes tend to be informative for forecasting and financial planning. For coffee producers, these results are particularly relevant, as they indicate that recent price variations and market shocks may affect returns in subsequent periods, thereby supporting decision-making related to production marketing, sales planning, and the adoption of risk management strategies.

The application of the ARCH-LM (Autoregressive Conditional Heteroskedasticity – Lagrange Multiplier) test to the residual series of the ARIMA

Revista Conhecimento Contábil
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((1,0,2)) model revealed the presence of conditional heteroskedasticity, as the probability values associated with the null hypothesis of no conditional heteroskedasticity were statistically insignificant, leading to its rejection (Table 4).

Table 4: Results of the ARCH–LM test.

Lag	Test Statistic	Probability
1	15.791	7.07e-05
6	19.972	0.002801
12	43.764	1.67e-05
24	53.548	0.000489

Source: Research results.

Given the presence of conditional volatility in the return series, models from the ARCH family were estimated. Initially, an ARIMA ((1,0,2)) model was specified for the mean equation of returns, and simultaneously, a GARCH ((1,1)) model was estimated for the conditional variance equation. The estimation results are presented in Table 5.

It is observed that all estimated coefficients, except for the intercept, were statistically significant at the 1% level. The conditional volatility equation indicates that current variance depends both on recent shocks, with an estimated coefficient of approximately 0.11, and on lagged conditional variance, with a coefficient of approximately 0.88, reflecting a high degree of volatility persistence. The sum of these parameters amounts to 0.98, indicating strong persistence, suggesting that shocks exert long-lasting effects on the variance of the return series. Therefore, risk management mechanisms such as futures contracts and forward sales, as well as monitoring tools such as Value at Risk (VaR), are essential, given the increased uncertainty surrounding future revenue from coffee production.

Table 5: Estimates of the GARCH ((1,1)) model for the return series of coffee prices.

Variables	Coefficient	Standard Error	t-statistic	p-value
Constant	0.001083	0.001726	0.62757	0.530282
AR (1)	0.953955	0.023220	41.08268	0.000000
MA (1)	-0.638630	0.008397	-76.05760	0.000000
MA (2)	-0.336764	0.009231	-36.48110	0.000000
Conditional Variance				
Parameter	**Coefficient**	**Standard Error**	**t-statistic**	**p-value**
ω (Intercept)	0.000106	0.000056	1.91087	0.056021
α (ARCH effect)	0.107093	0.031911	3.35602	0.000791
β (GARCH effect)	0.877139	0.031948	27.45538	0.000000

Information Criteria	Value
AIC	-2.5971
HQ	-2.5681

Notes: AIC: Akaike Information Criterion; HQC: Hannan–Quinn Information Criterion.
Source: Research results.

This result is consistent with that reported by Campos (2007) for coffee price returns, which was 0.96. Campos (2007) also found that the sum of the error component and conditional variance was 0.89 for corn, 1.04 for live cattle, and 0.90 for soybeans. Similarly, Pereira et al. (2010) reported values of 0.92 for soybeans, 0.90 for coffee, and

DOI:
ISSN: 2447 - 2921

0.99 for live cattle. Silva et al. (2005) obtained a sum of 0.88 for the coffee series and 0.96 for the soybean series. The present study corroborates these findings, as well as those reported by Rodrigues (2020) for the GARCH ((1,1)) model, which found the sum of coefficients to be 0.97 for coffee.

In order to verify the existence of asymmetry in the volatility of the return series, a TARCH ((1,1)) model was additionally estimated. As shown in the conditional variance equation presented in Table 6, the terms associated with the lagged error and lagged conditional variance were statistically significant. However, the dummy variable related to the error term, responsible for capturing potential asymmetry effects in volatility, was not statistically significant. Given the absence of evidence of asymmetry in volatility, the TARCH ((1,1)) model was not employed in the estimation of conditional volatility nor in the calculation of the Value at Risk (VaR) metric.

Table 6: Estimates of the TARCH ((1,1)) model for the return series of coffee prices.

Variables	Coefficient	Standard Error	t-statistic	p-value
Constant	0.001102	0.001770	0.622371	0.533698
AR (1)	0.954179	0.024139	39.529090	0.000000
MA (1)	-0.638583	0.010521	-60.696981	0.000000
MA (2)	-0.336983	0.012228	-27.558222	0.000000

Conditional Variance

Parameter	Coefficient	Standard Error	t-statistic	p-value
ω (Intercept)	0.000106	0.000056	1.910045	0.056127
α (ARCH effect)	0.107933	0.037852	2.851425	0.004352
γ (Asymmetry effect)	-0.001847	0.042713	-0.043243	0.965508
β (GARCH effect)	0.877171	0.031925	27.476097	0.000000

Notes: AIC: Akaike Information Criterion; HQ: Hannan–Quinn Information Criterion. **Source:** Research results.

This result differs from that reported by Pereira et al. (2010), who, when estimating a TARCH ((1,1)) model, identified the presence of asymmetry in the return series of coffee and soybeans, although without a leverage effect. Silva et al. (2005) also found asymmetry using the TARCH ((1,1)) model for coffee and soybean return series, but without evidence of a leverage effect, indicating that negative shocks do not increase volatility more than positive shocks in these series.

However, the present study corroborates the findings of Rodrigues (2020), who did not detect asymmetry when estimating a TARCH ((1,1)) model for the coffee return series. As in Rodrigues (2020), the coefficients associated with the error term and volatility persistence were found to be statistically significant. In the present study, the persistence coefficient was 0.88, whereas in Rodrigues (2020) it was 0.78.

Finally, the EGARCH ((1,1)) model was estimated. The results presented in Table 7 indicate that, in the conditional variance equation, the term associated with past errors was not statistically significant at the 10% significance level. In contrast, the lagged conditional variance term, with a coefficient of 0.96, and the parameter capturing volatility asymmetry were statistically significant at the 1% level.

These findings indicate that the coffee return series exhibits a high degree of persistence in response to shocks, as well as asymmetric volatility behavior, suggesting

DOI:
ISSN: 2447 - 2921

that positive and negative shocks of the same magnitude have different impacts on conditional volatility. However, no evidence of a leverage effect is observed.

This result is consistent with that reported by Pereira et al. (2010) for coffee and soybeans. By applying the EGARCH ((1,1)) model, the authors found a good model fit and identified asymmetry in the series, although without a leverage effect. The present study is also consistent with the findings of Rodrigues (2020), who identified asymmetry without a leverage effect in the coffee price series. Moreover, similarly to the present study, Rodrigues (2020) detected high volatility persistence, with a coefficient of 0.93 in the EGARCH ((1,1)) model, while the reaction coefficient was not statistically significant. Finally, the present study also corroborates the findings of Silva et al. (2005), who identified asymmetry without a leverage effect in coffee and soybean return series using the EGARCH ((1,1)) model.

Table 7: Estimates of the EGARCH ((1,1)) model for the return series of coffee prices.

Variables	Coefficient	Standard Error	t-statistic	p-value
Constant	0.000856	0.000813	1.05296	0.292357
AR (1)	0.946518	0.030933	30.59895	0.000000
MA (1)	-0.623123	0.006813	-91.45561	0.000000
MA (2)	-0.352802	0.005489	-64.27152	0.000000

Conditional Variance

Parameter	Coefficient	Standard Error	t-statistic	p-value
ω (Intercept)	-0.222244	0.106379	-2.08918	0.036692
$\ln(\sigma_{(t-1)}^2)$	0.957015	0.019469	49.15637	0.000000
	$\varepsilon_{(t-1)}$	$/ \sigma_{(t-1)} - \sqrt{(2/\pi)}$	0.010951	0.028093
$\varepsilon_{(t-1)} / \sigma_{(t-1)}$	0.227149	0.061957	3.66626	0.000246

Information Criteria	Value
AIC	-2.5821
HQ	-2.5490

Notes: AIC: Akaike Information Criterion; HQ: Hannan–Quinn Information Criterion.
Source: Research results.

Considering that the GARCH ((1,1)) model presented all coefficients of the conditional volatility equation as statistically significant, and that the EGARCH ((1,1)) model showed statistical significance in the parameters associated with volatility persistence and asymmetry, both models were selected to estimate the conditional volatility of the coffee price return series. The estimates obtained from these models are presented in Figure 4.

Figure 4: Conditional variance estimated by the GARCH ((1,1)) and EGARCH ((1,1)) models, from 07/1994 to 12/2025.

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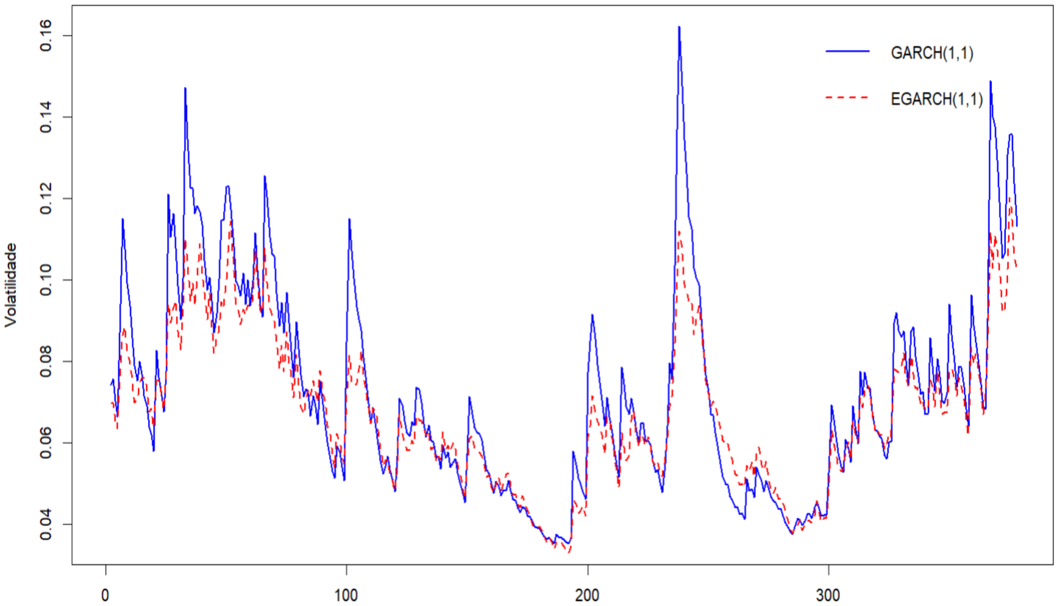
ISSN: 2447 - 2921



Source: Research results.

The Value at Risk (VaR) estimates obtained from both models are presented in Table 8. The calculated VaR represents the monthly risk associated with an investment in one kilogram of unprocessed coffee beans in the state of Paraná, considering confidence levels of 90%, 95%, and 99%.

According to the results in Table 8, a producer holding one kilogram of coffee in December 2025, valued at BRL 31.73, would be exposed—under the GARCH ((1,1)) model—to a VaR of BRL 3.69 at the 90% confidence level, implying a maximum monthly loss of 11.62% of the invested value. In contrast, the EGARCH ((1,1)) model estimated a maximum loss of BRL 3.44, corresponding to 10.83% of the investment. These results indicate that, with 90% confidence, there is only a 10% probability that the monthly loss for the coffee producer will exceed BRL 3.44, highlighting a slight difference between the models.

Table 8: VaR estimates based on the GARCH ((1,1)) and EGARCH ((1,1)) models for different confidence levels.

Confidence Level	GARCH (1,1) VaR (BRL)	VaR/Revenue	EGARCH (1,1) VaR (BRL)	VaR/Revenue
90%	BRL 3.69	11.62%	BRL 3.44	10.83%
95%	BRL 4.40	13.86%	BRL 4.10	12.92%
99%	BRL 5.81	18.33%	BRL 5.42	17.09%

Source: Research results.Pereira et al. (2010) applied conditional volatility models to estimate the Value at Risk (VaR) of returns for the commodities soybean, coffee, and live cattle. At the 95% confidence level, the authors reported VaR/Revenue values of 5.69% for soybeans, 7.49% for coffee, and 2.79% for live cattle. Although these results refer to different periods and contexts from those analyzed in the present study, they allow for a qualitative comparison of the risk associated with these commodities.

It is observed that coffee exhibited a substantially higher level of risk in the present study, as the estimated VaR/Revenue values reached 13.86% under the GARCH model and 12.92% under the EGARCH model, both at the 95% confidence level, indicating

Revista Conhecimento Contábil
DOI:
ISSN: 2447 - 2921

greater exposure to adverse price fluctuations. The divergence between the results of this study and those reported in the literature may be attributed, first, to differences in the price series used, both in terms of time period and data frequency.

Additionally, as evidenced in Figure 4, coffee market volatility increased in recent years, which may also contribute to the discrepancy in results. This increase in volatility is primarily associated with declining global inventories, rising demand, and adverse climatic conditions, factors that have intensified price instability in the coffee market.

The evaluation of model performance in predicting losses was conducted through a backtesting procedure, as proposed by Kupiec (1995). This method involves comparing VaR estimates with the returns actually observed over the analyzed period, allowing for an assessment of the adequacy of risk forecasts (Jorion, 2003).

In the Kupiec test, the null hypothesis states that the observed proportion of violations is statistically consistent with the failure rate implied by the adopted confidence level. When the value of the likelihood ratio (LR) statistic exceeds the critical value of the chi-square distribution with one degree of freedom ((\chi^2 = 3.84)), the null hypothesis is rejected, indicating that the model performs inadequately in measuring risk (Jorion, 2003; Halilbegovic & Vehabovic, 2016).

According to Table 9, returns exceeded the VaR limits estimated by the GARCH ((1,1)) model on only two occasions at the 90% confidence level. The calculated likelihood ratio (LR) statistic was 2.07, which is lower than the critical value of the chi-square distribution with one degree of freedom (3.84), implying that the null hypothesis cannot be rejected. This result indicates that the GARCH ((1,1)) model provides satisfactory performance for managing the risk faced by coffee producers in the state of Paraná. Furthermore, the results show that the null hypothesis was also not rejected at the other significance levels analyzed, and they confirm that the EGARCH ((1,1)) model also demonstrated efficiency in risk prediction, although it exhibited a higher number of violations.

Table 9: Backtesting results of the GARCH ((1,1)) and EGARCH ((1,1)) models.

Nível de confiança	GARCH (1,1)			EGARCH (1,1)		
	Teste LR	Valor crítico	Conclusão do teste	Teste LR	Valor crítico	Conclusão do teste
90%	2,07 (2)	3,84	Não rejeita	0,95 (3)	3,84	Não rejeita
95%	0,16 (7)	3,84	Não rejeita	0,44 (10)	3,84	Não rejeita
99%	0,08 (11)	3,84	Não rejeita	0,75 (13)	3,84	Não rejeita

Note: (.) Number of model violations.
Source: Research results.

4. FINAL CONSIDERATIONS

This study aimed to analyze the risk associated with fluctuations in coffee prices in the state of Paraná using conditional volatility models from the ARCH family. Based on the real price series of unprocessed coffee beans from July 1994 to December 2025, it was possible to characterize the dynamic behavior of volatility and to quantify the market risk faced by producers through the Value at Risk (VaR) metric.

The empirical results indicated that the GARCH ((1,1)) and EGARCH ((1,1)) models provided the best fit to the return series, revealing strong persistence of volatility over time. In particular, the EGARCH ((1,1)) model identified the presence of asymmetry

Revista Conhecimento Contábil
DOI:
ISSN: 2447 - 2921

without a leverage effect, meaning that negative price shocks do not exert a greater impact on volatility compared to positive shocks. This behavior underscores the importance of models capable of capturing nonlinear effects in the analysis of risk in agricultural commodities.

With regard to risk measurement, the VaR estimates obtained from both models were similar, indicating that coffee producers in Paraná are exposed to economically significant monthly losses. The magnitude of the estimated VaR suggests that a substantial portion of the invested value may be lost over short time horizons, particularly during periods of heightened price instability, highlighting the vulnerability of the activity to market conditions.

Finally, the backtesting procedures, particularly the Kupiec test, indicated good predictive performance of the models, as the number of observed violations was consistent with the adopted confidence levels. These results suggest that GARCH and EGARCH models constitute appropriate tools for managing price risk in the coffee market, supporting decision-making related to production, commercialization, and the formulation of public policies aimed at mitigating the risks faced by producers.

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