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Hedging Effectiveness in Natural Gas Markets

Kovlaka Konstantina

SID: 3303180003

SCHOOL OF SCIENCE & TECHNOLOGY

A thesis submitted for the degree of

Master of Science (MSc) in Energy and Finance

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THESSALONIKI – GREECE

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Supervisor:	Prof. Panos Pouliasis
Supervising Committee Members:	Assoc. Prof. Name Surname
	Assist. Prof. Name Surname

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To the memory of my beloved and unforgettable mother.

Abstract

This dissertation was written as a part of the MSc in Energy and Finance at the International Hellenic University. The purpose of the study is to examine the hedging effectiveness of natural gas prices using different econometric models including least squares regression, vector autoregression, exponential weighted moving average variance-covariance, GARCH models and regime switching. The recent literature suggests that conventional methods are inefficient, however, more sophisticated and complex methods do not achieve superior results in terms of variance reduction of the hedged portfolio. Using natural gas Henry Hub prices in the United States, optimal hedge ratio is estimated through different techniques for two different hedging horizons (weekly vs. monthly), and then relative performances are being assessed to determine relative gains. Finally, cash flow variance reduction from hedging is examined for periods of backwardation and contango and finding suggests marked asymmetries.

Kovlaka Konstantina

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All of my students, my adorable kids. Whenever I was blue, your simplest gestures make me reconsider everything.

My love, thank you for all those years and the uncountable memories, Charis.

And my family. We, the Kovlakas family, never give up!

Contents

Contents of Tables

Contents of Figures

1 Introduction

A great deal of controversy surrounds the issue of climate change. The United Nations Framework Convention on Climate Change (UNFCCC) at 1992, the Kyoto Protocol at 2005, as well as the Paris Agreement at 2016 are some of the attempts to minimize the consequences of climate change. For instance, an aspect of climate change is the increase in the earth's mean temperature, attributing mainly to the carbon dioxide emissions in the atmosphere and causing new and abnormal weather patterns.

For this reason, any attempts to prevent these threats, which cover a general socio-economic spectrum, are mostly focused on the reduction of greenhouse gas emissions (Stern, 2007). This has triggered the necessity to use more clear energy sources than coal, with oil being the answer for many decades. However, nowadays natural gas gains ground and constantly prevails upon any other sources. In general, natural gas prices were depended on oil prices (mainly though oil-price indexing), yet, this changes in the recent years and natural gas markets is an incessantly developing field (Hulshof et al., 2016) and a profound number of investors have shift their attention at it.

On the other hand, natural gas suffers from high volatility and this causes a number of issues in any attempt to study the behavior of natural gas prices. Many researchers have tried to examine the hedging performance of natural gas, using futures contracts as instruments to minimize risk. The results, however, show that hedging techniques do not work as efficiently for natural gas, as it does with oil prices or other commodities.

The underlying objective when hedging with futures contracts, is the estimation of hedge ratio; that is, the number of futures contracts to sell/ but of every unit hold in the spot market, based on the investor's risk tolerance (Culp, 2001). Ederington (1979) suggested that hedging decisions are similar to any investment decisions, indicating that Markowitz (1952) Portfolio Theory (MPT) surpass the preceding approaches, that is the traditional and the Working's (1953) theories. Ederington's (1979) approach, however, became a subject of criticism, focusing mainly in the decision of an OLS regression in order to estimate the optimal hedge ratio (OHR). Nowadays, many econometric models are used in order to estimate the optimal hedge ratios; among them, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are widely chosen, due to the model's specification to allow the variance to fluctuate as new market information is disseminated, instead of remaining constant.

Natural gas has become a subject of testing the suitability of these models, upon being declared an emerging market. As mentioned above, natural gas prices exhibit relatively high volatility levels (Pindyck, 2004b). These abrupt price movements, stemming from many aspects such as the storage capacity and the demand (Hailemariam and Smyth, 2019), influence the hedging performance in natural gas markets. Hofstadter (2012) pointed out that natural gas futures contracts is an exceptional case. A profound number of studies have been focusing on finding ways to amend the overall hedging capability/performance of financial instruments.

The main results suggest that an expansion in the hedging duration, will affect positively the performance, even scarcely regarding natural gas markets (Martinez and Torro, (2015). Brinkmann and Rabinovitch (1995) pointed out that hedging performance considering natural gas, varies among geographical regions, while Ghoddusi (2016) expressed the importance of cross-hedging, which is almost a norm in natural gas markets where location and weather conditions play an important role.

In this paper, we examine the hedging performance of natural gas futures, using the Henry Hub spot and NYMEX futures prices (traded on the New York Mercantile Exchange; NYMEX, Chicago Mercantile Exchange Group) both on weekly and monthly basis for the period 1997 to 2020. The hedging effectiveness, as well as the corresponding portfolio risk, are estimated through nine different prediction models; the unhedged and naïve one-to-one hedge position and according to OLS, VAR, GARCH, Risk Metrics with three different lambda values, as well as Markov Switching Regime estimations. The analysis applies both in- and out-of sample exercises. Furthermore, the sample has been divided into two categories, when prices are in contango (spot prices< futures prices) or in backwardation (spot prices> futures prices). This is an attempt to better understand the correlation between spot and futures prices, when the first is above the latter and vice versa.

The objective of the study is to obtain constant, as well as time varying hedge ratios, using as tools econometric models with different fundamentals, and compare the estimated hedging effectiveness of each model, during the varying relationship between spot and futures prices.

The structure of the paper is as follows. Section 2 presents an overview of hedging and natural gas literature, Section 3 presents the econometric methodology to be used, Section 4 presents the empirical results and as a final point, Section 5 provides a summary of the paper and the conclusion.

2 Literature Review

Even though risk management is an emerging field, there is proof of its applied existence since the 1700's, when the first futures contracts of rice in Japan are found. However, the use of portfolio theory for hedging purposes goes back to 1960s, as we mention later on (Dionne, 2013). The most prevailed definition is that risk management is the identification, evaluation and prioritization of risks in order to minimize, monitor and control the probability or impact of unfortunate events (Hubbard, 2009). The essential key component to do so is through hedging.

Despite the fact that means to reduce risks or losses appear in our everyday life worldwide, insurance companies are a typical example of comprehending the hedging techniques. Since the basic goal is to offset possible losses, futures contracts are used as instruments (Speranda and Trsinski, 2015) to create offsetting cash flows against the physical positions. The question of how many of these contracts to be used is addressed by risk management techniques through futures hedging. Before processing in the main course, it is important in this point to define some of the terminology used.

Hedge ratio, as defined by Culp (2001), is the *proportion of the spot position hedged with futures contracts*. If δ is the fraction, Q_f and Q_s are the quantity of units traded in the futures and spot market respectively. Then the hedge ratio can be expressed mathematically as:

$$\delta=\frac{Q_f}{Q_s} \qquad (1).$$

Consequently, the minimum variance hedge ratio (MVHR), is the proportion of futures to spot position, that minimize the variance, in other words the risk (Kenourgios *et al.*, 2008). If $\sigma_{s\,f}$ is the covariance of spot and futures prices changes, while $\sigma^2{}_F$ is the variance of futures prices changes, then, MVHR can be wtitten as:

$$b = \frac{\sigma_{s\ f}}{\sigma_F^2} \qquad (2).$$

According to Pennings and Meulenberg (1997), hedging effectiveness (HE) is the *percentage reduction in the variance of the return on the portfolio.*

$$\text{HE}= 1- \frac{VAR\ (R)}{VAR\,(U)} \qquad (3),$$

where VAR(R) is the minimum variance of the portfolio using futures contracts and VAR (U) is the variance of the unhedged position.

However, this effectiveness differs across different approaches. There are three hedging theories: the traditional, the Working's (1953) and the portfolio theory approach. The traditional hedging theory is focused on risk avoidance (Ederington, 1979). Traditional theory postulates that spot and futures prices move together, therefore we can hedge one-to-one; that is, our position in the futures market is of the same magnitude but opposite sign of our cash market position (Ederington, 1979). Given that risk is measured by the variance, traditional theory implies that the variance of a hedged position of *X* units is less than the variance of an unhedged position of the same amount of units.

Working's (1953) theory on the other hand suggests that hedgers are speculators. He argues that risk avoidance is not the primal reason for hedging. On the contrary, he suggested that hedging in futures takes place either to facilitate decisions and provide more flexible business actions, or to assist in the storage of the commodity surpluses for future use, when the spot prices are not preferable (Working, 1953)[1]. As a consequence, hedgers are no longer risk averters but profit maximizers and all the decisions are basis oriented. Providing that basis risk[2] is the difference between spot and futures prices, an investor is to hedge if he expects the basis to fall or not to hedge if it is expected to rise.

The last approach is the portfolio theory, which has prevailed upon the methods in the recent years. Initiators of this theory are Johnson (1960) and Stein (1961). Johnson (1960) observed that neither the traditional nor Working's (1953) theory are sufficient, based on the fact that an investor could hold both hedged and speculative positions with respect to his expectations. Stein (1961), on the other hand, associated the interrelation of the fluctuations on spot and futures prices with the excess supply of a commodity, as well as with the changes in price expectations. Following this approach, Heifner (1972) agrees that traditional theory is relevant only under the restricting assumption that spot and futures are perfectly correlated. However, this assumption does not always hold[3], hence the author concluded that portfolio theory provides a better solution in order to minimize risk with respect to the expected profits (see also Anderson and Danthine, 1980; Ederington, 1979).

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[1] Storage theory is attributed to Working (1933). Storage is essential for many reasons since it counterbalance for seasonal supply, very common in agricultural commodities; for uneven demand, for instance energy commodities, since there is a greater demand for energy in winter for heating and during summer for cooling; as well as for any other supply or logistical issue.

- According to the storage theory, when a commodity is in scarce spot prices increase, since consumers are willing to purchase for any price in order to secure supply. Market participants, however, realize that this scarcity will encourage for an increase in the future supply, therefore, the futures prices will not be affected. This effect, when spot prices are greater than the futures prices, is known as backwardation.
- The opposite effect, when spot prices are less than the futures prices, is known as contango. Contango motivates for a "cash-and-carry-arbitrage"; that is, a market participant buys the commodity at the low spot price, sells futures contracts at the higher price and stores the units until the delivery date of the futures contracts (Geman and Smith, 2013).

[2] Benhamou (N.D.) describes basis risk as the incompatible relationship between the spot asset position and the respective futures contracts. The more essential factors resulting in the accession of basis risk are interest, storage and transportation costs, while among the components diminishing basis risk are the shortage of the commodity supply and the gain of positive dividends and cash flows stemming from the underlying asset of the futures contracts.

[3] The correlation between spot and futures prices tents to be lower in the presence of weak contango or backwardation, but pretty close to 1 (perfect correlation) in the existence of strong contango (Gulley and Tilton (2014); Tilton *et al.* (2011)).

Ederington (1979) examined the Government National Mortgage Association and T-Bill futures contracts making use of the Markowitz (1952) Portfolio Theory (MPT) and concluded that hedging decisions do not differ from any other investment decision. Given that an investor seeks to the optimal combination in order to minimize risk and maximize returns, the basic portfolio theory applies. Not only that, but the study also argues that both the traditional and the Working's (1953) theories are special cases of the portfolio theory[4].

The main goal of portfolio theory is to calculate the minimum variance hedge ratio, b; that is to find the optimal proportion of futures and spot position that minimize the variance, in other words, the risk. In his research, Ederington (1979) argues that an optimal hedge ratio less than 1 surpasses the outcomes of a b=1, which is the case in traditional theory.

This theory gained many supporters from the beginning and has been gradually enhanced. Following Ederington's results, Benninga, Eldor and Zilcha (1984) suggested that minimum variance hedge ratio is the optimal hedge ratio when futures markets are unbiased, which appears to be the case in many markets and in different kind of commodities. As time went by, and the portfolio theory gained ground, it also became a subject of controversy.

Carter and Loyns (1985) were among the first ones that regressed the spot price changes against futures price changes, in order to examine and measure the effect of foreign exchange rate changes on futures. Hill and Schneeweis (1982) compared the hedging effectiveness of futures contracts of foreign currency, suggesting that hedging the asset price movements are more appropriate. Generalizing the issue, Bond, Thomp-

[4] Ederington (1979) pointed out that both traditional and Working's (1953) theories are special cases of the basic portfolio theory. Regarding the first theory this occurs when spot and futures prices move together, while concerning the latter one, when the market participants decide a completely hedged or unhedged position.

son and Lee (1987) and Witt, Schroeder and Hayenga (1987) discussed the compatibility of the variables, and if they should be in levels, changes or returns. Brown (1985) pointed out that the fact of spot and futures prices moving together in the long run, violates the assumptions of ordinary least squares (OLS) regression model.

Generally, from an econometric perspective Ederington's (1979) approach was profoundly criticized. Mainly, this stemmed from the choice of OLS as a regression technique, which answers to some severely strict assumptions. Following Franckle (1980), Herbst, Kare and Caples (1989) rejected the OLS regression since the presence of serial correlation in the error terms provided biased estimators. First, they suggested an autoregressive model; nevertheless, correlation was still present across time. Ultimately, the study's proposition was the Box and Jerkins (1970) autoregressive, integrated moving average (ARIMA) model in order to encounter the autocorrelation induced drawbacks. The authors also concluded that estimations of the ARIMA model outperform those of the OLS model, since they provide a substantially lower risk and enhanced hedging outcomes; that is, a diminished hedge ratio, leading to a decrease of the initial amount required to open a trading position, also known as margin deposit, as well as the accompanying transaction costs.

Bell and Krasker (1986) pointed out the information inefficiency regarding the OLS regression. To address this issue, Hilliard (1984) applied the multivariate model. With the underlying goal being to decrease the interest rate risks in a fixed portfolio, the authors argue the minimum variance hedge is succeeded if a spot portfolio is supported by a portfolio of financial futures; claiming that this approach is the best possible one. Myers and Thompson (1989), however, challenged this conclusion; they debated that the criteria of selecting the appropriate model in order to estimate the optimal hedge ratio, varies on *the model determines equilibrium between spot and futures price movements*.

Castelino (1990) pointed out that when MVHRs calculated under the assumption that spot and futures prices converge at maturity, the initiation timing is of no importance, since the MVHRs are bound to the timing of lifting the hedge. Viswanath (1993) combined the previous studies of Myers and Thompson (1989) and Castelino (1990), by altering the procedure, nonetheless, bearing in mind the possibility of spot-futures convergence, as well as the dependence of the hedge ratio on the hedge duration and time left to maturity. Viswanath (1993) regressed the changes of spot price on the changes of futures price and the current basis, hence the obtained hedge ratios, accounting for both the traditional and the basis-corrected method, provide a smaller variance; that is, a risk reduction in the hedged portfolio.

Considering previous research, such as Hill and Schneeweis (1982); Marmer (1986); and Chen, Sears and Tzang (1987), Lindahl (1992) tests for the hedge ratio's stability regarding the hedge duration and time to contract expiration, seeking for trends and statistical comparisons among the estimated hedge ratios of other approaches. Lindahl (1992) states that there is a growth in the minimum variance hedge ratio as long as the hedge duration goes for one to four weeks. Complying with Castelino (1992) results, Lindahl (1992) points out that around the contract expiration date the MVHR goes up, bearing in mind that the sample is categorized by weeks to expiration. Consistent with Lo and MacKinlay (1988) and Malliaris and Urrutia (1991) outcomes, Lindahl (1992) also points out that if hedging an established cash position, hedging with futures should be considered as a dynamic process, while adjusted as the futures hedges increase in duration and approach the expiration date.

Applying a bivariate Generalized Autoregressive Conditional Heteroskedastic (GARCH) model, Baillie and Myers (1991) estimates the optimal hedge ratios, regarding six different commodities, allowing for time-varying correlation between cash and futures prices. The authors pointed out that accounting for time- dependency in variances provides better estimations of the optimal hedge ratio (OHR), emphasizing that the assumption of a constant OHR is inappropriate.

Root and Lien (2003) expressed the importance of the correct specification between spot and futures prices, in order to estimate the hedge ratio and the hedging effectiveness. The authors tested for cointegration using a threshold cointegrated model[5], concluded that even when the model performs better for contracts with greater duration, the model does not significantly improve the overall hedging.

Having said the above, the movements of spot and futures prices are profoundly essential for the hedging decisions. For this reason, it is important at this point to discuss the factors influencing the fluctuations in the commodity to be studied; that is the volatility of natural gas prices.

From the financial perspective, volatility depicts the changes and the fluctuations of the historical data of a variable, with respect to the mean. That is, the more the fluctuations, the more unstable the predictions will be, due to mean averting effect. Given that nothing drives the prices back to the average price, the performance will most likely be arbitrary. Most commonly measured by standard deviation, volatility is profoundly associated with uncertainty, unpredictability and risk, in other words, the main underlying factors of the modern portfolio theory (Daly, 2011).

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[5] Threshold cointegration assumes that cointegrating relationships do not exist in a certain range, but holds when the system exceeds a threshold, away from the equilibrium (Esteve *et al.*, 2006).

Pindyck (2004a) examined how the shifts in volatility affect spot prices, futures prices and inventories, based on two main reasons. First, he argues that volatility affects the marginal convenience yield; that is, when dealing with volatile prices, in order to reduce marketing costs, as well as smoothing the production, more inventories are in order. Therefore, an increase in volatility will most likely result in an increase in demand, affecting the supplies and hence cause a rise in the prices, at least in the short run. And on the other hand, Pindyck (2004a) also implies that volatility, especially for a depletable resource, affects the total marginal cost of production through the "*option premium*". Total marginal cost is equal to direct marginal cost and the opportunity cost of exercising the incremental operating option, as a result, an increase in volatility will increase the value of this option as well as the associated opportunity cost, leading to the decrease of production.

This correlation is also being studied at Pindyck (2004b), where he also suggest that volatility's movements are of supreme importance for derivative valuation and for a number of financial and economic decisions to be made, such as hedging decisions or decisions to invest in physical capital attached to production and/or consumption of natural gas or crude oil.

Ever after the Stern's Review (2007) that raised the awareness of climate change, many attempts occured in order to decrease and eventually prevent the consequences. The Kyoto Protocol in 1997, as well as the Paris Agreement in 2015 initiated some measures regarding this issue. Given that one of the major issues for climate change is the emissions, there has been a shift in energy investments of low emissions (Pouliasis *et al*., 2020). For this reason, there is an incessantly increasing interest in natural gas markets.

In their study, Hailemariam and Smyth (2019) distinguish three stages of the undergoing transition of natural gas markets. The first period from 1976 to 1989, during which, there existed price ceiling and strict regulations, and resulting on either acute shortages or excess of supply, creating this way, appreciable shifts in prices. The second period took place at 1990s; due to deregulation as well as the excess of supply, this phase is associated with mostly stable price movements. Starting with the rise of millennium, the third period revealed an increase in natural gas price volatility, caused by economic scandals or crisis, for instance the California energy crisis caused by the Enron scandal around 2001, or the Global financial crisis in 2008; weather phenomena, such as hurricanes Katrina and Rita in 2005; market regulations, technological and policy changes.

Hailemariam and Smyth (2019) argue that high volatility reflects many and different aspects influencing supply and demand in the natural gas markets; for instance, the weather conditions, the emerge of new technologies, the shale revolution, as well as economic and political events. More particularly, Mu (2007) established the effect of the weather surprise on the conditional volatility of natural gas futures returns, emphasizing also that the information about market fundamentals is highly connected with natural's gas price volatility.

To be succinct, most of the studies regarding natural gas markets are focused on determining the correlation between natural gas prices and crude oil markets. Krichene (2002) concluded that natural gas prices are extremely volatile to oil shocks. Brown and Yucel (2007) proved the inefficiency of rules of thump to adequately explain the differential movements in crude oil and natural gas prices, standing to reason that natural gas prices can be partially independent of crude's oil. Following this rational, Ramberg and

Parsons (2012) argued that, despite the cointegration between natural gas and oil prices, there still exists a great amount of unexplained volatility in natural gas prices changes.

Siliverstovs *et al.* (2005) implied that the liberalization of natural gas markets will most likely result in the weakening of oil indexation of natural gas. This is in agreement with Hulshof *et al.* (2016), where they state that the assertion of explicitly linking the gas price to the oil price is not that strong any more. Indeed, oil indexation used to be the main pricing mechanism for gas; nevertheless, given the undergoing developments in the markets, natural gas is to claim this role. Moreover, they also exacerbated that natural gas prices are extremely reliant on weather and storage availability, while supply's significance is of no matter.

Nick and Theones (2014) discus that anomalies in temperature and supply shocks will have an effect on natural gas price, however, only in the short run; while in the long run, the prices are affected by cross-commodity effects, like the performance of crude oil and coal prices.

Considering the factors affecting the futures-spot spread, Ederington and Salas (2008) pointed out that, in efficient markets, accounting for the expected price changes enhance the overall hedging performance. Specifically, the authors mention that if such information is not addressed, traditional regression models overestimate the risk, not only in hedged but unhedged position as well, while underestimate the percentage reduction in risk stemming from the hedging.

Taking into account the Ederington and Salas (2008) framework, Martinez and Torro (2015) examined the hedging performance of natural gas in Europe. The main result of the research is that the Ederington and Salas (2008) approach amends the hedging performance, especially when increasing the hedging duration. However, the evidence of hedging effectiveness regarding natural gas is still scarce. Similar are the results of Pouliasis *et al*. (2020) for the case of the U.S. who employed also various forecast combination techniques.

Natural gas futures contracts are extremely associated with a natural gas pipeline system placed in Louisiana, Henry Hub. According to Sider and Matthews (2017), Henry Hub is *the most important place in the word for natural gas prices*; it has already been the benchmark for the U.S. gas contracts, and nowadays increasingly gains ground on the global market as well. However, the literature regarding the risk management essentials of natural gas futures contracts in U.S. is quite inadequate.

Hofstadter (2018) pointed out that hedging with futures with respect to natural gas differs from other markets, such as oil, gasoline or heating oil, due to limitations and difficulties related with the exportation, storage and transportation of natural gas.

Brinkmann and Rabinovitch (1995) examined the hedging effectiveness of New York Mercantile Exchange (NYMEX) natural gas futures contracts with respect to transport limitations. Natural gas markets in U.S. suffer from regional segmentation, that is, the production is concentrated on five stages, and distributed through pipeline systems to the rest stages. The authors concluded that hedging effectiveness varied among geographical regions, since hedging with futures provided an adequate hedge for East coast, but this was not the case for West coast (Hanly, 2017).

Ghoddusi (2016) pointed out that the hedge performance of natural gas markets is extremely affected by cross-hedging. For many commodities, futures contracts correspond to a small fraction of the underlying spot prices, resulting in the necessity of cross-hedging. Especially for natural gas markets, this is more essential since futures contracts are available only for the spot prices of Henry Hub. Ghoddusi (2016) concluded that the stronger the integration of physical and Henry Hub futures prices, the better the hedging performance.

Ghoddusi and Emamzadehfard (2017) claim that the impact of cointegration and time varying volatility do not profoundly enhance the hedging effectiveness, but the use of non-matching futures contracts does; that is, contracts which time-to-maturity slightly exceeds the hedge horizon.

Hanly (2017) studied the hedging performance for West Texas Intermediate Oil (WTI), Heating Oil and Natural Gas, concluding that the results are weak for natural gas, pointing out that this is due to higher levels of basis risk in natural gas hedges, and implying also that conventional hedging strategies do not perform favorably for natural gas.

Gebre-Mariam (2011) examined the efficiency of natural gas markets, claiming that accounting only for the relationship between futures and spot prices will not be sufficient to provide efficiency. That is, in order to forecast futures prices, it is important to study other variables that affect spot and futures prices as well, and not depend the forecasting excessively on the past movements of spot prices. This is in accordance with Modjtahedi and Movassagh (2005), who claim that the simple theory of storage neglects some important variables, and in order to achieve efficiency in natural gas markets, these variables need to be identified.

3 Econometric Methodology

In this chapter, we examine and understand the different methods of forecasting to be used in this paper, as well as the corresponding statistical tests.

3.1 Linear Regression Model: OLS Hedging

Regression studies the relationship among a dependent variable (y) and some other explanatory variables (x_i). It is an attempt to explain the movements in y according to changes in the explanatory variables x_i[6]

The OLS hedging regression can be summarised by the following linear equation

$$\Delta S_t = \mu + \delta \Delta F_t + u_t;\ u_t \sim iid(0, \sigma^2) \quad (4)$$

where ΔS_t is the dependent variable (spot price changes), ΔF_t is the explanatory variable (futures price changes), μ the constant term, δ the coefficient of the explanatory variables, i.e., the hedge ratio (see also equation 1), and u_t the error term.

It is due to error term being unobservable that the dependent variable is stochastic. The main issue of linear regression is that the estimation technique, ordinary least

[6] However, it should not be confused with the correlation between two variables, which in the essence it examines the degree of linear association; while with regression the main assumption is that the dependent variable is random and the explanatory variables are fixeδ, that is non- stochastic, taking values of a given sample.

squares (OLS), holds under some very strict assumptions, in order to provide unbiased and efficient estimations[7], which can be easily violated (Brooks, 2014).

3.2 Vector Autoregressive: VAR Hedging

Vector autoregressive models (VAR) are a generalization of the univariate autoregressive models and are mostly used when dealing with large- scale simultaneous equations structural models. Apart from the fact that it is a multivariate model, the main advantage is that there is not only one dependent variable. Due to the use of a vector, the dependent variables are regressed on the appropriate lagged values of all the variables.

$$\Delta \mathbf{X}_t = \sum_{i=1}^{p} \boldsymbol{\Gamma} \Delta \mathbf{X}_{t-1} +; \ \mathbf{u}_t = \binom{u_{S,t}}{u_{F,t}} | \sim \mathrm{IN}(0, \boldsymbol{\Sigma}) \quad (5)$$

where $\Delta \mathbf{X}_t = (\Delta S_t, \Delta F_t)'$ be the vector of spot and futures prices at time *t*, $\boldsymbol{\Gamma}$ is a 2x2 coefficient matrix measuring the short-run adjustment of the system to changes in $\Delta \mathbf{X}_t$ respectively, and $\mathbf{u}_t = (u_{S,t},\ u_{F,t})'$ is a vector, at time *t*, of Gaussian white noise processes with covariance matrix $\boldsymbol{\Sigma}$ (Watsham and Parramore, 1997). In this setting the hedge ratio, *b*, can be defined as in equation 2; the ratio of the covariance of futures-spot, over the variance of futures. The above specification can be analytically written as:

$$\Delta S_t = c_S + \sum_{i=1}^{k} \beta_{Si} \Delta S_{t-i} + \sum_{j=1}^{n} \theta_{Fj} \Delta F_{t-J} + u_{St}$$

[7] In order of the OLS to provide the best linear unbiased estimators the following assumptions must hold: 1) the regression is linear in the parameters, 2) the explanatory variables are not correlated to the disturbance term, 3) the expected value of the error term is zero, 4) constant variance, that is homoscedasticity, 5) no correlation between the error terms, 6) the model is correctly specified, 7) the error term follows the normal distribution with zero mean and constant variance, 8)there is no multicollinearity. (Watsham and Parramore, 1997).

$$\Delta F_t = c_F + \sum_{i=1}^{k} \beta_{Fi} \Delta S_{t-i} + \sum_{j=1}^{n} \theta_{Sj} \Delta F_{t-j} + u_{Ft} \quad (6)$$

Some other important advantages of these modes are the facts that: i) all the variables are endogenous; that is they are determined within the system and, ii) VAR models allow us to study every equation separately, using the OLS technique[8]. Among the drawbacks of this model is the use of one too many parameters, affecting the degrees of freedom, the most appropriate approach to determine the lag lengths of the model, the necessity of all the variables to be stationary, as well as the fact that VAR models are a-theoretical; that is, the inexistence of theoretical information among the relationship of the variables (Brooks, 2014).

Finally, the above model could be extended to include an error correction term using cointegration techniques. Cointegration suggests that two variables move together in the long run. The most common financial examples are the spot and futures prices for any commodity, the equity prices and dividends, as well as the ratio relative prices with the corresponding exchange rate. Cointegration between the prementioned cases stands to reason, considering the liner relationship binding the series. According to Engle and Granger (1987) two variables are cointegrated if they both are non-stationary, that is both series contains a unit root, hence they are *I(1)*, however their linear combination is *I(0)*, that is stationary. The interpretation of a cointegrated relationship is that the prices of the variables may fluctuate in the short run, but due to their association they move together in the long run. This relationship can be examined with the Error Correction

[8] Another benefit of this model is the structural decomposition and the impulse response. The first one answers to variance and historical decomposition. Variance decomposition provides the movements of the dependent variable generated by their own shocks, while historical decomposition provides the historical fluctuations of the time series to be examined. On the other hand, impulse response measures the responsiveness of the dependent variable, given a shock to the other variables. In general, it is worldwide accepted that VAR provides better forecasting estimations than traditional structural models.

Model (ECM), which provides the equilibrium relationship among the variables (Brooks, 2014).

3.3 Generalised Autoregressive Conditional Heteroscedasticity: GARCH Hedging

As we have already mention, volatility is an extremely crucial factor, for this reason there is a high motivation in modelling and forecasting standard deviation. This stands to reason, due to the fact that it changes over time and a period of high volatility is followed by a period of low volatility and vice versa, also known as volatility cluster. The most widespread method in doing so is the Autoregressive Conditional Heteroscedasticity (ARCH) model (Engle, 1982). Contrary to all the prementioned methods, this model allows the error term to be heteroscedastic, i.e., to vary over time. If y_t is the variable to be examined, and σ_t^2 the corresponding variance, then an ARCH model can be expressed as:

$$y_t = \beta_1 + \sum_{i=1}^{n} \beta_i x_i + u_t \qquad (7)$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2$$

where n conveys the number of the explanatory variables, x_i are the explanatory variables, q is the lagged number of the error terms and α_i ,β_i being the corresponding coefficients.

The vague nature of q, however, creates some difficulties, either because there is a yet an appropriate method to define it, or because the use a great number of lags may lead to overfitting. To encounter this problem Bollerslev (1986) and Taylor (1986) independently developed the Generalized Autoregressive Conditional Heteroscedasticity

(GARCH) model. GARCH allows the variance to depend not only on the lagged value of the squared error term, but also on its own previous lags, expressed as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \quad (8)$$

That said, we can reformulate the hedge ratio to be conditional on the information set at time *t*, i.e.,

$$b_t|\Omega_{t-1} = \frac{\sigma_{sf,t}}{\sigma_{F,t}^2} \quad (9)$$

There are various formulations of the variance-covariance matrix. In this research we implement the Diagonal DVECH (Bollerslev et al., 1988), therefore, the variance-covariance matrix is modeled as follows:

$$H_t = \begin{pmatrix} a_{0,11} & 0 & 0 \\ 0 & a_{0,12} & 0 \\ 0 & 0 & a_{0,22} \end{pmatrix} + \begin{pmatrix} a_{11} & 0 & 0 \\ 0 & a_{12} & 0 \\ 0 & 0 & a_{22} \end{pmatrix} \begin{pmatrix} u_{11,t-1}^2 \\ u_{11,t-1}u_{22,t-1} \\ u_{22,t-1}^2 \end{pmatrix} + \begin{pmatrix} b_{11} & 0 & 0 \\ 0 & b_{12} & 0 \\ 0 & 0 & b_{22} \end{pmatrix} \begin{pmatrix} h_{11,t-1} \\ h_{12,t-1} \\ h_{22,t-1} \end{pmatrix} \quad (10)$$

where $h_{11,t}$ represents the spot price variance ($\sigma_{s,t}^2$), $h_{22,t}$ stands for futures price variance ($\sigma_{f,t}^2$) and $h_{12,t}$ is the covariance between them ($\sigma_{sf,t}$). The GARCH error structure allows the variance and covariance of spot and futures prices to be time-varying.

3.3.1 Risk Metrics Variance Model

Riskmetrics models also allow the variance to vary over time (being a restrictive case of GARCH). These are essentially Exponentially Weighted Moving Average (EWMA) Models, similar but simpler than the GARCH model; as they do not involve parameter estimation, and the variance process is assumed to be integrated of order 1, i.e., *I(1)*. An EWMA variance-covariance model can be defined as

$$H_t = (1-\lambda)\begin{pmatrix} u_{11,t-1}^2 \\ u_{11,t-1}u_{22,t-1} \\ u_{22,t-1}^2 \end{pmatrix} + \lambda \begin{pmatrix} h_{11,t-1} \\ h_{12,t-1} \\ h_{22,t-1} \end{pmatrix} \quad (11),$$

where λ is the decay factor ($0<\lambda<1$) and r_t is the portfolio returns in month t (Bollen, 2015).

3.4 Markov Regime Switching: MRS OLS Hedging

Various studies recognize that the relationship between spot and futures returns may be state-dependent (e.g., Alizadeh *et al*., 2008). In the presence of regime shifts, conditional mean (Sarno and Valente, 2005) and variance (Lamoureux and Lastrapes, 1990) can be biased. Therefore, an alternative would be to assume hedge ratios that are regime dependent. These hedge ratios change with market conditions; regimes are treated as latent variables since they are estimated along with the other parameters of the model. Allowing equation (4) to switch between two states:

$$\Delta S_t = \mu_{s_t} + \delta_{s_t}\Delta F_t + u_t;\ u_t \sim iid(0, \sigma_{s_t}^2) \qquad (12)$$

The unobserved state variable $s_t = \{1,2\}$ follows a two-state, first order Markov process with the following transition probabilities:

$$\boldsymbol{Prob} = \begin{pmatrix} \Pr\,(s_t = 1|s_{t-1} = 1) & \Pr\,(s_t = 1|s_{t-1} = 2) \\ \Pr\,(s_t = 2|s_{t-1} = 1) & \Pr\,(s_t = 2|s_{t-1} = 2) \end{pmatrix} = \begin{pmatrix} 1-p_{12} & p_{21} \\ p_{12} & 1-p_{21} \end{pmatrix} \qquad (13)$$

where, p_{12} gives the probability that state 1 will be succeeded by state 2, p_{22} gives the probability that there will be no change in the following period state, etc. If $\pi_{s_t,t}$ is the probability of the regime being in state s_t, the regime switching model generates two state-dependent hedge ratios (γ_1 and γ_2) which act as lower and upper bounds. The hedge ratio, at any point, in time is the probability-weighted average of the two, i.e., $\delta_t = \pi_{1,t}\delta_1 + (1 - \pi_{1,t})\delta_2$.

4 Empirical Results

In this chapter, we present our data and implement the statistical tests, as well as the estimated results. The four sets of data describe the Henry Hub natural gas spot and futures prices, on weekly and monthly basis. The corresponding period regarding the weekly set of data is from the January 8th 1997 up to January 8th 2020, summing up to 1200 observations, while with respect to the monthly basis the period is from January 15th 1997 up to February 15th 2020, summing up to 276 observations.

Natural gas spot and futures price data are obtained from the website of the U.S. Energy Information Administration (www.eia.gov). The futures contract used in this study is the nearest to expiry as this has been proved to be the most effective risk management instrument (relative to more distant contracts that do not reflect current market conditions with the same degree of responsiveness). Chen *et al.* (1987) state: "*the most effective hedge is the nearby contract*"; this is the most liquid contract where traded volumes are higher. To add, this is also the most common contract used in the literature either for natural gas (e.g., Pouliasis *et al.*, 2020) or, in general, energy commodities (Alizadeh *et al.*, 2008) and/or other financials such as exchange rates (Sarno and Valente, 2005) and stock indices (Alizadeh and Nomikos, 2004).

Before proceeding with the statistical specification of our data, it is important to observe and comprehend the movements of the series during the period to be examined. Figure 1. below depicts the historical movements of the natural gas prices on weekly basis.

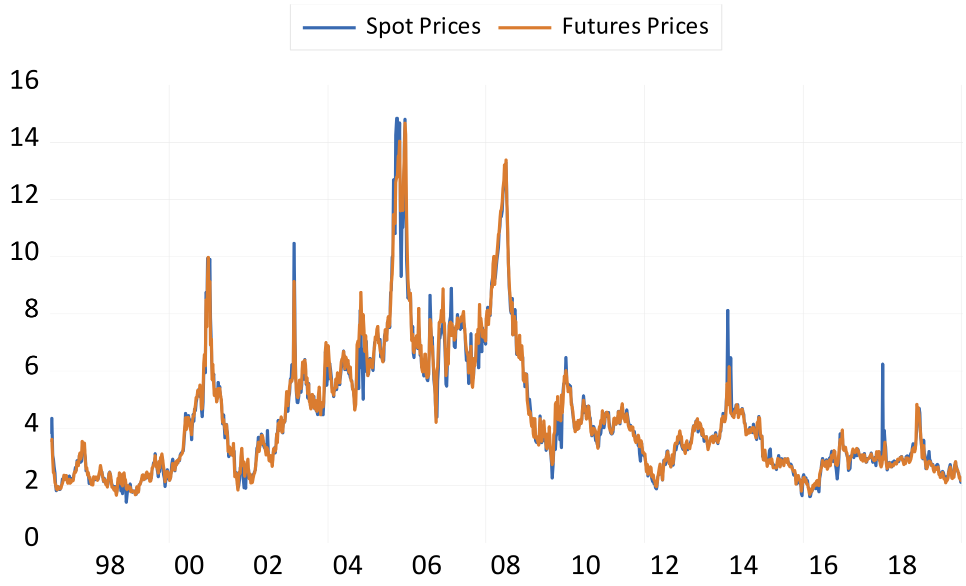

Figure 1. The Natural Gas Spot and Futures Prices Series on Weekly Basis

As shown in Figure 1. the two series appear to be closely correlated. However, high levels of fluctuation exist in the series, while the peaks being about four times greater than the mean. To be succinct:

- The 2000 high prices are caused from the California energy crisis,
- The 2003 peak is the result of weak supply, as well as the lowest record of efficient productivity,
- The 2004 and 2005 fluctuations derived from the hurricanes Ivan, Katrina respectively, and the 2008 high prices are the result of two hurricanes Ike and Gustave,
- Prices drop around 2011 due to high levels of production, warm winter conditions and strong inventories,
- The cold weather conditions, on the other hand, during 2013-2014 cause a small increase in prices

- High levels of production, combined with warm winters and strong supply allowed the prices to fluctuate around the mean, apart from the cold winter of 2018 that forced the prices to rise (CME Group).

Figure 2. below presents the monthly movements of natural gas spot and futures prices.

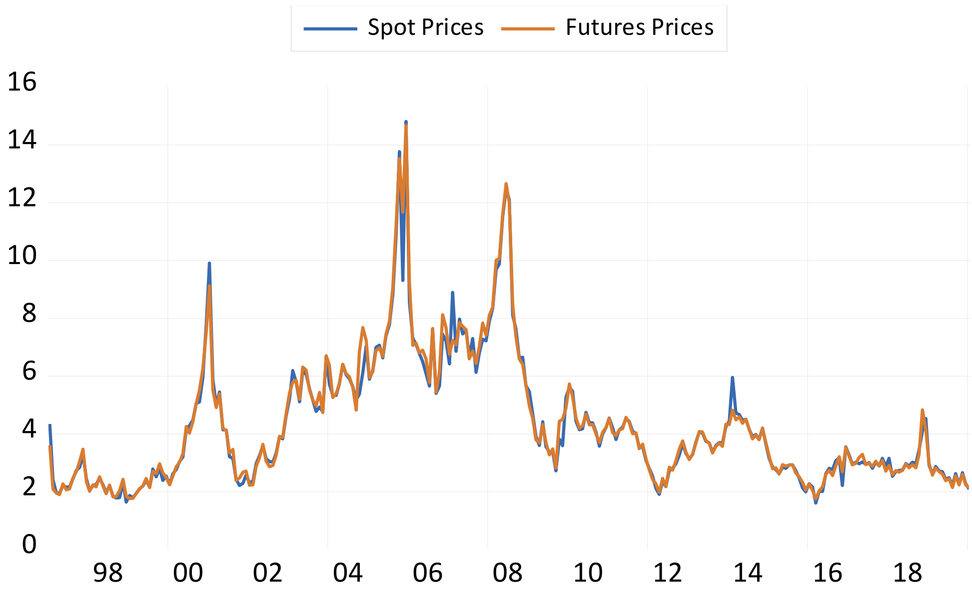

Figure 2. The Natural Gas Spot and Futures Prices Series on Monthly Basis

Figure 2. shows the historical movements of the natural gas spot and futures prices on monthly basis. In this case the two series appear to move together in the long run as well. The movement of the monthly series seems to be in accordance with the weekly ones, while the overall fluctuation follows an identical pattern, standing to reason since they are influenced from the same events previously mentioned.

4.1 Descriptive Statistics

In this part, we study the time series behavior of our sets of data. It is crucial to mention at this point that the statistical results applied on the logged prices of the series, and not the raw data, while the returns are the first differences of the logged series. From now onward, when referring to prices, we imply the logged series of the prices.

Table 1. below presents the descriptive statistics regarding the weekly sets of data, for the spot and futures prices, as well as their corresponding returns.

	Spot Prices	Futures Prices	Spot Returns	Futures Returns
Mean	1.347037	1.354258	-0.000498	-0.000413
Maximum	2.697326	2.686418	0.815750	0.398047
Minimum	0.336472	0.501987	-0.680408	-0.278522
Std. Dev.	0.458260	0.458776	0.090282	0.074075
Skewness	0.471372	0.485236	0.549068	0.249201
Kurtosis	2.621175	2.549650	13.89982	5.093015
Jarque- Bera	51.61375	57.23161	6000.601	231.4559
Probability	[0.000]	[0.000]	[0.000]	[0.000]

Notes: Estimation of the descriptive statistics is performed on the whole sample; that is 1200 weekly observations, spanning from January 1997 up to January 2020. Standard deviation measures the variation from the mean; a standard normal distribution corresponds to a unity standard deviation and a zero mean. Skewness and kurtosis measure the symmetry and the tails of a set of data respectively; a normally distributed set has a skewness equal 0 and a kurtosis equal 3. Jarque- Bera test examines whether the skewness and the kurtosis of the series equal 0 and 3 respectively, under the null hypothesis of a normally distributed set of data.

Table 1. **Descriptive Statistics of Spot and Futures Prices and Returns on Weekly Basis**

According to the values shown above in Table 1., the Jarque and Bera (1980) normality test indicates that we have to reject the null hypothesis of normality in all sets of data. That is, we can safely conclude that none of the series follows the normal distribution. One more important indication of non-normality is the fact that kurtosis is different than 3 in all cases; with respect the logged series, where the kurtosis is less than 3 both in spot and futures prices, the distribution appears to be platykurtic, whereas for the returns, where the kurtosis is greater than 3, the distribution is leptokurtic for both series.

Next, Table 2. conveys the descriptive statistics of the monthly basis series, for the spot and futures prices, as well as their corresponding returns.

	Spot Prices	Futures Prices	Spot Returns	Futures Returns
Mean	1.345125	1.352386	-0.002648	-0.001894
Maximum	2.695303	2.686418	0.469440	0.450378
Minimum	0.476234	0.560758	-0.584107	-0.546821
Std. Dev.	0.457729	0.460895	0.152482	0.140970
Skewness	0.465123	0.488559	-0.367399	-0.338056
Kurtosis	2.563259	2.543683	4.775185	4.458957
Jarque- Bera	12.14514	13.37434	42.44890	29.73534
Probability	[0.002]	[0.001]	[0.000]	[0.000]

Notes: Estimation of the descriptive statistics is performed on the whole sample; that is 276 monthly observations, spanning from January 1997 up to February 2020. Standard deviation measures the variation from the mean; a standard normal distribution corresponds to a unity standard deviation and a zero mean. Skewness and kurtosis measure the symmetry and the tails of a set of data respectively; a normally distributed set has a skewness equal 0 and a kurtosis equal 3. Jarque- Bera test examines whether the skewness and the kurtosis of the series equal 0 and 3 respectively, under the null hypothesis of a normally distributed set of data.

Table 2. Descriptive Statistics of Spot and Futures Prices and Returns on Monthly Basis

According to the estimations presented in Table 2, and more specifically the Jarque and Bera (1980) test outcomes, none of the series is normally distributed. To be more precise, both of the prices series appear to follow a platykurtic distribution, while the returns a leptokurtic one.

4.2 Unit Root Tests

In order to examine the stationarity of a series, we have to test for unity roots (Appendix A). The autocorrelation function (acf) is an empirical method widely used to examine whether the series is stationary or not. If the first is the case, then the acf should tend geometrically to zero. However, this method might be imprecise and statistical tests, like the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979), are in order.

Table 3. below presents the observed statistics of the ADF test applied to the weekly series of spot and futures prices and returns.

	Spot Prices	Futures Prices	Spot Returns	Futures Returns
ADF Test Stat.	-2.847594	-2.658512	-39.74185	-37.09774
Probability	[0.0521]	[0.0817]	[0.000]	[0.000]

Notes: The obtained critical values correspond to the whole sample; that is 1200 weekly observations. Dickey and Fuller (1979) test examines the existence of a unit root in the series, under the null hypothesis of non-stationarity.

Corresponding critical values at: 1% significance level is -3.4355
5% significance level is -2.8637
10% significance level is -2.5679

Table 3. Outcomes of the ADF Test for the Weekly Series

The obtained results shown on Table 3. read as follows. A unit root exists in both price series; at least at the 5% significance level. At the 10% level, we cannot reject the nool of a unit root test for log-prices. On the other hand, we reject the null hypothesis of non-stationarity regarding returns in both cases, indicating that both series are *I(1),* at the 5% significance level.

Figure 3. below shows the movements of spot and futures returns on the weekly basis; indicating and adding to our previous conclusion of stationarity for the returns series, and consequently that the both price series are *I(1)*.

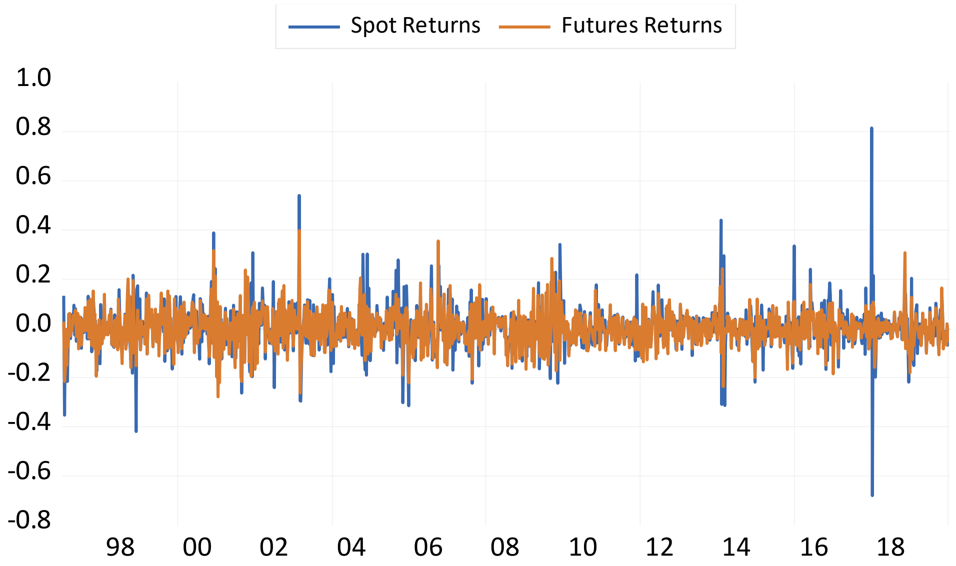

Figure 3. The Natural Gas Spot and Futures Returns Series on Weekly Basis

Figure 3. above verifies the mean reverting process of the weekly returns.

Following on Table 4. are the corresponding results of the ADF test regarding the spot and futures prices and returns for the monthly basis series.

	Spot Prices	Futures Prices	Spot Returns	Futures Returns
ADF Test Stat.	-2.20231	-2.40328	-20.1225	-17.9585
Probability	[0.2060]	[0.1418]	[0.000]	[0.000]

Notes: The obtained critical values correspond to the whole sample; that is 276 monthly observations. Dickey and Fuller (1979) test examines the existence of a unit root in the series, under the null hypothesis of non-stationarity.

Corresponding critical values at: 1% significance level is -3.4359
5% significance level is -2.8718
10% significance level is -2.5723

Table 4. Outcomes of the ADF Test for the Monthly Series

According to the results on Table 4., we fail to reject the null hypothesis, as far as the two prices series are concerned at 5% level of significance. The nool of a unit root is rejected for the returns series, standing to reason to conclude that the returns in both series are stationary, while the price series on monthly basis are *I(1)* as well, at 5% level of significance.

Figure 4. below, depicts the returns movements on monthly basis.

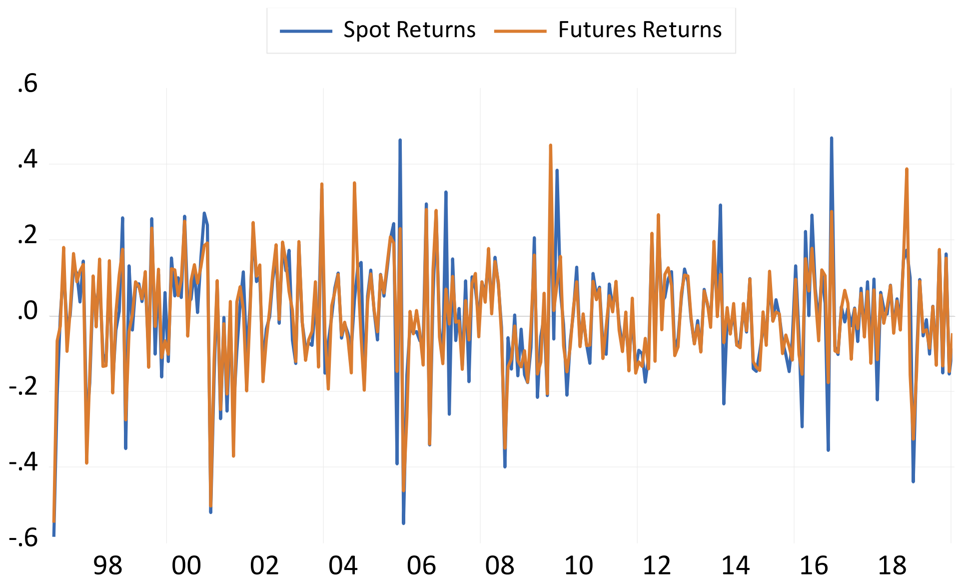

Figure 4. The Natural Gas Spot and Futures Returns Series on Monthly Basis

The depiction on Figure 4. regarding the monthly series confirms stationarity, nevertheless, high levels of fluctuation exist.

4.3 Regression Outcomes

In order to test our analysis, the sets of data to be examined were divided into two samples, the in-sample and the out-of-sample sets. Both for weekly and monthly series, the in-sample set reach up to January 2015, summing up to 940 observations for the first one and 217 observations for the latter. The remaining observations are considered to be the out-of-sample set of data. For each subclass, different forecasting methods are to be applied, in order to obtain and compare the corresponding hedging effectiveness.

4.3.1 VAR Model

One of the most important decisions regarding VAR models, is the determination of the optimal number of lags to be included in the system. For this reason, we applied the lag length criteria, that is, 6 different information criteria indicating the optimal number of lagged values to efficiently fit the model.

Each criterion serves a different approach. The most widely known are the Akaike (1974) Information Criterion (AIC) and the Schwarz (1978) Criterion (SC), also known as Bayesian Information Criterion (BIC); the first one measures the fit of goodness for the model to be estimated, while the latter one is a model selection criterion.

Table 5. shows the outcomes of the information criteria with respect the weekly in-sample set of data.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	2295.260	NA	2.59e-05	-4.884473	-4.874154	-4.880539
1	2403.202	215.1940	2.08e-05	-5.105862	-5.074904	-5.094060
2	2446.281	85.69963	1.91e-05	-5.189098	-5.137502	-5.169428
3	2469.272	45.63779	1.84e-05	-5.229545	-5.157312*	-5.202008
4	2476.743	14.79973	1.82e-05	-5.236939	-5.144068	-5.201534
5	2485.677	17.65894	1.80e-05	-5.247449	-5.133939	-5.204175
6	2495.877	20.11634*	1.78e-05	-5.260653	-5.126505	-5.209512*
7	2500.012	8.139373	1.78e-05*	-5.260942*	-5.106156	-5.201933
8	2501.165	2.263699	1.79e-05	-5.254878	-5.079453	-5.188001

Notes: Estimation of the criteria values is performed on the in-sample data; that is, 940 weekly observations spanning from January 1997 to January 2015.

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final Prediction Error

AIC: Akaike Information Criterion

SC: Schwarz Information Criterion

HQ: Hannan- Quinn Information Criterion

*indicates the lag order selected from each criterion

Table 5. Information Criteria for the Weekly Set of Data

Table 5. conveys the information criteria regarding the VAR model for the in-sample weekly set of data. Providing that the underlying goal is to select the model that minimizes the information criteria, the Schwarz (1978) Criterion (SC) suggests that the appropriate lag length for our system is 3.

Table 6. shows the corresponding results of the information criteria with respect the monthly in-sample set of data.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	485.3822	NA	9.30e-05	-3.607330	-3.580531	-3.596566
1	518.3293	65.15665	7.49e-05	-3.823353	-3.742958	-3.791063
2	531.8338	26.50504	6.98e-05	-3.894282	-3.760290*	-3.840465
3	540.9770	17.80877	6.72e-05	-3.932664	-3.745075	-3.857320
4	552.5745	22.41612	6.35e-05	-3.989362	-3.748177	-3.892491
5	560.2851	14.78818*	6.17e-05*	-4.017053*	-3.722271	-3.898654*
6	561.8550	2.987413	6.29e-05	-3.998918	-3.650538	-3.858992
7	562.6696	1.538002	6.44e-5	-3.975146	-3.573170	-3.813693
8	564.5084	3.444368	6.54e-05	-3.959018	-3.503445	-3.776038

Notes: Estimation of the criteria values is performed on the in-sample data; that is, 217 monthly observations spanning from January 1997 to January 2015.

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final Prediction Error

AIC: Akaike Information Criterion

SC: Schwarz Information Criterion

HQ: Hannan- Quinn Information Criterion

*indicates the lag order selected from each criterion

Table 6. Information Criteria for the Monthly Set of Data

The information criteria presenting on Table 6. correspond to the in-sample set of the monthly series data. Providing that the requirement is to identify the lag length that minimizes that criteria, 2 lags are to be included based on the Schwarz (1978) Criterion (SC).

Moving forward with our analysis, the VAR model is estimated. The estimated parameters with respect the weekly and monthly in-sample sets respectively, accompanied with their corresponding t-Statistic in the brackets, are presented on Table 7. below.

	Weekly Set of Data		**Monthly Set of Data**	
	Spot Returns	Futures Returns	Spot Returns	Futures Returns
Spot Returns (-1)	-0.436846	0.125476	-0.803319	-0.280684
	[-9.17429]	[2.88368]	[-5.94165]	[-2.11330]
Spot Returns (-2)	-0.236829	0.123457	-0.293286	-0.102589
	[-4.58032]	[2.61291]	[-2.15786]	[-0.76835]
Spot Returns (-3)	-0.212711	-0.011737	-	-
	[-4.60414]	[-0.27801]		
Futures Returns (-1)	0.509022	-0.191572	-0.694751	0.197517
	[9.69516]	[-3.99293]	[4.95257]	[1.43328]
Futures Returns (-2)	0.305911	-0.091706	0.396139	0.110977
	[5.20916]	[-1.70888]	[2.74777]	[0.78359]
Futures Returns (-3)	0.180427	0.054193	-	-
	[3.34112]	[1.09820]		
Constant Term	0.000109	0.000165	-0.000169	0.000169
	[0.04005]	[0.06640]	[-0.01999]	[0.02046]

Notes: Estimation of model parameters is performed on the in-sample data; that is 940 weekly observations and 217 monthly observations spanning from January 1997 to January 2015. The optimal lag structure for each model is provided by the Bayesian information criterion; that is 3 (2) lags for the weekly (monthly) set of data. Numbers in [·] are the corresponding t-statistics.

Table 7. Vector Autoregression Estimates

With respect the weekly set of data obtained estimations, the above results read as follows. Most of the coefficients appear to be statistically significant, nevertheless, we are encouraged to question the fit of the model to our sample, since the values of R-squared and Adjusted R-squared are profoundly close to zero, 0.103349 and 0.097608, respectively. However, this model fitting is mainly carried out to address the series autocorrelation together with cross-dependencies as it is common in the hedging literature.

The outputs addressed to the monthly series of data, indicate that half of the estimated coefficients are statistically different than zero. Again, the fit of the data does not perform well, since in this case as well, both R-squared and Adjusted R-squared are close to zero, 0.128440 and 0.115480 respectively.

The VAR could be examined also in the context of cointegration. However, we do not proceed with such an approach as, according to Engle and Granger (1987) two variables are cointegrated if they both are *I(1)* and their linear combination is *I(0)*. However, based on the unit root results, especially for the weekly series this holds only marginally; therefore, the interpretation of cointegration would not be feasible or problematic. This is not expected to have a significant impact on our results or alter the findings since most studies report only marginal differences of cointegration on hedging effectiveness (see for example, Alizadeh *et. al*., 2008 and Lien and Tse, 2002).

4.3.2 OLS, GARCH, MARKOV Outcomes

In this part, we present and interpret the obtained OLS, GARCH and Markov model estimations. The upcoming Table 8. illustrates the estimated parameters for the OLS, GARCH and Markov models answering to the weekly and monthly in-sample set of data.

	Weekly Set of Data		Monthly Set of Data	
Variable	Coefficient	Std. Error	Coefficient	Std. Error
Panel A: OLS Regression				
Constant Term	3.09E-05	(0.0021)	-0.00099	(0.0047)
Futures Returns	0.75424^{*}	(0.0279)	0.95412^{*}	(0.0323)
Panel B: GARCH				
Spot Variance				
Constant Term	4.44E-05	1.84E-05	0.12629	-
Lagged Residuals	0.23029^{***}	(0.0177)	0.15962^{***}	(0.0642)
Lagged Variance	0.80169^{***}	(0.0100)	0.21070^{***}	(0.1809)
Futures Variance				
Constant Term	4.34E-06	1.56E-05	0.00823	-
Lagged Residuals	0.18065^{***}	(0.0176)	0.19583^{***}	(0.0440)
Lagged Variance	0.84097^{***}	(0.0115)	0.38964^{***}	(0.0780)
Covariance				
Constant Term	-	-	0.01048	-
Lagged Product of Res.	0.16984^{***}	(0.0177)	0.14966^{***}	(0.0560)
Lagged Covariance	0.83999^{***}	(0.0102)	0.27469^{***}	(0.1408)
Panel C: Markov Regime Switching				
Regime 1				
Constant Term	-9.97E-05	(0.0012)	-0.002651	(0.0084)
Futures Returns	0.842104^{***}	(0.0217)	0.972334^{***}	(0.0499)
Log. of Variance	-3.498690^{***}	(0.0562)	-2.410549^{***}	(0.0751)
Trans. Prob. $\{P_{11}\}$	{95.65}		{86.63}	
Regime 2				
Constant Term	0.00030	(0.0075)	0.00236	(0.0024)
Futures Returns	0.67368^{***}	(0.0696)	0.89139^{***}	(0.0265)
Log. of Variance	-2.14017^{***}	(0.0602)	-3.96374^{***}	(0.1547)
Trans. Prob. $\{P_{22}\}$	{88.37}		{82.45}	

Notes: Estimation of model parameters is performed on the in-sample data; that is 940 weekly observations and 217 monthly observations spanning from January 1997 to January 2015. Panel A shows the OLS hedge ratio model. In Panel B we report the estimates of the GARCH model with diagonal VECH parameterization. For monthly data we use variance targeting (instead of estimating nine coefficients, this reduces to six). Note that the GARCH error structure is applied to the residuals of a VAR model with lag structure optimised by the Bayesian information criterion; that is 3(2) lags for weekly (monthly) data. Panel C shows the Markov regime switching estimates. We specify regime 1 as the one with highest expected duration, calculated as $1/(1- P_{ii})$. Transition probabilities P_{11} and P_{22} are shown in $\{\cdot\}$ in % terms. Finally, *** Asterisks indicate significance at 1% significance levels. Numbers in $(\cdot)$ are the corresponding standard errors.

Table 8. Estimated Parameters of OLS, GARCH and Markov Hedging Models

The interpretation of the estimated coefficients for every model individually, reads as follows. Regarding the OLS obtained coefficients with respect the weekly set of data, the constant term has no statistical significance, on the contrary, futures returns are statistically different than zero, having a great impact on the dependent variable, considering the profoundly high level of t-Statistic; indicating that if everything else remains constant, a 1% increase in futures returns will cause an increase of approximately 0.75% in spot returns. With respect to the monthly set of data, however, the constant term has no influence in spot returns, while on the contrary, the futures returns are highly significant, indicating that a 1% increase in futures returns will cause an increase of 0.95% in spot returns, if everything else remains constant.

With respect the GARCH coefficients[9], and more particularly the ones answering to spot's variance of the weekly set of data, all the coefficients are statistically significant. The adjustment to previous shocks, expressed by the lagged residuals, is low, while the changes in volatility has an extreme impact in the series, as common in the GARCH literature. It is worth mentioning that there is highly volatility persistence in our series, providing that the sum of the lagged residuals and lagged variance coefficients is greater than 1. On the other hand, with respect the futures' variance based on the weekly set of data, the speed of adjustment is low, while the influence of changes in volatility is high, implying that once again the existence of volatility persistence in the series, which is confirmed by the sum of the corresponding coefficients. Note that, when the lagged residuals and lagged variance coefficients is greater than 1, this implies explosive variance process and variance forecasts might be impaired from the existence of structural breaks (see for example, Lamoureux and Lastrapes, 1990). However, since our forecast-

[9] Note that a two-stage approach is followed. First the spot and futures returns are filtered/modelled through the VAR specification. Second the residuals are then used to estimate GARCH coefficients.

ing exercise is based on one-step ahead forecasts we choose not to restrict these coefficients (to sum equal or less than 1).

With respect the CARCH model and the monthly set of data, and more precisely the spot's variance, the obtained outcomes are very interesting. Briefly, the lagged variance coefficient is statistically significant, while the speed of adjustment is low. Regarding the futures' variance, however, all the coefficients are statistically different than zero, with a low speed of adjustment and a lessen level of influence of the changes in volatility, indicating a quick decay of the shocks in the series, which is also verified from the sum of the corresponding coefficients. It is worth noting that lagged variance coefficients are relatively low and this might be also due to the fact of small sample size.

Regarding the Markov regime switching model, a two state process has been estimated for both series. The futures returns and the logged variance are highly significant in both sets of series. With respect to the weekly in-sample set of data, there is a 95.65% probability that the process, when being in state 1 remains in the first state; this here seems to be the state characterised by low variance and high hedge ratio. Also, there is a 4.35% probability to switch to regime 2, characterised by high variance and low hedge ratio. According to our estimations, the process will tend to remain in the first regime. These results are in line with other studies in the literature, such as Alizadeh and Nomikos (2004) or Alizadeh *et al*. (2008).

On the other hand, with respect to the monthly in-sample set of data, based on the outputs, given that the process is in regime 1, there is a 86.63% probability it remains in the first state, indicating that state 1 is specified by low variance and high hedge ratio. Yet, there is a 13.37% probability to switch to regime 2, where high variance and low hedge ratio prevail.

Figure 5. below depicts the conditional probabilities of being in the low variance regime.

Markov Switching Smoothed Regime Probabilities

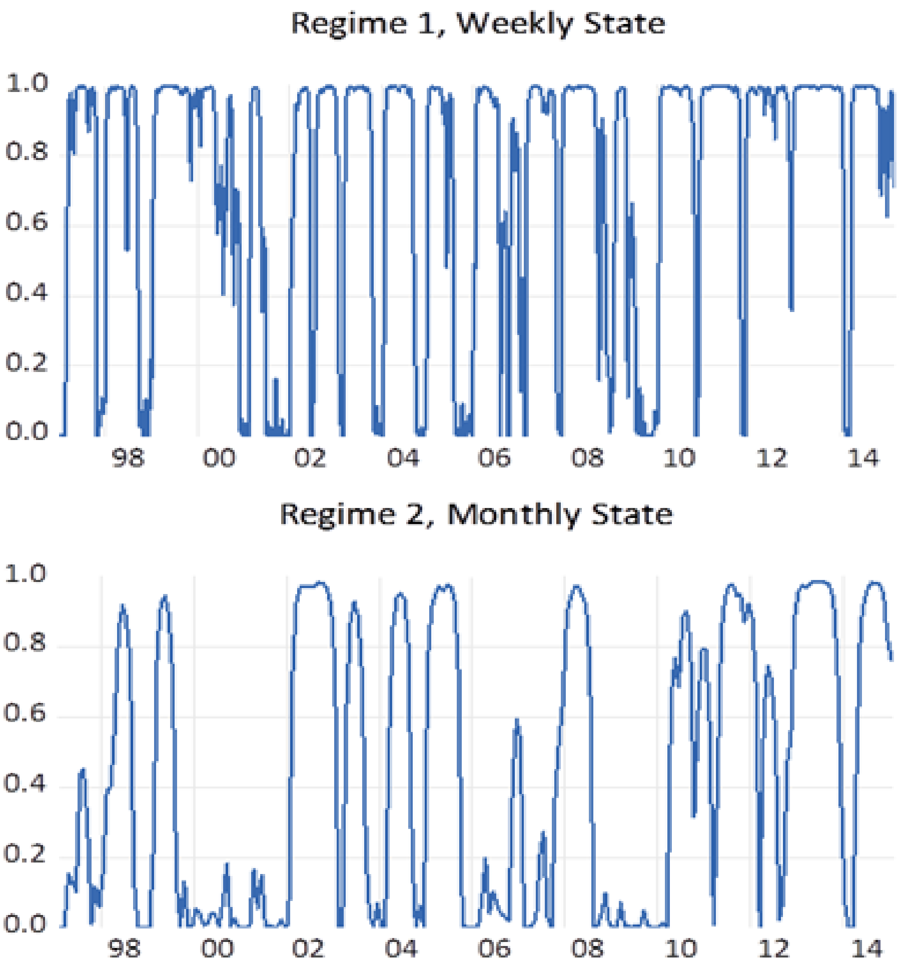

Figure 5. Smoothed Regime Probabilities of Low Variance State

(State 1 Weekly Set of Data; State 2 Monthly Set of Data)

Figure 5. shows the smoothed regime probabilities of low states for the weekly and monthly set of data. Regarding the regime 1, of the weekly state, the variance is low, while there is high hedge ratio. On the other hand, with respect regime 2, of the monthly state, both the variance and the hedge ratio appear to be low. This is due to the fact that the weekly data capture variance fluctuations as extreme events, whereas for the month-

ly data the effect of any change adjust throughout the duration, providing more balanced and smoothed regimes.

4.3.3 Hedging Effectiveness

The estimated in-sample hedging effectiveness are to be presented in this section. Before proceeding to the main results, however, it is worthwhile mentioning some specifications. The obtained risk metrics hedge ratios correspond to three different lamda (λ) values, 0.98, 0.96 and 0.94 respectively. Furthermore, the in-sample set of data has been divided in Backwardation and Contango states, in order to observe the portfolio variance and the hedging effectiveness when spot prices are greater than futures prices and vice versa, respectively.

Tilton *et αl*. (2011) define the relationship between spot and futures prices into three categories: strong contango, weak contango and backwardation. Contango occurs during periods of excess supply of a commodity, causing spot prices to drop. On the other hand, strong contango takes place when futures prices are highly above spot prices, sufficient enough to cover the storage and the interest costs. Investors, in order to gain from the arbitrage, buy spot and sell futures. This leads to a shift adding to futures supply, eventually forcing the spot prices to decrease.

Weak contango occurs when futures are greater than spot prices, yet inadequate to cover the storage costs. When markets are in backwardation or weak contango, the relationship between spot and futures prices is not that strong (Gulley and Tilton, 2014). Backwardation derives from scarce supplies in the commodity, as well as the excess in the demand (Pouliasis *et al*., 2020). The higher futures prices affect the spots markets as well. Investors buy on futures, alleviating the current demand (Tilton *et al*., 2011).

Table 9. below shows the estimated hedging effectiveness and the corresponding risk for the whole in-sample set, and during backwardation and contango, obtained through 9 different approaches.

Position	Whole Sample		Backwardation		Contango	
	Portfolio Variance	Hedging Effectiveness	Portfolio Variance	Hedging Effectiveness	Portfolio Variance	Hedging Effectiveness
Unhedged	0.00788	-	0.00820	-	0.00751	-
Naïve	0.00482	38.91%	0.00395	51.85%	0.00459	38.91%
OLS	0.00445	43.53%	0.00395	51.88%	0.00419	44.16%
VAR	0.00447	43.27%	0.00388	52.62%	0.00422	43.80%
GARCH	0.00443	43.82%	0.00390	52.45%	0.00423	43.64%
Risk Metrics						
λ=0,98	0.00449	43.09%	0.00398	51.47%	0.00421	43.96%
λ=0,96	0.00448	43.16%	0.00398	51.45%	0.00421	43.92%
λ=0,94	0.00448	43.19%	0.00397	51.60%	0.00423	43.65%
Markov	0.00440	44.19%	0.00390	52.43%	0.00412	45.13%

Notes: Estimations correspond to the in-sample data; that is 940 weekly observations spanning from January 1997 to January 2015. The columns show the estimated variance and hedging effectiveness for the whole sample, when prices are in backwardation (spot prices < futures prices) and when in contango (spot prices > futures prices), while holding 9 different positions.

Table 9. Portfolio Variance and Hedging Effectiveness for the Weekly In-Sample Series

According to the results appear in Table 9. regarding the weekly in-sample set of data, the most efficient method is obtained through the Markov approach, providing the better hedge effectiveness and the lower risk, both of the whole sample, as well as during contango. In periods of backwardation, however, the more decreased risk rate as well as the highest performance of hedging effectiveness is providing by the VAR approach.

Table 10. below conveys the values of the portfolio variance, as well as the hedging effectiveness based on the different approaches used previously, addressing the in-sample monthly set of data.

Position	Whole Sample		Backwardation		Contango	
	Portfolio Variance	Hedging Effectiveness	Portfolio Variance	Hedging Effectiveness	Portfolio Variance	Hedging Effectiveness
Unhedged	0.02415	-	0.02578	-	0.02104	-
Naïve	0.00481	80.10%	0.00383	85.14%	0.00414	80.33%
OLS	0.00476	80.29%	0.00386	85.02%	0.00401	80.95%
VAR	0.00478	80.21%	0.00394	84.73%	0.00397	81.14%
GARCH	0.00488	79.79%	0.00413	83.97%	0.00421	79.99%
Risk Metrics						
λ=0,98	0.00491	79.68%	0.00396	84.62%	0.00418	80.12%
λ=0,96	0.00502	79.23%	0.00401	84.43%	0.00436	79.27%
λ=0,94	0.00509	78.94%	0.00401	84.43%	0.00451	78.57%
Markov	0.00475	80.34%	0.00383	85.16%	0.00401	80.95%

Notes: Estimations correspond to the in-sample data; that is 217 monthly observations spanning from January 1997 to January 2015. The columns show the estimated variance and hedging effectiveness for the whole sample, when prices are in backwardation (spot prices < futures prices) and when in contango (spot prices > futures prices), while holding 9 different positions.

Table 10. Portfolio Variance and Hedging Effectiveness for the Monthly In-Sample Series

According to the estimated values shown on Table 10., the hedging effectiveness appears to be more efficient during backwardation, with the highest value when undertaking the Markov approach, which is also the case for the whole sample. In the period of contango, however, the position based on VAR model provides the better efficiency.

4.4 Forecasting Results

The forecasting results correspond to the last 5 years of our sample, summing to 260 observations for the weekly series and 60 observations for the monthly series. Model parameters are those obtained from the in-sample results, i.e. there is no updating which could create coefficient stability problems.

4.4.1 Hedging Effectiveness

Following on Table 11. are the estimated portfolio variance and hedging effectiveness, obtained from each forecasting models.

Position	Whole Sample		Backwardation		Contango	
	Portfolio Variance	Hedging Effectiveness	Portfolio Variance	Hedging Effectiveness	Portfolio Variance	Hedging Effectiveness
Unhedged	0.00915	-	0.01120	-	0.00578	-
Naïve	0.00639	30.12%	0.00818	26.97%	0.00266	54.03%
OLS	0.00640	30.03%	0.00838	25.25%	0.00264	54.25%
VAR	0.00643	29.71%	0.00840	25.00%	0.00268	53.57%
GARCH	0.00636	30.48%	0.00836	25.40%	0.00253	56.20%
Risk Metrics						
λ=0,98	0.00654	28.58%	0.00844	24.66%	0.00279	51.75%
λ=0,96	0.00666	27.17%	0.00869	22.46%	0.00271	53.10%
λ=0,94	0.00679	25.80%	0.00896	20.04%	0.00262	54.73%
Markov	0.00639	30.20%	0.00831	25.80%	0.00265	54.19%

Notes: Estimations correspond to the out-of-sample data; that is 260 weekly observations from February 2015 to January 2020. The columns show the estimated variance and hedging effectiveness for the whole sample, when prices are in backwardation (spot prices < futures prices) and when in contango (spot prices > futures prices), while holding 9 different positions.

Table 11. Portfolio Variance and Hedging Effectiveness for the Weekly Out-of-Sample Series

The forecasted portfolio variance and hedging effectiveness addressing to the weekly out-of-sample set of data, do not agree with the within-sample ones. To be more precise, the obtained values suggest that the most efficient hedging approach, both for the whole sample, as well as during contango, is through GARCH. In period of backwardation, however, the most optimal hedge is succeeded through 1-1 naïve approach.

Table 12. shows the estimated portfolio variance and hedging effectiveness based on the monthly out-of-sample set of series.

Position	Whole Sample		Backwardation		Contango	
	Portfolio Variance	Hedging Effectiveness	Portfolio Variance	Hedging Effectiveness	Portfolio Variance	Hedging Effectiveness
Unhedged	0.02008	-	0.01499	-	0.02680	-
Naïve	0.00507	74.75%	0.00283	81.11%	0.00503	81.23%
OLS	0.00505	74.87%	0.00280	81.33%	0.00507	81.08%
VAR	0.00517	74.24%	0.00285	80.99%	0.00526	80.38%
GARCH	0.00552	72.53%	0.00189	87.37%	0.00731	72.72%
Risk Metrics						
λ=0,98	0.00543	72.95%	0.00273	81.78%	0.00586	78.13%
λ=0,96	0.00574	71.44%	0.00257	82.88%	0.00665	75.17%
λ=0,94	0.00589	70.65%	0.00244	83.73%	0.00711	73.46%
Markov	0.00501	75.05%	0.00288	80.78%	0.00493	81.62%

Notes: Estimations correspond to the out-of-sample data; that is 60 monthly observations from February 2015 to February 2020. The columns show the estimated variance and hedging effectiveness for the whole sample, when prices are in backwardation (spot prices < futures prices) and when in contango (spot prices > futures prices), while holding 9 different positions.

Table 12. Portfolio Variance and Hedging Effectiveness for the Monthly Out-of-Sample Series

With respect the monthly out-of-sample set of series, the optimal approach for the whole sample complies with the corresponding indication regarding the monthly in-sample set of series. In both cases, the Markov approach provides the lowest risk with highest levels of effectiveness. Regarding the two subclasses, however, the approaches do not agree with the ones concluded in the in-sample set of data. More particularly, during backwardation, the GARCH model is considered to be more appropriate, rather than the Markov model, while during contango the Markov appears to be more efficient, instead of the VAR model that we concluded for the in-sample set of data.

5 Conclusion

Climate change imposed the necessity to reduce CO_2 emissions in the atmosphere and requesting a shift in more clear energy resources. This has contributed in the designation of the natural gas market as an emerging one. The incessantly increasing interest regarding hedging with natural gas futures contracts has questioned the overall performance. Natural gas, in general, shows some basic inhibitions; the storage theory (Siliverstovs *et al.*, 2005), the dependence on oil prices (Hulshof *et al.*, 2016), as well as the existence of high volatility in natural gas prices (Pindyck, 2004b), accompanied with the issue of the cross-hedging affect (Ghoddusi, 2016) the performance of hedging effectiveness of natural gas futures contracts.

In this study, we estimated the hedging effectiveness and the corresponding portfolio risk of natural gas returns. More particularly, we studied the relationship of spot and futures Henry Hub prices from 1997 to 2020. The series were divided into within- and out-of sample in order to compare the forecasted estimations. Furthermore, another classification took place, specifying the subsamples during periods of contango (spot prices< futures prices) and backwardation (spot prices> futures prices).

For each category the hedging effectiveness, as well as the portfolio risk were obtained through different techniques; the unhedged and the naïve position, the OLS, the VAR, the GARCH, the Markov and Risk Metrics based on 3 different values of lambda estimations. Due to characteristics of data structure, the long-run relationship has not been examined, since not all of our series fulfil the necessary requirements of *I(1)* series.

The overall comparison of the obtained hedging effectiveness between the within and out-of sample sets of data, however, do not seem to be in accordance. In most cases, the concluded approaches regarding the within and out-of sample results do not agree. The only exception is the case of the whole monthly series sample, where the Markov switching regimes technique appears to be the appropriate one, both for the within- and out-of sample. This result indicates that the ability to switch from high to low variance position amends the overall hedging performance.

In this research can be extended in many directions. Using the basis (futures minus spot prices) as a tool to capture the *expected* spot price changes (partially predictable spot prices) will amend the overall performance (Martinez and Torro, 2015). In particular, hedging only the part of the spot series that cannot be predicted is a way to increase hedging effectiveness, as proven in Ederington and Salas (2008) and further applied by Pouliasis *et al.* (2020). Both studies used the basis as a predictor of the spot. Finally, accounting for seasonality, is also a way forward. For example, one could estimate seasonality dependent hedge ratios which might improve the obtained results. However, through our models of regime switching and volatility it is expected that, to a certain degree, seasonal fluctuations are already captured. Finally, another interesting proposal would be to study other periods that might have an effect on hedging effectiveness, for example, bull vs bear markets, high vs low oil price periods, winter vs summer and/or, high vs. low working gas period. We leave this for further research.

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Appendix

Appendix A: Unit Root Tests

A stationary series is one with

1) constant mean ($E[y_t]=\mu$ for every t=1,2,..),
2) constant variance ($E[y_t-\mu]\ E[y_t-\mu]= Var(y_t)=\sigma^2 <+\infty$),
3) constant autocovariances ($E[y_{t_n}- \mu][y_{t_{n+1}}-\mu]= \gamma_{t_{n+1}-t_n}$[10]).

Stationarity is very essential because in its absence we may end up with a spurious regression; that is, a trend appears between the variables, however they are completely unrelated.

In the given autoregressive description:

$$Y_t= a + \gamma y_{t-i}+ u_t;$$

If $\gamma=1$ then it has a unit root, hence the model is non-stationary, and more particularly, generating a random walk, which cannot be forecasted. On the contrary for every $|\gamma|<1$ the model is stationary (Dickey and Fuller, 1979).

An obvious way to test for a unit root is to examine the autocorrelation function (acf) of the series. However, this method is not appropriate since it is possible for a unit root to exist, but the acf will eventually approach zero. The most widely appropriate used techniques in order to examine for stationarity are the Augmented Dickey- Fuller (ADF) test (Dickey and Fuller, 1981) and the Kwiatkowski- Philips- Schmidt- Shin (KPSS) test (Kwaitkowski *et. al.*, 1992).

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[10] γ reflects how the variable varies at two different points in time.

Given a non-stationary series, the main goal of this test is to examine how many times y_t has to be differenced (d) in order to become stationary. [11]

Dickey and Fuller (1979) formed a hypothesis test, checking for the possibility if the true data generating process for y, have at least one unit root.

Provided that:

$$y_t = \varphi\, y_{t-1} + \mu + \lambda t + u_t\,,$$

or consequently

$$\Delta y_t = \psi\, y_{t-1} + \mu + \lambda t + u_t;$$

where μ and λ represent drift and a time trend respectively, the two corresponding hypothesis are :

- H_0 : $\varphi=1$ or $\psi=0$ or $y_t \sim I(1)$ or "The series contains a unit root"
- H_1 : $\varphi<1$ or $\psi\neq 0$ or $y_t \sim I(0)$ or " The series is stationary".

Nevertheless, in the presence of autocorrelation, the Dickey and Fuller (1979) test is no longer valid. This motivated the enhancement of this technique, achieved by including lagged values of the dependent variable (p), known as augmented Dickey-Fuller test (ADF) (Dickey and Fuller, 1981). Under the same hypothesis, the previous tests are now transformed into:

$$\Delta y_t = \psi\, y_{t-1} + \sum_{i=1}^{p} \alpha_i\, \Delta\, y_{t-i} + u_t.$$

However, as mentioned above, this method examines whether a unit root exists in the series, or not. That is, by rejecting the null hypothesis, we can only safely assume that a unit root does not exist, but stationarity is not necessarily established. For instance, if the sample size is small the results may be misleading. For example, if $\varphi=0.98$

[11] Then y_t is said to be integrated of order d, and it is written $y_t \sim I(d)$. For instance, if $y_t \sim I(3)$, means that the series contains three unit roots, and we have to take the differences three times so as to achieve stationarity.

then we reject the null hypothesis, but this may occur either because φ is actually different than one, or due to insufficient information in the given sample.

This limitation triggered the necessity for a stationarity tests. The Kwaitkowski, Phillips, Schmidt and Shin presented the homonym (KPSS) test (Kwaitkowski *et. al.*, 1992), examining stationarity, instead of a unit root. In this test the hypothesis are:

- H_0 : $y_t \sim I(0)$ or " The series is stationary"
- H_1 : $y_t \sim I(1)$ or " The series contains a unit root".

A combination of these tests will provide a more certain conclusion, since the results should comply with each other. For example, if we reject the null at the ADF test and we fail to reject the null at the KPSS test, then the series is stationary.