

The behavior of West Texas Intermediate crude-oil and refined products prices volatility before and after the 2008 financial crisis: an approach through analysis of futures contracts

Comportamiento de la volatilidad de los precios del petróleo crudo West Texas Intermediate y productos refinados antes y después de la crisis financiera de 2008: un abordaje a través del análisis de contratos futuros

Thaís C. Azevedo¹ Fernando L. Aiube¹ Carlos P. Samanez¹
Claudio S. Bisso² Leticia A. Costa¹

Recibido 16 de octubre de 2013, aceptado 11 de noviembre de 2014

Received: October 16, 2013 Accepted: November 11, 2014

ABSTRACT

By analyzing futures contracts, this paper examines the volatility of West Texas Intermediate (WTI) crude oil and refined product prices (short, medium and long-term) before and after the financial crisis of 2008. Daily historical data from January 2000 to June 2008 (pre-crisis period) and from May, 2009 to October, 2012 (post-crisis period) were evaluated. AR-GARCH models were adjusted to these series, with the purpose of estimating volatilities and the persistence of shocks. After the crisis, the short-term volatility of the three commodities diminished. The persistence of shocks increased for most contracts after the 2008 crisis. The relevance of this type of analysis is related to the importance of volatility, not only to the agents who negotiate the physical products but also to the traders and their daily positions on exchanges.

Keywords: Volatility modeling, crude oil prices, GARCH models, persistence of shocks.

RESUMEN

Al analizar contratos futuros, este artículo examina la volatilidad de los precios del petróleo crudo WTI (West Texas Intermediate) y de productos refinados (a corto, medio y largo plazo) antes y después de la crisis de 2008. Fueron evaluados datos históricos de enero de 2000 a junio de 2008 (precrisis) y de mayo de 2009 a octubre de 2012 (postcrisis). Ajustamos modelos AR-GARCH a estas series con el objetivo de estimar las volatilidades y persistencia de los choques. Después de la crisis la volatilidad a corto plazo de las 3 commodities disminuyó. La persistencia de los choques aumentó en la mayoría de los contratos después de la crisis de 2008. La relevancia de este tipo de trabajo se relaciona con la importancia de la volatilidad no solo a los agentes que negocian los productos físicos, sino también en los mercados de bolsa y en el gerenciamiento de carteras que incluyen commodities del sector de petróleo.

Palabras clave: Volatilidad, precio del petróleo crudo, modelos GARCH, persistencia de los choques.

INTRODUCTION

WTI (West Texas Intermediate) crude oil, which is derived from the main oil region of the United States,

is a light, sweet and high-quality crude oil, i.e., it possesses a low sulfur content. This type of crude oil provides a high yield when processed because it generates products with high added value, such

¹ Pontifícia Universidade Católica do Rio de Janeiro. Departamento de Engenharia Industrial. Rua Marques de S. Vicente 225. Rio de Janeiro, Brasil. E-mail: thaiscchagas@ig.com.br; aiube@puc-rio.br; cps@puc-rio.br; leticiacosta@esp.puc-rio.br

² Universidade Federal do Rio Grande do Sul. Programa de Pós-graduação em Economia Aplicada - PPGE. Av. João Pessoa, 52 sala 33B. Porto Alegre/RS, Brasil. E-mail: cbisso42@gmail.com

as gasoline and diesel fuel. The quality and cost of refinement and transportation are reflected in the price of crude oil. Reformulated blend stock for oxygenating the blending (RBOB) gasoline and diesel are the main products derived from the processing of crude oil. RBOB gasoline can be blended with ethanol to address environmental issues and conform to specifications of regulatory agencies.

Both crude oil and refined products are traded through futures contracts on the New York Mercantile Exchange (NYMEX). Futures markets allow agents who are exposed to the volatility of commodities to assume positions by mitigating their original exposure. Among all existing futures markets of global commodities, the crude oil futures markets are the most important in terms of the amount traded.

Crude oil prices are influenced by several short-term and long-term factors, which can be summarized as follows: the supply of producer countries, especially the participants of the OPEC (Organization of the Petroleum Exporting Countries), the global demand for fuel, the level of stocks in countries that depend heavily on fuel and geopolitical factors related to the conflicts in the Middle East.

At the beginning of this century, increased demand in emerging countries was an important factor for the rising price of crude oil and its refined products. In addition, a low supply resulted from scarce investments in exploration activities. In 2007, the weakness of the US dollar and the beginning of the recession in the United States attracted investors to the commodities market. Because of its significant liquidity, the crude oil and refined products markets received a large quotient of investments. Thus, in July 2008, WTI crude oil prices reached the highest prices on the NYMEX by exceeding USD\$140/barrel.

Due to the American real estate crisis in 2008, investors withdrew their investments from the stock market pushing down the equity prices; However, the level of storage in Cushing, Oklahoma (delivery point for crude oil traded on the NYMEX), proved too high. A decline in demand due to the recession and the high level of storage caused a sharp reduction in WTI crude oil prices. After July 2008 (when the historical peak occurred), prices decreased by 77%, with a decline of 27% (the highest decline

since the Gulf War) in a single week, even after the OPEC announced a production cut of 9% (higher than expected) in an attempt to halt the downward trend in prices.

The present study aims to analyze the volatility term-structure of futures contracts of WTI crude oil and the refined products, before and after the 2008 financial crisis. The study also assesses the influence of the crisis on the average volatility of short-, medium- and long-term contracts of these commodities and the extent of the influence.

The autoregressive conditional heteroscedasticity (ARCH) model of volatility was established more than 30 years ago by Engle [5]. It was subsequently generalized by Bollerslev [1] introducing GARCH (generalized ARCH) model. Since that time, researches on this subject has developed significantly by the inclusion of other stylized facts, such as the asymmetry of shocks. Numerous studies have used GARCH class models to analyze the volatility of financial time series. In particular, a study by Hadsell, Marathe and Shawky [8] applies this model to the analysis of the volatility of the electricity prices in several U.S. markets.

The present article is divided into five sections: The first section contains the introduction, which provides a context for the problem and presents the objective of the study. The second section presents the data used in the study. The third section presents the estimation of the volatility models. The fourth section summarizes the main results, and the fifth section concludes the study. The appendices present some details related to the analysis.

DATA SELECTION

Historical data of futures prices of WTI crude oil and its refined products were collected from the Bloomberg platform. The prices correspond to the daily closing prices in USD\$/bbl.

In this study, we use the F_i notation to represent futures contracts maturing i months ahead. For example, F_1 is the contract that matures one month ahead and F_{20} is the contract that matures 20 months ahead. The first future contract was used as a short-term reference, the twentieth future contract was utilized as a medium-term reference

and the fortieth future contract was employed as a long-term reference.

Data selected excluded the high-volatility period that occurred during the 2008 crisis (especially during the second half of 2008). Contracts matured until 5 months ahead of the reference date were considered as short-term, contracts matured 35 months ahead of the reference date as medium-term and contracts matured 40 months ahead of the reference date as long-term. Tables 1 and 2 exhibit the contracts analyzed and their respective periods. A total of 29 series were analyzed for the period before the crisis and the same amount for the period after the crisis.

Figure 1 shows the behavior of the F1, F20 and F40 contracts for crude oil before the 2008 crisis and Figure 2 shows the behavior of the same contracts of crude oil after the crisis. Some basic statistics of the price series of crude oil and its refined products are presented in Tables 8 and 9 of Appendix 1.

METHODOLOGY FOR FITTING THE HETEROSCEDASTIC MODELS TO THE SERIES

The advantages of return series are twofold: first return contains information of greater interest to investors; secondly return series presents more attractive statistical properties.

The return series (or the log-return series based on daily frequency) was constructed as follows:

$$r_t = \ln p_t - \ln p_{t-1} \quad (1)$$

The close of the model was based on the minimization of the Bayesian information criterion (BIC) (Schwarz criterion), which resulted in parsimonious models. The innovations on returns (see Equation (3) below) were based on normal, student's t and GED distributions. The analysis of residuals and squared residuals after the fittings shows that they

Table 1. Data for each commodity: pre-crisis period.

Contracts		Commodity		
		Crude Oil-WTI	Gasoline-RBOB	American Diesel-Heating Oil
Pre-Crisis	Short-term (F1, F3, F5)	01/04/2000 to 06/30/2008 (2120 observations)	10/03/2005 to 06/30/2008 (688 observations)	01/04/2000 to 06/30/2008 (2120 observations)
	Medium-term (F10, F15, F20, F27, F30, F35)	01/04/2000 to 06/30/2008 (2120 observations)	02/13/2007 to 06/30/2008 (348 observations)	04/17/2007 to 06/30/2008 (344 observations)
	Long-term (F40, F50)	02/10/2006 to 06/30/2008 (598 observations)	–	–

Table 2. Data for each commodity: post-crisis period.

Contracts		Commodity		
		Crude Oil-WTI	Gasoline-RBOB	American Diesel-Heating Oil
Post-Crisis	Short-term (F1, F3 and F5)	05/01/2009 to 10/25/2012 (881 observations)	05/01/2009 to 10/25/2012 (881 observations)	05/01/2009 to 10/25/2012 (881 observations)
	Medium-term (F10, F15, F20, F27, F30, F35)	05/01/2009 to 10/25/2012 (881 observations)	05/01/2009 to 10/25/2012 (881 observations)	05/01/2009 to 10/25/2012 (881 observations)
	Long-term (F40, F50)	05/01/2009 to 10/25/2012 (881 observations)	–	–

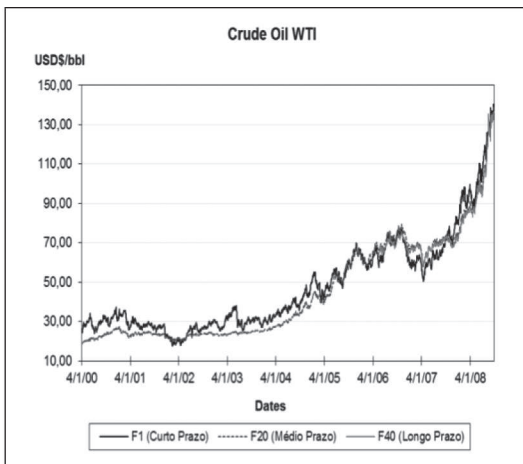


Figure 1. WTI Prices: pre-crisis period.

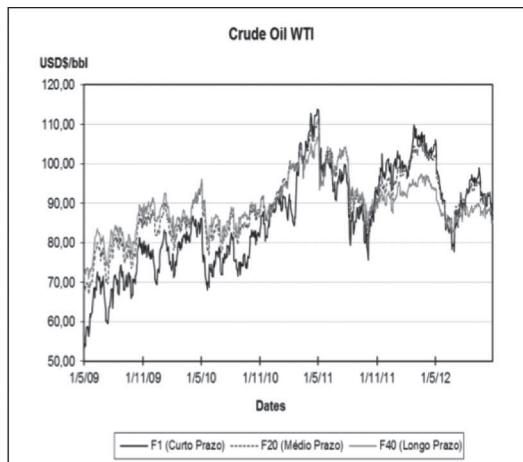


Figure 2. WTI Prices: post-crisis period.

are uncorrelated and independent (these assumptions were verified by autocorrelation analyses using the Box-Pierce test [2] and the Ljung-Box test [7] and by independence analyses using the BDS test, which was developed in [3]). The ARCH-LM (ARCH-Lagrange Multiplier) test, proposed in [6], was used in each series to verify the remaining ARCH effect.

The GARCH family models were adjusted for each series using the normal distribution, Student's t-distribution and Generalized Error Distribution (GED). All selected models showed better results when fitted by Student's t-distribution.

Linear models, such as Engle's ARCH model [5] and Bollerslev's GARCH model [1], as well as the nonlinear Nelson's Exponential GARCH (EGARCH)

model [9], and Threshold ARCH (TARCH) model [11] were used.

The majority of series in the pre-crisis period were fitted using the autoregressive GARCH (AR-GARCH) (p, q) model described as follows:

$$r_t = a_0 + b_1 dum_1 + b_2 dum_2 + b_3 dum_3 + \sum_{i=1}^k \phi_i r_{t-i} + v_t \quad (2)$$

$$v_t = h_t^{1/2} \varepsilon_t \quad (3)$$

$$h_t = \omega + \sum_{i=1}^q \alpha_i v_{t-i}^2 + \sum_{j=1}^p \beta_j h_{t-j} \quad (4)$$

Where b_i accounts for seasonal effects. It's a well-known fact that the crude oil doesn't exhibit seasonal pattern.

However, the series for most horizons in the post-crisis period were fitted best by the autoregressive TARCH (AR-TARCH) (p, q) model. This model belongs to the class of nonlinear heteroscedastic models that capture the effect of asymmetric shocks. The variance equation for the TARCH (p, q) model is expressed as follows:

$$h_t = \omega + \sum_{i=1}^q \alpha_i v_{t-i}^2 + \sum_{j=1}^p \beta_j h_{t-j} + \sum_{k=1}^r \gamma_k v_{t-k}^2 [1 - I(v_{t-k} > 0)] \quad (5)$$

Whenever the shock in $t-k$ is positive $v_{t-k} > 0$, $I(v_{t-k}) = 1$ and the impact on the variance is given by α . If $v_{t-k} < 0$, i.e., if the shock is negative, then, $I(v_{t-k}) = 0$ and the impact on the variance is given by $\alpha + \gamma$. The asymmetric effect occurs when $\gamma \neq 0$, and the leverage effect is observed when $\gamma > 0$.

Tables 3, 4 and 5 list the parameters obtained in the respective models.

Appendix 2 provides additional details on the procedure for selection of the most suitable models for the series.

ANALYSIS OF THE RESULTS

The inherent risk in a financial asset is closely related to the variance of the return of the asset or

Table 3. Adjusted models before and after crisis: crude oil.

		Contract	Model	Parameters	p-value
Crude Oil - WTI	Pre-Crisis	F1 (Short-term)	AR-GARCH (1,1)	$\varphi = -0.043855$	0.0413
				$\omega = 1.05 \times 10^{-5}$	0.0334
				$\alpha_1 = 0.027744$	0.0007
				$\beta_1 = 0.951459$	0.0000
		F20 (Medium-term)	AR-GARCH (2,1)	$a_0 = 0.001058$	0.0001
				$\varphi_1 = -0.166881$	0.0000
				$\omega = 1.35 \times 10^{-6}$	0.0518
				$\alpha_1 = 0.13$	0.0000
				$\alpha_2 = -0.094340$	0.0030
				$\beta_1 = 0.956998$	0.0000
		F40 (Long-term)	AR-GARCH (1,1)	$a_0 = 0.001093$	0.0307
				$\varphi_1 = -0.09885$	0.0151
				$\omega = 1.3 \times 10^{-5}$	0.0681
				$\alpha_1 = 0.160515$	0.0003
				$\beta_1 = 0.701217$	0.0000
	Post-Crisis	F1 (Short-term)	TARCH (0,2)	$\omega = 1.26 \times 10^{-6}$	0.0249
				$\beta_1 = 1.456873$	0.0000
				$\beta_2 = -0.468562$	0.0002
				$\gamma_1 = 0.288871$	0.0004
				$\gamma_2 = -0.272649$	0.0006
		F20 (Medium-term)	TARCH (0,2)	$\omega = 9.8 \times 10^{-7}$	0.0249
				$\beta_1 = 1.443936$	0.0000
				$\beta_2 = -0.459485$	0.0004
				$\gamma_1 = 0.360421$	0.0003
				$\gamma_2 = -0.339023$	0.0004
		F40 (Long-term)	TARCH (0,2)	$\omega = 1.89 \times 10^{-7}$	0.0226
				$\beta_1 = 1.677063$	0.0000
				$\beta_2 = -0.68023$	0.0000
				$\gamma_1 = 0.194152$	0.0000
				$\gamma_2 = -0.191114$	0.0000

Table 4. Adjusted models before and after crisis: gasoline.

		Contract	Model	Parameters	p-value
Gasoline - RBOB	Pre-Crisis	F1 (Short-term)	ARCH (1)	$\omega = 0.000479$	0.0000
				$\alpha_1 = 0.109560$	0.0713
		F20 (Medium-term)	AR-ARCH (1)	$a_0 = 0.002414$	0.0030
				$\varphi_1 = -0.142602$	0.0125
	$\omega = 0.000207$			0.0000	
	$\alpha_1 = 0.222040$	0.0281			
	Post-Crisis F20	F1 (Short-term)	GARCH (1,1)	$b_3 = 0.003366$	0.0111
				$\omega = 4.86 \times 10^{-5}$	0.0749
F20 (Medium-term)		TARCH (0,1)	$\alpha_1 = 0.065762$	0.0218	
			$\beta_1 = 0.816418$	0.0000	
			$\omega = 3.02 \times 10^{-5}$	0.0142	
			$\beta_1 = 0.799841$	0.0017	
			$\gamma_1 = 0.178410$	0.0000	

Table 5. Adjusted models before and after crisis: American diesel.

		Contract	Model	Parameters	p-value
American Diesel-Heating Oil	Pre-Crisis	F1 (Short-term)	AR-TARCH (1,1)	$a_0 = 0.001293$ $\varphi_1 = -0.044155$ $\omega = 1.15 \times 10^{-5}$ $\alpha_1 = 0.057122$ $\beta_1 = 0.942398$ $\gamma_1 = -0.036110$	0.0075 0.0465 0.0157 0.0000 0.0000 0.0137
		F20 (Medium-term)	AR-GARCH (0,1)	$a_0 = 0.002797$ $b_1 = -0.002962$ $\varphi_1 = -0.199434$ $\omega = 1.98 \times 10^{-6}$ $\beta_1 = 0.968255$	0.0009 0.1009 0.0002 0.0000 0.0000
	Post-Crisis	F1 (Short-term)	TARCH (0,3)	$b_3 = 0.001951$ $\omega = 2.86 \times 10^{-7}$ $\beta_1 = 1.401966$ $\beta_2 = -0.367607$ $\beta_3 = -0.038872$ $\gamma_1 = 0.270554$ $\gamma_2 = -0.264855$	0.0846 0.1584 0.0000 0.0000 0.0000 0.0000 0.0000
		F20 (Medium-term)	TARCH (1,1)	$a_0 = 0.001598$ $\omega = 7.26 \times 10^{-5}$ $\alpha_1 = -0.106173$ $\beta_1 = 0.590173$ $\gamma_1 = 0.319118$	0.0146 0.0015 0.0039 0.0000 0.0006

its standard deviation. The historical volatility of the return series, which is one of the measurements used to determine the risk of an asset, is defined by the standard deviation of the series.

Engle and Patton [6] emphasized that an acceptable model of conditional volatility should capture the following characteristics of volatility: reversion towards the mean, volatility clusters, which are periods of certain intensity followed by periods of the same intensity in the volatility, and its half-life. These characteristics are essential because they are related to the longevity of the effect of a shock in a price/return series.

Shocks tend to gradually disappear over time, making volatility returns to an average level, which is called long-term volatility or unconditional volatility. Volatility is persistent if, for example, a shock that occurred today has a significant influence on future volatility (Carrol and Collins [4]). Although this

persistence can be measured in several ways, we use the concept of volatility half-life in this study.

After the appropriate fitting of the models we computed the unconditional variance, as shown in the first column of Table 6. The means of the conditional volatilities were also computed. The resulting unconditional volatilities were similar to the average of the conditional volatilities series, as shown in Tables 12, 13 and 14 of Appendix 3. These results represent long-term volatilities.

Figures 3, 4 and 5 illustrate the term structure of volatilities in pre- and post-crisis periods. In Appendix 3, Table 11 presents the data that was used to construct these figures.

The behavior of the term structure of the three commodities exhibits a pattern. The average short-term volatility of crude oil and refined products exhibited a significant decrease after the crisis.

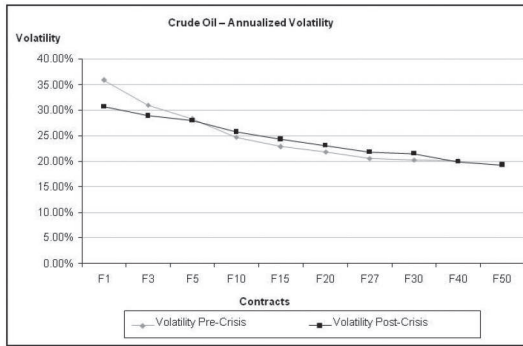


Figure 3. Term structure of annualized volatility for WTI prices.

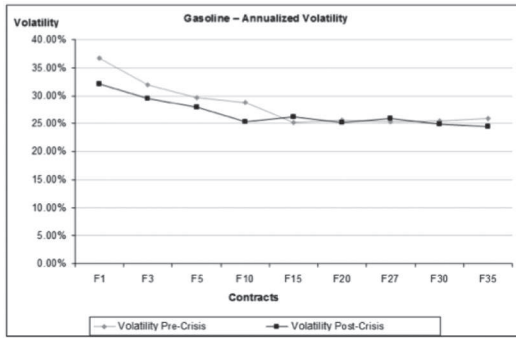


Figure 4. Term structure of annualized volatility for gasoline prices.

Conversely, the average medium-term and long-term volatilities exhibited little variation, either by a small increase or a small decay. Diesel experienced the greatest short-term reduction among the three commodities.

One of the possible reasons for the increased volatility prior to the crisis is the significant presence of

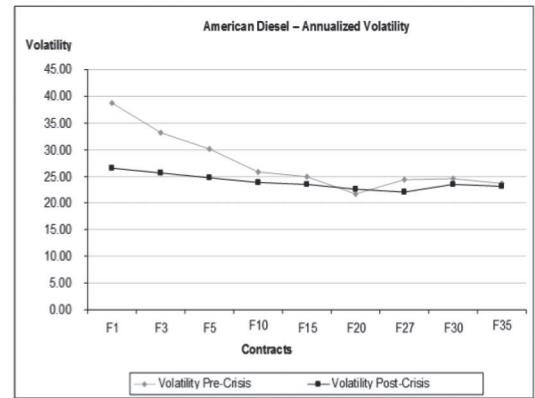


Figure 5. Term structure of annualized volatility for diesel prices.

investment funds (especially hedge funds) acting on commodity markets. The behavior of commodity prices after 2000 attracted these funds, which included positions in short-term futures contracts in their portfolio due to their great liquidity. This effect was more pronounced after 2007 due to the recession in the US economy; when stocks became less attractive.

The persistence of shocks in volatility was quantified before and after the crisis. First, we define the volatility half-life (τ), which is one of the measurements of the persistence of volatility shocks. The half-life is the time required for the effect of a shock on volatility to reduce its long-term value V by half. In a study by Carroll and Collins [4], τ is the smallest value for k such that

$$|h_{t+k|t} - V| = \frac{1}{2} |h_{t+1|t} - V| \quad (6)$$

Table 6. Unconditional Volatility and half-life.

Model	v (unconditional volatility)	τ (half-life)
GARCH (p, q)	$\left[\left(\frac{\omega}{1 - \sum_{i=1}^p \alpha_i - \sum_{j=1}^q \beta_j} \right) \times 252 \right]^{1/2}$	$\frac{\ln \left(\frac{1}{2} \left(\sum_{i=1}^p \alpha_i + \sum_{j=1}^q \beta_j \right) \right)}{\ln \left(\sum_{i=1}^p \alpha_i + \sum_{j=1}^q \beta_j \right)}$
TARCH (p, q)	$\left[\left(\frac{\omega}{1 - \sum_{i=1}^p \alpha_i - \frac{1}{2} \sum_{k=1}^r \gamma_k - \sum_{j=1}^q \beta_j} \right) \times 252 \right]^{1/2}$	$\frac{\ln \left(\frac{1}{2} \left(\sum_{i=1}^p \alpha_i + \frac{1}{2} \sum_{k=1}^r \gamma_k + \sum_{j=1}^q \beta_j \right) \right)}{\ln \left(\sum_{i=1}^p \alpha_i + \frac{1}{2} \sum_{k=1}^r \gamma_k + \sum_{j=1}^q \beta_j \right)}$

Table 7. Half-life of shocks: pre-and post-crisis.

Commodity	Contracts	τ (Days)	
		Pre-Crisis	Post-Crisis
Crude oi-WTI	F1(Short-term)	33.9814	194.378
	F20(Medium-term)	116.4478	143.5701
	F40 (Long-term)	9.568649	419.9801
Gasoline-RBOB	F1(short-term)	1.313459	6.52929
	F20(Medium-term)	1.460594	6.893793
American Diesel -Heating Oil	F1(Short-term)	38.04901	417.3333
	F20(Medium-term)	78.35999	257.2684

Table 6 displays the equations used to define the half-lives of the volatilities of the fitted models. The equations for τ are derived from equation (6) and are detailed in [4]. Table 7 displays the half-life values of the shocks (τ) for the contracts.

Despite the reduction in average volatility for short-term contracts, the half-lives of shocks increased after the crisis, regardless of the horizon analyzed. In other words, the average volatility of commodities exhibited a reduction in the short term, but the persistence of shocks increased after the crisis. Although the average level of volatility of medium- or long-term contracts did not exhibit large displacements, the persistence of shocks in these horizons for most of the post-crisis contracts also increased.

CONCLUSIONS

This study aimed to analyze the volatility in the term structure of futures contracts of WTI crude oil, RBOB gasoline and U.S. diesel and to identify the effects of the 2008 financial crisis.

AR-GARCH models were fitted to the return series to remove nonlinear dependence and serial autocorrelation.

The key features of the volatility were observed: the tendency for reversion towards the mean; the presence of clusters; and the persistence, which is the influence of current volatility on future volatility.

Among all commodities that were examined, a reduction in volatility was identified after the 2008 crisis compared to the pre-crisis values on short-term contracts. Diesel exhibited the greatest decrease in volatility; the shocks in volatility were more

persistent, and a considerable length of time passed before the volatility returned to an average level.

A natural extension of this study is an analysis of the behavior of the implied volatility, which is derived from options traded on futures contracts before and after the 2008 crisis. Other extension is the comparison of this study with another including structural breaks [10]. The monitoring of volatility is critical to the management of the exposure of agents who negotiate products on the physical market, traders in the futures market, and for managers of portfolios containing futures and options positions on commodities in energy sector.

REFERENCES

- [1] T. Bollerslev. "Generalized Autoregressive conditional heteroskedasticity". *Journal of Econometrics*. Vol. 31, pp. 307-327. 1986.
- [2] G.E.P. Box and D.A. Pierce. "Distribution of residual autocorrelations in autoregressive-integrated moving average time series models". *Journal of the American Statistical Association*. Vol. 65, pp. 1509-1526. 1970.
- [3] W.A. Brock, J.A. Scheinkman, W.D. Dechert and B. Lebaron. "A test of independence based on correlation dimension". *Econometric Reviews*. Vol. 15, pp. 197-235. 1986.
- [4] T. Carroll and J. Collins. "Volatility models and the ISEQ index". *Journal of Financial Report*. Vol. 23, pp. 12-24. 2007.
- [5] R.F. Engle. "Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation". *Econometrica*. Vol. 50, pp. 987-1007. 1982.
- [6] R.F. Engle and A.J. Patton. "What good is a volatility model?". *Quantitative Finance*. Vol. 1, pp. 237-245. 2001.

- [7] G.M. Ljung and G.E.P. Box. "On a measure of lack of fit in time series models". *Biometrika*. Vol. 65, pp. 297-303. 1978.
- [8] L. Hadsell, A. Marathe and H.A. Shawky. "Estimating the Volatility of wholesale electricity spot prices in the US". *The Energy Journal*. Vol. 25, pp. 23-40. 2004.
- [9] D.B.Nelson. "Conditional heteroskedasticity in asset returns: a new approach". *Econometrica*. Vol. 59, pp. 347-370. 1991.
- [10] A.A. Salisu and I.O. Fasanya. "Modelling oil price volatility with structural breaks". *Energy Policy*. Vol. 52, pp. 554-562. 2013.
- [11] J.M. Zakoian. "Threshold heteroskedastic models". *Journal of Economic Dynamics and Control*. Vol. 18, pp. 931-955. 1994.

APPENDIX 1

Tables 8 and 9 present some basic statistics of the price series of crude oil and its refined products.

Table 8. Basic Statistics of the price series: pre-crisis period (US\$/bbl).

Contracts	Mean	Standard Deviation	Maximum	Minimum
<i>Crude oil-WTI</i>				
Short-term (F1)	47.79	24.35	140.21	17.45
Medium-term (F20)	44.93	25.78	139.10	18.55
Long-term (F40)	76.93	17.11	136.35	59.23
<i>Gasoline-RBOB</i>				
Short-term (F1)	88.64	20.10	149.02	56.92
Medium-term (F20)	94.44	17.67	142.93	70.35
<i>American Diesel-Heating Oil</i>				
Short-term (F1)	55.91	29.54	166.94	21.00
Medium-term (F20)	104.67	23.87	168.02	81.27

Table 9. Basic Statistics of the price series: post-crisis period (US\$/bbl).

Contracts	Mean	Standard Deviation	Maximum	Minimum
<i>Crude Oil-WTI</i>				
Short-term (F1)	86.02	12.35	113.93	53.20
Medium-term (F20)	89.92	12.00	111.17	66.94
Long-term (F40)	89.67	11.71	108.52	69.51
<i>Gasoline-RBOB</i>				
Short-term (F1)	104.05	20.35	145.52	63.73
Medium-term (F20)	100.56	11.89	122.75	68.21
<i>American Diesel-Heating Oil</i>				
Short-term (F1)	105.98	22.23	139.43	58.31
Medium-term (F20)	105.73	14.78	140.02	77.32

APPENDIX 2

This appendix presents the fit of a series of returns from F1 contract to AR-GARCH model. The other series of returns were adjusted similarly.

(i) Model adjusted aiming at minimizing the BIC (Scharwz criterion).

$$r_t = -0.043855r_{t-1} + v_t$$

$$v_t = h_t^{1/2} \varepsilon_t$$

Where $\varepsilon_t \sim t - Student$ and,

$$h_t = 1.05 \times 10^{-5} + 0.027744v_{t-1}^2 + 0.951459h_{t-1}$$

(ii) The Box-Pierce test statistic and Ljung-Box test for the standardized residuals. In parentheses are given the p-value.

$Q(1) = 0.8407 (0.359)$; $Q(5) = 2.7921 (0.732)$;
 $Q(10) = 8.4848 (0.582)$; $Q(20) = 16.846 (0.663)$.

(iii) The Box-Pierce test statistic and Ljung-Box test for the squared standardized residuals.

$Q(1) = 0.7835 (0.376)$; $Q(5) = 5.5874 (0.348)$;
 $Q(10) = 6.5653 (0.766)$; $Q(20) = 12.846 (0.884)$.

(iv) The BDS test of independence in the residual series embedding dimension $m = 2, \dots, 6$ and distance ξ , from 0.5 to 1.5 times the standard deviation of the series. Results are shown in Table 10.

Table 10. BDS test statistic values for considered series.

Embedding dimension	$0.5 \times \sigma$	$1.0 \times \sigma$	$1.5 \times \sigma$
2	0.4923	0.6643	0.9500
3	0.3022	0.3373	0.4726
4	0.6298	0.4918	0.5400
5	0.7820	0.5164	0.4885
6	0.7979	0.7712	0.6074

(v) The ARCH-LM test was performed in residual series for 1, 5 and 10 lags. In all tests we do not

reject the null hypothesis that the ARCH effects are not present on it, i.e., was not detected in the conditional heteroscedasticity in the residual series.
 (vi) The QQ-plot for verification of adherence to the standardized residual series to Student's-t distribution is shown in Figure 6.

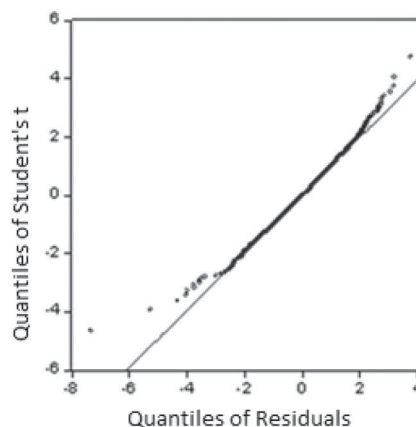


Figure 6. QQ-plot for residuals.

APPENDIX 3

Table 11 of this Appendix constitutes the basis for the construction of the term structure of commodity volatilities studied. The Tables 12, 13 and 14 compare unconditional volatility with the average conditional volatility obtained by fitting the models.

Table 11. Average Volatility used in the definition of the term structure of volatility of each commodity.

Contracts		Pre- Crisis			Post- Crisis		
		Crude Oil (%)	Gasoline (%)	American Diesel (%)	Crude Oil (%)	Gasoline (%)	American Diesel (%)
Short-term	F1	35.83	36.70	38.74	30.63	32.14	26.53
	F3	31.05	31.94	33.13	28.92	29.52	25.65
	F5	28.35	29.64	30.20	27.99	27.90	24.75
Medium-term	F10	24.71	28.78	25.91	25.84	25.33	23.76
	F15	22.87	25.21	24.88	24.38	26.12	23.40
	F20	21.81	25.55	21.70	23.15	25.19	22.67
	F27	21.18	25.27	24.30	21.79	25.83	22.05
	F30	20.59	25.53	24.61	21.53	24.88	23.53
	F35	–	25.89	23.71	–	24.43	23.08
Long-term	F40	20.19	–	–	19.91	–	–
	F50	20.12	–	–	19.34	–	–

Table 12. Average conditional and unconditional volatilities of crude-oil futures prices.

		Contracts	Average Volatility (%)	V (unconditional volatility) (%)
Crude Oil - WTI	Pre-Crisis	F1(Short-term)	35.83	35.67
		F20(Medium-term)	21.81	23.84
		F40 (Long-term)	20.19	20.53
	Post-Crisis	F1(Short-term)	30.63	29.79
		F20(Medium-term)	23.15	22.56
		F40(Lon- term)	19.91	16.97

Table 13. Average conditional and unconditional volatilities of gasoline futures prices.

		Contracts	Average Volatility (%)	V (unconditional volatility) (%)
Gasoline - RBOB	Pre-Crisis	F1(Short-term)	36.70	36.82
		F20(Medium-term)	25.55	25.89
	Post-Crisis	F1(Short-term)	32.14	32.24
		F20(Medium-term)	25.19	26.19

Table 14. Average conditional and unconditional volatilities of diesel futures prices.

		Contracts	Average Volatility (%)	V (unconditional volatility) (%)
American Diesel- Heating Oil	Pre-Crisis	F1(Short-term)	38.74	39.54
		F20(Medium-term)	21.70	23.65
	Post-Crisis	F1(Short-term)	26.53	20.81
		F20(Medium-term)	22.67	22.65