

The Influence of Investors' Behavior on Setting Coffee Futures Prices

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Abstract: *The great challenge for this research work is to show that the biases of investors' behavior can affect the formation of coffee futures prices. This research work uses auto-regressive conditional heteroscedasticity (ARCH) models to analyze results that show that the volatility has an impact on the formation of coffee futures prices. The positive volatility asymmetry coefficient of the TARCH model shows the presence of the leverage effect, where negative shocks have a greater impact on the volatility of returns in coffee futures prices than positive shocks. The presence of the leverage effect includes information related with investors' behavior which has influence on the formation of coffee futures prices and corroborates the Prospect Theory.*

Model results also show that investors' reactions to bad news are statistically significant in the coffee futures market and suggest that Behavioral Finance can contribute to the understanding of the formation of coffee futures prices.

Keywords: *Coffee Futures Prices, Volatility, Prospect Theory, Behavioral Finance*

1. INTRODUCTION

This research work analyses the influence of investors' behavioral on the context of coffee futures prices. Pereira (2009) showed that volatility has an impact in the pricing of cocoa, making it impossible to explain by the traditional financial theories. Her research work suggested that volatility may also result from investors' decisions because of psychological problems that arise when forming their beliefs and preferences. Her study revealed that Behavioral Finance can contribute to the understanding of the formation of cocoa futures prices and the results of her approach corroborate the Prospect Theory. This study focuses on the influence of investors' behavioral on the coffee futures prices, since the coffee is an important agricultural commodity in many regions and countries.

Africa has exhibited negative growth over the last 50 years. Africa's share in world coffee production has declined from 25% to an average of 14%. The decline in coffee production was attributable to structural factors and ageing coffee trees as well as the economic liberalization programs implemented in the 1990s and other factors related to the regional conflicts that has affected certain countries.

Asia and Oceania recorded the strongest coffee production growth in the course of the last 50 years, representing 23.5% of world production. Coffee production in crop year 2012/13 was estimated at 42.4 million bags. There has not been any regular biennial cycle of high and low production years, since observations have shown lengthy periods of successive increases in production followed by short-term falls (ICC, 2014).

Central America and Mexico produced an annual coffee averaging 18 million bags during the period from 1990 to 2012. Coffee production in the region as a whole does not seem to show high volatility from one crop year to the next. Nevertheless, its share in world production fell to an average of 15.9% during the free market period compared to 18.1% in the previous period. However, the recent outbreak of coffee leaf rust disease could cause a reduction in the production levels of many countries in the region (ICC, 2014).

South America is the world's leading producing region with an annual coffee production averaging 52.5 million bags since 1990/91, a level representing 46.6% of the total. This pattern in the region's total production is largely attributable to Brazilian production. Brazil produced an annual average of 35.7 million bags for the period 1990/91 to 2012/13. Despite this pattern of Brazilian production, it

produced an annual average of 50.8 million bags in 2012/13. There has been a regular biennial cycle of high and low production years attributable mainly to the impact of climate shocks such as frosts and droughts (ICE, 2012).

The agricultural sector has some economic characteristics that distinguish it from industrial and commercial sectors, among others, the high economic risk arising from the dependence on climatic factors; period of time that some agricultural crops remain in the field without displaying the expected return on investment; and, the difficulty of marketing due to the high perishability of products. Furthermore, it is remarkable volatility and doubts about the prices will be received, which makes agricultural activities, in certain moments, a true game of uncertainties and high financial risk (Bialoskorski Neto, 1995).

The agricultural commodities are a way to provide "insurance" against the risk that participants assume in this market and offer a "guarantee" about the evolution of prices. On the one hand, these markets can be an effective way to eliminate one of the major risks of farming due to price uncertainty in future time, when farmers sell their crops. On the other hand, the futures markets play an important role in decision making with a focus on maximizing returns. In particular, the study of volatility is an essential tool in this market, especially for asset pricing and risk management. A class of Autoregressive Conditional Heteroscedasticity models (ARCH) is used to assess the impact of volatility and the influence of investors' behavior on the formation of agricultural commodities prices. These models exhibit characteristics that take into account the changing variance over time. The conditional variance provided by these models will be used as a proxy for the volatility of coffee returns (Pereira, 2009).

The problem statement of this research work is to identify the effect of volatility and investors' behavior on setting the coffee futures prices. This problem is important for decision making of economic agents in the spot markets for coffee, as well as for investors who operate in the coffee futures markets, which will provide information about the coffee futures prices.

2. METHODOLOGY

This work differs from most studies on volatility, which assume that investors are rational and their behavior is consistent with the assumptions of the Efficient Market Hypothesis. This hypothesis argues that prices reflect the correct values of assets, since all investors have the same information and have homogeneous expectations. Thus, the market is efficient, the current prices of these assets should reflect all information available at that time, it was not possible to gain abnormal profits adjusted for risk (Roberts, 1967; Fama, 1970; and, Lo, 2007). In this type of market, there are not returns outweigh the risks or possibility of obtaining returns without risk (Milanez, 2001; Barberis and Thaler, 2003). It would not be expected having an excessive volatility in futures markets, and then, there would be no difference of opinions among investors (Thaler, 1999).

Behavioral Finance considers that, given a certain underlying asset pricing problem, the correction in prices with deviations caused by a less rational investor does not happen so quickly, warning that the ways to fix the price can be extremely expensive and risky, so no attractive. As a result, the distorted price may remain incorrect (Aldrighi and Milanez, 2005). This theory identifies factors, such as beliefs and preferences that can influence the investors' behavior in order to cause price deviations in the market. The beliefs are related to the way in which investors form their expectations in market, while the preferences influence the way that investors assess risk situations. Thus, to understand the formation of prices base of assets is necessary to know the preferences of investors and how they react to risks. Behavioral Finance believe that those cases, in which it does not appear to apply the Expected Utility Theory, are important for the understanding of some factors that cause market shifts. It was from these cases that came to Prospect Theory, in which an investor before a loss, he'd rather take the risk of not losing, and before a gain, he'd rather not take the risk to get a higher gain (Kahneman and Tversky, 1979). This theory contradicts the microeconomic concept of utility, which assumes that an investor assesses the risk of an investment in agreement with the change which provides on his level of wealth. Unlike the Expected Utility Theory, where utilities have positive and negative symmetrical weights in the Prospect Theory for the same monetary value, the perception of damage generated by loss is seen at about 2.5 times greater than the benefit produced by a gain (Tversky and Kahneman, 1992).

Despite the Modern Finance Theory and their hypotheses are able to explain the volatility in asset prices, this research adopts the Prospect Theory as a theoretical approach for considering other factors that might explain prices in the futures markets such as economic shocks correlated with a commodity; positive and negative information flows about prices and quantities in other markets; and, variations in agents' expectations.

The good and bad news daily posted influence the expectations and the investors' behavior and play an essential role in most financial decisions. Therefore, investors make mistakes that cause variations on the price of an asset which is incompatible with the Efficient Market Hypothesis, resulting in strong speculative movements in futures markets.

Coffee futures prices are highly volatile to any disturbance or information related to this commodity. The changes in coffee futures prices observed in recent years may be due to economic and behavioral factors. Investors are more sensitive to negative information (i.e. bad news) which has a greater impact on volatility and influence on setting coffee futures prices. The leverage effect supports the arguments of Prospect Theory in the sense that investors are more sensitive to losses than to gains (Kahneman and Tversky, 1979). A class of Autoregressive Conditional Heteroscedasticity (ARCH) models, namely, Generalized Autoregressive Conditional Heteroscedasticity (GARCH), Threshold Generalized Autoregressive Conditional Heteroscedasticity (TARCH) and Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) models are used to assess the impact of volatility and behavioral factors on coffee futures prices.

The ARCH model determines that the conditional variance is the weighted average of the squared non-expected returns in the past. The various shocks which cover the periods (t-1) to (t-p) produce different impacts on the behavior of residues (ε_t). This model assumes that the conditional distribution of the innovations is usually distributed with zero mean and variance σ_t^2 . So σ_t^2 is a function of quadratic past innovations, where p represents the model order (Stock and Watson, 2004). The ARCH(p) model is presented as follows:

$$\varepsilon_t | \Omega_{t-1} \sim N(0, \sigma_t^2) \quad (1)$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \dots + \alpha_p \varepsilon_{t-p}^2 \quad (2)$$

where:

α_0 - the constant term;

α_i - the parameter of the volatility reaction.

The variance of the ARCH(p) model at time t depends on a constant term plus square errors in periods from t-1 to t-p. On the one hand, if the coefficients $\alpha_0, \alpha_1, \alpha_2, \dots, \alpha_p$ are greater than zero, and the squares of the recent errors are large, the model predicts that the square of the current error is large in magnitude and its variance is also large. On the other hand, if there is no correlation between the variances of the errors, the coefficients $\alpha_0, \alpha_1, \alpha_2, \dots, \alpha_p$ are not statistically different from zero and the model will present homoscedasticity. Engle (1982) demonstrated that, for various econometric models, it is not reasonable to assume a constant conditional variance of the forecast errors. To verify the presence of autoregressive conditional heteroscedasticity in the models, we use the Lagrange Multiplier test.

After the development of the ARCH model, other models have emerged such as GARCH, TARCH and EGARCH models with wide application in time series. These models have been applied to the analysis of conditional volatility in time series of coffee futures returns.

Bollerslev (1986) generalizes the ARCH model, proposing the GARCH model in order to capture both the mean and variance of a time series with an ARMA process. The GARCH model expresses in a more parsimonious manner (with few parameters) the time dependence of the conditional variance. Sets up the GARCH model by:

$$\sigma_t^2 = \omega + \sum_{i=1}^p \alpha_i \varepsilon_{t-p}^2 + \sum_{j=1}^q \beta_j \sigma_{t-q}^2 \quad (3)$$

where:

ω - the constant term;

α_i - the parameter of the volatility reaction; and,

β_j - the parameter of the volatility persistence.

This model is well defined, if the following restrictions ($\omega > 0, \alpha_i \geq 0, \beta_j > 0$) are satisfied.

The intuition for the parameters of this model is: a) large β coefficients indicate that shocks take a long time to dissipate (volatility persistence); and, b) large α coefficients reveal that the volatility tends to be more "sharp" (having a high volatility reaction). The sum of α and β less than one indicates that the time series is stationary. We can see that the persistence of the shocks to the volatility of the commodity return is also checked by the sum of α and β . Values close to zero indicate that a shock on volatility cause a transient response on the behavior of the time series, converging, in the short term, to its historical mean, while values near one indicate that the shock will take longer to disappear. We can observe that periods of low prices are followed by a high volatility, while the periods of high prices, there is less intensity in volatility. This is due to the leverage effect, in which positive and negative shocks tend to have different effects on volatility. These asymmetries can be captured by the EGARCH and TARARCH models. The GARCH models have limitations, because the impact of shocks on volatility is symmetric (Nelson, 1991). This problem was overcome by the development of the EGARCH models that capture the asymmetric impacts in a time series. The EGARCH model is characterized by the volatility asymmetry, where shocks have an exponential and non-quadratic effect. The EGARCH model is represented as follows:

$$\ln(\sigma_t^2) = \omega + \sum_{j=1}^q \beta_j \ln(\sigma_{t-j}^2) + \sum_{i=1}^p \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{i=1}^p \gamma_i \frac{\varepsilon_{t-i}}{|\sigma_{t-i}|} \quad (4)$$

where:

ω - the constant term;

α_i - the parameter of the volatility reaction;

β_j - the parameter of the volatility persistence; and,

γ_i - the parameter of the volatility asymmetry (leverage effect).

The leverage effect occurs when $\gamma_i < 0$, allowing that the volatility responds more quickly to negative shocks than positive shocks.

The TARARCH model assumes that negative information, such as overproduction, falling dollar, political instability, etc., distort the market (Zakoian, 1994). This model also allows capturing the leverage effect and the asymmetric behavior is not only captured by the sign of the shock, but mainly by the size of this shock. The TARARCH model is represented as follows:

$$\sigma_t^2 = \omega + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^p \gamma_i d_{t-i} \varepsilon_{t-i}^2 \quad (5)$$

where:

$$d_{t-i} = \begin{cases} 1 & \varepsilon_{t-i} < 0 \text{ (bad news)} \\ 0 & \varepsilon_{t-i} \geq 0 \text{ (good news)} \end{cases}$$

where:

ω - the constant term;

α_i - the parameter of the volatility reaction;

β_j - the parameter of the volatility persistence; and,

γ_i - the parameter of the volatility asymmetry (leverage effect).

When $\gamma_i = 0$ indicates that the variance does not show the leverage effect and the model collapses to the standard GARCH form. If $\gamma_i \neq 0$, there is a differential impact of positive and negative shocks on volatility. The ε_{t-i}^2 has different effects on the conditional variance σ_t^2 : when ε_{t-i} is nonnegative, the total effects are given by $\alpha_i \varepsilon_{t-i}^2$; when ε_{t-i} is negative, the total effect are given by $(\alpha_i + \gamma_i) \varepsilon_{t-i}^2$. When γ_i is significant and positive, negative shocks (i.e. bad news) have a larger impact on the volatility of the time series than positive shocks (i.e. good news).

The leverage effect can be understood as a proxy for the emergence of new information in the market and investors' behavior, so that the higher volatility of returns in the period is a consequence of the investors' reaction to shocks. Moreover, the leverage effect corroborates the Prospect Theory in the

sense that investors are more sensitive to losses than to gains and these investors are more sensitive to negative information (i.e. bad news) which might have influence on their emotions, affects and cognitive errors and have a larger impact on volatility, which has impact on the formation of coffee futures prices.

3. DATA AND INFORMATION

The data used in this research work correspond to coffee futures prices obtained from a secondary source, with daily frequency, quoted in the months of March, May, July, September and December, in U.S. dollars per pound, using daily closing prices, relative to second position in the New York Board of Trade (NYBOT), covering the period from January 6th, 1995 to December 31th, 2014, which represents 5,124 observations. The selected period allows contemplate different times of shocks on the market. Pereira (2009) divided the selected period into four periods of time to capture the stylized facts in each period. This research work considers five periods of time described as follows: 1/06/1995 - 1/05/1999 (1,043 observations); 1/06/1999 - 1/03/2003 (1,043 observations); 1/06/2003 - 1/03/2007 (1,043 observations); 1/04/2007 - 1/03/2011 (1,043 observations); and, 1/04/2011 - 12/31/2014 (1,042 observations).

The data were used by a class of Autoregressive Conditional Heteroscedasticity models (ARCH), namely, GARCH, TARCH and EGARCH models, assuming two essential aspects: a) volatility in each period; and, b) valid values for all observations. The presence of observations on New York Board of Trade, in a period, means that the percentage of days on which there was at least one contract of coffee futures held. When there are no trading days, the asking price remains unchanged and the daily return is zero. It is noteworthy that the selection of coffee futures contracts available on the New York Board of Trade ensures the restrictive nature of liquidity in each one of the time series. Coffee futures prices show strong oscillations in certain periods like 1999 (Brazilian crisis), 2002/03 (dollar appreciation), 2007/08 ("bubble" of commodities and the American crisis) and 2011 (European sovereign crisis) (Figure 3.1).

The time series of coffee futures prices (p_t) are transformed in natural logarithms (\ln) which allow the computation of returns of coffee futures (r_t) as follows: $r_t = \ln(p_t) - \ln(p_{t-1})$.

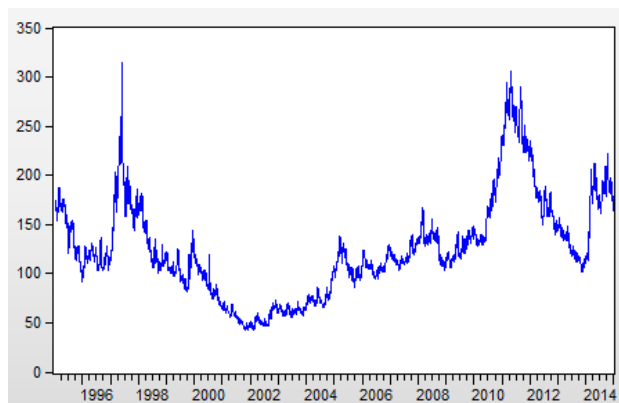


Fig3.1. Coffee futures prices, 1995 - 2014

Source: Research results

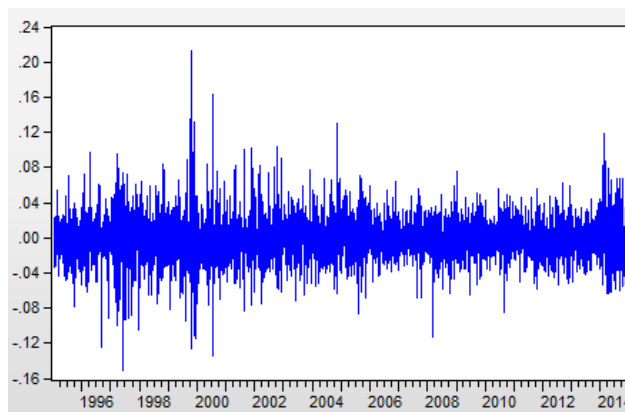


Fig3.2. Returns of coffee futures, 1995 - 2014

Source: Research results

The figures 3.1 and 3.2 show trends of high and low coffee futures prices as well as periods of high and low coffee returns, followed by periods of high and low volatility, signaling that the coffee futures market is quite volatile. The minimum and maximum values achieved by coffee futures prices in the period analyzed were U.S. \$ 42 / lb. (on 11/29/2001) and U.S. \$ 314.80 / lb. (on 5/29/1997), respectively.

Table3.1. Descriptive statistics of coffee futures prices returns

Period	Mean	Maximum	Minimum	St Deviation	Skewness	Kurtosis	C Variation
1	-0.000370	0.097501	-0.150309	0.027189	-0.483940	5.802036	73.483784
2	-0.000637	0.211999	-0.133851	0.028608	0.575933	9.734781	44.910518
3	0.000673	0.129720	-0.087098	0.021084	0.301303	5.264494	31.328380
4	0.000638	0.075102	-0.112541	0.018440	-0.322826	5.661269	28.902821
5	-0.000352	0.117892	-0.064002	0.021048	0.482611	5.295573	59.795455
Total	-0.000009	0.211999	-0.150309	0.023559	0.119191	7.988514	2511.620469

Source: Research results

The main descriptive statistics of coffee futures returns for the data collected in this research work are reported in Table 3.1. The results show that the mean of the coffee futures returns has a small negative value in the first, second, fifth and total periods of time and a small positive value in the other periods of time. The values of the standard deviation are very small for each one of the periods of time. Coffee futures returns show a left skewed distributions for the first and fourth periods and a right skewed distributions for all the other periods. The kurtosis, in all the analyzed periods, shows that coffee futures returns distributions showed deviations from normality characterizing them as leptokurtic distributions. The skewness and kurtosis show a pattern that diverges from normal distribution in all periods of time which is corroborated by the Jarque-Bera test. The coefficients of variation for all periods are very high. These measures provide a rough estimate of return trends and volatility patterns for coffee futures returns, however, their lack of accuracy and compliance with coffee futures returns behavior is very likely to induce misleading conclusions. For this reason, we utilize more robust models to assess and estimate volatility in coffee futures market.

4. RESULTS

The time series of commodity prices are mostly nonstationary. The time series of coffee futures prices are clearly non stationary, with intense volatility in certain periods (Figures 3.1 and 3.2).

Table4.1. Stationarity tests for a time series of coffee futures prices

Variable	Without trend		With trend	
	ADF test	5% critical value	ADF test	5% critical value
Coffee Futures Price	-2.336699	-2.861899	-2.206807	-3.140667
Δ Coffee Futures Prices	-40.262250	-2.861899	-40.263950	-3.410667

Note: Δ corresponds to the first difference

Source: Research results

The results confirm that coffee futures prices have a stochastic trend, when the Augmented Dickey-Fuller Unit Root test is performed with or without tendency and the null hypothesis of the presence of unit root is not rejected. If the first difference is used, the time series will be stationary (Table 4.1).

This research work tested the coffee futures returns for total period and five periods of time as it is described in the data and information chapter.

Table4.2. Stationarity tests for a series of coffee futures returns

Periods	Beginning	End	Obs. Number	The ADF test	1% critical value
Total period	01/06/1995	12/31/2014	5214	-41.22026	-3.959799
First Period	01/06/1995	01/05/1999	1043	-17.58387	-3.966905
Second Period	01/06/1999	01/03/2003	1043	-33.30192	-3.966879
Third Period	01/06/2003	01/03/2007	1043	-32.29023	-3.966879
Fourth period	01/04/2007	01/03/2011	1043	-33.84203	-3.966879
Fifth Period	01/04/2011	12/31/2014	1042	-34.21386	-3.966888

Source: Research results

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The ADF test presented in table 4.2 shows that the time series of daily returns of coffee futures reject the null hypothesis of nonstationarity for a 1% critical value. This study found high kurtosis values, indication of variance clustering and nonlinear dependence that suggest a specification of an ARCH-type structure.

Table 4.3. Model Identification

Periods	Models	AIC criterion
First Period	GARCH(1,1)	-4.48183
	GARCH(2,1)	-4.46405
	TARCH(1,1)	-4.47734
Second Period	EGARCH(1,1)	-4.46302
	GARCH(1,1)	-4.50934
	TARCH(1,1)	-4.51094
Third Period	EGARCH(1,1)	-4.43583
	GARCH(1,1)	-4.88785
	GARCH(2,1)	-4.87582
Fourth Period	TARCH(1,1)	-4.88058
	EGARCH(1,1)	-4.88824
	GARCH(1,1)	-5.16006
Fifth Period	GARCH(2,1)	-5.15818
	TARCH(1,1)	-5.16370
	EGARCH(1,1)	-5.17993
Total Period	GARCH(1,1)	-4.97259
	GARCH(2,1)	-4.96597
	TARCH(1,1)	-4.96575
Total Period	EGARCH(1,1)	-4.95883
	GARCH(1,1)	-4.77774
	GARCH(2,1)	-4.76456
Total Period	TARCH(1,1)	-4.77747
	EGARCH(1,1)	-4.76305

Source: Research results

The existence of asymmetric effects in the time series of coffee futures returns is captured by the EGARCH and TARCH models. Engle and NG (1993) make a comparison between these models and find that the TARCH model has higher performance than the EGARCH model. Thus, we identify the best model estimated by the lowest value of the AIC criterion for each one of the periods (Table 4.3). This shows the selected models for each one of the periods of time to corroborate the identification of volatility as a tool for coffee futures pricing.

The GARCH(1,1) and TARCH(1,1) models were selected in the first period of time and their variances are presented as follows:

$$\sigma_t^2 = 0.000026 + 0.058394 \varepsilon_{t-1}^2 + 0.9056506 \sigma_{t-1}^2 \quad (6)$$

(0.000) (0.000) (0.000)

$$\sigma_t^2 = 0.0000265 + 0.0181426 \varepsilon_{t-1}^2 + 0.9044515 \sigma_{t-1}^2 + 0.0867195 d_{t-1} \varepsilon_{t-1}^2 \quad (7)$$

(0.001) (0.002) (0.000) (0.000)

The values in parentheses represent the p-values in all models presented in this research work. The coefficients of the above models are statistical significance at 1% critical value. The persistence of shocks to volatility in the GARCH(1,1) model is measured by the sum of the coefficients α and β (0.964), which indicates that more time becomes necessary for the shock to dissipate. This might be explained by a left-skewed and a leptokurtic distribution in this period of time. The TARCH(1,1) model captures the evidence of asymmetry in the dynamics of reversion to the mean through the γ coefficient (0.0867) which is positive. The positive sign of the γ coefficient in the TARCH(1,1) model shows the presence of the leverage effect, where negative shocks (i.e. bad news) have a greater impact on the volatility of coffee futures returns than positive shocks (i.e. good news). The leverage effect can be understood as a proxy for the emergence of new information in the coffee futures

market, so that the higher volatility of coffee futures returns in the period is a consequence of the reaction of investors to shocks. Moreover, the leverage effect includes information related with investors' behavior which could have influence on the formation of coffee futures prices and corroborates the Prospect Theory in the sense that investors are more sensitive to losses than to gains and these investors are more sensitive to bad news which have a greater impact on volatility. Therefore, the volatility feedback effects indicate that the emergence of new information in market increases the volatility of the return of the commodity and lowers its price, accentuating the negative skewness of this return. The results of the TAR(1,1) model confirm the theoretical arguments and corroborate the volatility feedback effects and, especially, the Prospect Theory.

The TAR(1,1) and GARCH(1,1) models were selected in the second period of time and their variances are presented as follows:

$$\sigma_t^2 = 0.0000783 - 0.05952126 \varepsilon_{t-1}^2 + 0.8128435 \sigma_{t-1}^2 + 0.280527 d_{t-1} \varepsilon_{t-1}^2 \quad (8)$$

(0.001) (0.000) (0.000) (0.000)

$$\sigma_t^2 = 0.000118 + 0.154088 \varepsilon_{t-1}^2 + 0.696196 \sigma_{t-1}^2 \quad (9)$$

(0.000) (0.000) (0.000)

The coefficients of these models are statistically significant at 1% critical value. The γ coefficient (0.281) in the TAR(1,1) model, which captures the asymmetry of volatility, is positive. The positive coefficient means that negative shocks have a greater impact on the volatility of coffee futures returns than positive shocks. This result confirms the theoretical arguments, and corroborates the volatility feedback effects and, especially, the Prospect Theory. The magnitude of the persistence coefficients (0.750) in the GARCH(1,1) model is less than one, which means that any shock have a shorter persistent effect over periods of volatility in the time series. This might be explained by a right-skewed distribution and a leptokurtic distribution which shows a much higher peak around the mean.

The EGARCH(1,1) and GARCH(1,1) models were selected in the third period of time and their variances are presented as follows:

$$\ln(\sigma_t^2) = -0.400080 - 0.994668 \ln(\sigma_{t-1}^2) + 0.021214 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + 0.020542 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (10)$$

(0.000) (0.000) (0.000) (0.000)

$$\sigma_t^2 = 0.000526 + 0.020385 \varepsilon_{t-1}^2 + 0.204746 \sigma_{t-1}^2 \quad (11)$$

(0.000) (0.000) (0.000)

The coefficients of these models are statistically significant at 1% critical value. The γ coefficient (0.0205) in the EGARCH(1,1) model, that show the leverage effect, is positive. This coefficient means that positive shocks (good news) generate lower volatility than negative shocks (bad news) and investors are less sensitive to good news. The magnitude of the persistence coefficients (0.225) in the GARCH(1,1) model is far away from one, so that any shock does not have a persistent effect over periods of volatility in the time series. This might be explained because the statistical distribution is right-skewed and leptokurtic. The kurtosis in this period of time has the lowest value.

The EGARCH(1,1) and GARCH(1,1) models were selected in the fourth period of time and their variances are presented as follows:

$$\ln(\sigma_t^2) = -0.148771 - 0.980786 \ln(\sigma_{t-1}^2) + 0.066999 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + 0.042632 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (12)$$

(0.001) (0.000) (0.000) (0.000)

$$\sigma_t^2 = 0.000009 + 0.029818 \varepsilon_{t-1}^2 + 0.9457056 \sigma_{t-1}^2 \quad (13)$$

(0.007) (0.000) (0.000)

The coefficients of these models are statistically significant at 1% critical value. The γ coefficient (0.043) in the EGARCH(1,1) model, that show the leverage effect, is positive. This positive coefficient generates lower volatility and investors are less sensitive to good news. The magnitude of the persistence coefficients (0.976) in the GARCH(1,1) model is near one, which means that any

shock have a persistent effect over long periods of volatility in the time series. This might be explained because the statistical distribution is left-skewed and leptokurtic.

The GARCH(1,1) and TAR(1,1) models were selected in the fifth period of time and their variances are presented as follows:

$$\sigma_t^2 = 0.000009 + 0.044740 \varepsilon_{t-1}^2 + 0.236396 \sigma_{t-1}^2 \quad (14)$$

(0.007) (0.000) (0.000)

$$\sigma_t^2 = 0.000008 + 0.032379 \varepsilon_{t-1}^2 + 0.908853 \sigma_{t-1}^2 + 0.092779 d_{t-1} \varepsilon_{t-1}^2 \quad (15)$$

(0.010) (0.000) (0.000) (0.000)

The coefficients of these models are statistical significance at 1% critical value. The sum of the coefficients α and β (0.281) in the GARCH(1,1) model, which indicates that the variance tends to converge to its historical mean. This might be explained by a right-skewed and a leptokurtic distribution. The positive sign of the γ coefficient (0.0928) in the TAR(1,1) model shows the presence of the leverage effect, where negative shocks have a greater impact on the volatility of coffee futures returns than positive shocks. The higher volatility of coffee futures returns in the period is a consequence of the reaction of investors to shocks. Moreover, the leverage effect corroborates the Prospect Theory in the sense that investors are more sensitive to losses than to gains and are more sensitive to negative information which have a greater impact on volatility. The leverage effect includes information related with investors' behavior which can have influence on the formation of coffee futures prices.

The GARCH(1,1) and TAR(1,1) models were selected in the total period of time and their variances are presented as follows:

$$\sigma_t^2 = 0.000014 + 0.049412 \varepsilon_{t-1}^2 + 0.424704 \sigma_{t-1}^2 \quad (16)$$

(0.000) (0.000) (0.000)

$$\sigma_t^2 = 0.000023 + 0.010828 \varepsilon_{t-1}^2 + 0.902269 \sigma_{t-1}^2 + 0.088004 d_{t-1} \varepsilon_{t-1}^2 \quad (17)$$

(0.000) (0.002) (0.000) (0.000)

The coefficients of these models are statistical significance at 1% critical value. The magnitude of the persistence coefficients (0.474) in the GARCH(1,1) model reveals that shocks to volatility will not last long and indicates that the variance tends to converge to its historical mean. The low persistence observed in this model in the total period will influence the decisions made by investors, especially for those who trade coffee futures contracts for long maturity. This might be explained by a right-skewed and a leptokurtic distribution

The γ coefficient (0.088) of the TAR(1,1) model revealed the existence of leverage effect, because it is significantly different from zero and positive. The leverage effect shows that negative information has greater impact on volatility which corroborates the Prospect Theory and emphasizes the sensitivity to losses.

5. CONCLUSIONS

The great challenge for this research work is to show that the biases of investors' behavior are predictable and can affect the formation of coffee futures prices. This study uses auto-regressive conditional heteroscedasticity models to analyze results that show that the volatility has an impact on the formation of coffee futures prices. The presence of the leverage effect in the TAR models shows that negative shocks have a greater impact in the volatility of coffee futures returns than positive shocks. The leverage effect can be understood as a proxy for the appearance of new information in the coffee futures market, so the high volatility of coffee futures returns is a result of investors' reaction to shocks. The presence of the leverage effect in the TAR models corroborates the Prospect Theory, which states that a great volume of bad news generates an increase in the volatility of coffee futures returns. One aspect is that high levels of volatility are closely associated with the presence of the leverage effect in the TAR models. Another aspect is the leverage effect may include information related with investors' behavior which can have influence on the formation of coffee futures prices.

Model results also show that investors' reactions to bad news are statistically significant in coffee futures markets and suggest that Behavioral Finance can contribute to the understanding of the formation of coffee futures prices.

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