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NATURAL GAS PRICE VOLATILITY AND OPTIMAL HEDGE RATIOS

Abstract. *Natural gas represents one of the most important commodities for the world economy and this importance is growing. The paper analyzes the evolution of U.S. natural gas spot and futures prices and estimates static and time varying optimal hedge ratios (OHR) through several methods.*

The findings show that the natural gas price evolution is highly volatile, with greater variations in the case of spot market. Also, the data series are characterized by volatility clustering, making the hedging even more necessary and valuable.

We estimate the static OHR using two ordinary least squares methods (conventional and by incorporating the market expectations in the regression) and an error-correction model (ECM). The time varying OHR are estimated through OLS method with different rolling window lengths and bivariate GARCH model with ECM errors (B-GARCH). The main findings show that the time varying OHR outperform their static counterparts.

Keywords: *hedging, volatility, optimal hedge ratio, hedging effectiveness, natural gas*

JEL Classification: G13, G15, G32

I. Introduction

Natural gas represents one of the most important commodities at a global level and its importance is growing. Paltsev et al. (2011) show that the outlook for gas is favorable for the next several decades. Also, the shale gas allows production to increase, adding to the resource base. Natural gas has the highest competitive advantage in the electric generation field, being likely the preferred alternative to coal or other fossil fuels, especially in the light of a CO_2 emissions reduction and price-based policies. Mohr and Evans (2011) focused on the long-term forecast of natural gas production, showing that it is expected for the production from both conventional and unconventional sources to grow further. The increasing importance of natural gas, outlined in the reminded studies, represents one of the reasons of selecting this commodity for this paper. In addition, as we will further show, the natural gas price has a highly volatile behavior, inducing great risks for both producers and consumers. In the light of these arguments, the efficient way to hedge such risks becomes an important issue.

The simplest way of hedging is through futures contracts for the linearity in their payoff. In order to hedge a spot position, the naive recommendation is to use a hedging ratio of one. In the case that the spot and futures prices are perfectly correlated, the naive hedge ratio minimizes the risk of the hedged portfolio because the changes in the spot price would be perfectly netted by the changes of the futures price. However, the spot and futures markets are characterized by basis risk: the spot and futures prices are not perfectly correlated and converge only at the maturity of the contract. Thus, during the life of the hedge, the changes in the value of the spot position cannot be perfectly offset by the changes in the futures prices. In this case, the naive hedge ratio does not minimize the risk of the hedged portfolio and appears the need to estimate the optimal hedge ratio (OHR).

After analysing the volatile nature of the natural gas prices, this paper estimates static and time varying OHR for the case of U.S. natural gas market. The static OHR are estimated using OLS methods and ECM. The OHR that vary through time are estimated using OLS method with different rolling window lengths and the bivariate GARCH model with ECM errors (B-GARCH). The results show the superiority of the time varying hedge ratios for the U.S. natural gas market. Also, a negative relationship exists between the rolling window length and hedging effectiveness and the B-GARCH hedge ratios exhibit the greatest volatility.

The paper is organized as follows: after the introduction is realized in this section, the next section presents the main finding in the literature regarding the natural gas price dynamics and the OHR estimation. In the third section are presented the models and the methodology used. The results and conclusions are discussed in the last two sections.

II. Literature review

The evolution of natural gas prices is affected by several factors such weather and storage, alongside with demand and supply dynamics. Mu (2007) examined the way that weather shocks influence short-term price dynamics in the US natural gas futures market and shown that weather has a significant effect on both the conditional mean and volatility of natural gas futures returns. Geman and Ohana (2009) found a negative correlation between price volatility and inventory for natural gas only during the periods of scarcity when the inventory is below its historical average. The authors also found that the correlation increases during the winter periods. Modjtahedi and Movassah (2005) found that spot and futures natural gas prices are non-stationary stochastic processes and that the observed time trends in the prices are due to a positive drift in the random walk component rather than possible deterministic time trends. However, the authors found that market forecast errors are stationary, futures incorporating the long-run behavior of the spot prices. Serletis and Andreadis (2004) found that the Henry Hub natural gas prices follow a random fractal model, while the West Texas Intermediate (WTI) oil is characterized by a random multifractal turbulent structure. Masih et al. (2010) analyzed the relationship between natural gas and methanol prices, concluding that the natural gas is the main driver for methanol prices especially in the United States and Europe. Gebre-Mariam (2011) showed that the natural gas prices are stationary after first differencing and the spot and futures prices move in a similar direction in the Northwest US natural gas markets. In addition, the efficient market hypothesis holds true for contracts with about a month to expiry.

Other studies examined the relationship between the crude oil and natural gas prices. Serletis and Rangel-Ruiz (2004) showed that US natural gas and WTI crude oil prices decoupled as a result of oil and gas deregulation in the United States. The authors also found that the Henry Hub price trends define the North American natural gas prices. Erdős (2012) found that after 2009 the UK gas price remained integrated with oil price while the US gas price decoupled from both. Ramberg and Parsons (2012) show that although the natural gas and oil prices are cointegrated, the confidence intervals are large.

Given the importance of the subject, numerous papers in the existing literature are dedicated to the proper estimation of the OHR that minimizes the risk of the hedged portfolio. Ederington (1979) used the OLS regression for the estimation of the minimum variance hedge ratio. Given that in many cases the spot and futures prices are cointegrated, there were developed error-correction models for the estimation of the OHR (Chou et al., 1996; Alexander and Barboza, 2007). Baillie and Myers (1991) and Kroner and Sultan (1993) introduced the GARCH models for the estimation of time varying OHR. Different types of GARCH models were used to estimate the OHR for numerous markets. For example, Chang et al. (2011) examined the hedging effectiveness of several multivariate volatility models, namely CCC, BEKK and diagonal BEKK for crude oil markets and concluded that the diagonal BEKK was the best model for optimal hedge ratio estimation in terms of the reduction in the variance of the hedged portfolio. Adams and Gerner (2012) investigated the performance of Brent, WTI, heating oil and gasoil forward contracts as instruments used to cross hedge the exposure to the jet fuel prices, using static and time varying hedge ratios.

Power et al. (2013) used a non-parametric Copula-based GARCH model to estimate the time varying hedge ratios for live cattle and corn markets, but found that this method does not bring additional reduction in the variance of the hedged portfolio compared to the static hedge ratio. Lien et al. (2002) found that the rolling window OLS (RW OLS) performs better than the constant correlation bivariate GARCH model using a database of three currencies, five commodities and two stock index futures contracts. Moon et al. (2009) applied the RW OLS method for the Korean stock market, while Bhattacharya et al. (2011) used the same method for the Indian stock market. Although the natural gas market has a great importance, there are few papers that estimate the OHR for its case. For example, Ederington and Salas (2008) estimated minimum variance hedge ratios for the North American natural gas market using the conventional OLS method and by incorporating the expected change in the spot price in the regression. Our paper fills the gap in the literature by estimating static and time varying optimal hedge ratios for this important market.

III. Methodology

We proceed with our analysis by describing the evolution of natural gas prices for the observed period. The database consists in weekly spot and futures prices of U.S. natural gas during the period from 04.10.2000 to 26.09.2012 (626 weekly price observations and 625 weekly returns). The spot price is represented by the Henry Hub natural gas price. For the futures price, the New York Mercantile Exchange (NYMEX) natural gas futures contracts are considered. In order to construct the futures price series, we considered the nearby contract price, with rollover after two weeks from the beginning of the expiration month. Also, the day of the week that was chosen is Wednesday and in the case that Wednesday was not a business day, the next business day was considered. The prices are expressed in USD per MMBtu (million of British thermal units).

Next, we compute and discuss the descriptive statistics of the weekly prices and relative variations (spot and futures): mean, median, maximum, minimum, skewness, kurtosis, standard deviation and the annualized volatility. For simplifying reasons, we will refer to the relative variations in prices as weekly returns. In order to compute the annualized volatility, the following formula was applied:

$$Annualized\ Volatility = \sigma_r \sqrt{52} \qquad (1)$$

where σ_r is the standard deviation of the weekly returns and 52 represents the number of weeks in a year.

The returns are computed as differences between the spot or futures prices logarithms:

$$r_{X_t} = ln(X_t) - ln(X_{t-1}) \quad (2)$$

Where *X* represents the spot or futures price.

In order to test for the time series stationarity, we applied the Augmented Dickey-Fuller (ADF) unit root test. Also, for testing the cointegration between the spot and futures prices, the Johansen cointegration test was considered. As shown in Juhl et al. (2012), the proper specification of the model used to estimate the OHR depends on the involved time series characteristics.

Following, we focused on the evolution of the basis, which causes the inefficiency of the naive hedge ratio and represents the main argument for estimating the OHR. We also provide the main descriptive statistics of the basis. Its value is computed as the difference between the logarithms of the futures and spot prices:

$$Basis_t = ln(F_t) - ln(S_t) \quad (3)$$

The next step of the methodology consists in computing and plotting the absolute spot and futures returns. In order to emphasize the volatility clustering that characterizes the data series we followed the methodology proposed by Tseng and Li (2011). First, we sorted the values of the absolute returns and established the benchmarks for the largest 15% of the movements, respectively for the smallest 15% of the absolute returns. Next, we computed the probabilities of occurrence for the largest moves after the largest, smallest after smallest, etc. in the sample. In the case of a normal distribution of the absolute returns, the probability of one of the largest returns appearance after a largest one should be 15%. A higher observed probability would signal the volatility clustering.

Further, it is considered the case of a seller of natural gas that has a long initial position on the spot market. In order to hedge the spot position, the hedger has to sell a specific amount of futures contracts. By combining the two positions, one can compute the weekly return of the hedged portfolio.

$$r_{H_t} = r_{s_t} - hr_{f_t} \quad (4)$$

Where h represents the hedge ratio between the quantity traded on the futures market and the quantity representing the spot exposure.

$$h = Q_F/Q_S \quad (5)$$

The risk of the hedged portfolio can be assessed by its variance and is given by:

$$Var(r_{H_t}) = Var(r_{s_t}) + h^2Var(r_{f_t}) - 2hCov(r_{s_t}, r_{f_t}) \quad (6)$$

By solving the minimum problem, one can derive the OHR as:

$$h^* = \frac{Cov(r_{s_t}, r_{f_t})}{Var(r_{f_t})} \quad (7)$$

In order to quantify the efficiency of the hedging it is computed the Ederington (1979) hedging effectiveness indicator (HE). The HE shows the proportion of the variance of the spot position that is reduced through hedging.

$$HE = 1 - \frac{Var(r_{H_t})}{Var(r_{S_t})} \tag{8}$$

In the existing literature are used different methods to estimate the OHR. We estimate the static OHR using OLS method and ECM. Also, we take into consideration the method proposed by Ederington and Salas (2008) that incorporates the expected change in the spot price in the regression. We will further refer to this method as OLS basis. The OHR that varies through time is estimated using OLS method with different rolling window lengths and the bivariate GARCH model with ECM errors (B-GARCH).

Starting from the bivariate model proposed by Pesaran (1997), we can obtain the OLS and error-correction models used to estimate the OHR, a methodology that was also used by Lee et al. (2009). Adapted for the case discussed here, the Pesaran (1997) model can be written as:

$$r_{S_t} = a_S(1-\phi_S) - (1-\phi_S)ln(S_{t-1}) + \lambda ln(F_{t-1}) + u_t \tag{9}$$

$$r_{f_t} = a_F(1-\phi_F) - (1-\phi_F)ln(F_{t-1}) + \delta ln(\mathrm{S}_{t-1}) + v_t \tag{10}$$

assuming that

$$\begin{pmatrix} u_t \\ v_t \end{pmatrix} \sim iid\ (0, \Sigma),\ \ \Sigma = \begin{pmatrix} \sigma_u^2 & \sigma_{u,v} \\ \sigma_{u,v} & \sigma_v^2 \end{pmatrix} \tag{11}$$

where $\sigma_{u,v}$ is the covariance between u_t and v_t, and σ_u^2 and σ_v^2 are the variances of u_t and v_t.

Assuming that both spot and futures prices follow a random walk, it can be set that $\phi_S = \phi_F = 1$ and $\lambda = \delta = 0$ in the above bivariate model. In this case, the model appears as follows:

$$r_{S_t} = u_t \tag{12}$$

$$r_{f_t} = v_t \tag{13}$$

Having u_t and v_t jointly normally distributed, then:

$$u_t = \left(\frac{\sigma_{u,v}}{\sigma_v^2}\right) v_t + \varepsilon_t \tag{14}$$

Where $\sigma_{u,v}/\sigma_v^2$ represents the regression coefficient of u_t on v_t, and ε_t is distributed independently of v_t. Thus, the OLS model can be further estimated.

$$r_{S_t} = \alpha + \beta r_{f_t} + \varepsilon_t \tag{15}$$

$$\varepsilon_t \sim N(0, \sigma^2)$$

The estimation of the OHR is given by β equalling $\sigma_{u,v}/\sigma_v^2$ under the jointly normally condition.

Ederington and Salas (2008) proposed the integration of the expected change in the spot price in the OLS regression (referred here as OLS basis). We estimate the OHR through the OLS basis method by considering the expectations as the differences between the logarithms of the futures and spot prices (the basis).

$$r_{s_t} = \alpha + \beta r_{f_t} + \gamma[ln(F_t) - ln(S_t)] + \varepsilon_t \tag{16}$$

The following model that we use to estimate the OHR is the ECM. The long run relationship between spot and futures price is represented by:

$$\ln(S_t) = a + bln(F_t) + \varepsilon_t \tag{17}$$

If the series are cointegrated and the spot and futures prices are unit root processes, then it must be either $|\phi_S| < 1, \phi_F = 1,\ \lambda \neq 0,\ \delta = 0$ or $|\phi_F| < 1,\ \phi_S = 1, \delta \neq 0,\ \lambda = 0$ in the bivariate model. Taking into consideration the first case, we have:

$$r_{s_t} = a(1-\phi_S) - (1-\phi_S)S_{t-1} + \lambda ln(F_{t-1}) + u_t \tag{18}$$

$$r_{f_t} = v_t \tag{19}$$

If u_t and v_t are jointly normally distributed and $u_t = \beta v_t + \varepsilon_t$, the equation that estimates the OHR can be written as follows:

$$r_{s_t} = \alpha + \lambda\hat{\varepsilon}_{t-1} + \beta r_{f_t} + \mathrm{e}_t \tag{20}$$

$$e_t \sim N(0,\sigma^2)$$

Where $\hat{\varepsilon}_{t-1} = ln(S_{t-1}) - [\hat{a} + \hat{b}ln(\mathrm{F}_{t-1})]$ is the lagged error term from the long-run relationship and e_t is the error term. The coefficient β is the estimation of the OHR using the ECM.

The first type of time varying OHR is estimated using the OLS method with different rolling window lengths. The RW OLS equation has the following form:

$$r_{s_t} = \alpha_0 + (\beta_t|\Omega_{t-n+1,t})r_{f_t} + \varepsilon_t \tag{21}$$

Where $\beta_t|\Omega_{t-n+1,t}$ is the OHR estimated at time *t*, based on the information from moment *t–n+1* to moment *t* and *n* represents the number of periods from the rolling window. In this paper, *n* is set to 50, 100, 200 and 469 periods. The last rolling window length (469 periods) represents the number of weekly returns from the sample period.

We also estimated the OHR using the bivariate GARCH with ECM errors model. The mean equations of the model are:

$$r_{s_t} = \omega_S + \beta_S\left(ln(S_{t-1}) - \hat{a} - \hat{b}ln(F_{t-1})\right) + \varepsilon_{S_t} \tag{22}$$

$$r_{f_t} = \omega_F + \beta_F\left(ln(S_{t-1}) - \hat{a} - \hat{b}ln(F_{t-1})\right) + \varepsilon_{F_t} \tag{23}$$

Where:

$$\begin{bmatrix} \varepsilon_{S_t} \\ \varepsilon_{F_t} \end{bmatrix} \mid \psi_{t-1} \sim N(0, H_t) \quad (24)$$

$$H_t = \begin{bmatrix} h_{S_t}^2 & h_{SF_t} \\ h_{SF_t} & h_{F_t}^2 \end{bmatrix} = \begin{bmatrix} h_{S_t} & 0 \\ 0 & h_{F_t} \end{bmatrix} \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \begin{bmatrix} h_{S_t} & 0 \\ 0 & h_{F_t} \end{bmatrix} \quad (25)$$

The conditional mean and variance-covariance equations are given by:

$$h_{S_t}^2 = c_S + a_S \varepsilon_{S_{t-1}}^2 + b_S h_{S_{t-1}}^2 \quad (26)$$

$$h_{F_t}^2 = c_F + a_F \varepsilon_{F_{t-1}}^2 + b_F h_{F_{t-1}}^2 \quad (27)$$

$$h_{SF_t} = \rho_t \cdot h_{S_t} \cdot h_{F_t} \quad (28)$$

The OHR is given by the ratio between the conditional covariance and the conditional variance of the futures returns.

$$h_t^* = \frac{h_{SF_t}}{h_{F_t}^2} \quad (29)$$

The database was split in two parts. The sample period consists in the first 9 years (from 04.10.2000 to 30.09.2009) and contains 470 weekly price observations and 469 weekly returns (spot or futures). This period is used in order to estimate the static OHR (OLS, OLS basis and ECM), the parameters of the B-GARCH model and the first value of the RW OLS optimal hedge ratio. The second period is used to estimate the time-varying OHR (RW OLS and B-GARCH) and to compute the variances of the hedged and unhedged portfolios. These values are next used to compute the HE indicator for each model. Also, for comparison, we computed the HE of the naive hedge ratio.

IV. Results

In Figure 1 is shown the evolution of natural gas spot and futures prices during the analyzed period. In can be easily observed that the two prices are highly correlated, except for some periods when one of the prices exhibits an increased volatility. Also, it can be noticed that the evolution of both prices is characterized by important variations and spikes.

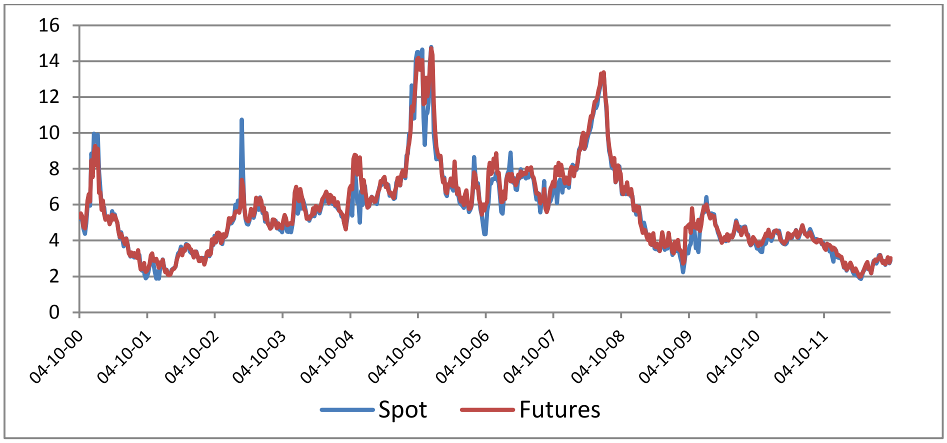

Figure 1. Spot and futures price evolution

In Table 1 are synthesized the main descriptive statistics of the spot and futures prices and returns. It can be observed that the statistics values are similar for spot and futures. Also, the prices are characterized by a great volatility, shown especially by the extreme values of the series. Thus, the ratio between the maximum and minimum value is around 8 in the case of spot and 7.4 in the case of futures prices. In addition, the annualized volatility of returns is high (65.39% for spot and 57.21% for futures). It can also be mentioned that the spot volatility is greater than that of the futures price, the weather conditions and shortages having a higher impact on the spot market. The statistics show that the return distribution is asymmetric and leptokurtic.

	Spot		Futures	
	Price	Return	Price	Return
Mean	5.53	-0.09%	5.68	-0.09%
Median	5.19	-0.18%	5.32	-0.27%
Maximum	14.79	55.36%	14.73	51.08%
Minimum	1.85	-32.98%	1.98	-31.61%
Skewness	1.17	0.60	1.12	0.51
Kurtosis	4.87	6.74	4.59	6.20
St dev	2.39	9.07%	2.42	7.93%
Annualized Volatility	65.39%		57.21%	

Table 1. Descriptive statistics of prices and returns

The results of the ADF test (Table 2) show that the spot and futures price levels are non-stationary, but their returns are stationary. In order to avoid spurious results we will use in estimating the regressions the stationary data (the returns). The Johansen test results (Table 3) show that the spot and futures prices are cointegrated, suggesting that a model that accounts for this feature of the data will be well fit.

	Spot		Futures	
	t-stat	p-value	t-stat	p-value
Level	-3.1145	0.1038	-2.4596	0.3484
Log return	-26.0861	0.0000	-26.3701	0.0000
Critical values: 1%: -3.972; 5%: -3.417; 10%: -3.131				

Table 2. ADF test results

Hypothesis	No cointegrating vector	At most one
Value	59.1904	7.1654
Critical values: None: 1%: 20.04; 5%: 15.41; At most one: 1%: 6.65; 5%: 3.76		

Table 3. Johansen test results

In Figure 2 and Table 4 are emphasized the evolution and the main descriptive statistics of the basis. Thus, the basis is characterized by a high volatility, with short periods when the spot and futures prices become decoupled, the difference between them reaching values near 40-50%. Also, it can be observed that the futures price is higher than the spot in average with 2.94%, while the median value is 1.64%.

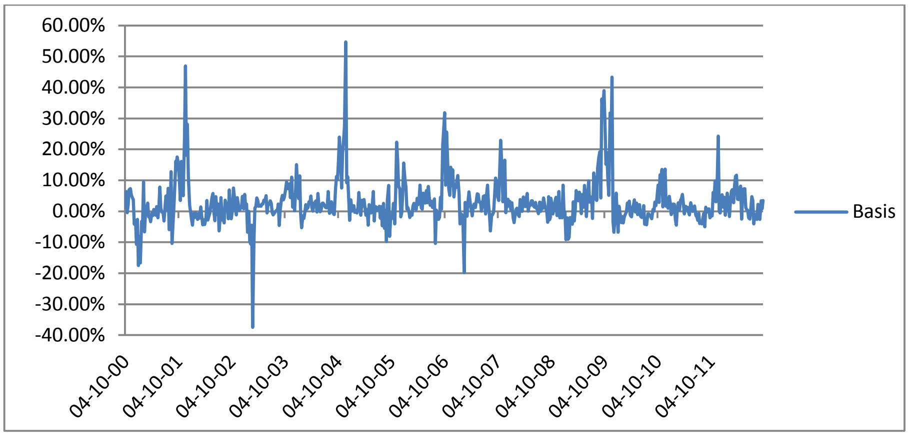

Figure 2. Basis evolution

Mean	Median	Maximum	Minimum	St dev
2.94%	1.64%	54.68%	-37.48%	7.48%

Table 4. Descriptive statistics for basis

It can be observed from Figure 3 that the absolute returns tend to be highly correlated during short periods of time, suggesting the presence of volatility clustering.

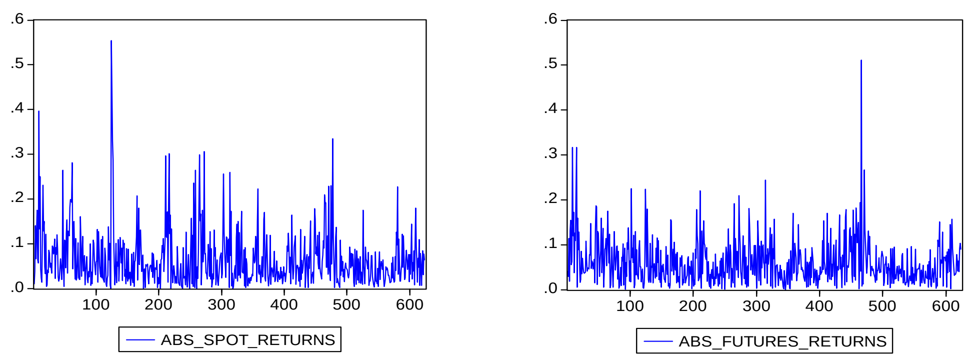

Figure 3. Spot and futures absolute returns

The presence of volatility clustering in the data series is better highlighted in Table 5. The reading of the table should be done in the following way: there are shown the occurrence probabilities that the types of movements wrote in the column come after those in the row. For example, the probability of occurring one of the largest 15% of the movements after one of the smallest 15% is 11.83%. The probabilities of occurrence of largest changes after other largest movements are 32.26% in the spot case, respectively 24.73% for the futures, significantly higher than 15% probability in the case of a normal distribution. This represents evidence of volatility clustering, and the presence of this feature in the data series increase the risks that a company is faced in the natural gas market. After an important shock in the price, it is very probable for the increased volatility to continue, making thus hedging more valuable.

15%	Spot			Futures		
after…	Largest	Smallest	Rest	Largest	Smallest	Rest
Largest	**32.26%**	11.83%	11.85%	**24.73%**	15.05%	12.76%
Smallest	12.90%	15.05%	15.26%	15.05%	13.98%	15.03%
Rest	54.84%	73.12%	72.89%	60.22%	70.97%	72.21%
Total	100%	100%	100%	100%	100%	100%

Table 5. Probabilities of different price movements

We continue the analysis by estimating the OHR values through different methods. Figure 4 shows the evolution of the time varying OHR comparative with the static OHR for the out of sample period.

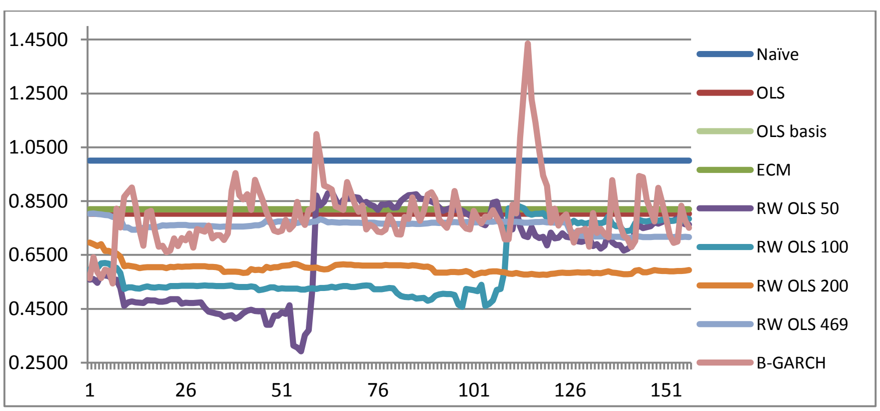

Figure 4. OHR evolution

The estimated static OHR using the OLS method and ECM are significantly smaller than the naive hedge ratio (the OLS OHR is 0.8037, the OLS basis OHR is 0.8195 and the ECM OHR is 0.8205). It can be observed that generally the OHR is below the naive one-to-one hedge ratio. The highest OHR is estimated by the B-GARCH model and is near 1.45. The smallest OHR is estimated by the RW OLS with 50 periods' window length and is near 0.30. Also, the OHR estimated by the B-GARCH model is the most volatile, while the evolutions of the OHR estimated by the OLS method using longer rolling window periods are smoother.

With a greater importance than the OHR itself is the hedging effectiveness. Table 6 presents the hedging effectiveness (HE) indicators for the OHR estimated using each of the described models.

Hedge ratio	Naïve	OLS	OLS basis	ECM	RW OLS 50	RW OLS 100	RW OLS 200	RW OLS 469	B-GARCH
HE	0.1913	0.2708	0.2665	0.2662	0.2910	0.2900	0.2804	0.2714	0.2774

Table 6. Hedging effectiveness

The naive hedge ratio obtains the smallest hedging effectiveness: a reduction in the variance of the hedged portfolio of only 19.13%. Also, all the time varying hedge ratios are characterized by higher HE indicators than the static ones. This shows the superiority of the time varying hedge ratios for the U.S. natural gas market. Among the time varying hedge ratios, the OLS method using rolling windows of 50 periods' length produces the greatest hedging effectiveness, a reduction in the variance of the hedged portfolio of 29.10%. Another remark to be made is that a negative relationship exists between the rolling window length and hedging effectiveness. Also, the B-GARCH model improves the hedging effectiveness only compared to the OLS that uses the longest rolling window.

V. Conclusions

Natural gas represents one of the most important commodities for the world economy, with an increasing importance. Several studies dedicated to this market emphasized the unpredictable and volatile behavior of the natural gas prices, thus the efficient way to hedge such risks becoming an important issue. Because of the basis risk, the naive hedge ratio does not minimize the risk of the hedged portfolio and appears the need to estimate the optimal hedge ratio (OHR). Although the natural gas market has a great importance, there are few papers that estimate the optimal hedge ratio for its case and our article comes to fill this gap in the literature.

First, we analyze the behavior of the natural gas prices during the period from 04.10.2000 to 26.09.2012, finding that the natural gas prices are characterized by a high volatility, with greater variations in the case of spot price. Also, the phenomenon of volatility clustering is present, making the hedging even more valuable. Then, we estimate the OHR and compute the hedging effectiveness for several methods. We find that the time-varying OHR outperform their static counterparts for natural gas market.

ACKNOWLEDGMENTS

This work was cofinanced from the European Social Fund through Sectoral Operational Programme Human Resources Development 2007-2013, project number POSDRU/159/1.5/S/134197 „Performance and excellence in doctoral and postdoctoral research in Romanian economics science domain".
This work was financed through IOSUD ASE (Institution for Doctorate Studies, Academy of Economic Studies).

REFERENCES

[1]**Adams Z., Gerner, M. (2012),** ***Cross Hedging Jet-fuel Price Exposure*****.** *Energy Economics*, 34, 1301–1309;
[2]**Alexander C., Barboza, A. (2007),** ***Effectiveness of Minimum-Variance Hedging: The Impact of Electronic Trading and Exchange-traded Funds***. *Journal of Portfolio Management*, 33, 46–59;
[3]**Baillie, R.T., Myers, R.J. (1991*),*** ***Bivariate GARCH Estimation of the Optimal Commodity Futures Hedge***. *Journal of Applied Econometrics*, 6, 109-124;
[4]**Bhattacharya, S., Singh, H., Alas, R.M. (2011*),*** ***Optimal Hedge Ratio with Moving Least Squares – An Empirical Study Using Indian Single Stock Futures Data*****.** *International Research Journal of Finance and Economics*, 79, 98–111;
[5]**Chang, C-L., McAleer, M., Tansuchat, R. (2011*),*** ***Crude Oil Hedging Strategies Using Dynamic Multivariate GARCH***. *Energy Economics*, 33, 912-923;
[6]**Chou, W.L., Fan, K.K., Lee, C.F. (1996),** ***Hedging with the Nikkei Index Futures: The Conventional Model versus the Error Correction Model***. *The Quarterly Review of Economics and Finance*, 36, 495–505;

[7]**Ederington, L.H. (1979),** ***The Hedging Performance of the New Futures Markets***. *Journal of Finance*, 34, 157–170;
[8]**Ederington, L.H., Salas, J.M. (2008),** ***Minimum Variance Hedging when Spot Price Changes are Partially Predictable***. *Journal of Banking & Finance*, 32, 654–663;
[9]**Erdős, P. (2012),** ***Have Oil and Gas Prices Got Separated****?. Energy Policy*, 49, 707–718;
[10]**Gebre-Mariam, Y.K. (2011),** ***Testing for Unit Roots, Causality, Cointegration and Efficiency: The Case of the Northwest US Natural Gas Market***. *Energy*, 36, 3489-3500;
[11]**Geman, H., Ohana, S. (2009),** ***Forward Curves, Scarcity and Price Volatility in Oil and Natural Gas Markets***. *Energy Economics*, 31, 576–585;
[12]**Juhl, T., Kawaller, I.G., Koch, P.D. (2012),** ***The Effect of the Hedge Horizon on Optimal Hedge Size and Effectiveness when Prices are Cointegrated***. *Journal of Futures Markets*, 32, 837-876;
[13]**Kroner, K. F., Sultan, J. (1993),** ***Time-Varying Distributions and Dynamic Hedging with Foreign Currency Futures***. *Journal of financial and quantitative analysis*, 28, 535-551;
[14]**Lee, C.-F., Lin, F. L., Tu, H. C. and Chen, M. L. (2009),** ***Alternative Methods for Estimating Hedge Ratio: Review, integration and empirical evidence***. Working paper, *Rutgers University*;
[15]**Lien, D., Tse, Y.K., Tsui, A.K.C. (2002),** ***Evaluating the Hedging Performance of the Constant Correlation GARCH Model***. *Applied Financial Economics*, 12, 791–798;
[16]**Paltsev, S., Jacoby, H.D., Reilly, J.M., Ejaz, Q.J., Morris, J., O'Sullivan, F., Rausch, S., Winchester, N., Kragha, O. (2011),** ***The Future of U.S. Natural Gas Production, Use and Trade***. *Energy Policy*, 39, 5309–5321;
[17]**Pesaran, M.H. (1997),** ***The Role of Economic Theory in Modeling the Long Run***. *Economic Journal*, 107, 178–191;
[18]**Power, G.J., Vedenov, D.V., Anderson, D.P., Klose, S. (2013),** ***Market Volatility and the Dynamic Hedging of Multi-commodity Price Risk***. *Applied Economics*, 45, 3891–3903.;
[19]**Ramberg, D. J., Parsons, J. E. (2012),** ***The Weak Tie Between Natural Gas and Oil Prices***. *The Energy Journal*, 33, 13-35;
[20]**Mansur, A., Masih, M., Albinali, K., DeMello, L. (2010),** ***Price Dynamics of Natural Gas and the Regional Methanol Markets***. *Energy Policy*, 38, 1372–1378;
[21]**Modjtahedia, B., Movassagh, N. (2005),** ***Natural-gas Futures: Bias, Predictive Performance and the Theory of Storage.*** *Energy Economics*, 27, 617– 637;

[22]**Mohr, S.H., Evans, G.M. (2011),** ***Long Term Forecasting of Natural Gas Production***. *Energy Policy*, 39, 5550–5560;
[23]**Moon, G.-H., Yu, W.-C., Hong, C.-H. (2009),** ***Dynamic Hedging Performance with the Evaluation of Multivariate GARCH Models****:* Evidence from KOSTAR Index Futures. *Applied Economics Letters*, 16, 913–919;
[24]**Mu, X. (2007),** ***Weather, Storage and Natural Gas Price Dynamics: Fundamentals and Volatility***. *Energy Economics*, 29, 46–63;
[25]**Serletis, A., Andreadis, I. (2004),** ***Random Fractal Structures in North American Energy Markets***. *Energy Economics*, 26, 389– 399;
[26]**Serletis, A., Rangel-Ruiz, R. (2004),** ***Testing for Common Features in North American Energy Markets***. *Energy Economics*, 26, 401–414;
[27]**Tseng, J.J., Li, S.P. (2011),** ***Asset Returns and Volatility Clustering in Financial Time Series***. *Physica A*, 390, 1300–1314.