INTERNATIONAL HELLENIC UNIVERSITY

"The Efficiency of Natural Gas Futures Markets"

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School of Science & Technology

A thesis submitted for the degree of

Master of Science (MSc) in Energy Management

DECEMBER 2016

THESSALONIKI – GREECE

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ABSTRACT

The target of this study is to investigate the pricing efficiency of natural gas futures markets across different maturities, for 1, 2, 3, 6, 9 and 12 months, and whether these tools can effectively be utilized by market participants. More specifically, the paper examines the Unbiased Expectations Hypothesis (UEH) among futures and spot prices in the natural gas market of New York Mercantile Exchange (NYMEX). The following procedures include of the use of econometric techniques which test whether or not futures prices hold as unbiased forecasts of the expected spot prices by using single regressions and cointegration analysis. Due to the presence of positive or non-constant forward premium, EGARCH models are employed which permit for time varying premium and investigating more extensively the factors that conduct to the biasedness of futures contracts for all months to maturity. Although the existence of bias, futures prices for all months to maturity are found to accurately predict the expected spot prices compared to forecasts that are produced from ARIMA and random walk models.

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CHAPTER 1

1. Introduction

The association among futures and spot markets obtains significant importance academically and induces considerable argument in diverse futures and forward markets. More specifically, the great interest of market contributors is to which degree the value of futures prices reproduces more accurate signals of unbiased expectations predictors of the spot prices on the maturity day.

It is widely known that if there is bias in futures prices, the cost of hedging will augment (Kavussanos and Nomikos, 1999). For example, when futures prices are higher than the spot ones, long hedgers purchase the futures contracts at a premium over the price they anticipate to overcome on the maturity day. At the same time, futures markets can provide the ability to reveal valuable sources for upcoming stable prices in spot market tendencies. The revealing role of futures contracts is used to counterbalance asset price risk in the future as well as to reduce the position to price variations. To be more accurate, corporations and financiers exchange futures contracts to hedge alongside with the realized risks, therefore defending their portfolios in circumstances that unexpected price fluctuations occurred. In addition, futures contracts reproduce the present prospects of the market considering the sequence of currency prices at specific positions in the future. Thus, futures markets may possibly proceed as principal indicators for the imminent arrangements in the spot market. The capability of data information considering that expected (or future) spot prices deliver indications of supply and demand, could conclude to a contribution to further efficient distribution of financial resources. In case that future prices are bias forecasts, so they do not produce accurate signals for the prediction of future spot prices, then it is unlikely to accomplish efficient price findings.

During the last thirty years, the accurate forecast prediction of futures markets contributes significant role in academic studies which examine the relationship among futures and spot markets for diverse commodities. The first investigation was completed by Garbade and Silber (1983), who tested the connections among futures and spot prices for a set of assets. In another investigation, Movassagh and Modjtahedi (2005) provide strong evidence about the forecasting capability of futures prices against the spot ones, even though there is invalidity from the opposite direction. On the other hand, according to plethora of different studies (such as Quan, 1992), it is concluded that spot prices tend to lead futures.

Regarding the nexus among natural gas futures and spot markets, the investigation of which is rare and sporadic. This fact can be comprehensible due to the comparative immature natural gas futures market relatively to those markets of other energy assets, such as crude oil. Therefore, there is no hesitation that disclosing the precise nature of the relationship, for the natural gas spot and futures prices, is of great importance.

Natural gas is progressively developing a worldwide commodity that is traded among regions. Intrinsically, international natural gas markets are experiencing a significant modification in market formation and association, as well as in supply and demand. These continuing fluctuations generate challenges for modeling and forecasting international natural gas supply, demand, and price. Considering the fundamental operators of market development is a vital foundation for categorizing both new market tendencies and changes in the rate of variation of continuing trends.

The motivation for this study stems from the fact that futures markets provide as well as precious material about prospects for supply and demand circumstances in the physical market that will arrange the price for gas scheduled for delivery on a definite future date. This price discovery function is valuable since it delivers information to market participants who can best respond by, for instance, depositing supplementary gas in storage or taking steps to change to a diverse fuel. This accessibility of information regarding future spot prices offers signals that lead supply-and-demand conclusions in behaviors that subsidize to a more effective distribution of economic funds. If futures prices are not unbiased predictors, then they may not accomplish their price discovery function resourcefully due to the fact that they do not signify precise forecasters of expected spot prices. This study, then, by examining the unbiasedness hypothesis in the natural gas futures markets, in many circumstances subsidizes to the prosperity of investigations in other futures markets. By performing the appropriate prolonged econometric techniques in order to testify the unbiasedness hypothesis of futures markets, it is concluded some stimulating results.

The remainder of this study is structured as follows: in Chapter 2 will be mention briefly the literature review which investigates the unbiasedness expectations hypothesis (UHE) of futures prices. Chapter 3 includes the adopted methodology. In Chapter 4 is presented the preliminary econometric analysis of data and the test of stationarity. Chapter 5 consists of the empirical results and an analysis about the findings while in Chapter 6 is concluded the outcomes of this research.

CHAPTER 2

2. Literature Review

During the past decades, there is an augmenting extend of empirical studies dedicated to the grid among spot and futures markets for quite a few energy commodities, such as crude oil, natural gas, electricity etc. Given that the emphasis of the empirical investigation testing exclusively with the natural gas markets is relatively inadequate, in contrast with plethora of studies that focus mainly on the two other major energy commodities (i.e. electricity and crude oil), this study will emphasize on the connection among natural gas spot and futures contracts.

Modjtahedi and Movassagh (2005) examine the predictive performance and biasedness of natural-gas futures prices against futures spot prices. This particular study is supported by some hypotheses concerning the biasedness in future prices as predictors of spot prices and whether they are statistical significant in this prediction. One other hypothesis that is examined is the consistency of the behavior of basis with the theory of storage. First of all, spot and future prices are non-stationary due to positive drifts in random walk process. According to unit root tests -Augmented Dickey Fuller (1981) and Phillips Perron (1988) - against to the prices and forecast errors, the existence of positive trend is due to a linear trend or a positive drift in non-stationary series. However, the joint hypothesis of no trend is rejected by F-test. Consequently, the series are non-stationary and the positive random walk drift is the cause for the increase in prices. Furthermore, market forecast errors are stationary and behave in a long run way around a constant mean. They follow Moving Average (MA) (k-1) processes, where *k* is the number of lags, and an increase in volatility is observable when time to maturity augments. As a result, this fact leads to the outcome that future prices are backwardated[1] (less than the expected future spot prices).

Although Movassagh and Modjtahedi (2005) imply a MA (k-1) error processes, it has not taken into consideration the problem of autocorrelation of the residuals in a Generalized Least Squares (GLS) environment (introduced by Stock and Watson 1993) which tests the cointegration between future and spot prices. Williams and Wright (1991, p.186) develop the approach that due to the nature of storable commodities, the unbiasedness expectation hypothesis (UEH) confronts statistical problems. Regressing the current spot prices on lagged future ones and taking into account the unexpected growth of the production of commodities, having as a result the reduce of current spot prices and the error terms. Consequently, the error terms will be correlated with future prices and thus there will be a distortion of the t and χ^2- statistics.

The same approaches are used by Pederzoli and Torricelli (2013) in their study, concerning the futures market efficiency and unbiasedness of corn during the financial crisis. They attempt to verify the unbiased prediction of futures prices against the underlying spot prices, taking into account the relative trading volume of corn and its significance in the dietary treatment of many countries. For this purpose, cointegration analysis imposes two outcomes by using Johansen (1988) test. Applying this test, a strong evidence is recognized among futures and expected spot prices and as a corresponding result the market is long run efficient. However, there is a rejection of the unbiasedness by testing restrictions, which may be associated to

[1] According to Keynesian theory of normal backwardation (Keynes 1930) and hedging theory, producers are willing to pay speculators a compensation, which is the risk premium, in the form of future prices which are lower than the expected spot ones. Thus, biasedness is increased in an upward direction with the time to maturity (time-varying bias).

inefficient market or to a positive risk premium that prevents the validity of predicting the expected spot prices. Due to the non-stationary spot and futures prices, the implementation of the Error Correction Model (ECM) is necessary in order to estimate market efficiency in the short run. Consequently, the outcome of this analysis imposes the inefficiency of the market and the biasedness of futures prices as an estimator of the underlying spot prices. Thus, despite the existence of a time varying risk premium, and the latter financial crisis as well, the unbiasedness is produced by market inefficiency.

Alizadeh and Nomikos (2004) examine the efficiency of the forward bunker markets across different geographical locations and against different times to maturity. During this investigation, the authors examine the validity of market efficiency, using bunker fuel derivatives for hedging in shipping industry, following a variety of statistical tests. Considering shipping industry is one of the most volatile, the market participants confront essential business risk which derived from fluctuations of bunker prices, cargo rates and even from instability in interest rate and exchange rates. In order to defend themselves from such risks, market participants apply some risk management techniques by using swaps, futures and options. As a result, two exchange-trade futures contracts were developed -the Singapore Futures Exchange and the International Petroleum Exchange in London- in order to deal with these risks. However, both of them failed to stimulate the interest of market participants due to low trading volume since the trade system of physical bunker is taking place in different geographical locations whereas the futures contracts are delivered in specific places. Thus, the effectiveness of futures contracts is low since futures prices do not succeed precisely in the fluctuations of bunker fuel prices in different geographical areas. The efficiency of forward bunker prices was examined by using a variety of statistical tests for different times to maturity. Consequently, the outcomes of these tests have shown that the unconditional volatilities (standard deviations) of bunker prices differ across the variety of ports around the world. Furthermore, Alizadeh and Nomikos (2004) indicate that forward prices provide unbiased forecast predictors for the spot prices at the maturity day for 1, 2 and 3 months to maturity. As a result, forward prices are more accurate predictors of futures spot prices compared to random walk models. In addition, this outcome provides evidence that forward prices could be efficient for hedging against instabilities in bunker prices; consequently, the shipping industry can use forward rates as accurate signals in their decisions in the physical market.

Sebastian (2016) investigate the price formation and arbitrage efficiency of the European natural gas market, between spot and futures prices. This study employs econometric approaches which examine the non-linearities that occurred by the low-liquidity structure and by technical constraints of the physical activity of gas hubs markets. Testing for causality provides that price formation generally exists on futures markets, according to Dergiades et al. (2012), in which investigation there is an exploration in linear and non-linear causality between the connection of spot and futures prices at the U.S. gas hub. Thus, futures markets participants are taking more accurate decisions than traders at spot markets (see for instance Gebre-Mariam (2011) who are testing for causality between spot and futures market prices and whether there is market efficiency as well by using cointegration methods). Moreover, storage theory seems to prevail in the long run at all hubs making possible the existence of arbitrage between futures and spot markets. However, this error correction process creates some misspecification problems concerning the liquidity of hubs. Although the arbitrage opportunities are efficiently utilized during the years, the price formation of error correction process in combination with arbitrage activities, indicate similarities for all the hubs despite the liquidity.

On the contrary, Brenner and Kroner (1995) investigate the existence of cointegration between spot and futures prices by using a no-arbitrage, cost-of-carry (COC) model. It is widely documented, that in foreign currency markets there is cointegration between spot and futures prices, with a cointegrated vector (1, -1) whereas in commodity spot and futures prices there is no cointegration (see for instance Campbell and Shiller (1987), Hakkio and Rush (1989), and Lai and Lai (1991)). In addition, Brenner and Kroner (1995) examine whether or not the net cost-of-carry is stationary or illustrates a stochastic trend by using some tests for the unbiasedness hypothesis. Finally, they conclude to the outcome that a no-arbitrage assumption would provide more accurate findings in financial models than the unbiasedness hypothesis while the persistence of shocks in the first differences of the model indicates persistence in forward premium and the basis.

Kavussanos and Nomikos (1999) examine the UEH of futures markets in the freight future markets. In order to investigate this hypothesis, they use cointegration techniques which lead to the outcome that futures prices one and two months before the day of maturity are unbiased forecast predictors of the expected spot prices whereas there is a bias after the third month of maturity. Plethora of studies in the previous years has shown evidence of unbiasedness hypothesis of futures prices. For instance, Lai and Lai (1991) provide results that strongly support the unbiasedness hypothesis before one month to maturity for some exchange rates; such as Japanese yen, British pound, Swiss franc, German mark and Canadian dollar. In addition, Crowder and Hamed (1993) examine the same hypothesis on the oil futures markets finding out that oil future prices are unbiased predictors of the expected spot ones. However, despite the large number of studies in commodities and financial markets (such as Krehbiel and Adkins 1994), the existence of evidence of unbiased expectation hypothesis on futures markets is not valid due to the substantial volatility of shipping industry (characterize by low trading activity).

Despite the biasedness on futures prices above the third month of maturity, Kavussanos and Nomikos (1999) provide evidence that future prices indicate more accurate forecast signals of the expected spot prices compare to forecasts produced from random walk, VECM, ARIMA and Holt-Winters models. Consequently, this outcome underlines the significant role of freight futures markets as an efficient price detection center until 2002 when London International Financial Futures and Options Exchange (LIFFE) stopped trading BIFFEX contracts due to the fact that trading volumes have not reversed in a sufficient way in order to verify the BIFFEX contract's presence for LIFFE.

Taking a different point of view, Kavussanos et al (2004) examine the UEH of Forward Freight Agreement (FFA) prices against the freight over-the-counter (OTC) forward market trades. In this research, cointegration analysis is used in order to verify the unbiasedness hypothesis. FFA prices are found to be unbiased predictors of the expected spot freight prices for all explored shipping routes against one and two months before maturity day. For the third month to maturity, FFA prices are unbiased predictors of the realized spot prices only for panama Pacific routes, while for panama Atlantic routes are biased predictors of the expected spot freight prices. Results indicate that the unbiasedness hypothesis depends on the specific characteristics of the market, the maturity of the contract and the selected routes of trade. These findings are confirmed by of Moore and Cullen (1995) who verify the validity of unbiasedness for one and two months to maturity commodity forward prices as well as Barnhart et al (1999). However, Norrbin and Reffett (1996) provide evidence of unbiased hypothesis for the third month to maturity foreign exchange forward prices, in comparison with the previous investigations. As a result, the characteristics of the market, the maturities of contracts and the investigated routes determine the unbiased hypothesis and market agents can take into consideration the FFA prices as indicators of the expected realized spot prices, making their decisions in the physical market more efficient.

Kawamoto and Hamori (2010) examine market efficiency among futures and spot prices with different times to maturity. The authors introduce the issue of consistently efficient and unbiased market within 8-months to maturity. For this purpose, the validity of market efficiency and unbiasedness among futures oil prices is examined by cointegration tests and short-term market efficiency is investigated by error correction model and GARCH in mean ECM as well. The outcome of this analysis illustrates that West Texas Intermediate (WTI) futures prices are consistently efficient up to 8-month maturity and unbiased as well within 2-month maturity. A long time to maturity futures price indicates the expected market in short time to maturity futures price at expiration day. From this point of view, market efficiency is obtained from both long and short-term equilibrium approaches, according to the researches of Beck (1994) and McKenzie and Holt (2002). As a result, the consistent efficiency and unbiasedness indicate their existence between n-months to maturity futures prices and n-months to maturity spot prices afterwards. In addition, the validity of tests for efficiency and unbiasedness between spot and futures prices augments as long as the sample size period reduced by one month. Consequently, different times to maturity contribute to greater testing validity for efficiency and unbiasedness.

From another point of view, Lean et al (2010), investigate the market efficiency of spot and futures prices in oil market, by using a mean variance (MV) and stochastic dominance (SD) analysis. They find out that there is no evidence of any relationship between these two approaches against spot and futures prices which leads to the outcome of non-existence of arbitrage opportunity. As a result, spot and futures prices do not dominate each other, so investors have no interest to invest in spot or futures, a fact that provides efficiency and rationality in WTI crude oil markets.

Fedderke and Joao (2001) investigate the efficiency in the financial markets during the financial crisis (1997-1998) among South Africa stock index futures markets and the fundamental stock market index. The authors provide strong evidence for the presence of cointegrating vector among the spot, futures prices and the cost-of-carry term. Through the cointegration analysis of Johansen (1988) tests (VECM) and Autoregressive Distributed Lag (ARDL) estimations, it is observable the statistical significance of unitary elasticity between spot and futures prices as well as the negative expected statistically significant connection between the spot price and the COC. In addition, the existence of an equilibrium connection among the three variables is confirmed by the presence of error correction of both cointegration estimations (VECM and ARDL). One other evidence of the stable relationship is verified by an investigation of impulse responses to shocks to the cointegrating vector. Thus, the results of this study indicate the existence of the cost-of-carry arbitrage connection between the spot and futures markets in South Africa. Furthermore, the impact of this relationship imposes long run equilibrium between these two markets. Consequently, futures prices provide accurate signals of price discovery in financial markets, enhancing information in markets and allowing them to arrange on stable prices immediately.

Generally, the unique trustworthy inference that can be induced is that the literature produces combined outcomes with respect to the unbiased hypothesis among spot and futures prices. These diverges in the unbiasedness inferences can be ascribed to many agents, in conjunction with the methodological framework assumed, the characteristics of the investigated energy commodity, and the degree of the examined time period maturity. Considering the natural gas spot and futures markets, it has been unveiled that a fertile ground is present for additional investigation. In the next chapters, it will be mentioned the methodology framework more exclusively as well as the preliminary analysis and the empirical results of this study.

CHAPTER 3

3. METHODOLOGY

3. 1. Unbiased Expectations Hypothesis (UEH) of futures prices

In accordance with the Unbiased Expectations Hypothesis (UEH), in which the theoretical connection among futures and realized spot prices is included, futures prices before the maturity date of the contract demonstrate a related trend with futures spot prices, considering insignificance exchange cost and an antagonistic market. Taking into account these conditions, market efficiency is defined which contains level-headed market participants with no-particular risk willingness (risk premium). The level of validity of the aforementioned declaration indicates futures prices as the most verify forecasting method which provides strong evidence of the hypothetical presence of systematic premium. This method posits that futures[2] contract price at a specific time t, which expires at the next n periods, is equal to the expected spot contract price that will be delivered at time t+n, considering all the obtainable and related information defined at time t, such as indicated by equation (1).

$$E_t S_{t+n} = F_{t;t+n} \tag{1}$$

The former equation represents the futures prices as an indicator of the most ideal forecast for the futures spot prices. In order to examine this hypothesis, it is obliged to substitute the future spot price with the realized spot price at t+n periods ahead,

[2] As futures price, it is defined the price stated for delivering a particular amount of a commodity at a specific time and location in the future. On the other hand, spot price is defined as the price for an one-time open market exchange for instantaneous delivery of a particular amount of an asset at a particular place where the asset is bought "on the spot" at contemporary market rates.

considering always the logical formation of the spot prices' expectations. Therefore, futures prices ($F_{t;\,t+n}$) is equal to the spot ones (S_{t+n}) plus the disturbance term (ε_{t+n}). Thus, equation (1) leads to:

$$E_t S_{t+n} = S_{t+n} + \varepsilon_{t+n} \quad ; \quad \varepsilon_{t+n} \sim iid\,(0,\sigma^2) \qquad \textbf{(2)}$$

From (1) and (2) it is concluded to:

$$F_{t;t+n} - S_{t+n} = \varepsilon_{t+n} \quad ; \quad \varepsilon_{t+n} \sim iid\,(0,\sigma^2) \qquad \textbf{(3)}$$

Although futures prices are characterized as unbiased predictors of the expected spot prices, in fact, they do not always produce zero forecast error. In order to be comprehensible, the definition of an unbiased predictor, it should be mentioned that the outcome of futures prices should not fluctuate compare to actual realized spot prices in an efficient way. Regarding the detected forecast errors, they should be erased one another in such way that their sum must be nearly to zero. For instance, in equation (3), forecast error defines a random variable which corresponds to a white noise error process. As a result, futures prices may miscalculate the realized spot prices until the expired maturity day of the contract. Therefore, futures prices, in order to be unbiased predictors, they should be stationary namely, having a constant variance and a conditional zero mean.

Taking into consideration the Unbiased Expectations Hypothesis, a set of parameter restrictions is required between the expected spot prices and the futures ones before the day of maturity. In order to adopt the UEH, the following two assumptions are necessary:

1. The value of the price of futures contract before the day of maturity is equal to the realized spot price on the expiration day of the contract (i.e. the expected forecast error is equal to zero).
2. The expected spot price is generated logically.

Experimentally, these two assumptions can be analyzed by examine the parameter constraints, $(\beta_1, \beta_2) = (0, 1)$, according to equation (4):

$$S_{t+n} = \beta_1 + \beta_2 F_{t;t+n} + \varepsilon_{t+n} \ ; \ \varepsilon_t \sim iid(0, \sigma^2) \qquad \textbf{(4),}$$

The above-mentioned constraints follow the statement of market efficiency which stipulates that the fluctuations of prices should be unpredictable, from one period to the other, regarding the contemporaneous information set. Therefore, futures prices $F_{t;\, t+n}$ would be unbiased predictors of the expected spot prices as long as they encompass all the appropriate information to predict the forward spot prices S_t. The investigation of the above equation indicates the non-appearance of risk premium, therefore the risk neutrality, and the rationally formation of expectations (absence of irregular returns), representing the intercept and slope respectively. The joint hypothesis can be rejected by an infraction in one of two hypotheses which impose an equal essential position in testing for efficiency. Additional assumptions are required for the degradation of these two hypotheses concerning the extent of market participants' risk unwillingness and the method the expectations are realized. The joint hypothesis assumes that data-knowledge is being dispersed homogeneously to all market agents. Therefore, market efficiency is insurance by the absence of predictive returns.

Considering the fact that futures and spot prices are non-stationary time series, according to empirical evidence across different forward markets, an alternative approach should be introduced in order to be investigated the unbiased hypothesis. The standard method of Ordinary Least Squares (OLS) cannot be used, due to the non-stationarity of financial time series that creates biasedness and spurious regressions which might conclude to misjudging results. A non-stationary time series must be differenced *d* times, order of d, before it becomes stationary. Afterwards, it is said to be integrated, symbolized as I(d), of order of d where $d \neq 0$. Therefore, regarding the issue of non-stationarity, Hakkio and Rush (1989) and Lai and Lai (1991), imposed different testing approaches for the unbiased hypothesis. According to these alternative methods, an adjustment to the OLS is required in order to estimate the coefficients β_1, β_2 and to take into consideration any autocorrelation of residuals of the standard errors of equation (4). The approximation of both coefficients and standard errors are entirely modified and equivalent to maximum likelihood estimates.

One other method that can be used in order to overcome the problem of stationarity is to subtract current spot prices S_t from both sides of equation (4). Thus, it is formulated the rate of change in the expected spot prices ($\Delta_n S_{t+n} = S_{t+n} - S_t$) and the basis ($Basis_t = F_{t;\,t+n} - S_t$) and by regressing ($\Delta_n S_{t+n}$) on the basis ($Basis_t$) the validity of unbiasedness is tested by the same parameter restrictions (β_1, β_2) = (0, 1) in the equation below:

$$(S_{t+n} - S_t) = \beta_1 + \beta_2(F_{t;t+n} - S_t) + \varepsilon_{t+n};\ \ \varepsilon_t \sim iid(0,\sigma^2),$$ otherwise

$$\Delta_n S_{t+n} = \beta_1 + \beta_2\ Basis_t + \varepsilon_{t+n}\ ;\ \ \varepsilon_t \sim iid(0,\sigma^2)$$ **(5),**

where S_t contemporaneous spot prices.

According to equation (5), as long as the null hypothesis is not rejected (H_0: $\beta_1=0$ & $\beta_2=1$) and the following assumptions are valid: S_{t+n} ~ I (1) and $Basis_t$ ~ I (0), therefore both sides of equation are stationary (I(0)), then futures prices and current spot prices are cointegrated with a cointegrated vector of (1,-1). Consequently, all the variables in the former equation are I(0), so there is no issue for spurious regression and the F-and t- statistics are consistent. By applying $\beta_1=0$ and $\beta_2=1$ in equation (5), it is resulted that:

$$\begin{aligned} &\Delta_n S_{t+n} = Basis_t + \varepsilon_{t+n} \Rightarrow \Delta_n S_{t+n} - Basis_t = \varepsilon_{t+n} \Rightarrow \\ &\Rightarrow (S_{t+n} - S_t) - (F_{t;t+n} - S_t) = \varepsilon_{t+n} \Rightarrow \\ &\Rightarrow S_{t+n} - F_{t;t+n} = \varepsilon_{t+n}; \varepsilon_{t+n} \sim iid(0,\sigma^2) \rightarrow \varepsilon_{t+n} \sim \mathrm{I}(0) \end{aligned} \tag{6}$$

Equation (6) indicates that ($S_{t+n} – F_{t;\,t+n}$), which is the forecast error, moves around a zero mean and futures prices and realized spot prices are cointegrated with a vector of (1, -1).

3.2 Unbiased Expectations Hypothesis and Cointegration

In order to solve the issue of non-stationarity of time series, Engle and Granger (1987) propose a method in testing the unbiased hypothesis of futures prices. As stated in Engle and Granger' (1987) definition of cointegration, the linear combination of two integrated variables, denoted as I(d) and I(b) with d>b>0, will be stationary as well as there will be at least one vector of coefficients (β_1, β_2) such as $\varepsilon_{t+n} \sim$ I(d-b). A cointegrating relationship might be seen as well as a long-term relationship which is noted as an equilibrium relationship, resulting that these two series could not wander apart from each other in the long run. More exclusively, in this particular investigation, the two integrated variables are futures and realized spot prices, $F_{t;\,t+n}$ and S_{t+n}, of order one, consequently there might be a vector of coefficients (β_1, β_2) such that $\varepsilon_{t+n} \sim$ I(0). In addition, the Granger (1987) representation theorem imposes that any cointegrating relationship can be clearly stated as an equilibrium error correction model (ECM), as equations (7) & (8).

$$\Delta F_{t;t+n} = \alpha_{1,0} + \sum_{i=1}^{q} \gamma_{F,i} \Delta F_{t\text{-}1;t+n\text{-}i} + \sum_{i=1}^{p} \gamma_{S,i} \Delta S_{t\text{-}i} + \alpha_F(\beta_2 S_{t\text{-}1} + \beta_1 F_{t\text{-}1;t+n\text{-}1} + \beta_0) + \varepsilon_{F,t} \tag{7}$$

$$\Delta S_t = \alpha_{2,0} + \sum_{i=1}^{q} \lambda_{F,i} \Delta F_{t\text{-}1;t+n\text{-}i} + \sum_{i=1}^{p} \lambda_{S,i} \Delta S_{t\text{-}i} + \alpha_S(\beta_2 S_{t\text{-}1} + \beta_1 F_{t\text{-}1;t+n\text{-}1} + \beta_0) + \varepsilon_{S,t} \quad \textbf{(8)}$$

Nevertheless, the Engle Granger's method occurs two major issues. First of all, the order of variables might affect the outcome of stationarity of the residuals in a small sample even if this might be excluded in large samples. Moreover, due to the fact that this method depends on two step procedure, any problem that takes place in this estimation would be persevered on the next step as well. For this purpose, in order to avoid these issues, Johansen (1988) proposed a different more sophisticated approach. Regarding this approach, Johansen imposes a multivariate econometric technique, in which the examination of unbiased hypothesis occurred via a modified model, the Vector Error Correction Model (VECM).

$$\Delta X_t = \mu + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-1} + \varepsilon_t ; \varepsilon_t \sim iid(0,\Sigma) \quad \textbf{(9)}$$

Where,

X_t: 2x1vector of $(S_{t+n}\ F_{t;\,t+n})' \sim I(1)$,

μ: 2x1vector of deterministic segments constituted by a linear trend term, a constant term or both,

Δ: first difference operator,

ε_t:: 2x1 vector of white noise error procedures $(\varepsilon_{1,t}\ \ \varepsilon_{2,t})'$,

Σ: 2x2 variance/ covariance matrix of the last one,

Π: 2x2 matrix of coefficients in long-run, denoted as $\Pi=(\sum_{i=1}^{k} \beta_i) - I_2$,

Γ: 2x2 matrix of coefficients in short-run, denoted as $\Gamma=(\sum_{j=1}^{i} \beta_j) - I_2$.

According to Johansen and Juselius (1990), in order to test the cointegrating relationship between futures ($F_{t;\ t+n}$) and spot (S_{t+n}) prices, it is required to examine the rank (r) of matrix Π, where 0<r<2, via its eigenvalues (λ_{trace} and λ_{max}). More specifically:

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \ln(1-\hat{\lambda}_i) \quad \textbf{(10)}$$

$$\lambda_{\max}(r, r+1) = -T \ln(1-\hat{\lambda}_{r+i}) \quad \textbf{(11)},$$

where $\hat{\lambda}_i$ and $\hat{\lambda}_{r+i}$ are the estimated value for each eigenvalue that received from Π that symbolizes the matrix and T the observations' number respectively. Hence, the higher degree the $\hat{\lambda}_i$ appears, the more negative will be the sign of the $\ln(1-\hat{\lambda}_{r+i})$. In such a way, the test statistic maximizes itself, provided that each eigenvalue is strongly associated with a diverse vector, presented here as eigenvectors[3]. The λ_{trace} is a joint test that examines the null hypothesis in which the total amount of cointegrating vectors is at most equal to *r,* whereas the alternative one suggests that this number of vectors is more than *r*. The λ_{max} includes diverge tests on each eigenvalue separately, in which the null hypothesis tests whether the number of cointegrating vectors equals to *r* against the alternatively that is equal to r+1. The critical values for these statistics are yield from Osterwald-Lenum (1992).

Regarding the rank (r) of Π matrix, there are three cases with regard to the cointegration relationship between futures and spot prices (0<r<2):

1. rank (Π) = 0 ⇒ Π_{2x2} matrix equals to zero which indicates that futures prices and spot prices are not cointegrated, thus the error correction term equals

[3] An eigenvalue that diverges significantly from zero, indicates as well a significant cointegrating vector.

to zero, modifying the model to a Vector Autoregressive (VAR) in first differences.

2. rank (Π) =2 ⇒ Π_{2x2} matrix with a full rank, thus spot and futures prices are stationary time series so the more appropriate model is a VAR in levels.
3. rank (Π) = 1⇒Futures and spot prices are cointegrated together with a single relationship so the most applicable model is the VECM model. ΠX_{t-1} denoted as the error correction term, in which, Π can be separated into two matrices: α (2x1) and β (3x1) such that Π = α β΄. The matrix α = (α_F α_S) constitutes the vector error correction coefficients which scales the speed of adjustment in the long-run, whereas β΄ = (β_0 β_1 β_2) is a vector that includes the cointegrating parameters, embedding the intercept term (β_0).

Based on the former assumptions of VECM methodology, the validity of unbiased expectations hypothesis is testified only if the rank of matrix Π is equal to unity. Consequently, there is a single cointegrating relationship among futures and spot prices and by prescribing the parameter restrictions β΄= (β_0 β_1 β_2) = (1 0 -1) on the cointegrating equation, it is produced a long run relationship so forecast error obtains zero mean.

3.3 Time Varying Risk Premium

Due to the presence of heteroscedasticity on the residuals, the error term does not apply, ε_{t+n} ~ iid (0, σ^2), thus, σ^2 is time varying. Consequently, the OLS estimators are not Best Linear Unbiased Estimators (BLUE), therefore there is no linear dependency among the spot settlement prices and the basis. For this purpose, it is obligatory to apply Generalized Autoregressive Conditional Heteroscedasticity models (GARCH), in order to examine the hypothetical presence of time varying premium and to investigate the dynamics of volatility.

Engle (1982) provided evidence that extensive shocks take place in clusters and consequently the representation of the graph of frequency distributions of shocks (histogram) presents fatter tails than in normal distribution. The reason of this fact is caused by the autoregressive structure of these shock, thus the need of using ARCH models is obligatory. Therefore, Bollerslev (1986) developed one step forward these models by generalizing the process (GARCH) in which the dependency of conditional variance is based not only on its own lagged values but on lagged squared error terms as well. In addition, GARCH models are more parsimonious and avoid overfitting as well as they are less likely to breech non-negativity constraints. More specifically in equation (12) below:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-1}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j} \tag{12}$$

Where,

$\alpha_0 > 0$ & $0 < \sum \alpha_i < 1 \Rightarrow \sigma^2 > 0$ and stationary under the assumption that the following equation exists: $\sum_{i=1}^{p} a_i + \sum_{j=1}^{q} \beta_j < 1$

p, q: the number lags, otherwise the order of the model.

Naturally, the use of GARCH models requires the detection of Autoregressive Conditional Heteroscedasticity in the residuals of the mean equation. However, GARCH models involve some issues regarding the violation of non-negative constraints as well as incapability for leverage effects. In order to be more precise, Nelson (1991) proposed that the best estimation of this examination involves the use of an asymmetric model, the Exponential GARCH in mean model (EGARCH (1,

1) – M). On the contrary with GARCH models, EGARCH favors for leverage effects (i.e. shocks with various signs and magnitudes having divergent effects on volatility). Another advantage of these models compare to those of GARCH is that, EGARCH models allow capturing the effect of seasonality, due to the relationship among futures and spot prices, by embedding quarterly seasonal dummies in the mean equation. As a result, the forward premium is constructed by including the unknown term of volatility in such a manner that the equation of conditional variance is modified as below:

$$\Delta_n S_{t+n} = \beta_1 + \beta_2 Basis_t + \gamma_1 \log(\sigma^2_{t+n}) + \sum_{i=1}^{q} \delta_i D_i + \varepsilon_{t+n} \ , \qquad 0 \leq q < 4 \qquad \textbf{(13)},$$

$$\log(\sigma^2_{t+n}) = \alpha_0 + \sum_{i=1}^{p} \alpha_i g(z_{t+n-i}) + \sum_{j=1}^{q} \lambda_j \log(\sigma^2_{t+n-j}) \qquad \textbf{(14)}$$

Where, $g(z_{t+n}) = \theta(z_{t+n}) + \gamma(|z_{t+n}| - E|z_{t+n}|)$, indicate the extent (ARCH impact) and sign (leverage effect), with $z_{t+n} = \sigma^{-1}_{t+n}\ \varepsilon_{t+n}$, $z_{t+n} \sim N(0, 1)$. Considering the asymmetrical impacts and the high levels of risk in company with the insistence of volatility, the main purpose remains to apprehend the connection between futures and spot prices.

By using VECM models the investigation is augmented in such a way that futures and settlement prices returns is approximated via an ECM with EGARCH (1, 1) – M error model. The main goal is to apprehend the connection among the divergences in futures and settlement prices through a model of variance as a function of asymmetric historical novelties. By simplifying the form of the VECM model, the ECM model is produced and can be used in the mean equation. Therefore, one equation is extracted, instead of a system of equations, and ECM occurs combining legged dependent variables and lagged regressors. As long as the validity of the restrictions that introduced by VECM is testified, the Error Correction Term depicts the approximated forecast errors.

3.4 Forecast Error

Assuming the hypothesis that the values of a series depends on the past values in combination with the current and forward values of a white noise error term, the need of constructing forecast errors is essential. According to Box and Jenkings approach (1976), a basic step in the attempt to make forecasting is to create and use the Moving Average (MA), the Autoregressive (AR) and the Autoregressive Integrated Moving Average models (ARIMA). MA process is non-theoretical model used in order to predict growth rates of short time horizons or even in the case of inadequate data. More specifically, MA models use the lagged value of a random variable in order to predict a non-random independent variable. The process involves the calculation of the average sample observations and the use of this tool as a forecast for the next period. The term MA is used because every time a new observation enters in the sample, a new average is calculated and replaces the previous one. Thus, every new forecast includes the most recent observation.

AR model is an alternative method to forecast with the main difference that now the variable of interest uses a linear combination of past values of this specific variable. AR models are generally more preferable than MA if the horizon of analysis is relatively short. However, both AR and MA are significant tools of forecasting because actually the one constitutes the reflection of the other.

The linear combination of AR and MA models compose ARIMA models. The model is referred as ARIMA (p, d, q) where p is the number of autoregressive terms, d imposes the number of non-seasonal differences and q the moving average terms. It is also an important forecasting instrument, as it combines both characteristics of AR and MA models. The forecasting model typically used is of the form:

$$f_{t,s} = \mu + \sum_{i=1}^{p} \varphi_i f_{t,s-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} + \varepsilon_t ; \varepsilon_t \sim iid(0, \sigma^2)$$

Where,

- $f_{t,s} = X_{t,s}$, $s \leq 0$, s are the steps in the future

- $\varepsilon_t = 0$, $s > 0$ & $\varepsilon_t = \varepsilon_{t+s}$, $s \leq 0$

CHAPTER 4

4. Data Analysis

The natural gas prices dataset that is used in this study contains futures prices for monthly contracts for 1,2,3,6,9 and 12 months to maturity, in combine with daily spot prices for the period of 28th October 1993 to 14th July 2016, resulting 271 observations. The entire data information is received from 'Thomson Reuters datastream' and 'New York Mercantile Exchange (NYMEX)' as well, for spot and futures prices respectively. All the prices are derived from the delivery at the Henry Hub in Louisiana. The prices are officially closing at 2:30 p.m. daily from the marketplace of the NYMEX $/Barrel for a precise transfer month. A futures contract agreeing the earliest delivery day. As it regards natural gas contracts, they expire three business days according to previous calendar day of the expiring month. Therefore, the delivery month for the first contract is the datebook month ensuing the exchange date. Even the NYMEX commenced exchanging natural gas futures contracts after 1990. NYMEXs' futures contracts are deliverable 18 months ahead[4] at Henry Hub which is a natural gas pipeline that takes place in Erath, Louisiana and functions as the authorized delivery place for futures contracts on the NYMEX. The whole North America natural gas market adopts the settlement prices as benchmarks. In futures contracts, the delivery point is the location where the asset will be transported. As a result, the selected place will have a consequence on the net delivery price or cost. The transportation cost from the source to the delivery place affects the price of natural gas which diverges for different locations.

[4] "The current year plus the next twelve calendar years. A new calendar year will be added following the termination of trading in the December contract of the current year" according to Henry Hub Natural Gas Futures Contracts Specs

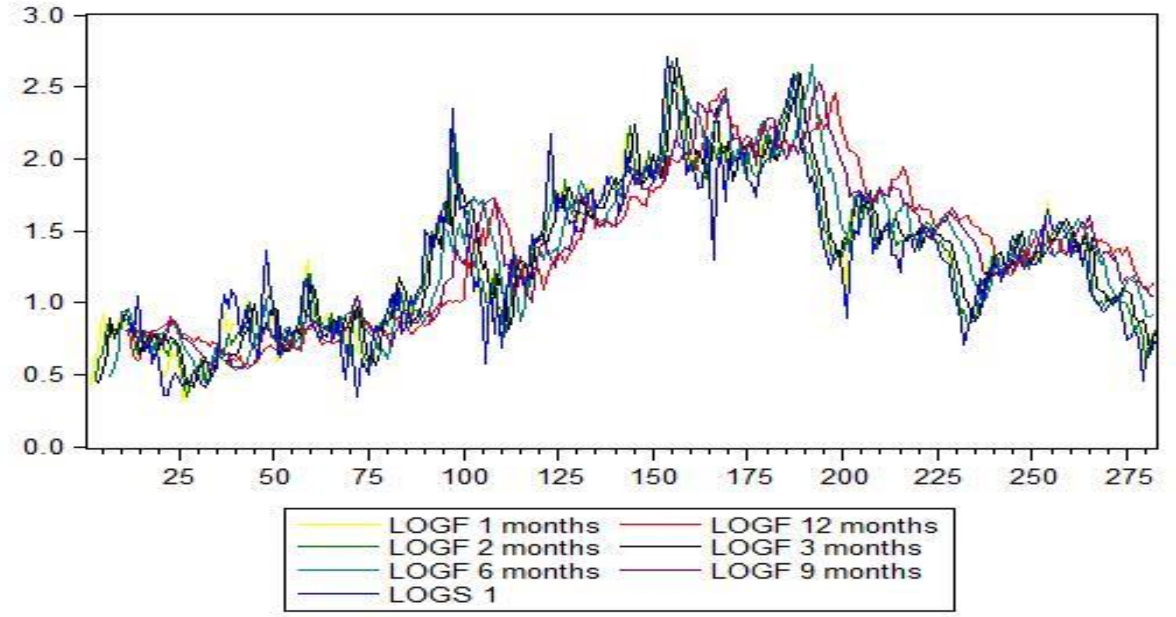
Closing spot and futures natural gas prices are obtained from Thomson Reuters Datastream. In order to calculate the values with accuracy, it is taken an unweighted average of the everyday spot prices at the closing time –for the delivered commodity- over the particular period. To be more accurate, spot prices defined as the price for a one-time accessible marketplace exchange for rapid conveyance of a particular amount of commodity at a particular region where the product is obtained "on the spot" at existing market rates.

This chapter investigates the vigorous effectiveness of futures, settlement and spot prices as well as their principal statistical attributes and several crucial relations among them.

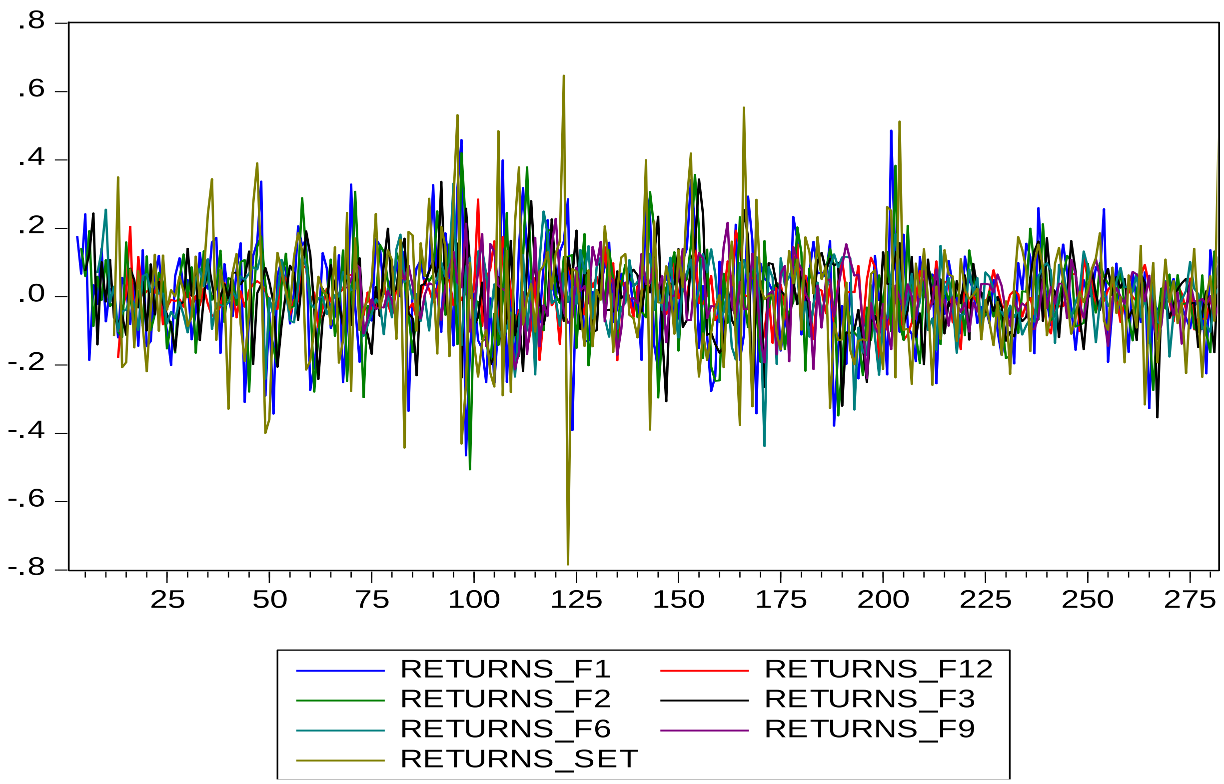
4.1. Price Behavior

In this section, the performance of log futures, settlement and spot prices and their log differences are analyzed in order to illustrate the behavior of natural gas prices for the last two decades, before proceeding into the investigation of their statistical properties. According to their graphs, futures and spot prices illustrate related patterns even though spot prices appear to present greater volatility. Although spot prices appear to deviate from the standard price attitudes of financial market in the short run, the parallel movement of the futures prices imposes evidence of dynamic correlation among the contracts. The graphs below illustrate the co-movement of log futures and contemporaneous spot prices as well as the returns of futures and settlement prices.

Graph 4.1: Illustration of log of futures and contemporaneous spot prices



Graph 4.2: Illustration of returns of futures and settlements prices

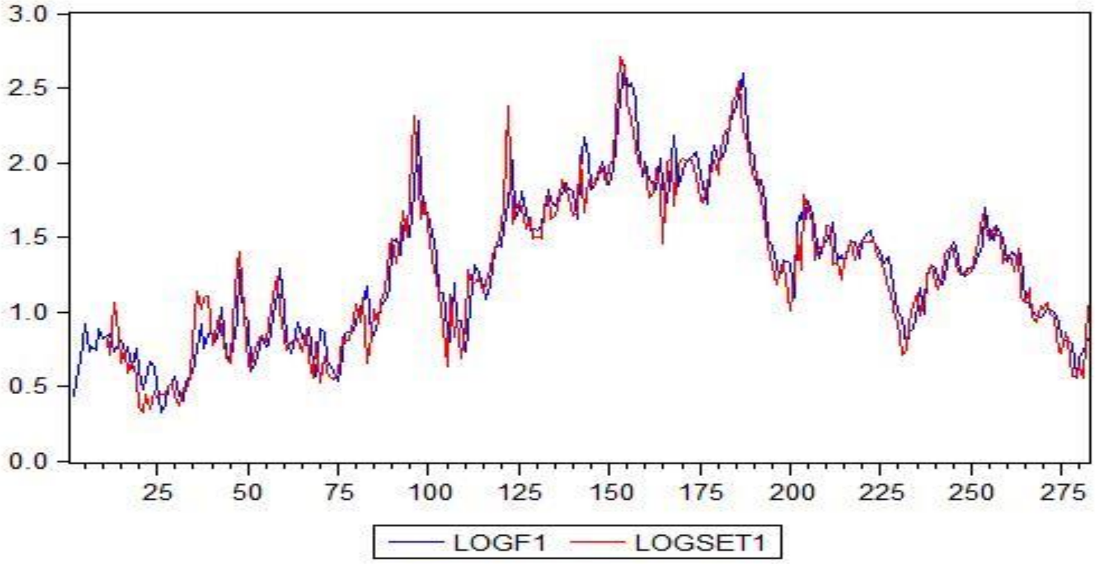


Based on the graph 4.1, there are some noteworthy patterns. First of all, in the first month to maturity, futures prices are moving similar to the spot ones considering as well that their volatility is relatively high. On the contrast, in the 12th month to maturity, futures prices appear to drift apart the co-movement with the spot price and they are much less volatile as well. In addition, there is a clearly positive trend to both prices, futures and spot, for all times to maturities. However, these patterns do not follow the general view that commodity prices in the long run should revert back to their mean. Finally, it is observable the high volatility of the variables in the current years, as it is illustrated on graph 4.2. Therefore, the time-varying volatility imposes significant inferences considering the estimation of the regressions.

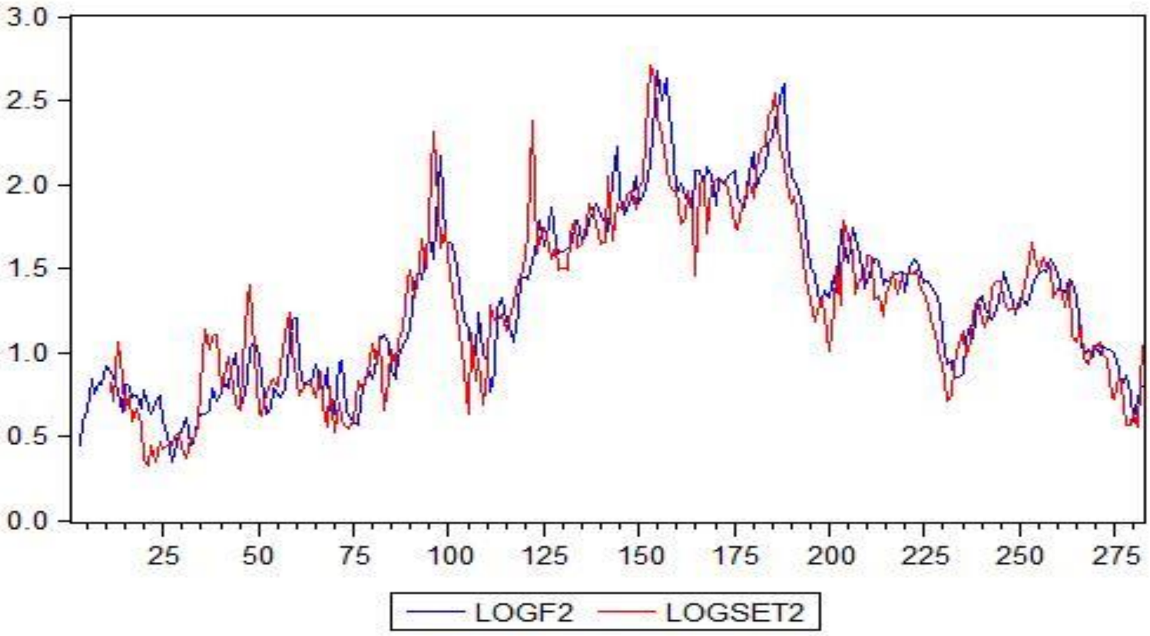
Taking into account the aforementioned patterns, in most occasions, volatility, spikes and jumps in nature gas prices are explicated by the nature of the commodity. The existence of the observable seasonality in jumps and spikes is owed to the balance of demand and supply, the dependency of which is based on weather conditions. The need of heat in winter is the most important cause of natural gas demand and in most cases the extreme variations in temperatures indicate significant effect in the balance of supply and demand, resulting prices to be fluctuated during cold period. Despite the presence of instability in prices, the production of natural gas, in U.S, augments at a steady rate, overwhelming the impact on natural gas prices.

The graphs below describe the association among futures prices of 1, 2, 3, 6, 9 and 12 months to maturity and settlement prices, rather than contemporaneous spot. As the figures illustrate, even though settlement prices impose greater volatility than futures ones, generally, futures prices have been overhead settlement prices.

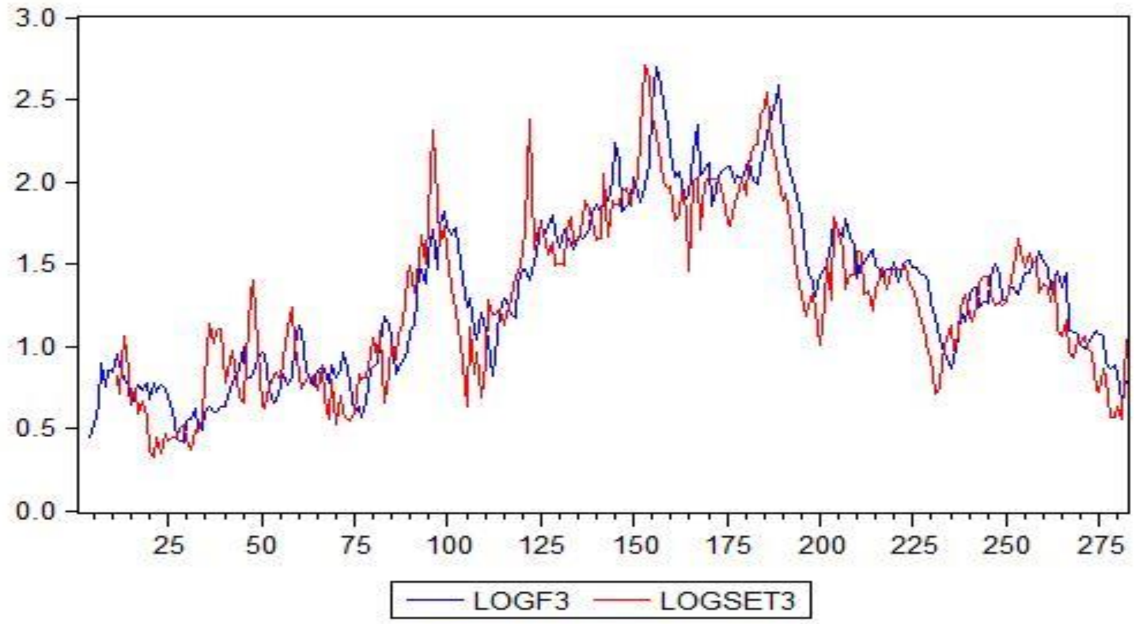
Graph 4.3: Illustration of log of 1 month of futures and settlement prices



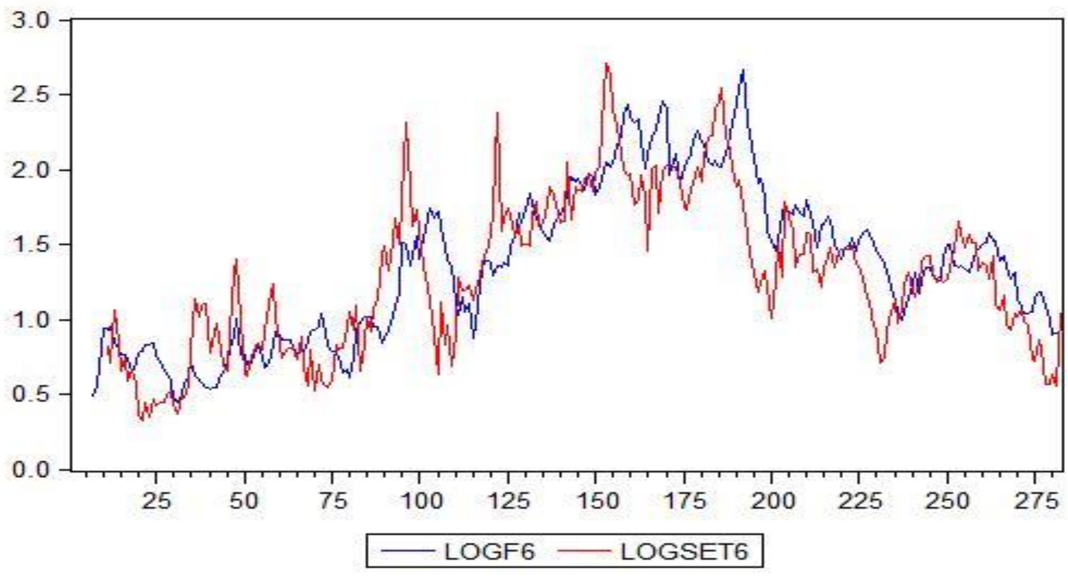
Graph 4.4: Illustration of log of 2 months of futures and settlement prices



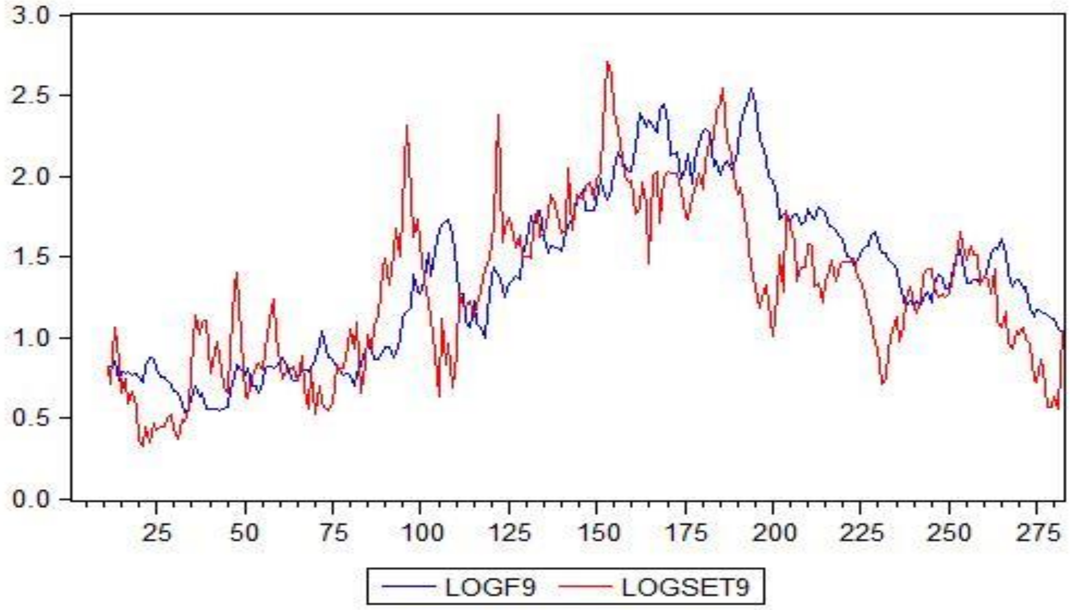
Graph 4.5: Illustration of log of 3 months of futures and settlement prices



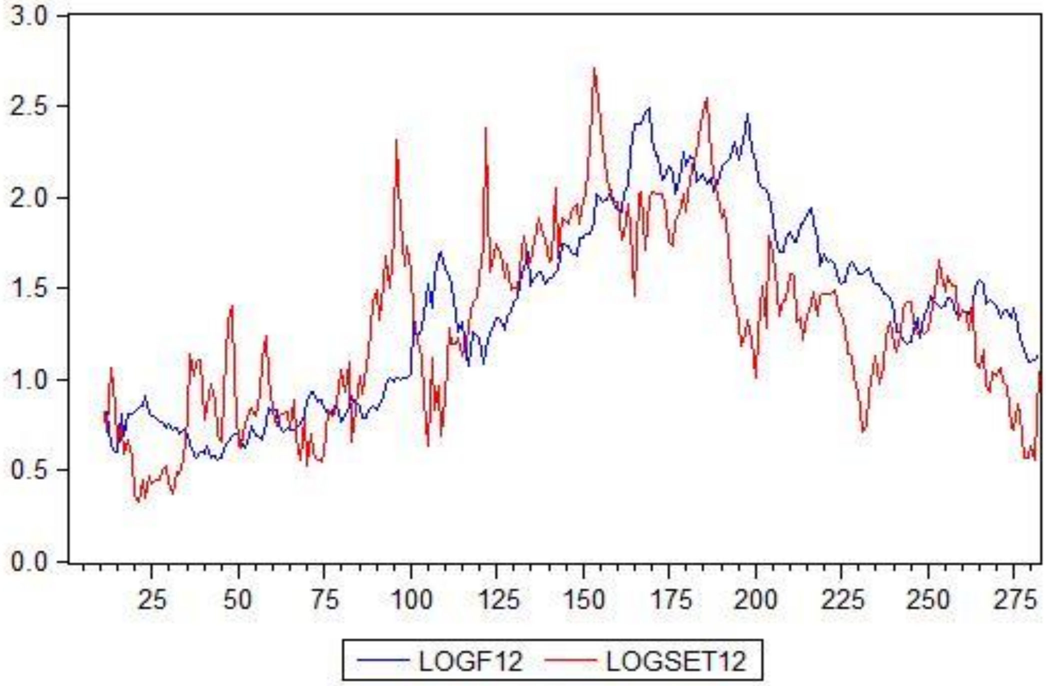
Graph 4.6: Illustration of log of 6 months of futures and settlement prices



Graph 4.7: Illustration of log of 9 months of futures and settlement prices



Graph 4.8: Illustration of log of 12 months of futures and settlement prices



4.2. Descriptive Statistics

In this study, the skewness of futures, spot and settlements' returns seem to be positive (right tails) for the first and the last month to maturity whereas for the rest they impose left tails (negative skewness). According to Bessembinder and Lemmon (2002), wherever there are upward fluctuations in the marginal cost of production, positive skewness intimates high probability of extreme prices to ensue[5]. Whether there is a large frequency of variations in prices and in structural brakes (jumps/spikes), the distribution of the time series tends to be leptokurtic, as it occurs in this study where all the time series present a leptokurtic curve in all time to maturities.

As it concerns the Jarque-Bera statistic, JB-test measures the difference between skewness and kurtosis of the series with those coming from the normal distribution. It is based on the OLS residuals. Normal distribution indicates that the null hypothesis of normality is resolutely rejected considering the returns on futures, settlement prices and the basis. The information of these data, in levels, in combine with the information of changing rates of settlement prices is normally distributed. Firstly, the test computes the skewness and kurtosis, then measures of the OLS residuals and uses the following test statistic. For a normally distributed variable, S = 0 and K = 3 and the value of the JB statistic is equal to zero.

$$JB = \frac{n}{6}\left[S^2 + \frac{(K-3)^2}{4} \right] \sim \chi^2_{(2)} \tag{16}$$

---

[5]Regarding the moments (mean, variance, skewness and kurtosis), it is known that the mean measures the expected returns, whereas the variance, measures the expected risk/uncertainty. Skewness measures the degree of asymmetry in the model, comparing the concentration of data on the left and on the right tail. The skewness for the normal distribution is always zero.
On the contrary, kurtosis measures the flatness (or peakedness). The Kurtosis for the normal distribution is respectively equal to three. This is something to be also approved using the Jarque-Bera (JB) (1980) test for normality. A distribution of a time series that obtains a number of kurtosis greater than three, tends to be called leptokurtic (otherwise, K<3, platykurtic).

Where: n = sample size, S = skewness coefficient, and K = kurtosis coefficient.
In addition, Ljung-Box (1978) Q-statistic tests serial correlation via the correlogram of the residuals. The verification of the absence of serial correlation is testified by the correlations' equality to zero, apart from random fluctuation. Q-statistic follows the χ^2 distribution.

In the table below (4.1), the descriptive statistics of the returns of futures, contemporaneous spot and settlement prices as well as the settlements' prices changing rates ($\Delta_n S_{t+n}$) and the $basis_t$ are presented. Futures prices, generally, are above settlement prices, according to conditional mean whereas their volatility is lower than settlements'. As it regards the basis, its volatility becomes higher as the months to maturity augments. Therefore, the predictability of the basis ascents when the delivery dates lie ahead. On the contrary, it is observable that in futures prices their volatility is decreasing while the months to maturity augments, a fact that signifies the lower risk of contracts with larger remaining trading life consistent with the Samuelson (1965) effect.

Table 4.1: Descriptive statistics of returns of log futures-spot-settlement natural gas prices

	N	Mean	STD	Skew	Kurt	Normality	Autocorrelation	
						J-B	Q (1)	Q (8)
1 Month to maturity								
Futures								
Returns	272	5.02e-05	0.15015	0.02467	3.6092	4.0233[0.1204]	0.0862[0.769]	17.068[0.029]
Basis	271	0.0233	0.0754	0.9555	9.1875	473.544[0.000]	47.373[0.00]	59.325[0.00]
2 Months to maturity								
Futures								
Returns	272	-0.0004	0.1304	0.0009	4.0087	11.5305[0.0031]	1.7908[0.181]	19.892[0.011]
Basis	270	0.0397	0.1176	0.3170	9.4046	465.9785[0.00]	77.638[0.00]	95.472[0.00]
3 Months to maturity								
Futures								
Returns	272	-0.0002	0.1118	-0.1356	3.6357	5.4138[0.0667]	3.9319[0.047]	12.9[0.115]
Basis	269	0.0517	0.1506	-0.6147	8.6863	379.3453[0.00]	95.477[0.00]	137.56[0.00]
6 Months to maturity								
Futures								
Returns	272	-3.61e-05	0.0931	-0.5330	5.0035	58.3696[0.00]	8.3333[0.004]	25.925[0.002]
Basis	266	0.0723	0.1833	-1.0250	7.2687	248.5412[0.00]	132.12[0.00]	236.73[0.00]
9 Months to maturity								
Futures								
Returns	214	0.0011	0.0840	-0.0912	3.2583	0.8915[0.6403]	6.8254[0.009]	15.897[0.044]
Basis	263	0.0793	0.2056	-1.2166	9.6258	545.9638[0.00]	114.44[0.00]	266.2[0.00]
12 Months to maturity								
Futures								
Returns	270	0.0012	0.0699	0.1776	4.3455	21.7860[0.00002]	08181[0.366]	12.386[0.135]
Basis	260	0.0844	0.2055	-0.1873	4.6341	30.4486[0.00]	149.67[0.00]	481.11[0.00]
Spot Prices								
Spot								
Returns Spot	270	-0.0006	0.1757	0.1688	4.2047	17.6093[0.0001]	3.3388[0.068]	18.104[0.02]
Settlement Prices								
Settlement								
Returns								
Settlement	271	0.0008	0.1809	0.1259	4.89991	41.4743[0.00]	5.5984[0.018]	14.722[0.065]
$\Delta_1 S_{t+1}$	271	0.0018	0.1691	0.3875	5.3357	68.3827[0.00]	5.6019[0.018]	21.008[0.007]
$\Delta_2 S_{t+2}$	270	0.0026	0.2292	0.3688	4.7155	39.2286[0.00]	19.792[0.00]	38.598[0.00]
$\Delta_3 S_{t+3}$	269	-0.0034	0.2661	0.2136	3.5981	6.0542[0.0485]	84.107[0.00]	117.2[0.00]
$\Delta_6 S_{t+6}$	266	-0.0035	0.3562	-0.0968	3.2970	1.3992[0.4983]	152.38[0.00]	319.77[0.00]

$\Delta_9 S_{t+9}$	263	-0.0063	0.4287	-0.4877	3.9859	21.0757[0.00003]	159.07[0.00]	402.17[0.00]
$\Delta_{12} S_{t+12}$	260	0.0046	0.4579	-0.2483	3.6616	7.4138[0.0246]	180.55[0.00]	544.33[0.00]

- The period of the sample begins form 22/1/1993 until 28/6/2016. The values in [ ] refer to the p-values.
- The order of sample's serial correlation is represented by the Ljung-Box (1978) Q statistics of Q (1) and Q (8) (first and eighth order of autocorrelation).

4.3 Preliminary Analysis

4.3.1 Unit Root Tests

Stationarity is one of the basic assumptions for econometric analysis (random walk process). Non-stationary time-series-variables are not helpful for the forecasting procedure, because the regression analysis will be spurious. Moreover, the t-ratio, as well as the R^2 coming from the regressions lead to invalid inferences. In order to verify that the variables are stationary or not, it should be examined whether stationarity is present. If this assumption is valid, then all the econometric procedures are statistically valid. On the other hand, unless it is present, it is necessary to make the variables stationary by taking the first logarithmic differences (integrated of order 1) and taking the returns/growth rates of them.

There are many reasons to choose this technique. First of all, the use of growth rate overcomes the problem of non-stationarity and as a consequence facilitates forecasting and all the other procedures. Non-Stationarity means non-constant variance and the existence of trends, so first differences process seems a necessity. Secondly, the effect of heteroscedasticity and the scale to measure things are simultaneously reduced. Thirdly, the technique of differences makes it possible to measure changes and elasticities and in this way, determine the future according to what happened in the past.

A way to check for stationarity is using the correlogram of the time series, which consists of both the autocorrelation function (ACF) and the partial autocorrelation function (PACF). Autocorrelation Function is the variable that measures the strength and the duration of memory of one time-serie. In other words, it counts the average correlation between two observations (one today and one yesterday). The major application of autocorrelation plotting is checking the randomness in the data set. The idea is that if the autocorrelations are near zero for any and all time lags, then, the data set is random. Another application is the identification of the order of an Autoregressive and a Moving Average process (as it mentioned previously). Partial Autocorrelation Function measures the correlation between an observation k period-s ago and the current one, after controlling for all the intermediate lagged observations. The PACF plot or partial correlogram is commonly used for model identification in Box-Jenkins models.

Considering now that a time-serie is stationary, the variables are moving around a standard mean (irrespectively of the time) and the variance remains constant. In the current case of autocorrelation, it is a fact that the stationary series approaching zero in a quick rate, whereas the non-stationary ones in a relatively slow, as long as the number of lags increases. The structure of the graphs of ACF and PACF is a signal of non-stationarity as well, presenting a slow diminishing rate. The slow change of the ACF indicates the fact that the time-series are forgetting slowly, so the memory of the model is really strong. Moreover, the existence of the probability equals to zero in all of the cases represents that everything in the model is significant.

One other, and most common, way to detect the non-stationarity is the use of Unit Root Tests. As it mentioned previously, a time series that is stationary obtains the attribute of systematic mean reversion. In other words, there is no systematic trend; therefore, the variance is constant over time. For this purpose, there is plethora of unit root tests that could be introduced in order to detect whether the time series ensue a unit root process. The most commonly used tests are the Augmented Dickey – Fuller (1981) (ADF), Phillips – Perron (1988) (PP), Kwiatkowski, Phillips, Schmidt and Shin (1992) (KPSS).

To begin with, ADF test impose that there is a unit root under the null hypothesis (H_0: $\rho = 1$), where ρ is the coefficient of τ_μ – statistics, against the alternative one that states absence of unit root (H_1: $\rho < 1$) in the equation below, in which an autoregressive process of order q+1 is expressed, AR (q+1):

$$\Delta X_t = \alpha_{0,1} + \beta t + (\rho - 1) X_{t-1} + \sum_{i=1}^{q} \alpha_i \Delta X_{t-1} + \varepsilon_t \quad ; \quad \varepsilon_t \sim iid(0, \sigma^2) \qquad \textbf{(17)}$$

Where τ_μ–statistics denotes as t-statistics but with the difference that the τ_μ–statistics follows the normal distribution whereas t-statistics not. Thus, the critical values of t-statistics cannot be used in this case.

According to this equation, the presence of serial correlation in the residuals ε_t is negligible, due to the lags (q) of the dependent variable ΔX_{t-1}. All of these particular tests encompass a constant but no trend (t = 0). This fact can be understandable, because the trend is insignificant whereas at the same time lag length reduces Schwartz Information Criterion (SIC).

Phillips Perron unit root test is a more generalized form of the ADF test, in which ε_t procedures that are not following normal distribution, are allowed by introducing a non-parametric correction. Therefore, the null hypothesis is examined by a modification in statistics:

$$Z(\tau_{\mu}) = (S_{\varepsilon} / S_{p})\tau_{\mu} - \frac{1}{2}(S_{\varepsilon}{}^{2} - S_{p}{}^{2})[S_{p}T^{2}\sum_{t=1}^{T}(X_{t} - X_{t})^{2}]^{\frac{1}{2}}]^{-1} \qquad \textbf{(18),}$$

where S_ε and S_p represent the variances of the residuals of the sample and population respectively. According to the theory of Phillips and Perron, serial correlation in the error correction term augments from their own difference. Finally, following the Newey – West (1994) bandwidth selection, the optimal lag length is chosen.

Although ADF and PP tests investigate the presence or absence of unit root, they do not refer directly to the issue of stationarity. Therefore, there are, occasionally, some deluding results, considering the behavior of the variables. To be more accurate, the power of these two tests is referred to be analogously indistinct in the case of marginal unit root process or in the presence of negative autocorrelations. Thus, in order to overpower this obstacle, Kwiatkowski, Phillips, Schmidt and Shin (1992) proposed a method in which, the null hypothesis is modified to *H_0: the series is stationary* against the alternative one *H_1: no stationary*. Henceforth, this new test reports directly to the problem of stationarity. The new statistic equation is denoted below:

$$KPSS_t = T^{-2}\sum_{t=1}^{T} K_t^{\,2} / K^2(L) \qquad \textbf{(19)}$$

Where,

- K_t is the accumulative sum of the residuals (ε_t) referred to a regression on a constant (or linear trend),
- $K^2(L) = T^{-1} \sum_{t=1}^{T} \varepsilon_t^2 + 2T^{-1} \sum_{K=1}^{L} (1 - K/(L+1)) \sum_{t=K+1}^{T} \varepsilon_t \varepsilon_{t-k}$, where L denoted as the truncation lag parameter, which selected automatically by Newey-West bandwidth selection.

In the table below, it is presented the results of preliminary analysis by using the aforementioned unit root tests.

Table 4.2: Preliminary Analysis of log of futures-spot-settlement natural gas prices and returns

	N	ADF		PP		KPSS	
		Levels	Returns	Levels	Returns	Levels	Returns
1 Month to maturity							
Futures	281	-2.6713	-14.0454	-2.5678	-17.234	0.7453	0.1409
Basis	270	-10.4938	----	-10.1902	----	0.1133	----
2 Months to maturity							
Futures	277	-1.9998	-13.743	-2.3268	-15.3481	0.7638	0.1521
Basis	270	-9.0092	----	-8.7359	----	0.20404	----
3 Months to maturity							
Futures	278	-2.0899	-14.7809	-2.1911	-14.6795	0.8221	0.1972
Basis	268	-8.20004	----	-8.2014	----	0.4379	----
6 Months to maturity							
Futures	274	-2.0536	-13.7092	-1.9713	-13.4915	0.9072	0.251
Basis	265	-6.8264	----	-6.8188	----	0.5878	----

9 Months to maturity							
Futures	270	-1.5986	-12.1423	-1.5093	-12.1423	1.1118	0.3244
Basis	262	-7.3776	----	-7.2683	----	0.5772	----
12 Months to maturity							
Futures	270	-1.3197	-15.6584	-1.3904	-15.6812	1.2163	0.2516
Basis	258	-4.7014	----	-5.9258	----	0.56401	----
Spot Prices							
Spot	270	-2.7858	-14.702	-2.4967	-18.5285	0.7242	0.0925
Settlement	271	-2.994	-18.7303	-2.8436	-18.9857	0.7115	0.0645
$\Delta_1 S_{t+1}$	269	-15.1274	----	-19.1996	----	0.1419	----
$\Delta_2 S_{t+2}$	268	-13.0297	----	-11.95	----	0.1146	----
$\Delta_3 S_{t+3}$	263	-7.3295	----	-7.5413	----	0.1058	----
$\Delta_6 S_{t+6}$	253	-5.284	----	-6.2889	----	0.1485	----
$\Delta_9 S_{t+9}$	253	-4.3548	----	-6.0424	----	0.1962	----
$\Delta_{12} S_{t+12}$	247	-4.1688	----	-5.2572	----	0.258	----

- The sample size begins form 22/1/1993 until 28/6/2016
- ADF and PP unit root tests are investigated in 1%, 5% and 10% confidence intervals by using the MacKinnon critical values -3.4556, -2.8725 and -2.5727 respectively, considering always a constant term.
- KPSS unit root test examines the null hypothesis in which the series is stationary I(0) against the alternative one H_1: I(1), in 1%, 5% and 10% confidence intervals with the critical values (with a constant) 0.739, 0.463 and 0.347 respectively.

4.3.2 Cointegration Tests

One other method in order to examine the stationarity on the basis is to make use of Johansen's (1988) procedure. According to Johansen's cointegration tests (λ_{trace} & λ_{max} statistics), futures prices and contemporaneous spot prices are cointegrated together for all times to maturity of the futures contracts. Thus, the presence of a long run relationship is clearly proved as long as the basis ensues a unit root process. Although the initial selections of VECM lag structure help to reduce the (SIC), further omitted tests were taken place in order to make the model better. In accordance with the restrictions of the parameters, the cointegrating vector should be (1 -1 0) via all the months to maturities. In the table below, it is presented the Johansen's cointegration tests among the futures natural gas prices and the contemporaneous ones.

Table 4.3: Johansen Cointegration tests among futures and contemporaneous spot natural gas prices

$$\Delta F_{t;t+n} = \alpha_{1,0} + \sum_{i=1}^{q} \gamma_{F,i} \Delta F_{t-1;t+n-i} + \sum_{i=1}^{p} \gamma_{S,i} \Delta S_{t-i} + \alpha_F(\beta_2 S_{t-1} + \beta_1 F_{t-1;t+n-1} + \beta_0) + \varepsilon_{F,t}$$

$$\Delta S_t = \alpha_{2,0} + \sum_{i=1}^{q} \lambda_{F,i} \Delta F_{t-1;t+n-i} + \sum_{i=1}^{p} \lambda_{S,i} \Delta S_{t-i} + \alpha_S(\beta_2 S_{t-1} + \beta_1 F_{t-1;t+n-1} + \beta_0) + \varepsilon_{S,t}$$

			λ_{trace}	λ_{max}	Coefficients of Error Correction		Normalized CV	LR test	
Lags	**H_0**	**H_1**	**Stat**	**Stat**	**α_F**	**α_s**	**(1 β_2 β_0)**	**(1 -1 0)**	**p-value**
Panel A: 1 month to maturity futures and settlement prices									
2	r = 0	r = 1	41.6624	36.0965	-0.4273	0.2957	(1 -1.033 0.021)	0.174	0.025

	r = 1	r = 2	5.5659	5.5659	(0.073)	(0.151)			
Panel B: 2 months to maturity futures and settlements prices									
2	r = 0	r = 1	48.1946	43.1237	-0.3187	0.1718	(1 -1.0499 0.027)	21.4217	0.013
	r = 1	r = 2	5.0701	5.0701	(0.045)	(0.093)			
Panel C: 3 months to maturity futures and settlement prices									
2	r = 0	r = 1	42.6067	38.6718	-0.3168	-0.0561	(1 -0.9396 -0.028)	-2.3598	0.004
	r = 1	r = 2	3.9349	3.9349	(0.0793)	(0.051)			
Panel D: 6 months to maturity futures and settlement prices									
2	r = 0	r = 1	46.734	44.1305	-0.1203	0.051	(1 -1.1278 0.0914)	5.1583	0.098
	r = 1	r = 2	2.2603	2.2603	(0.018)	(0.037)			
Panel E: 9 months to maturity futures and settlement prices									
2	r = 0	r = 1	64.1834	61.664	-0.0644	0.0527	(1 -1.149 0.1056)	0.0934	0.193
	r = 1	r = 2	2.5119	2.5193	(0.013)	(0.0311)			
Panel F: 12 months to maturity futures and settlement prices									
2	r = 0	r = 1	44.527	42.4325	-0.04	0.0531	(1 -0.8437 -0.1244)	-1.1191	0.3251
	r = 1	r = 2	2.0944	2.0944	(0.011)	(0.0278)			

- r: number of cointegrating vectors
- α_F & α_S: speed of adjustment coefficients of ECM which imposed by the normalized cointegrating vectors and tested by t-statistics in () under the null hypothesis H_0: $\alpha_i = 0$

- λ_{trace} statistics' critical values under the null hypothesis (for 95% confidence interval) of r = 0 against r = 1 are 19.96, as well as 9.24 under the null of r = 1 against r = 2
- λ_{max} statistics' critical values under the null hypothesis of r = 0 against r = 1 are 15.67, as well as 9.24 under the null of r = 1 against r = 2
- LR statistic $= -T[\ln(1-\hat{\lambda}_1^*) - \ln(1-\hat{\lambda}_1)$, with $\hat{\lambda}_1^*$ and $\hat{\lambda}_1$ yield as the maximum eigenvalues of the constrained and unconstrained models, respectively. LR statistic examines the hypothesis on the cointegrating vector (β_1 β_2 β_0), following the χ^2 distribution in which the number of degrees of freedom is equal to the number of the constraints inflicted by the cointegrating vector
- Critical values acquired from Osterwald-Lenum (1992)

CHAPTER 5

5 Empirical Results

According to the previous preliminary analysis concerning the stationarity of the variables, the levels of futures, settlements and spot prices have one unit root, I(1), whereas the basis is stationary, I(0). After having analyzed the descriptive statistical properties of the data as well, the main purpose of this section is to investigate if futures prices are unbiased predictors of the spot ones. Therefore, in accordance with the unbiasedness hypothesis, in order to carry out these tests, it is essential to introduce two main methods that are considered to be more appropriate. The first one is to run a regression of the changes of settlements prices on the basis and the second one is to construct the VECM framework by utilizing cointegration methods. For this purpose, the tests that will be performed are Wald Tests and Likelihood Ratio Tests, which test the validity of the restrictions. Furthermore, some other models will be introduced, in order to model forecast errors, as well as GARCH group models that estimate the risk premium.

5.1 Market Efficiency of Futures Prices

To begin with, due to the fact that there is strong evidence of autocorrelation and heteroscedasticity in the regression of the changes of settlements prices ($\Delta_n S_{t+n}$) on the basis, it is essential to correct the issue of autocorrelation, which arises because of the overlapping observations. The problem of overlapping observations is occurred due to the moving average consequences in the residuals is such a way that provoke memory maintenance (forget very slowly depending on the lag length). In order to test the Unbiasedness Expectations Hypothesis, there are some restrictions that must be verified in the estimation of OLS regression, such as $\beta_1 = 0$ & $\beta_2 = 1$. By remaining valid the joint hypothesis of these constraints on the coefficients, futures contracts are unbiased predictors of the expected spot prices. According to Wald tests, due to the rejection of null hypothesis for all the months to maturities, at 1% significance level, natural gas futures contracts are biased estimators of natural gas spot prices. However, in order to investigate the main responsible cause of this inefficiency (the intercept or the slope), the null hypothesis should be diverted into two hypotheses. Table 5.1 illustrates the regression of changes in real settlement prices on the basis where the slope diverges significantly from one at 1% level of significance as well as the constraint that enforced on the constant term, at 10% level of significance, fails to be rejected. The above outcome infers the strong evidence of the presence of a positive risk premia, due to the fact that the intercept tends to zero and the constant term of the basis is less than one. Mathematically speaking $F_{t-1;\,t+n-1} > S_{t+n-1}$.

Table 5.1: Test for unbiasedness of natural gas futures prices

$$\Delta_n S_{t+n} = \beta_1 + \beta_2 Basis_t + \varepsilon_{t+n}$$

Panel A: Model Estimation

	1 month	2 months	3months	6months	9 months	12 months
β_1	-0.0152	-0.0277	-0.0393	-0.0626	-0.0831	-0.0767
	(0.0106)	(0.0173)	(0.0158)	(0.0397)	(0.0512)	(0.0583)
	[0.15]	[0.1096]	[0.0136]	[0.1165]	[0.1061]	[0.1893]

β_2	0.7346	0.7633	0.6945	0.8174	0.968	0.9630
	(0.1926)	(0.1275)	(0.0994)	(0.1216)	(0.1526)	(0.1923)
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
R-bar Square	0.104	0.1503	0.151	0.174	0.2125	0.1837
Panel B: Residual Diagnostics						
LM (1)	6.1861	43.5537	115.2195	176.7721	194.02	203.2167
	[0.0454]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Q (1)	0.6759	34.391	109.61	175.35	195.44	203.36
	[0.411]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Q (8)	12.062	40.917	146.29	410.2	613.33	756.89
	[0.148]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ARCH (1)	20.2426	1.1348	19.75	69.8313	101.5494	107.2203
	[0.000]	[0.2868]	[0.000]	[0.000]	[0.000]	[0.000]
ARCH (8)	23.0385	2.4017	21.64	74.5701	107.8394	109.9891
	[0.003]	[0.9662]	[0.006]	[0.000]	[0.000]	[0.000]
JB	33.457	34.6905	19.3391	1.3963	2.8535	2.2770
	[0.000]	[0.000]	[0.000]	[0.4975]	[0.2401]	[0.3203]
Panel C: Wald tests						

β_1=0, β_2=1	8.0286	9.1666	23.0219	6.952	3.7902	2.6337
	[0.018]	[0.0102]	[0.000]	[0.0309]	[0.1503]	[0.268]
β_1=0	1.8987	3.4476	9.4415	2.2559	0.0441	0.037
	[0.168]	[0.0633]	[0.002]	[0.1331]	[0.8337]	[0.8476]
β_2=1	2.085	2.5777	6.1734	2.4804	2.6301	1.7322
	[0.1487]	[0.1084]	[0.03]	[0.1153]	[0.1049]	[0.1881]

- The period of the sample begins form 22/1/1993 until 28/6/2016. The values in [] and in () as well refer to the p-values and standard errors, respectively.
- The order of sample's serial correlation is represented by the Q statistics of Q (1) and Q (8) (first and eighth order of autocorrelation).
- n = 1, 2, 3, 6, 9 and 12 for the 1, 2, 3, 6, 9 and 12 monthly data, respectively.
- The model is estimated by using OLS and standard errors are adjusted for heteroscedasticity and autocorrelation.
- LM (1) is the Breusch (1978) - Godfrey (1978) Lagrange Multiplier test for autocorrelation of order 1 and asymptotically follows $\chi 2$ (1).
- ARCH is the Engle (1982) test for ARCH consequences using 1 and 8 lags, follow $\chi 2$ (1) and $\chi 2$ (8) respectively.
- JB tests normality. Jarque - Bera (1980) statistics distributed as $\chi 2$ (2).

In the second method, the use of the VECM framework that introduced by Johansen (1991), investigates the validity of the unbiasedness of futures contracts. Within the VECM framework, cointegration tests are implemented at the same time. In contrast with the initial purpose of VECMs lag structure to minimize the Schwartz (1978) criterion, the need of optimization the model requires additional tests to exclude lags. Consequently, the model will be said to be 'well specified' as long as the issue of the serial correlation of the residuals -due to the overlapping observations- would overpower.

Table 5.2 displays the normalized coefficients of the cointegrating vectors as well as the λ_{trace} and λ_{max} statistics which demonstrate a unique long run equilibrium connection among futures and settlement prices for all times to maturity, respectively. Regarding the error correction coefficients for the futures prices, at 95% confidence interval, all entail negative signs and are statistical significant (except for the 1st month to maturity) while the coefficients of spot prices have not negative sign apart from one, at the 3rd month to maturity, but are still significant as well (at 90% confidence interval). The above outcome demonstrates the direction of futures and spot prices prior to congruity at maturity day. This direction that indicated by the signs of the coefficients which describe the presence of positive forecast error as long as the cointegration is affirmed. More specifically, when a positive forecast error occurs at time t-1 then the futures prices will augment at the same time whereas spot prices will augment as well in an effort to converge to the long run and remove the non-equilibrium. In mathematical meaning, this affirms the relation $F_{t-1; t+n-1} > S_{t+n-1}$.

The cointegrating vector $\beta' X_t = (F_{t; t+n-1} \beta_0 S_{t+n})$, with $\beta' = (1, 0, -1)$, is tested so that to confirm whether the lagged basis should be involved as an Error Correction Term

(ECT) in the VECM model. The constraint is being examined by using likelihood tests, according to table 5.3. The outcomes are in accordance with the past method since the joint hypothesis concerning the unbiasedness of the futures contracts is not accepted at 90% confidence interval for all maturities, against the alternative one that futures prices are biased estimators of the spot ones. Nevertheless, the null hypothesis is rejected for all times to maturity at 5% level of significance. In addition, the individual tests that have taken place, H_0: $\beta_0 = 0$ and H_0: $\beta_2 = -1$, examine if the source of the denial of unbiasedness is derived from the constraint on the intercept or from the coefficient of settlement prices. Taking into account the joint hypothesis, it is concluded that futures prices are biased estimators of spot but then again inconsistencies of the individuals' tests (without to impose one restriction on each time) indicate the presence of time varying risk premium.

The unbiasedness hypothesis is rejected (at 5% level of significance), due to comparatively low liquidity regarding that the spot market is confined to contributors that take possession of a physical grid relationship. One other fact that should be taken into consideration, is that asymmetries in the inducements, considering risk management, are obvious. To conclude, according to the nature and behavior of the market, the shocks that occurred not only in liquidity but in paper market as well provide asymmetric reactions that are affirmed by EGARCH method, giving growth to inequities which successively produce biases and premia ensuing a positive systematic error. Table 5.2 illustrates the Johannsen' (1991) cointegration tests among futures and expected spot natural gas prices.

Table 5.2: Johansen (1991) Cointegration tests between expected spot and futures natural gas prices

$$\Delta F_{t-n,t} = \sum_{i=1}^{p} \gamma_{F,i} \Delta F_{t-n-i,t-i} + \sum_{i=1}^{p} \gamma_{S,i} \Delta S_{t-i} + \alpha_F (\beta_1 F_{t-n-1,t-1} + \beta_2 S_{t-1} + \beta_0) + \varepsilon_{F,t}$$

$$\Delta S_t = \sum_{i=1}^{p} \lambda_{F,i} \Delta F_{t-n-i,t-i} + \sum_{i=1}^{p} \lambda_{S,i} \Delta S_{t-i} + \alpha_S (\beta_1 F_{t-n-1,t-1} + \beta_2 S_{t-1} + \beta_0) + \varepsilon_{S,t}$$

			λ_{trace}	λ_{max}	Coefficients of Error Correction		Normalized CV
Lags	**H_0**	**H_1**	**Stat**	**Stat**	**α_F**	**α_s**	**(1 β_2 β_0)**
Panel A: 1 month to maturity futures and spot prices							
2	r = 0	r = 1	43.4517	38.2881	-0.0251	0.5142	(1 -1.013 -0.011)
	r = 1	r = 2	5.1636	5.1636	(0.151)	(0.1678)	
Panel B: 2 months to maturity futures and spot prices							
2	r = 0	r = 1	41.4729	37.1785	-0.0307	0.3998	(1 -1.035 0.005)
	r = 1	r = 2	4.2943	4.2943	(0.078)	(0.105)	
Panel C: 3 months to maturity futures and spot prices							
2	r = 0	r = 1	42.6067	38.6718	-0.3168	-0.0561	(1 -0.9396 -0.028)
	r = 1	r = 2	3.9349	3.9349	(0.0793)	(0.051)	
Panel D: 6 months to maturity futures and spot prices							
2	r = 0	r = 1	43.3328	39.9531	-0.1965	0.0431	(1 -0.9485 0.007)
	r = 1	r = 2	3.3797	3.3797	(0.0625)	(0.033)	
Panel E: 9 months to maturity futures and spot prices							
2	r = 0	r = 1	42.297	39.7312	-0.0367	0.2191	(1 -1.083 0.023)
	r = 1	r = 2	2.5658	2.5658	(0.0251)	(0.0609)	

Panel F: 12 months to maturity futures and spot prices

2	r = 0	r = 1	26.2317	24.2031	-0.0001	0.1567	(1 -1.1197 0.061)
	r = 1	r = 2	2.0287	2.0287	(0.0214)	(0.0536)	

Panel E: VECM Residual Diagnostics

	1 month		2 month		3 month		6 month		9 month		12 month	
	$\varepsilon_{F,t}$	$\varepsilon_{S,t}$	$\varepsilon_{F,t}$	$\varepsilon_{S,t}$	$\varepsilon_{F,t}$	$\varepsilon_{S,t}$	$\varepsilon_{F,t}$	$\varepsilon_{S,t}$	$\varepsilon_{F,t}$	$\varepsilon_{S,t}$	$\varepsilon_{F,t}$	$\varepsilon_{S,t}$
LM (1)	9.8703		5.958		5.003		8.123		4.044		3.448	
	[0.043]		[0.202]		[0.287]		[0.087]		[0.400]		[0.486]	
LM (8)	16.302		13.97		6.869		6.305		9.526		5.531	
	[0.003]		[0.007]		[0.143]		[0.178]		[0.049]		[0.237]	
Q (1)	0.45	0.318	0.169	0.006	0.002	0.0002	0.005	0.0003	0.024	0.0001	2.E-06	0.003
	[0.502]	[0.573]	[0.681]	[0.94]	[0.967]	[0.99]	[0.945]	[0,986]	[0.878]	[0.992]	[0.999]	[0.96]
Q(8)	6.402	3.737	7.62	3.516	3.025	5.231	3.91	7.033	7.624	5.184	10.523	4.86
	[0.602]	[0.88]	[0.471]	[0.898]	[0.933]	[0.733]	[0.865]	[0.533]	[0.471]	[0.738]	[0.23]	[0.78]
ARCH (1)	6.868	10.039	0.007	11.157	20.104	0.734	23.806	1.745	11.361	35.295	2.913	19.32
	[0.009]	[0.002]	[0.932]	[0.001]	[0.000]	[0.392]	[0.000]	[0.187]	[0.001]	[0.000]	[0.089]	[0.00]
ARCH (8)	9.348	11.308	14.469	18.588	25.895	11.372	27.242	11.001	65.001	36.478	23.512	22.64
	[0.314]	[0.185]	[0.07]	[0.017]	[0.001]	[0.181]	[0.001]	[0.202]	[0.000]	[0.000]	[0.003]	[0.004]
JB	0.248	2.445	7.569	9.582	47.489	9.152	58.136	55.91	3.039	1118.6	24.29	39.86
	[0.883]	[0.294]	[0.023]	[0.008]	[0.000]	[0.010]	[0.000]	[0.000]	[0.219]	[0.000]	[0.00]	[0.00]

Table 5.3: Likelihood Ratio tests of parameter restrictions on the Normalized cointegrating vectors (1 β_2 β_0)

	H_0	H_1	LR test	p-value	H_0	LR test	p-value
Panel A: 1 month futures and settlement prices							
	$\beta_2=-1$	$\beta_2\neq-1$	0.108	[0.742]	$\beta_2=-1$,	13.4202	[0.0012]
	$\beta_0=0$	$\beta_0\neq0$	2.752	[0.097]	$\beta_0=0$		
Panel B: 2 months' futures and settlement prices							
	$\beta_2=-1$	$\beta_2\neq-1$	0.305	[0.581]	$\beta_2=-1$,	11.4027	[0.0033]
	$\beta_0=0$	$\beta_0\neq0$	0.539	[0.463]	$\beta_0=0$		
Panel C: 3 months' futures and settlement prices							
	$\beta_2=-1$	$\beta_2\neq-1$	0.612	[0.434]	$\beta_2=-1$,	11.1036	[0.0039]
	$\beta_0=0$	$\beta_0\neq0$	0.210	[0.647]	$\beta_0=0$		
Panel D: 6 months' futures and settlement prices							
	$\beta_2=-1$	$\beta_2\neq-1$	1.089	[0.297]	$\beta_2=-1$,	9.6526	[0.008]
	$\beta_0=0$	$\beta_0\neq0$	0.01	[0.92]	$\beta_0=0$		
Panel E: 9 months' futures and settlement prices							
	$\beta_2=-1$	$\beta_2\neq-1$	2.038	[0.153]	$\beta_2=-1$,	10.2799	[0.0059]
	$\beta_0=0$	$\beta_0\neq0$	0.076	[0.783]	$\beta_0=0$		
Panel F: 12 months' futures and settlement prices							
	$\beta_2=-1$	$\beta_2\neq-1$	2.107	[0.147]	$\beta_2=-1$,	7.5947	[0.0224]
	$\beta_0=0$	$\beta_0\neq0$	0.256	[0.613]	$\beta_0=0$		

5.2 Time Varying Risk Premium

In the previous sectors, by testing the efficiency of natural gas futures prices that are traded on NYMEX and detecting the presence of positive forecast errors, the connection among futures and spot prices is being examined extensively in the prior GARCH family models. More analytically, the empirical results, that are resulted from the permission of asymmetric effects via the EGARCH (1, 1) – in – Mean framework, provide some signals of further consideration.

The main target of the first approach is to investigate the hypothetical presence of time varying risk premium. The model consists of two equations, one of mean and one of variance equation (illustrated in Table 5.4). Obviously, if the log variance term in the mean equation is statistically significant then volatility reliant on risk premium is existing. In accordance with the Maximum Likelihood approximates of the asymmetric GARCH model, the coefficient of slope converges to unity more drastically in comparison to the outcomes of the single regression process demonstrating that volatility holds the dynamic to clarify the exoduses from market efficiency.

Additionally, if the conditional variance coefficient, γ_1, in the mean equation is positive and pointedly statistically different from zero, for all maturities, then it is signified robust relative to the conditional mean and presented steadiness in the connection among returns and volatility. Therefore, higher returns are linked to higher risk premium. Moreover, whether coefficient λ_1, lagged variance, is significant, thus, it demonstrates that there is a reliance of conditional variance and past risk signifying insistence as well. Due to the fact that it drifts away to unity, shocks that are occurred to volatility are doubtful to be persistent i.e. they disappear more rapidly. The required evidence is given by Ljung-Box statistics. On the contrary, ARCH effects appear to die out, at least at higher order lags, in comparison to the regression model. Regarding the Error distribution structure, it was nominated to be Normal (Gaussian). The hypothesis of normality is rejected by Jarque and Bera (1980) statistic for the 2^{nd} and the 12^{th} month as well, so standard errors and covariance's approximated with maximum likelihood method, whereas it failed to be rejected for the rest months to maturity.

Table 5.4: EGARCH (1, 1) -in- Mean

Mean Equation: $\Delta_n S_{t+n} = \beta_1 + \beta_2 \text{ Basis}_t + \gamma_1 \log(\sigma^2) + +\varepsilon_{t+n}$

Variance Equation: $\log(\sigma^2_{t+n}) = \alpha_0 + \alpha_1 \theta(z_{t+n}) + \alpha_2 (|z_{t+n}| - E|z_{t+n}|) + \lambda_1 \log(\sigma^2_{t+n-1})$

	1 month	2 months	3 months	6 months	9 months	12 months
Panel A: Conditional Mean Parameters						
β_1	0.0358	1.4273	1.7925	-0.0418	-0.1741	-0.26
	[0.065]	[0.001]	[0.000]	[0.46]	[0.002]	[0.000]
β_2	0.4638	1.0296	0.9989	0.8489	1.0622	1.0843
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
γ_1	0.0111	0.4343	0.538	0.0008	-0.0465	-0.102
	[0.000]	[0.001]	[0.000]	[0.956]	[0.0033]	[0.000]
Panel B: Conditional Variance Parameters						
α_0	-2.2313	-3.5906	-1.6932	-2.2684	-1.9119	-1.8
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
α_1	0.7168	0.0868	0.0593	1.2875	1.2768	1.09
	[0.000]	[0.017]	[0.1363]	[0.000]	[0.000]	[0.000]
α_2	0.1822	0.2339	0.2531	0.0355	-0.0998	-0.2409
	[0.054]	[0.000]	[0.000]	[0.787]	[0.4367]	[0.042]
λ_1	0.5646	-0.0443	0.5221	0.5404	0.6573	0.6232

	[0.000]	[0.635]	[0.000]	[0.000]	[0.000]	[0.000]
Panel C: Residual Diagnostics						
R bar Square	0.0835	0.3015	0.523	0.1668	0.2291	0.2614
Q (1)	0.1033	0.0055	0.5878	100.39	124.97	122.99
	[0.748]	[0.941]	[0.443]	[0.000]	[0.000]	[0.000]
Q (8)	11.649	5.6945	15.329	253.58	418.76	466.24
	[0.168]	[0.681]	[0.053]	[0.000]	[0.000]	[0.000]
ARCH (1)	0.0097	7.067	0.7519	0.3834	0.4083	12.43
	[0.9217]	[0.0079]	[0.3859]	[0.5358]	[0.5228]	[0.000]
ARCH (8)	2.945	8.2277	3.151	8.3249	2.2251	16.185
	[0.9378]	[0.4116]	[0.9245]	[0.4024]	[0.9733]	[0.04]
J-B	1.1961	6.992	1.2498	1.9874	4.1984	12.36
	[0.5499]	[0.03]	[0.535]	[0.3702]	[0.1226]	[0.002]

- All models were nominated to follow a Normal Gaussian error structure.
- $Z_{t+n} = \varepsilon_{t+n} \sigma^{-1}_{t+n}$

5.3 Forecast Error

According to the aforementioned analysis that demonstrated evidence against the unbiased expectations hypothesis (UHE), the detected forecast error is computed by subtracting the expected settlement prices at the delivery day from futures prices with n periods forward maturity day, mathematical speaking $F_{t;\ t+n} - S_{t+n}$. This investigation is going to reveal whether this forecast error follows or not systematic patterns. For this purpose, it is necessary to follow the Box-Jenkings (1976) methodology in which the approximated ARIMA models are compared to the basis of Akaike Information Criterion and Schwartz Bayesian Information Criterion. Taking into consideration the ARMA terms, Autoregressive and Moving average, residual diagnostics and ARIMA auto-selection process. Taking into account the presence of significant ARCH effects in the mean equation, the final model selected for forecast errors according to SBIC is an ARMA (0, 0) for the 1st month to maturity, a Moving Average of first order MA (1) for the 2nd month and ARMA (0,2) for the 3rd month to maturity as well. In addition, the most preferable model for the 6th month is an ARMA (3, 2) while for the 9th and 12th months to maturity are AR (1) for both of them. By using the same approach in the changes of realized spot prices (ΔS_t), it is resulted that for the first three months and for the 6th as well the selected model is an AR (1) while for the 9th and 12th months to maturity is an ARMA (1, 1).

For comparison determinations, in order to exercise forecast, there are some other methods that should be introduced even though their predicting appearance weakens as the forecast horizon augments. Such methods are random walk and bivariate VECM models of which the latter outclasses these model conditions for predictions until 15 days ahead. Considering the random walk models, it is assumed that NYMEX prices at time *t-n* are the most precise forecasts of settlement prices at time t. Thus, this model memorizes information from the past spot prices in order to produce forecasts of the future settlement prices without requiring initial estimation.

For comparing purposes, it is obligatory to guarantee that the forecasts produced from the aforementioned models should correspond to the forecast suggested by futures prices. NYMEX prices come together to the settlement price at the expiry day of the contract, henceforth, the futures price n months from expired day offers a prediction of the settlement price for this specific day. Due to the fact that forecasts of time-series models are estimated in these certain trading days, the use of daily price data is required. Therefore, ARIMA, VECM and random walk models are estimated by applying the most current 300 daily observations of spot and futures prices of the contract that is closer to expiry day. In order to verify the forecasting accuracy of method, there are some criteria that should be taken into consideration such as the Mean Forecast Error (MFE), the Mean Absolute Error (MAE), which estimates the absolute deviation of the predicted value from the realized value, and the Root Mean Square Error (RMSE), which ascribes a greater weight to larger forecast errors. In accordance with MAE, VECM produces the best forecasts with the least errors as well as the RMSE criteria indicates the same results with the exception of 9th and 12th month to maturity. The following equations describe the aforementioned criteria:

$$MFE := \frac{1}{m}\sum_{i=1}^{m} f_i - \alpha_{s_{t+n}} , \tag{20}$$

$$RMSE := \sqrt{\frac{1}{m}\sum_{i=1}^{m} \left| f_i - \alpha_{s_{t+n}} \right|^2} , \tag{21}$$

$$MAE := \frac{1}{m}\sum_{i=1}^{m}\left|f_i - \alpha_{s_{t+n}}\right|, \tag{22}$$

Table 5.5: Comparison of forecast errors for alternative forecasting methods

	1-month	2-month	3-month	6-month	9-month	12-month
Panel A: ME - Mean Forecast Error						
Futures	-0.0893	-0.1662*	-0.2358*	-0.3357*	-0.3777*	-0.3588*
	(0.058)	(0.081)	(0.0940	(0.119)	(0.135)	(0.141)
RW	-0.0352	-0.0823	-0.1523	-0.3644	-0.8098*	-0.9865*
	(0.063)	(0.094)	(0.1193	(0.189)	(0.346)	(0.317)
Seasonal	-0.1108	-0.2028	-0.2511	-0.5171*	-0.8866*	-1.0033*
	(0.090)	(0.126)	(0.1389	(0.200)	(0.284)	(0.301)
ARMA	-0.0405	-0.0762	-0.1495	-0.3628	-0.9267*	-0.9739*
	(0.069)	(0.093)	(0.1184	(0.187)	(0.433)	(0.312)
VECM	0.0451	0.0829	0.0682	0.1589*	-0.1242	-0.0772
	0.0397	0.0453	0.0506	0.0509	0.1549	0.1263
Panel B: MAE - Mean Absolute Forecast Error						
Futures	0.5607 [2]	0.7897 [2]	0.9702 [2]	1.2819 [2]	1.4312 [2]	1.5572 [2]
RW	0.5953 [3]	0.9093 [4*]	1.1740 [3*]	1.7769 [3*]	2.4565 [3*]	2.8632 [5*]
Seasonal	0.8949 [5*]	1.2520 [5*]	1.5256 [5*]	2.1203 [5*]	2.5627 [4*]	2.8063 [3*]
ARMA	0.6208 [4*]	0.9034 [3*]	1.1717 [2*]	1.7774 [4*]	2.5716 [5*]	2.8573 [4*]
VECM	**0.3421 [1*]**	**0.4034 [1*]**	**0.4459 [1*]**	**0.4676 [1*]**	**1.1607 [1*]**	**1.2537 [1*]**
Panel C: RMSE - Root Mean Squared Forecast Error						
Futures	0.9194 [2]	1.2729 [2]	1.4937 [2]	1.9079 [2]	**2.1510 [1]**	**2.2328 [1]**
RW	0.9845 [3*]	1.4832 [4]	1.8779 [4*]	2.9943 [4*]	5.4883 [4*]	5.0737 [5*]
Seasonal	1.4139 [5*]	1.9990 [5]	2.1923 [5*]	3.1873 [5*]	4.5485 [3*]	4.8223 [3*]
ARMA	1.0767 [4*]	1.4718 [3]	1.8632 [3*]	2.9592 [3*]	6.8564 [5*]	4.9938 [4*]
VECM	**0.6249 [1*]**	**0.7160 [1]**	**0.7958 [1*]**	**0.8136 [1]**	2.4334 [2*]	2.9820 [2]

- Number of forecasts is in all cases equal to n = 247 (so as to be comparable), from 21/12/1995 until 28/6/2016. Forecasts are obtained from futures prices, random walk (RW), Seasonal (regression on monthly dummies), ARIMA and VECM models. Lag lengths for the latter two approaches are chosen on the basis of Schwartz criterion. Model forecasts were obtained using the rolling window method for a window of 300 observations.

- Panels A, B and C report the MFE, MAE and RMSE values, respectively. In Panel A, numbers in ( ) are the associated standard errors of the mean error, calculated as $s/\sqrt{n}$, where s indicates the standard deviation of the ME.
- Asterisk * indicates significance at 5% level: In Panel A the null hypothesis H_0: ME = 0 is tested; In Panel B the null hypothesis is H_0: $MAE_{futures} = MAE_{model}$; and Panel C H_0: $RMSE_{futures} = RMSE_{model}$; where model = {RW, Seasonal, ARMA, VECM}.
- In Panels B and C numbers in [ ] note the rank of the model, i.e. 1 being the best and 5 the worst; best models in each case are in bold. Numbers in [ ] note the rank of the model, i.e. 1 being the best and 5 the worst; best models in each case are highlighted in bold.

CHAPTER 6

6 Conclusions

The purpose of this study is to investigate the Unbiased Expectation Hypothesis in the natural gas futures markets. New York Mercantile Exchange (NYMEX) monthly futures contracts for 1, 2, 3, 6, 9 and 12 months to maturity are investigated by making use of a battery of statistical tests, during the period from January 1993 until June 2016. Even though there is wide presence of literature concerning the investigations of futures prices in various commodity markets, for natural gas futures markets research evidence is scant, thus, there are some areas that have not been analyzed extensively.

According to the preliminary analysis of the data, natural gas prices were detected to be non-stationary. Consequently, it was obligatory the introduction of more sophisticated approaches compare to mere statistical methods. By testing the coefficients in linear regression approaches, it is concluded the biased predictions of spot prices by the futures contracts of NYMEX market. In accordance with the aforementioned results were the estimated outcomes from the Johansen's parameter constraint cointegrating test among futures and expected settlement prices. In general, the existence of positive risk premium produces deviations from the unbiased expectations hypothesis. Additionally, in the original hypothesis, the econometric models were extended in order to permit for GARCH comportment and time varying risk premium. EGARCH methodology framework indicates auspicious results due to the fact that these approaches afford flexibility. In conclusion, the forecast error instituted to follow an ARMA process, which indicates signal of its systematic behavior. However, even though the presence of a bias, futures prices indicate precise predictions of the expected spot prices compare to the forecast that produced from ARIMA, seasonal and random walk models. Nevertheless, VECM models generate more accurate forecasts when compared to futures prices for all times to maturities.

As a result, futures prices indicate accurate signals of the expected spot prices compared to simple random walk models. In addition, considering that futures prices are unbiased anticipators of future settlement prices intimidating that futures contracts can be an efficient and effective implement for hedging against natural gas price fluctuations. Finally, the results denote that market participants receive accurate signals from futures prices and can utilize the information produced by these prices in order to guide their physical market decisions.

Although the findings of this study provide evidence that futures prices are almost accurate predictors of the expected spot prices, in reality, these methods cannot provide trustworthy results for all the occasions to the market participants. In other words, there are some limitations that cannot be interpreted. For instance, it does not take into deep consideration the presence of deterministic seasonality that was not significant due to the selection of the test for using dummies, for some months to maturity. In a different occasion, the econometric models would be more sophisticated and difficult to be investigated.

For this purpose, in a future study, more complex approaches such as VAR and multivariate GARCH models should be used in order to expand this investigation one step forward. Furthermore, the connection between futures and spot prices could be used in practical approaches for hedging effectiveness.

REFERENCES

Alizadeh, A. & Nomikos, N. (2004). The efficiency of the forward bunker market. International Journal of Logistics, 7(3), pp.281–296. Available at: Chinn, M.D. & Coibion, O., 2014. The Predictive Content of Commodity Futures. Journal of Futures Markets, 34, pp.607–636.

Akaike, H. (1973). Information theory and an extension of the maximum likelihood principle. In B. Petrov & F. Csake (Eds.), Second international symposium on information theory, Budapest: Academia Kiado.

Antoniou, A., & Holmes, P. (1996). Futures market efficiency, the unbiasedness hypothesis and variance bound tests: The case of the FTSE-100 futures contract. Bulletin of Economic Research, 48, 115–128.

Barnhart, S.W., R. McNown, and M.S. Wallace. (1999). "Non-Informative Tests of the Unbiased Forward Exchange Rate," *Journal of Financial and Quantitative Analysis* 34, 265–291.

Beck, S. (1994). Cointegration and market efficiency in commodities futures markets. Applied Economics, 26, 249–257.

Bera, A., & Jarque, C. (1980). Efficient tests for normality, heteroscedasticity, and serial independence of regression residuals. Economic Letters, 6, 255–259.

Bollerslev, T., Engle, R. F., & Nelson, D. B. (1994). ARCH models. In Engle, R. F. & McFadden, D. L. (Eds.), Handbook of econometrics (pp. 2959–3038), Amsterdam: North Holland.

Box, G., & Jenkins, G. (1970). Time series analysis, forecasting and control, San Francisco: Holden-Day.

Brenner, R.J. & Kroner, K.F., 1995. Arbitrage, Cointegration, and Testing the Unbiasedness Hypothesis in Financial Markets., 30.

Campbell, J. Y., and R. J. Shiller., (1987) "Cointegration and Tests of Present Value Models." Journal of Political Economy, 95, 1062–1088.

Cheung, Y., & Lai, K. (1993). Finite-sample sizes of Johansen's likelihood ratio tests for cointegration. Oxford Bulletin of Economic and Statistics, 55, 313–328.

Chinn, M.D. & Coibion, O., 2014. The Predictive Content of Commodity Futures. Journal of Futures Markets, 34, pp.607–636.

Chowdhury, A. (1991). Futures market efficiency: evidence from cointegration tests. The Journal of Futures Markets, 11, 577–589.

Copeland, L. (1991). Cointegration tests with daily exchange rate data. Oxford Bulletin of Economics and Statistics, 53, 185–198.

Dergiades, T., G. Christofidou and R. Madlener (2012). "The Nexus between Natural Gas Spot and Futures Prices at NYMEX: What about Non-Linear Causality" Institute for Future Energy Costumer Needs and Behavior, Working Paper No. 17/2012.

Dickey, D., & Fuller, W. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. Econometrica, 49, 1057–1072.

Engle, R. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50, 987–1008.

Engle, R. F., & Granger, C. W. (1987). Cointegration and error correction: Representation, estimation, and testing. Econometrica, 55, 251–276.

Fama, E. F. (1991). Efficient capital markets II. Journal of Finance, 46, 1575–1617.

Fedderke, J. & Joao, M., 1997. Arbitrage, Cointegration and Efficiency in Financial Markets in the Presence of Financial Crisis.

Garbade, K.D. and Silber, W.L. (1983). Price movement and price discovery in futures and cash markets. The Review of Economics and Statistics, Vol. 65 No. 2, pp. 289-97.

Gardner, E. (1985). Exponential smoothing: The state of the art. Journal of Forecasting, 4, 1–28.

Gebre-Mariam, Y. (2011). “Testing for Unit Roots, Causality, Cointegration and Efficiency: The Case of the Northwest US Natural Gas Market.” *Energy* 36(5): 3489-3500. http://dx.doi.Org/10.1016/j.energy.2011.03.055.

Haigh, M.S., (2000). Cointegration, Unbiased Expectations, and Forecasting in the BIFFEX Freight Futures Market., 20, pp.545–571.

Johansen, S. (1988). Statistical analysis of cointegrating vectors. Journal of Economic Dynamics and Control, 12, 231–254.

Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. Econometrica, 59, 1551–1580.

Johansen, S., & Juselius, K. (1990). The full information maximum likelihood procedure for inference on cointegration–with applications to the demand for money. Oxford Bulletin of Economics and Statistics, 52, 169–210.

Keynes, J., 2006. General theory of employment, interest and money. Available at: http://cas.umkc.edu/economics/people/facultyPages/kregel/courses/econ645/Winter2011/GeneralTheory.pdf.

Lai, K., & Lai, M. (1991). A cointegration test for market efficiency. The Journal of Futures Markets, 11, 567–575.

McKenzie, A. M., & Holt, M. (2002). Market efficiency in agricultural futures markets. Applied Economics, 34, 1519–1532.

Modjtahedi, B. & Movassagh, N., (2005). Natural-gas futures: Bias, predictive performance, and the theory of storage. Energy Economics, 27(4), pp.617–637.

Moore, M.J. and Cullen, R., (1995). "Speculative Efficiency on the London Metal Exchange," *The Manchester School* 63, 235–256.

Norrbin, S.C. and K.L. Reffett. (1996). "Exogeneity and Forward Rate Unbiasedness," *Journal of International Money and Finance* 15, 267–274.

Osterwald-Lenum, M. (1992). A note with the quantiles of the asymptotic distribution of the ML cointegration rank test statistics. Oxford Bulletin of Economics and Statistics, 54, 461–472.

Pederzoli, C. (2013). Efficiency and unbiasedness of corn futures markets: new evidence across the financial crisis., 23(24), pp.1853–1863.

Phillips, P., & Hansen, B. (1990). Statistical inference in instrumental variables regression with $I(1)$ processes. Review of Economic Studies, 57, 99–125.

Phillips, P., & Perron, P. (1988). Testing for a unit root in time series regressions. Biometrica, 75, 335–346.

Quan, J. (1992). Two step testing procedure for price discovery role of futures prices. Journal of Futures Markets 12, 139-149.

Samuelson, Paul A., (1965). Proof That Properly Anticipated Prices Fluctuate Randomly, Industrial Management Review, 6:2 (1965 : Spring) p.41., 2.

Schwarz, G. (1978). Estimating the dimension of a model. Annals of Statistics,6, 461–464.