The influence of behavior factors in setting the agricultural futures market prices

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Abstract

The great challenge for this research work is to show that the biases of investor behavior are predictable and may affect the coffee futures market prices. This research work uses auto-regressive conditional heteroskedasticity (ARCH) models to analyze results that cause deviations in the coffee futures market prices. The negative asymmetry coefficient of EGARCH model and the positive asymmetry coefficient of TGARCH model show the presence of the leverage effect where negative shocks have a greater impact in the volatility of returns in coffee than positive shocks. The presence of the leverage effect corroborates the Prospect Theory.

Model results also show that the reactions of investors to negative information were statistically significant in the coffee futures market and suggest that Behavioral Finance might contribute to the understanding of the formation of coffee futures market prices.

Key words: Futures Markets, Coffee, Volatility, Prospect Theory, Behavioral Finance

JEL Classification: C58, G02, G10, Q14

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1 - Introduction

This research work analyses the influence of behavioral factors in the context of futures market prices of agricultural commodities. Pereira (2009) showed that volatility has an impact on the pricing of cocoa, making it impossible to explain by traditional finance theories. Her research work suggested that volatility may also result from decisions of investors due to psychological issues 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 market prices and the results of her approach corroborate the Prospect Theory. This study focuses on the influence of behavioral factors 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 decreased 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 production growth in the course of the last 50 years, representing 23.5% of world production. 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.

Central America and Mexico produced an annual average of 18 million bags during the period from 1990 to 2012. Production in the region as a whole does not seem to show marked 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 preceding period. However, the recent outbreak of coffee leaf rust disease could cause a reduction in the production levels of many countries in the region.

South America is the world's leading producing region with an annual 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 futures markets for 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. Three variants of the class of models of Autoregressive Conditional Heteroskedasticity (ARCH), namely, GARCH, TGARCH and EGARCH models, which exhibit characteristics of modeling 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 in setting the coffee futures prices traded on the New York Stock Exchange. 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 futures market, 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 consistent with the assumptions of the efficient market hypothesis. Modern Financial theories predict that investors have homogeneous expectations. Investors have the same information and determine the same fair value of

assets. It would not be expected to have excessive volatility in commodity futures markets, and then there would be no difference of opinion among investors (Thaler, 2003).

Coffee futures prices are high volatile to any disturbance or information related to this commodity. The changes in coffee prices observed in the futures market in recent years are due to economic and behavioral factors. The global economic slowdown has caused a substitution of securities for commodities in financial decisions. 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). Investors are more sensitive to negative information which has a greater impact on volatility and influence in setting coffee futures prices. A class of Autoregressive Conditional Heteroskedasticity (ARCH) models, namely, Generalized Autoregressive Conditional Heteroskedaticity (GARCH), Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) and Threshold Generalized Autoregressive Conditional Heteroskedasticity (TGARCH) models are used to assess the impact of volatility and behavioral factors on coffee futures prices.

The ARCH(p) 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 that σ_t^2 is a function of quadratic past innovations, where p represents the model order (Stock and Watson, 2004). Sets up the ARCH(p) model by:

$$\varepsilon_t | \, \Omega_{t-1} \sim N(0, \sigma_t^2) \tag{2.1}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \ldots \alpha_p \varepsilon_{t-p}^2 \tag{2.2}$$

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. If the coefficients $\alpha_0, \alpha_1, \alpha_2, \ldots, \alpha_p$ 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 errors of the coefficients $\alpha_0, \ \alpha_1, \ \alpha_2, \ \ldots, \ \alpha_p$ are not statistically different from

zero and the model will present homoskedasticity. 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 heteroskedasticity in the models, we use the Lagrange Multiplier test.

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

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(p, q) model by:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-p}^2 + \sum_{j=1}^{q} \beta_j \, \sigma_{t-q}^2 \qquad (2.3)$$

This model is well defined, if the following restrictions ($\alpha_0 > 0,\ \alpha_i \geq 0,\ \beta_j > 0$) are satisfied.

The intuition for the parameters of this model are: a) large coefficients β indicate that shocks take a long time to dissipate (persistent volatility); and b) large coefficients α reveal that the volatility tends to be more "sharp" (having high reactivity). We can see that the persistence of the shocks to volatility of the return of a commodity is checked by the sum of α and β. Values close to zero indicate that a shock on volatility cause transient effects on the behavior of the time series, converging, in the short time, 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 high volatility, while the periods of high prices, there is less intensity in volatility. This is due to the leverage effect, where positive and negative shocks tend to have different effects on volatility. These asymmetries can be captured by EGARCH and TGARCH models. The ARCH/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 and ensuring the non-negativity of the

coefficients in this model. It is noteworthy that any imposition of restriction is not necessary to ensure the non-negativity of the model parameters. This model uses $\ln(\sigma_t^2)$, if the parameters are negative, the conditional variance is necessarily positive.

The EGARCH model is characterized by the asymmetry of volatility, where shocks have an exponential and non-quadratic effect. The EGARCH(1,1) model is represented as follows:

$$\ln(\sigma_t^2) = \alpha_0 + \beta_1 \ln(\sigma_{t-1}^2) + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (2.4)$$

where:

α - the coefficient of the reaction of volatility;

β - the coefficient of the volatility persistence; and,

γ - the coefficient that captures the asymmetry of volatility. The leverage effect occurs when $\gamma < 0$, allowing that the volatility responds more quickly to negative shocks than positive shocks.

The TGARCH 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 TGARCH(1,1) model is represented as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma_1 d_{t-1} \varepsilon_{t-1}^2 \quad (2.5)$$

where:

$$d_{t-1} = \begin{cases} 1 & \varepsilon_{t-1}^2 < 0 \ (bad\ news) \\ 0 & \varepsilon_{t-1}^2 > 0 \ (good\ news) \end{cases}$$

where:

α - the coefficient of the reaction of volatility;

β - the coefficient of persistent volatility; and,

γ - the coefficient of asymmetry.

When $\gamma \neq 0$, there is a differential impact of positive and negative shocks in volatility and if $\gamma > 0$ verifies the presence of the leverage effect in which the negative shocks have a greater impact on the volatility of the time series than positive shocks. The $\gamma = 0$ indicates that the variance does not show asymmetry and the model collapses to the

standard GARCH form. The leverage effect can be understood as a proxy for the emergence of new information in the market, so that the higher volatility of 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 these investors are more sensitive to negative information which have a greater impact on volatility.

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 March 1992 to March 2012, which represents 5,220 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 three periods of time described as follows: 03/23/1992 - 11/20/1998 (1,740 observations); 11/23/1998 - 7/22/2005 (1,740 observations); and 07/26/2005 - 3/23/2005 (1,740 observations).

The data were used by a class of Autoregressive Conditional Heteroskedasticity models (ARCH), namely, GARCH, TGARCH 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) and in 2007/08 ("bubble" of commodities and the American crisis) (Figure 3.1).

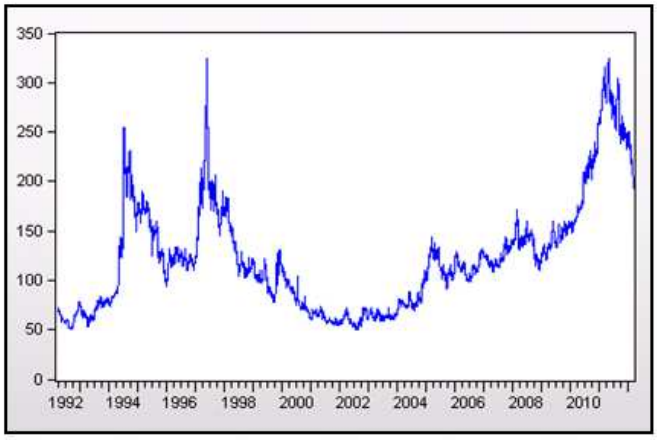

Figure 3.1 – Coffee futures prices, 1992 - 2012
Source: Research results

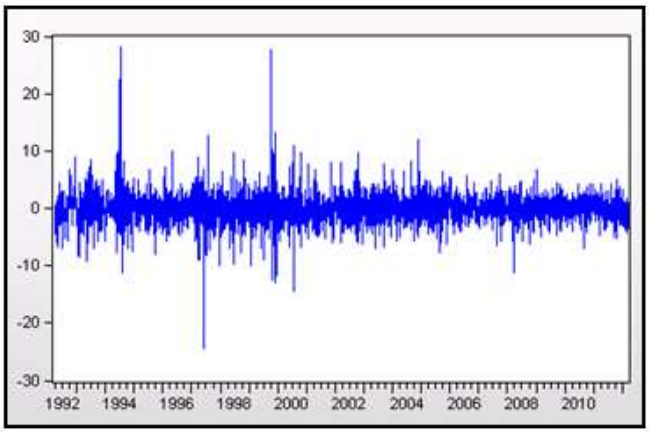

Figure 3.2 – Returns of coffee futures, 1992 - 2012
Source: Research results

The figures 3.1 and 3.2 show trends of high and low prices as well as periods of high and low 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. $ 50.05 / lb (on 7/29/2002) and U.S. $ 324.86 / lb (on 6/02/1997), respectively.

Period	Mean	Maximum	Minimum	St Deviation	Skewness	Kurtosis	JB test
1	0.025056	-24.409350	28.254930	2.583404	0.571418	20.601660	22543.56
2	-0.003778	27.703230	-14.483600	2.391111	0.842177	17.876810	16242.01
3	0.034295	6.799735	-11.300750	1.663897	-0.285608	5.746441	570.19
Total	0.018996	28.254930	-24.409350	28.254930	0.584315	20.164800	64366.83

Table 3.1 – Descriptive statistics of returns of coffee futures
Source: Research results

The main descriptive statistics of returns of coffee futures are reported in Table 3.1. The Jarque-Bera tests and their zero p-values suggest a rejection of the null hypothesis of normality. The values for skewness and kurtosis, in all the analyzed periods, show that

returns of coffee futures distribution showed deviations from normality characterizing it as leptokurtic.

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 3.5).

Without trend			With trend	
Variable	ADF test	5% critical value	ADF test	1% critical value
Coffee Price	-1.965117	-3.431422	-2.206807	-3.341422
Δ Coffee Price	-71.436970	-3.431422	-71.430450	-3.341422

Table 4.1 – Stationarity tests for a time series of coffee futures prices
Source: Research results
Note: Δ corresponds to the first difference

The results confirm that coffee futures 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 returns for total period and three periods of time as it is described in the data and information chapter.

Periods	Beginning	End	Obs. Number	The ADF test	1% critical value
Total period	03/23/1992	03/23/2012	5220	-52.35007	-3.431422
First Period	03/23/1992	11/20/1998	1740	-29.79590	-3.433912
Second Period	11/23/1998	07/22/2005	1740	-30.70286	-3.433912
Third Period	07/25/2005	03/23/2012	1740	-30.14458	-3.433912

Table 4.2 – Stationarity tests for a series of coffee futures returns
Source: Research results

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 a GARCH-type structure. The existence of asymmetric effects in the time series of returns of coffee futures is captured by the EGARCH and TGARCH models. Engle and NG (1993) make a comparison between these models and find that the TGARCH model has higher performance than the EGARCH model. Thus, we identify the best model estimated by the lowest values of the AIC and SBC criteria for each one of the periods (Table 4.3).

Periods	Models	AIC criterion	BIC criterion
First Period	**GARCH(1,1)**	4.581621	4.591042
	GARCH(2,1)	4.581714	4.594276
	TGARCH(1,1)	4.569752	4.582313
	EGARCH(1,1)	4.598443	4.605104
Second Period	**GARCH(1,1)**	4.479199	4.488620
	GARCH(2,1)	4.485706	4.498265
	TGARCH(1,1)	4.498791	4.511352
	EGARCH(1,1)	4.432721	4.445282
Third Period	**GARCH(1,1)**	3.839784	3.849205
	GARCH(2,1)	3.853724	3.865757
	TGARCH(1,1)	3.851829	3.864391
	EGARCH(1,1)	3.849265	3.861826
Total Period	**GARCH(1,1)**	4.314534	4.318305
	GARCH(2,1)	4.314721	4.319749
	TGARCH(1,1)	4.300269	4,305297
	EGARCH(1,1)	4.330665	4.335693

Table 4.3 – Identification of the models for each one of the periods of time
Source: Research results

The table 4.3 shows the selected models for each one of the periods of time to corroborate the identification of volatility as a tool for coffee pricing.

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

$$\sigma_t^2 = \underset{(0.0000)}{0.098461} + \underset{(0.0000)}{0.046051}\varepsilon_{t-1}^2 + \underset{(0.0000)}{0.940270}\sigma_{t-1}^2 \quad (4.1)$$

$$\sigma_t^2 = \underset{(0.0000)}{0.102991} + \underset{(0.0000)}{0.061313}\varepsilon_{t-1}^2 + \underset{(0.0000)}{0.943595}\sigma_{t-1}^2 + \underset{(0.0000)}{0.040288}\, d_{t-1}\varepsilon_{t-1}^2 \quad (4.2)$$

The results of the GARCH(1,1) model show statistical significance at 1% and the values in parentheses represent the p-values. The persistence of shocks to volatility is measured by the sum of the coefficients α and β (0.040 + 0.943 = 0.983) indicate that the occurrence of shocks to volatility will cause transient effects on the behavior of the time series and, after short-term, the variance tends to converge to its historical mean. Values near or greater than one indicate that more time becomes necessary for the shock to dissipate.

The TGARCH(1,1) model captures the evidence of asymmetry in the dynamics of reversion to the mean through the γ coefficient which is positive. The positive sign of the coefficient of asymmetry in the TGARCH(1,1) model shows the presence of the

leverage effect, where negative shocks have a greater impact on the volatility of the return of coffee futures than positive shocks. 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 returns of coffee futures 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 these investors are more sensitive to negative information 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 TGARCH(1,1) model confirm the theoretical arguments and corroborate the volatility feedback effects and, especially, the Prospect Theory.

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

$$\sigma_t^2 = \underset{(0.0000)}{0.586035} + \underset{(0.0000)}{0.091487}\varepsilon_{t-1}^2 + \underset{(0.0000)}{0.806139}\sigma_{t-1}^2 \quad (4.3)$$

$$\ln(\sigma_t^2) = \underset{(0.0000)}{0.99759} + \underset{(0.0000)}{0.048182}\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \underset{(0.0000)}{0.915872}\ln(\sigma_{t-1}^2) + \underset{(0.0000)}{0.201476}\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (4.4)$$

Models results show statistically significant at 1% and the values in parentheses represent the p-values. The magnitude of the persistence coefficients (0.09 + 0.81 = 0.90) in the GARCH(1,1) model is close to one, leading to the same conclusion obtained in the first period of time that any shock have a persistent effect over long periods of volatility in the time series. The γ coefficient that captures the asymmetry of volatility is positive in the EGARCH(1,1) model and positive shocks are more destabilizing than the negative shocks.

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

$$\sigma_t^2 = \underset{(0.0016)}{0.061756} + \underset{(0.0000)}{0.022761}\varepsilon_{t-1}^2 + \underset{(0.0000)}{0.954594}\sigma_{t-1}^2 \quad (4.5)$$

$$\ln(\sigma_t^2) = \underset{(0.0001)}{0.691086} + \underset{(0.0000)}{0.150848}\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \underset{(0.2398)}{0.208874}\ln(\sigma_{t-1}^2) - \underset{(0.0000)}{0.103472}\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (4.6)$$

Models results show statistically significant at 1% and the values in parentheses represent the p-values, except for the estimate of the coefficient β_1 in the EGARCH(1,1) model. The magnitude of the persistence coefficients (0.02 + 0.95 = 0.97) in the GARCH(1,1) model is close to one, leading to the same conclusion obtained in the first and second periods of time that any shock have a persistent effect over long periods of volatility in the time series. The γ coefficient that captures the asymmetry of volatility is negative in the EGARCH(1,1) model. This negative coefficient means that negative shocks (bad news) generate higher volatility than positive shocks (good news) and investors are more sensitive to negative information which has a greater impact on volatility which corroborates the Prospect Theory.

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

$$\underset{}{\sigma_t^2} = \underset{(0.0000)}{0.083472} + \underset{(0.0000)}{0.044439}\varepsilon_{t-1}^2 + \underset{(0.0000)}{0.939567}\sigma_{t-1}^2 \quad (4.7)$$

$$\underset{}{\sigma_t^2} = \underset{(0.0000)}{0.104428} + \underset{(0.0000)}{0.071428}\varepsilon_{t-1}^2 + \underset{(0.0000)}{0.943595}\sigma_{t-1}^2 + \underset{(0.0000)}{0.053900}\, d_{t-1}\varepsilon_{t-1}^2 \quad (4.8)$$

Models results show statistically significant at 1% and the values in parentheses represent the p-values. The magnitude of the persistence coefficients in both models is 0.98 and 1.01, revealing that shocks to volatility will last long. This means that the conditional variance of residuals for the time series of the return of coffee futures has a unit root and the delay of reversion to historical mean is higher. The high persistence observed by both models in the total period will influence the decisions made by investors, especially for those who trade coffee futures contracts for long maturity.

The γ coefficient of the TGARCH(1,1) model revealed the existence of asymmetric shocks in volatility, because it is significantly different from zero and positive. The leverage effect obtained by the asymmetry coefficient 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 investor behavior are predictable and may affect coffee futures market prices. This study uses auto-regressive conditional heteroskedasticy models to analyze results that cause deviations in coffee futures market prices. The negative asymmetry coefficient of EGARCH model and the positive asymmetry coefficient of TGARCH model show the presence of the leverage effect where negative shocks have a greater impact in the volatility of returns of coffee futures 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 returns of coffee futures is a result of investors' reaction to shocks. The evidence of asymmetry captured by the EGARCH and TGARCH models also indicates the presence of the leverage effect that corroborates the Prospect Theory, which states that a great volume of good or bad information generates an increase in the volatility of returns of coffee futures. Another aspect is that high levels of volatility are closely associated with negative asymmetries. Model results also show that the reactions of investors to negative information were statistically significant in coffee futures market and suggest that Behavioral Finance may contribute to the understanding of the formation of coffee futures market prices.

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