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DYNAMIC BEHAVIOR OF REGIME CHANGE IN ARABICA COFFEE COMMODITY PRICES IN BRAZIL USING MARKOV SWITCHING DYNAMIC REGRESSION MODEL

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Abstract

This article presents a quantitative analysis using the Markov Switching Dynamic Regression Model (MS-DR), with the aim of verifying the dynamics of Brazilian Arabica coffee commodity prices from January 2010 to June 2025. Two regimes (regime 1 - low volatility and regime 2 - high volatility) were used in the model so that market parameters would behave differently during economic crises with representative regimes. The Arabica coffee commodity remained in regime 1 (low volatility) for seven periods, totaling 121 months. In regime 2 (high volatility - crises of 2012/2013 and 2017/2019), it remained for about 40 months, i.e., 12 months in the 2012/2013 crisis and 28 months in the 2017/2019 crisis. In addition, regime 1 is more persistent, i.e., the probability of remaining in this regime in a subsequent period is approximately 92.13%, and that of changing to regime 2 is 7.87%. In regime 2, the probability of remaining in this regime in period t + 1 is 85.74%, while the probability of changing to regime 1 is 14.26%.

Keywords: *Markov Switching Dynamic Regression, Arabica coffee commodity, Probability of transition.*

INTRODUCTION

Exports are currently one of the main sources of income for the Brazilian economy, with considerable diversity over the last decade, ranging from agricultural products to higher value-added products.

Brazil stands out as one of the world's leading suppliers of agricultural goods. Among the main products that make up Brazilian commodity exports are cocoa, coffee, sugarcane, oranges, and

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soybeans. The importance of these crops is related to their production volume and share of the world market.

Coffee farming is an economically and socially important activity worldwide. In the Brazilian economy, coffee accounts for a significant share of agricultural production, resulting in a positive trade balance. According to data from the Brazilian Confederation of Agriculture and Livestock (CNA, 2024), Brazil coffee production represents 32% of total world production. Brazil stands out as the world largest coffee producer, as well as the largest exporter and second largest consumer. The agricultural sector is more sensitive to supply and demand shocks, which consequently affect product prices.

World coffee production is concentrated in Brazil, Vietnam, and Colombia, which together account for 54.0% of the 2024 harvest. The main producing states in Brazil are Minas Gerais, which leads national production with 57.5%. Espírito Santo is the second largest coffee-producing state in the country (35.2%). São Paulo is the third largest coffee-producing state, accounting for 12.1% of the country's total production (CNA, 2024).

The main destinations for Brazilian coffee exports were the United States, Brazil main trading partner for coffee in 2024. The Americans imported 8.131 million bags from January to December, which is equivalent to 16.1% of all exports and implies a 34% growth compared to 2023. Germany, with 15%, purchased 7.590 million bags (+51.3%), ranking second in the ranking. Next came Belgium, with imports of 4.348 million bags (+96.4%); Italy, with 3.914 million bags (+25%); and Japan, with 2.211 million bags (-6.3%) (CNA, 2024).

The econometric works on the estimation of regressions subject to regime changes that follow a Markov chain were developed by Quandt (1972), Goldfeld and Quandt (1973). Hamilton (1989) made important advances in the method developed by Goldfeld and Quandt (1973), by specifying that changes in regimes follow an auto-regressive process. In this sense, he developed a non-linear and smoothed estimation algorithm to find the high and low regimes of the economic series, seeking to maximize the likelihood function in relation to the parameters estimated in the model.

This methodology allowed statistical inferences to be made about the different regimes not observed in the series. The model endogenously estimates the dates of the structural changes in the series. Hamilton (1989) applied the method to investigate the nonlinear behavior of the growth of the United States economy and the results showed that the model can be used as an important tool for measuring business cycles.

Hamilton and Susmel (1994) use a model with changes, with respect to volatility. According to the authors, the regime change model, applied to the returns of the American stock market, fits the data better than the ARCH models without regime change.

Ang and Bekaert (2002) applied using a non-linear model to interest rates in the USA, Germany and the United Kingdom. Thus, the authors showed that interest rate regimes correspond reasonably well with USA economic cycles, being extremely important to study the effects of monetary policy shocks on the economy.

Ismail and Isa (2006) used regime change testing in their study to detect non-linear characteristics in the exchange rates of three Asian countries. They found that the null hypothesis of linearity is rejected and there is evidence of structural breaks in the exchange rate series.

Panda et al. (2017) examine the changing behavior of the dynamic Markov regime between the spot and the futures market in relation to interest rates in India. The study uses daily data on volumes, weighted average price, weighted average yield for the spot market and total values, open interest, settlement price from January 21, 2014 to October 30, 2014. All data come from Clearing Corporation of India Ltd. (CCIL) and the National Stock Exchange (NSE). The authors used regime change regression to capture the behavior of changes, as well as the estimated probability and estimated duration of each regime.

Ozdemir (2020) in his study is to assess the feed price driven dynamics of the U.S. wholesale beef prices in which regime switches are induced by transitions between Markov regimes. By allowing the transition probabilities to vary according to some main grain feed prices, we examine if the regime transition probabilities vary over time under two different states of the growth rate of beef prices as “low-mean growth” and “high-mean growth” price regimes. The results show that when the prices are in high-mean growth regime, the probability that it will remain in this regime is greater than that it will switch to low-mean regime. This findings also indicate that livestock feed prices provides some predicted power to the model of beef price regime switching process and supports livestock feed prices contributing to whether the beef price levels remains in low/high-mean regime. By employing Markov switching dynamic regression model, we also find that all types of the feed prices have a significant effect on the beef prices in low-growth regime, but only the prices of hay and sorghum significantly affect the beef prices in the high-growth regime.

Xaba et al. (2019) used a Markov-switching dynamic regression (MS-DR) model to estimate appropriate models for BRICS countries. The preliminary analysis was done using data from 01/1997 to 01/2017 and to study the movement of 5 stock market returns series. The study further determined if stock market returns exhibit nonlinear relationship or not. The purpose of the study is to measure the switch in returns between two regimes for the five stock market returns, and, secondly, to measure the duration of each regime for all the stock market returns under examination. The results proved the MS-DR model to be useful, with the best fit, to evaluate the characteristics of BRICS countries.

Choi and Hammoudeh (2010) use the Markov Switching model with two volatility regimes for the strategic commodity prices of Brent oil, WTI oil, copper, gold and silver, and the S&P 500 index, but with varying high-to-low volatility ratios. The dynamic conditional correlations (DCCs) indicate increasing correlations among all the commodities since the 2003 Iraq war but decreasing correlations with the S&P 500 index. The commodities also show different volatility persistence responses to financial and geopolitical crises, while the S&P 500 index responds to both financial and geopolitical crises.

Bismans and Roux (2013) use Markov-switching dynamic regression model to the real quarterly GDP time series from 1981 to 2010 in order to detect turning points in the South African business cycle. The model consists of several explicative variables. These include short and long term interest rates, monetary aggregates as well as the difference between long and short term interest rates.

Singhal and Biswal (2018) examine the impact of dynamic economic states on commodity portfolio performance using Markov Regime Switching Vector Autoregression (MRS-VAR). Empirical

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evidence reveals the prevalence of regime switching across all assets, suggesting their state-dependent behavior.

Shiferaw (2019) applies three state Markov-switching (MS) regression models. The data used in this study are the daily returns of agricultural commodity prices from 02 January 2007, to October 31, 2016, for corn, wheat, sunflower, and soybeans, and from 19 May 2010, to 31 October 2016, for corn. In addition, the data contain daily returns for crude oil, natural gas, coal, and exchange rates covering January 2, 2007, to October 31, 2016. The results indicate that the price of agricultural commodities was significantly associated with the price of coal, the price of natural gas, the price of oil, and the exchange rate.

This article performs a quantitative analysis using the Markov Switching Dynamic Regression model to examine the dynamics of Arabica coffee prices in Brazil from January 2010 to June 2025, when crises occurred in the agricultural sector. In particular, two regimes are used (regime 1- low volatility and regime 2 - high volatility).

METHODOLOGY AND DATA

Markov Switching Dynamic Regression Model

Hamilton (1989) proposed MS that is based on the assumption that the development of X_t can be explained by states (or regimes), where a two regime Markov-switching regression model can be expressed as:

$$\text{Regime 1: } Y_t = \mu_1 + \varphi Y_{t-1} + \varepsilon_t$$

$$\text{Regime 2: } Y_t = \mu_2 + \varphi Y_{t-1} + \varepsilon_t$$

where Y_t is the dependent variable,

μ_1 and μ_2 are the intercepts in each state (regime),

φ is the autoregressive coefficient and ε_t is the error at time t.

In the case where the state (regime) shifts are known, the two regime Markov-switching model can expressed as:

$$Y_t = S_t\mu_1 + (1-S_t)\mu_2 + \varphi Y_{t-1} + \varepsilon_t$$

where S_t represents the regime and is equal to 1 if the process is in regime 1 and 2 if it is in regime 2. However, in most cases it is not possible to observe in which regime S_t the process is currently in and therefore unknown. In Markov-switching regression models the regime S_t follows a Markov chain. A model with k regime-dependent intercepts, can be expressed as:

$$Y_t = S_t\mu_{st} + \varphi Y_{t-1} + \varepsilon_t$$

Where $\mu_{st} = \mu_1, \mu_2, \ldots\ldots\ldots, \mu_k$ for $S_t = 1,2,\ldots\ldots, k$ regimes.

The transition of probabilities between the regimes is carried out by a first order Markov process as follows:

$$\rho_{ij} = \Pr\left(S_t = j\right)|s_{t-1} = i)$$

On what ρ_{ij} refers to the probability of being on the regime *j* given that the process is in the regime

i, where $\sum_{i=1}^{N} \rho_{ij} = 1$ for all $i, j \in (1,2,\ldots\ldots N)$.

The transition probabilities in a square matrix of order *N*, known as the transition matrix and denoted by *P*, have the following form:

$$P = \begin{bmatrix} \rho_{11} & \rho_{12} \\ \rho_{21} & \rho_{22} \end{bmatrix}$$

where

$$\rho_{11} + \rho_{12} = 1 \quad \text{e} \quad \rho_{21} + \rho_{22} = 1$$

In the view of Doornik (2013) the Markov-switching models can be MS-AR (Markov-switching autoregression) and MS-DR (Markov-switching dynamic regression). The first is characterized by a more gradual adjustment, appropriate to the most stable series, whose autoregressive component is formed by the difference between the lagged endogenous variable and the average estimated for the endogenous variable in the S_{t-1} regime; and the second adjusts immediately to the new regime, with a more accentuated transition, since the autoregressive component covers only the endogenous variable.

In the present article, the series data are monthly, which chose to use the MS-DR model as an estimation method to identify regime changes, the number of periods, the duration and the probability of transition from one regime to another.

The MS-DR model can be specified as:

$$y_t = v(S_t) + \alpha y_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim N[0, \sigma^2]$$

Doornik (2013) adds that the MS-DR model with a structural component is important for analyzing time series that present alternations of values in the mean and variance. In this paper, the MS-DR is estimated with two regimes, which represent expansion and recession periods.

The maximum likelihood estimator is used to determine the parameters of the MS-DR. Therefore, the probability function of the model log with two regimes is expressed as follows:

$$\ln L = \sum_{t=1}^{T} \ln\left\{\sum_{j=1}^{2} f(y_t \mid S_t, y_{t-1}) \Pr(S_t = j \mid Y_{t-1})\right\}$$

Where the term $\Pr(S_t = j \mid Y_{t-1})$ is the probability of being in each regime. Given away $\Pr(S_{t-1} = i \mid Y_{t-1})$, i = 1,2.

Finally, from the transition matrix it determines the expected duration of each regime. The closer the probability is to one, the longer it takes to switch from another regime. Thus the expected duration can be expressed as:

$$Expected\ \ duration(D_i) = \frac{1}{1-\rho_{ij}}$$

The duration time in each of the two regimes can be determined as:

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$D_1 = 1/(1-\rho_{11})$ $\qquad$ $D_2 = 1/(1-\rho_{22})$

Data

The data used in this study refer to the monthly prices of Arabica coffee, covering the period from January 2010 to June 2025, with a total of 186 observations. The data were obtained from the website of the Center for Advanced Studies in Applied Economics (CEPEA-ESALQ/USP).

EMPIRICAL RESULTS

Preliminary Analysis

The daily returns were calculated using the formula: $r_t = \ln(P_t) - \ln(P_{t-1})$. This P_t represents the number of points at closing on day *t* and P_{t-1} the number of points at closing on the previous day (t-1). Figures 1 and 2 show the behavior of average monthly prices for Arabica coffee and the series of returns during the period considered.

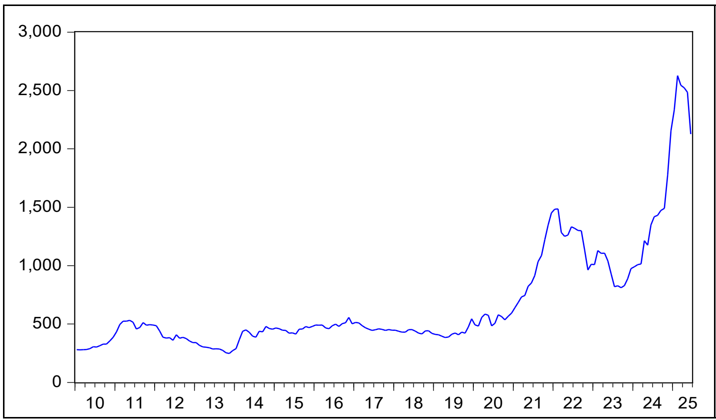


Figure 1. Monthly prices for Arabica coffee

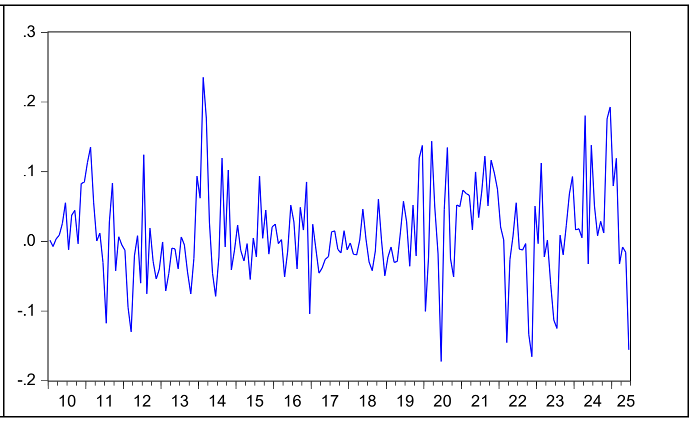
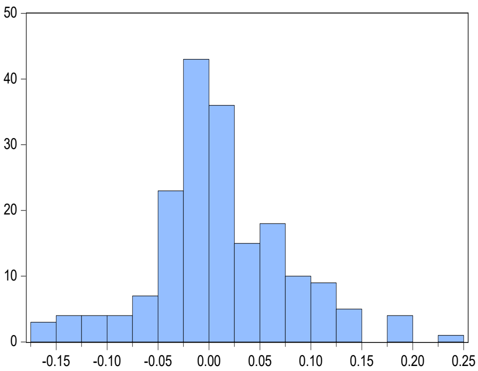


Figure 2. Monthly returns on Arabica coffee

In the visual inspection of Figure 2, during the analysis period, there is marked volatility in returns. Thus, it was necessary to test the normality and stationarity of the Arabica coffee return series for the application of the Markov Switching Dynamic Regression Model (MS-DR).

Some basic descriptive statistics are presented in Table 1. It can be observed that the monthly returns of Arabica coffee show a leptokurtic distribution due to the excess kurtosis (3.869106) in relation to the normal distribution (3.0), that is, it has a heavier tail. It can also be seen that the series is positively skewed, which would indicate that market highs are more likely than market lows. The variation between the minimum value (-0.172374) and the maximum value (0.235559) presented by the series can be explained by some significant fluctuations in price returns. The low standard deviation value (0.067803) indicates that, in general, high variations in the series occurred on few occasions, that is, during periods of positive and negative peaks. The Jarque and Bera (1987) statistic indicated the rejection of the normality of the series distribution, with a p-value equal to 0.016888.

Table 1 – Price returns of Arabic Coffee statistic summar



Series: Return
Sample 2010M01 2025M06
Observations 186

Mean	0.010893
Median	0.001964
Maximum	0.235559
Minimum	-0.172374
Std. Dev.	0.067803
Skewness	0.272880
Kurtosis	3.869106
Jarque-Bera	8.162296
Probability	0.016888

The Q-Q Plot represents one of the most used graphic methods to verify the normality of time series. The procedure used consists of graphically comparing the theoretical amounts of the normal distribution with the amounts of the sample data. Figure 3 shows a non-linear relationship between the theoretical and empirical quantiles, which is quite pronounced in the tails of the distributions, indicating heavier tails in the empirical distribution. Therefore, all tests rejected the hypothesis of normality of the analyzed series.

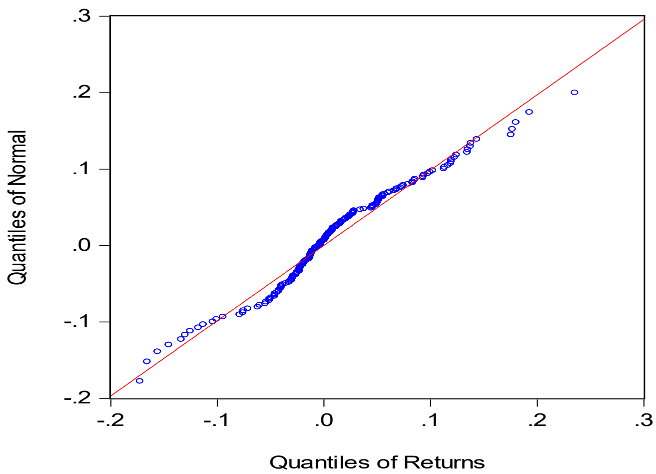


Figure 3 - Q-Q plot of Arabica coffee returns.

The Dickey and Fuller (1981); Phillips and Perron (1988); tests and Kwiatkowski, Phillips, Schmidt, and Shin (1992) tests with constant and trend, identified that the Arabica coffee returns series are stationary and do not contain unitary roots, as presented in the Table 2.

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Table-2. Stationary test for the Arabica coffee returns series

Variable	ADF	Critical Value (5%)	PP	Critical Value (5%)	KPSS	Critical Value (5%)
Arabica coffee	-9.7537	-3,4343	-9.7438	-3,4343	0,0556	0,1460

Source: : Elaborated by the author based on the research.

Markov-switching dynamic regression model (MS-DR)

Table 4 presents the estimates of the maximum likelihood method, using OxMetrics 6.0 software (PcGive14). The adjusted model refers to MS (2)-DR, variation in the mean and variance according to the regime (state). It can be seen that all parameters are significant. Regime (1) expresses positive average growth in Arabica coffee commodity prices. In regime (2), it presents a negative average result, i.e., a decline in prices. In regime 1, the estimated average monthly growth is 2.29% with a variance of 0.080. Regime 2 identifies a negative monthly growth of -1.38% with a variance of 0.005.

Portmanteau tests indicate that there is no autocorrelation of the residuals. The results of the ARCH-LM tests suggest acceptance of the model homoscedasticity hypothesis. As for the normality tests, Jarque-Bera (1987) does not reject the normality hypothesis. Thus, the model presents a positive diagnosis and an adequate fit.

In the transition and persistence matrix of the regimes, it can be seen that the current regime 1 is more persistent, i.e., the probability of remaining in this regime in a later period is approximately 92.13%, and the probability of changing to regime 2 is around 7.87%. In regime 2, the probability of continuing in this regime in period t + 1 is 85.74%, while the probability of changing to regime 1 is 14.26%. Thus, for the period from January 2010 to June 2025, the expected duration of the current regime 1 is 17 months. In regime 2, the estimated duration is 9 months. The unconditional probability in periods of growth is 65.05% and 34.95% in periods of contraction.

Figure 4 shows the behavior of returns, smoothed probabilities, and predicted probabilities for regimes 1 and 2 of the Arabica coffee commodity. The upper panel shows the series of returns, and the middle and lower panels plot the smoothed probabilities for the market in regime 1 (low volatility) and regime 2 (high volatility), respectively.

Table 4. Estimation of the MS (2)-DR model

Regime 1(low volatility)			Regime 2 (high volatility)		
Parameter	Coefficient		Parameter	Coefficient	
$\mu\,(s_1)$	0.02285	(0.00795)***	$\mu\,(s_2)$	-0.00933	(0.00548)*
σ^2	0.08030	(0.00625)***	σ^2	0.02738	(0.00448)***
ρ_{11}	0.9213	(0.05824)***	ρ_{22}	0.8574	(0.08698)***

Descriptive statistics		
Log-*likelihood*	255.5135	
Linearity RL test $(\chi^2)(4)$	36.7640	$(0,0000)^1$
Normality test $(\chi^2)(2)$	1.1107	$(0,5739)^1$
ARCH test (1-1) F (1, 178)	0.1792	$(0,6726)^1$
Pormanteau test - $\chi^2(36\,lags)$	50.6280	$(0,5370)^1$

Transition probability matrix			Average duration period of regimes		
	Regime 1	Regime 2		Probability	Duration period
Regime 1	0.9213	0.0787	Regime 1	0.6505	17
Regime 2	0.1426	0.8574	Regime 2	0.3495	9

Notes: ***, **, * denote statistical significance at the 1%, 5%, 10% , respectively.

Standard errors are in parentheses. p value (1).

Source: Prepared by the author based on the research.

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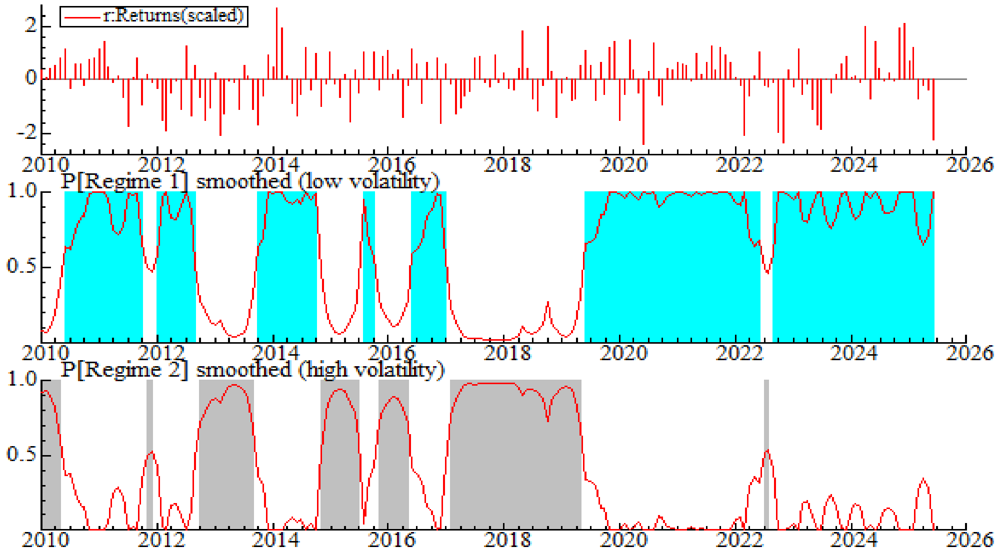

Figure 4. Smoothed probabilities of regimes 1 and 2 obtained in the MS(2)-DR model for Arabica coffee returns in the period from January 2010 to June 2025.

Based on the estimated probabilities, it is possible to obtain the specific dates of the low volatility (1) and high volatility (2) regimes, which are presented in Table 5. Arabica coffee remained under the low volatility regime for seven periods, totaling 121 months. It remained in the high volatility regime (crises) for approximately 65 months.

Table 5 - Specific dates of the regimes: MS(2)-DR model

Regime 1 (low volatility)			**Regime 2 (high volatility)**		
Period	**Months**	**Probability**	**Period**	**Months**	**Probability**
2010 (06) – 2011 (10)	17	0.854	2010 (01) – 2010 (05)	5	0.837
2012 (01) – 2012 (09)	9	0.833	2011 (11) – 2011 (12)	2	0.515
2013 (10) – 2014 (10)	13	0.925	2012 (10) – 2013 (09)	12	0.867
2015 (08) – 2015 (10)	3	0.729	2014 (11) – 2015 (07)	9	0.805
2016 (06) – 2017 (01)	8	0.768	2015 (11) – 2016 (05)	7	0.811
2019 (06) – 2022 (06)	37	0.926	2017 (02) – 2019 (05)	28	0.923
2022 (09) – 2025 (06)	34	0.902	2022 (07) – 2022 (08)	2	0.526
Total: 121 months (65.05%) with average duration of 17.29 months.			Total: 65 months (34.95%) with average duration of 9.29 months.		

Source: Prepared by the author based on the research.

From 2010 to 2024, Brazilian Arabica coffee faced multiple periods of crisis, characterized by declines in production, price volatility, and negative impacts on producers' incomes. These crises were mainly caused by a combination of climatic factors.

In 2010, the Arabica coffee market in Brazil did not face a crisis, but rather a period of appreciation and price increases. Although the country recorded a large harvest, the global scenario of low production and growing demand contributed to the appreciation of the product, driving prices to high levels. After a brief recovery, prices fell significantly in 2012.

The Arabica coffee crisis in Brazil in 2013 was marked by a continuous decline in prices, which reached their lowest levels in relation to previous years. The situation was considered the worst for coffee growers, due to the combination of low prices and high production costs (CEPEA/ESALQ).

The crisis between 2015 and 2022 had a significant impact on producers, who faced pressure from crop failures, increased costs, and volatility in the international market, which had already been on the rise in previous years. This scenario was the result of a combination of factors, mainly adverse weather conditions (CNA).

CONCLUSION

The objective of the study was to analyze variations in monthly Arabica coffee prices covering the period from January 2010 to June 2025 using the Markov Switching Dynamic Regression Model(MS-DR).

From 2010 to 2024, crises in Arabica coffee production in Brazil were mainly marked by extreme weather events, such as droughts and frosts, and by volatility in the international market. These factors caused structural disruptions in supply and impacted productivity and product prices.

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In the adjusted model, the mean and variance are modified according to the state regime. Regime (1) expresses a positive mean of Arabica coffee price returns, along with low volatility. In regime (2), it shows a negative average result and high volatility in Arabica coffee returns. In regime 1, the estimated average monthly return is 2.28% with a variance of 0.080. Regime 2 identifies a negative average monthly return of -0.933% with a variance of 0.027.

In the transition and persistence matrix of the regimes, it can be seen that the current regime 1 is more persistent, i.e., the probability of remaining in this regime in a later period is approximately 92.13%, and the probability of moving to regime 2 is around 7.87%. In regime 2, the probability of remaining in this regime in period t + 1 is 85.74%, while the probability of changing to regime 1 is 14.26%. Thus, for the period from January 2010 to June 2025, the expected duration of the current regime 1 is 17 months. In regime 2, the estimated duration is 9 months.

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