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Natural Gas Markets: How Sensitive to Crude Oil Price Changes?

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Abstracts

This paper investigates sensitivity of U.S. natural gas price to crude oil price changes, using time-varying coefficient models. Identification of the range of variation of the sensitivity of natural gas price to oil price change allows more accurate assessment of upper and minimum risk levels that can be utilized in pricing natural gas derivatives such as gas futures and option contracts, and gas storage facility contracts.

Keywords: Natural gas, Sensitivity, GARCH, Volatility, Skewness, Kurtosis
JEL Codes: C22,C32, Q4

1-Introduction:

For many years in the past, natural gas and refined petroleum products viewed as close substitutes, as major users of natural gas substituted one product for the other depending on the price level of each. As a result, a common view held by some (Brown and Yucel, 2007) is that natural gas prices adjust to crude oil prices which in turn determined by world oil market conditions. Such stable relationship between oil prices and natural gas prices led in the past to the use of rules of thumb in energy industry that relate natural gas prices to those for crude oil. The simplest of these rules predict a constant relationship between the two prices[1]. However, as oil prices surged upward in past recent years the association between the two energy prices seemed more complex than can be explained by the simple relationship implied by the rules of thumb. As a result, in recent years the

[1] One simple rule determine natural gas prices as one tenth of crude oil prices, whereas another rule that takes the energy content of a barrel of oil, determine natural gas price as one sixth of crude oil price. For more details about these rules see Brown and Yucel (2006).

relationship between crude oil prices and natural gas prices became the focus of research work in the field of energy economic.

Serletis and Ricardo (2004) investigate the strength of shared trends and shared cycles between crude oil prices and Henry Hub natural gas prices using testing procedure suggested by Engle and Kozicki (1993), and Vahid and Engle (1993) to reject the null-hypothesis of common and codependent cycles. Similarly, Bachmeir and Griffin (2006) indicate although natural gas prices in recent years have shown upward movements with crude oil prices, the natural gas prices seemed to lag well behind oil price movements. Serletis and Shahmoradi (2006) indicate price volatility in the US natural gas market is mainly due to seasonal effects and significant lead time effects associated with production and delivery. However, Villar and Joutz (2006), Asche and Sandsmark (2006) detect long-term relationship between oil and natural gas prices. In a different theoretical framework, Chen and Forsyth(2006), use stochastic regime switching models to confirm regime switching models explain better the dynamics of gas derivative prices. The findings of regime switching dynamic models support evidence of time-varying coefficient models rather than constant coefficient models implied by rules of thumb models. Drawing together the aforementioned studies it can be concluded that even though in the long term gas prices adjust to crude oil prices, in the short term the dynamics of each of the two prices is affected by different factors. While speculative events in oil future markets play important role in influencing short term oil prices, gas prices in the short term mainly affected by its own supply and demand disruptive shocks, such as extreme weather events (hurricanes-related production shut-ins in the Gulf of Mexico), seasonality, and supply storage constraints.

The primary objective in this paper to investigate the relationship between natural gas price and crude oil price changes using time-varying coefficient specification, under two different crude oil price levels, low and high oil prices (below and above $40 per oil barrel). The distinction between high and low oil price levels is based on the graphical illustrations included in the appendix, which indicate at low oil price levels (graph 3) both markets exhibit higher volatility, and at high oil prices (graph 2) they show more stability[2].

The remaining part of the paper structured as follows. Section two includes basic statistical analysis. Section three illustrates the methodology of the research. Section four includes estimation results, and the final section concludes the study.

2. Data analysis:

Data employed in this study are weekly Henery Hub natural gas prices and West Texas intermediate crude oil prices as reported in the Wall Street Journal and recorded in the data base of the Center for Energy Studies of Luisiana State University. The sample period covers from January-2-1996 to January-30-2008, including 516 observations. Price returns in this paper defined as the log first difference, $\log(p_t / p_{t-1})$. Results in table (1) indicate the two energy prices yield positive mean returns, and almost equal volatility levels. The positive skewness results indicate a higher probability of rise of the two prices during the sample period. The high value kurtosis statistics indicate the stock price returns distribution is characterized by high peakness (fat tailedness) which imply probability of a higher risk cannot be

[2] A factor that contributes to natural gas market volatility at low crude oil price, is the fuel oil substitution effect .

ruled out . The Jarque-Bera (JB) test statistic provides clear evidence to reject the null-hypothesis of normality for the unconditional distribution of the two price changes. The sample autocorrelation statistic indicated by Ljung-Box , Q statistic, show the Q(5) test statistic reject the null hypothesis of uncorrelated gas price returns for five lags, but fails to reject correlation in oil price returns. The high values for $Q^2(5)$ test statistic suggest conditional homoskedasticity can be rejected for the gas price, but not for oil price. However, to test the presence of hetroskidasticity more formally the LM test is employed. Results of LM statistics for ARCH(1) and ARCH(5) error terms confirm the significance of ARCH effects in both prices.

Table (1): Summary statistics of log-differenced Energy prices.

	Gas	**Oil**
Mean	**0.004**	**0.01**
Std.Deviation	**0.12**	**0.14**
Skewness	**2.62**	**18.1**
Excess kurtosis	**30.1**	**377**
JB test **p-value**	**18808** **(0.00)**	**24850** **(0.00)**
Q(5) **p-value**	**11.8** **(0.04)**	**0.60** **(0.98)**
Q^2(5) **p-value**	**40.7** **(0.00)**	**0.01** **(0.99)**
LM ARCH(1) **p-vlue**	**674** **(0.00)**	**98** **(0.00)**
LM ARCH(5) **p-value**	**837** **(0.00)**	**909** **(0.00)**

3- Methodology

3.1: Volatility modeling:

Although the simple GARCH specification is widely used in the empirical research of finance, there are substantial evidences that volatility of asset returns characterized by time varying asymmetry (Glosten, Jagannathan and Runkle (1993). As a result, to avoid misspecification of the conditional variance of natural gas price changes, in this paper the asymmetric GARCH model is adopted. The asymmetric GARCH specification allows a quadratic response of volatility for positive and negative shocks, but maintains the assertion that the minimum volatility will result when there is no shocks[3]. More specifically, the sensitivity of natural gas price change to crude oil price changes determined as follows:

$$\Delta G_t = \eta + \beta_t \Delta P_t + I_t D_t + e_t \qquad (1)$$

$$where \quad e_t \overset{d}{\sim} f(\mu, \sigma; \omega)$$

$$and \quad \sigma^2{}_t = \alpha_0 + \sum_{q=1}^{Q} \alpha_q e^2{}_{t-q} + \sum_{p=1}^{P} \delta_p \sigma^2{}_{t-p} + \varepsilon_t$$

where ΔP_t is the change in crude oil price, and ΔG_t is the change in natural gas price, D_t is a dummy variable reflecting change in demand for natural gas due to the regular seasonal effects[4]. η is a constant, β_t is time-varying coefficient, and e_t is a random error term specific to ΔG_t and assumed to be

[3] Any selection of an appropriate ARCH/GARCH model requires having a good idea of what empirical regularities the model should capture. Among documented other regularities in the literature are thick tails that characterize asset returns, and volatility clustering, which refers to the phenomena that large changes in volatility tend to be followed by large changes of either sign, and small changes to be followed by small changes.

[4] To take into account seasonal demand changes, set D_t=1 for all winter weeks from November to April, and zero otherwise.

uncorrelated with ΔP_t. The random term, e_t , is set to reflect the seasonal random shocks due to the extreme weather events like hurricanes.

f(.) is the density function of the random term, e_t, where $E(e_t) = \mu$, $v(e_t) = \sigma^2{}_t$, and ω is a vector of parameters reflecting skewness and kurtosis parameters. Given negative random shocks cause upward pressure on gas prices, it is assumed the error terms, e_t in equation (1) follow a half-normal distribution, so that the restriction $e_t \geq 0$ is imposed.

As the coefficient β_t varies over time, equation (1) hypothesize a nonlinear relationship between change in natural gas prices and crude oil price changes. The slope coefficient, β_t, is often called the measure of volatility sensitivity, or systematic risk. In this case it tells us that when change in crude oil price for a given period is 1% above its mean, the corresponding change of natural gas price is $\beta\%$ higher than its mean return, and the opposite is true when oil price change is 1% below its mean.

In GARCH-type models the variance covariance matrix of change in the prices of crude oil and natural gas are not constant over time. In this case the beta coefficient defined as:

$$\beta_t^{GARCH} = \frac{\operatorname{cov}(\Delta G_t, \Delta P_t)}{\operatorname{var}(\Delta P_t)} \qquad (2)$$

$$= \frac{\rho \sqrt{\operatorname{var}(\Delta G_t)}}{\sqrt{\operatorname{var}(\Delta p_t)}}$$

where ρ is the correlation coefficient between changes in the two prices. Thus, equation (1) becomes,

$$\Delta G_t = \eta + \beta_t^{GARCH} \Delta P_t + + I_t D_t + e_t \qquad (3)$$

One approach to estimating β_t^{GARCH} is to estimate conditional covariance, $Cov(\Delta G_t, \Delta P_t)$ and conditional variance $Var(\Delta P_t)$. Since no seasonal shocks attributable to crude oil markets, the conditional variance of oil price changes determined by symmetric GARCH- type specification . However, when estimating conditional variance of gas price changes we need to include seasonal random shocks that reflects hurricanes related disruptive changes in gas prices. Thus, when incorporating the constraint $e_t > 0$, in equation (1), the variance of gas price changes determined as:

$$v(\Delta G_t) \equiv \sigma^2{}_t = \gamma + \sum_{j,q} \alpha_i{}^{+} e^2{}_{t-j} + \sum_{j,p} \delta_j \sigma^2{}_{t-j} \qquad (4)$$

The condition that $\alpha^{+} > 0,$ captures the upward pressure on gas prices due to negative supply shocks.

3.2: Skewness effect:

It is well documented that even asymmetric GARCH models fail to fully account for skewness and leptkurtosis of high frequency financial time series when they are assumed to follow Normal or symmetric student's t-distributions. This has led to the use of asymmetric non-Normal distributions to better specify conditional higher moments. An important candidate in this respect is Hansen's (1994) distribution. Despite there are also other distributions that allow for skewness and excess kurtosis we choose Hansen's distribution due its superiority in empirical performance (Patton, 2004). Given the standardized errors $z_t = \frac{\varepsilon_t}{\sqrt{\sigma^2{}_t}}$, with mean zero and variance one, then Hansen's (1994) autoregressive conditional density model with skewed error terms can be specified as:

$$skt(z \setminus \phi, \theta) = \begin{cases} bc\left(1 + \dfrac{1}{\theta - 2}\left(\dfrac{bz + a}{1 - \phi}\right)^2\right)^{-(\theta+1)/2} & if \;\; z < -a/b \\ bc\left(1 + \dfrac{1}{\theta - 2}\left(\dfrac{bz + a}{1 + \phi}\right)^2\right)^{-(\theta+1)/2} & if \;\; z \geq -a/b \end{cases} \qquad (6)$$

where Γ is a gamma function, and

$$a = 4\phi c \frac{\theta - 2}{\theta - 1}, \quad b = 1 + 3\phi^2 - a^2 \ , \quad c = \frac{\Gamma(\theta + 1)/2}{\sqrt{\pi(\theta - 2)}\Gamma(\theta/2)} \qquad (7)$$

Specification of conditional distribution of the standardized residuals, $Z_{t,}$ in equation (6) is determined by two parameters, Kurtosis (θ) and the skewness parameter (ϕ).The two parameters are restricted to $\theta > 2,$ and $-1 < \phi < 1$.
When $\phi = 0,$ the skewed t-distribution tend to symmetric t-distribution, and when $\theta \to \infty$, tend to standardized Normal distribution.
Hansen's skewed t-distribution is fat tailed, and skewed to the left (right) when ϕ is less (greater) than zero. Similar to the case of Student's t-distribution, when $\theta > 2,$ Hansen's skewed t-distribution is well defined and its second moment exist, while skewness exist if $\phi \neq 0$ and kurtosis is defined if $\theta > 4,$.
The log-likelihood function of the GJR-skt is defined as:

$$L(\Omega;\Psi_{t-1}) = \sum_{t=2}^{T} \ln[SKt(z \setminus \theta,\phi;\Psi_{t-1})]$$

The maximum likelihood estimator for Ω is the solution of maximizing the log likelihood function with respect to the unknown parameters.

3.3: Performance Evaluation:

Since we have two competing models to determine conditional volatility of the two energy prices, it is important identifying which model better describes volatility dynamic of the two prices. In this paper the predictive power of volatility forecast, and the log-likelihood criterias employed to distinguish between the two models (skewed t-distribution and normal distribution).

To test the forecasting power of these models, for the natural gas, s-step ahead forecast for the conditional variance in equations (4) can be set as:

$$\hat{\sigma}^2{}_{t+s\setminus t} = \gamma + \alpha^{+} e^2{}_{t+s-1} + \delta\sigma^2{}_{t+s-1\setminus t} \qquad (5)$$

However, for crude oil a positive and negative shocks assumed to have equal chances, so that:

$$E(I(\varepsilon_t > 0) = p(\varepsilon_t > 0) = 0.5$$
$$E(I-1)(\varepsilon_t \le 0) = p(\varepsilon_t \le 0) = 0.5$$
and
$$E(\varepsilon_t{}^2 \setminus \Omega_t) = \sigma^2{}_t$$

Where ε_t is the error term corresponding to AR(q) specification of crude oil price changes.

Since $\varepsilon^2{}_t$ and the indicator function $I_t(\varepsilon_t)$ are uncorrelated, then s-step ahead forecast can be stated as:

$$\hat{\sigma}^2{}_{t+s\setminus t} = w + [(0.5\alpha^{+} + 0.5\alpha^{-}) + \delta]\sigma^2{}_{t+s-1\setminus t} \qquad (6)$$

The parameters of the two models estimated using the sample data up to three weeks before the end of the sample date (Jan/13/2007). And then a forecast of one week ahead (Jan-20 observation) is computed. Using the estimated parameters and the one week-ahead forecast value of volatility a new forecast for volatility of Jan-27, is computed from equations (5) and (6) to obtain two weeks ahead forecast value. This procedure is repeated until we exhaust the actual realized values.

To test the predictive power of the two competing models (normal and skewed t-distributions) the Root Mean Squared Error (RMSE) employed, which is computed by comparing the forecast values F_{t+j} with the actually realized values, A_{t+j}, or $RMSE(k)=\sqrt{\sum_{j=0}^{N_k-1}\frac{[F_{t+j+k}-A_{t+j+k}]^2}{N_k}}$

Where k=1,2,3 denotes the forecast step, N_k, is total number of k-steps ahead forecasts.

Diebold and Mariano (1995) (DM) test has been employed to compare the accuracy of forecasts. When comparing forecasts from two competing models; model A, (Normal distribution error terms model), and model B (skewed t-distribution error terms model), it is important to verify that prediction of either of these models is significantly more accurate, in terms of a loss function, DM(v), than the other one. The Diebold and Mariano test aims to test the null hypothesis of equality of forecast accuracy against the alternative of different forecasts across models. The null hypothesis of the test can be written as:

$$v_t = E(h(e_t^{\,A})-h(e_t^{\,B}))=0 \qquad (7)$$

where $h(e_t^{\,i})$ refers to volatility forecast error of model i =A, B, when performing k-steps ahead forecast. The Diebold and Mariano test uses the autocorrelation-corrected sample mean of v_t in order to test significance of equation (7). If N observations available, the test statistic is:

$$DM = [\hat{w}(\overline{v})]^{-1/2}\,\overline{v}$$

$$where \quad \hat{w}(\overline{v}) = \frac{1}{N}\{\hat{\rho}_0 + 2\sum_{h=1}^{K-1}\hat{\rho}_h\}$$

and

$$\hat{\rho}_h = \frac{1}{N}\sum_{t=h+1}^{N}(v_t - \overline{v})(v_{t-h} - \overline{v})$$

Under the null hypothesis of equal forecast accuracy, DM is asymptotically normally distributed.

4: Empirical results

The analysis in this paper investigate the association between conditional volatility of crude oil and natural gas prices assuming normal distribution and skewed-t distribution models. Graphical illustrations included in the appendix (Graphs 1- 3), indicate natural gas price is relatively more sensitive to crude oil price changes at low oil price levels (below $40 per oil barrel); as compared to the case of high oil price levels, which is relatively more stable. More formally, the sensitivity of natural gas price to crude oil price changes reported in table (2) include estimation result of time-varying coefficient model of equation (3), under two alternative specification of conditional volatility, normal distribution and skewed t-distribution models. Normal distribution parameters estimated using MLE method, whereas conditional skewness and kurtosis parameters of skewed t-distribution estimated using MLE and quasi-Newton optimization algorithm, which carried out using shazam (version 10) programming procedure.

Log likelihood values reported in tables (2) and (3), support the normal distribution specification over skewed t- distribution model. Also Diebold-Mariano test results reported in table (4), strongly suggest the normal distribution model outperforms skewed t-distribution model, as it yield the lowest values of the RMSE loss functions, implying the normal distribution specification yield superior forecast performance for forward-looking beta values. Given the normal distribution model better describes the dynamics of conditional volatility, we take into account results in table (2).

The mean values of beta coefficients in table (2), show at low oil price levels, natural gas price rise by 13 cents for each dollar increase in crude oil prices; whereas at the high oil price levels the sensitivity of natural gas price is 9 cents for each dollar increase in crude oil price. However, over longer period of time the adjustment of natural gas price changes to crude oil price change is 12 per cent.

Investigation of the range of the sensitivity values, show the mean value of sensitivity is closer to its minimum value, implying natural gas price sensitivity in general is highly skewed towards those values at the lower boundary. But at the same time it shows, there are certain periods of time where sensitivity of natural gas price change to oil price changes hit upper highest values, scoring up to 51 per cent. Results in table (2), also report significance of regular seasonal effects on changes in natural gas price.

Table (3) present estimation results of conditional volatility, indicated by equations (4) and (6). The significance of the coefficients (α^{-}) and (α^{+}) of crude oil price volatility imply negative and positive shocks have equally important effects on volatility of crude oil price. This result support the view held by some (Asch, et al., 2006), that speculative trading positions in oil future markets affect significantly oil price changes.

Table (2): Natural gas sensitivity (half-Normal distribution)

sectors	Low oil prices*	high oil price*	Full-sample
Beta: **(low/high)** **mean** **range statistic**	(0.05/0.51) 0.13 0.46	(0.07/0.23) 0.09 0.16	(0.04/0.48) 0.12 0.44
Seasonal effect: **D** **(p-value)**	--	---	0.015 (0.06)
Ln L	325	245	463

Note: The main entries are mean values of Betas.
*Low and high oil prices are respectively below and above $40 per oil barrel .

Table (3): Natural gas sensitivity (skewed t-distribution)

sectors	Low oil prices*	high oil price*	Full-sample
Beta: **(low/high)** **Mean** **Range statistic**	(0.01/0.22) 0.09 0.21	(0.004/0.13) 0.06 0.09	(0.01/0.16) 0.07 0.15
Seasonal effect: **D** **(p-value)**	--	---	0.023 (0.01)
Ln L	252	135	453

Note: The main entries are mean values of Betas.
*Low and high oil prices are respectively below and above $40 per oil barrel

Table (4):Conditional volatility parameter estimates

	Oil GARCH(1,1)		**Gas GARCH(1,1)**	
	Skew-t	**Normal**	**Skew-t**	**Half-Normal**
ω **(p-value)**	0.03 (0.04)	0.002 (0.00)	0.77 (0.38)	0.001 (0.00)
δ **(p-value)**	0.17 (0.01)	0.05 (0.23)	0.02 (0.34)	0.33 (0.00)

α^{+} **(p-value)**	0.03 (0.04)	0.01 (0.83)	0.11 (0.04)	0.04 (0.10)
α^{-} **(p-value)**	-0.05 (0.03)	0.018 (0.51)	-- --	---
ϕ **(p-value)**	0.32 (0.28)	-	0.16 (0.09)	-
θ **(p-value)**	3.86 (0.00)	-	4.21 (0.08)	-
LnL	1345	2466	1246	1750

The order of GARCH(1,1), determined based on convergence of Maximum Likelihood Function.

Table (5): RMSE Loss functions and Diebold & Mariano test.

	RMSE Loss Functions Normal	skew t	D&M statistic
High oil price (p-value)	0.11	0.28	9.2 (0.05)
Low oil price (p-value)	0.09	0.22	7.1 (0.06)

*The loss functions are based on three days ahead forecast errors. Root Mean Square Error (RMSE) and Diebold-Mariano (1995) test results in table (4) are based on the full sample period and on the low oil price period which is the period from January-2-1996 to July-14-2004, when crude oil price was below $40 per barrel.

5. Conclusion

Taking into account seasonality, and disruptive random shocks that affect natural gas storage capacity, the primary aim in this paper to identify the sensitivity of natural gas price changes to crude oil price changes, using time-varying coefficient specification. Unlike the fixed coefficient models, employed in previous similar researches, this approach has the benefit of measuring the range of variation of the sensitivity of natural gas price to oil price changes based on the covariance of the two prices. Identification of the range of variation of the sensitivity of natural gas price to oil price change allows better assessment of upper and minimum risk levels that can be utilized in pricing derivatives on natural gas such as gas futures and option contracts, and gas storage facility contracts. An important empirical regularities that have been taken into account in this paper are thick tail phenomena that characterize probability of extreme events occurrence, and skewness. To reflect surge in natural gas price due to extreme seasonal events such as hurricanes, half-normal distributed positive error terms adopted in the computation of conditional volatility of natural gas price. The findings in the paper indicate the association between the two prices has short term dynamics, reflected in wide range variability of natural gas price sensitivity to oil price changes. Taking into account the superior performance of the normal distribution model, compared to skewed t-distribution specification, estimation results in the paper indicate, on average, at low oil price levels (below $40 per oil barrel), natural gas price increase by 13 cents for each dollar increase in crude oil price; whereas for high oil prices the sensitivity of natural gas price estimated 9 cents for each dollar increase in crude oil price. However, over longer period of time the adjustment of natural gas price to change in crude oil price is 12 per cent on average. Looking at the range of the sensitivity values, it can be realized that, the mean value of sensitivity is closer to its minimum boundary value, implying natural gas price sensitivity in general is highly skewed towards those values at the lower boundary. But also indicate, even though the sensitivity values on average are low, there are certain periods of time where sensitivity of natural gas price to crude oil price changes hit upper extreme values, reaching up to 51 per cent.

The findings in the paper also shows regular seasonal demand effects remain a significant factor in natural gas price changes.

While the analysis in the paper related to short term dynamic analysis, an important future extension of this research include, investigation of the long term linkage between the two energy prices using non-linear cointegration techniques to accommodate the nonlinear dynamic nature of time-varying coefficient models.

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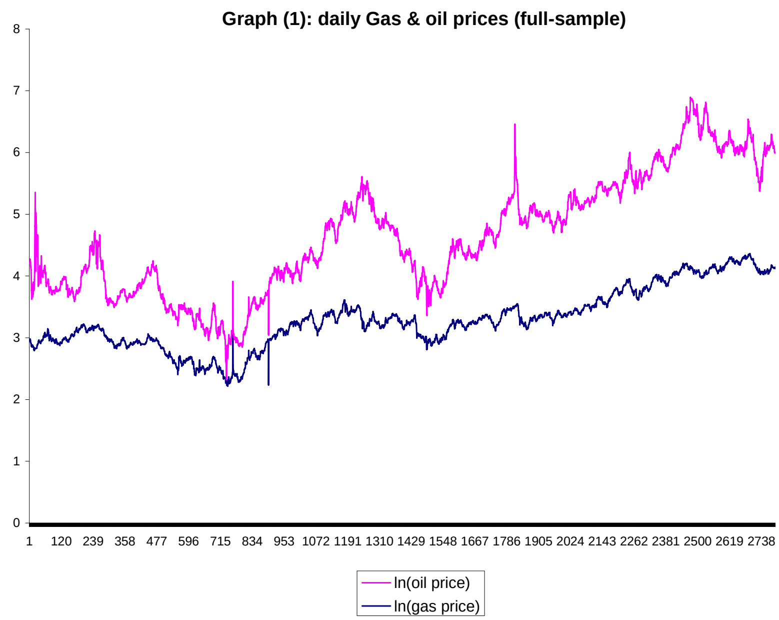
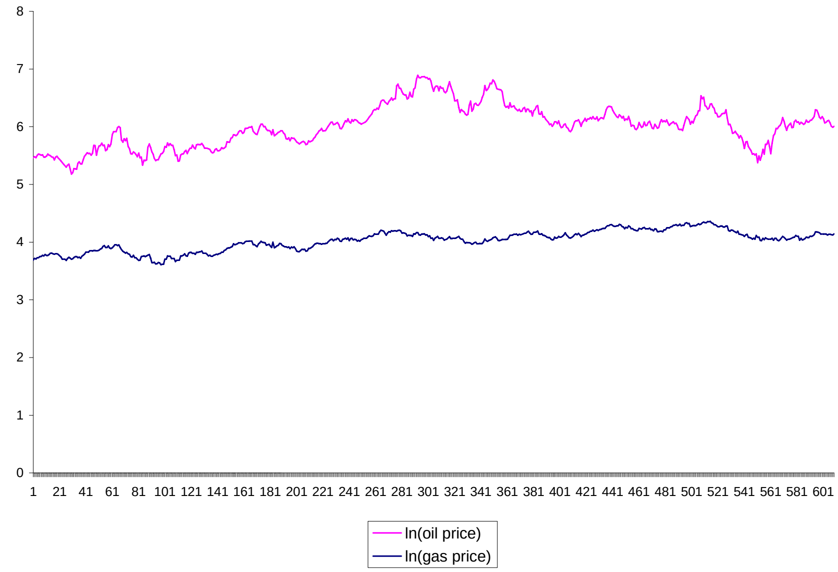
Appendix


Graph (1): daily Gas & oil prices (full-sample)
8
7
6
5
4
3
2
1
0
1 120 239 358 477 596 715 834 953 1072 1191 1310 1429 1548 1667 1786 1905 2024 2143 2262 2381 2500 2619 2738
ln(oil price)
ln(gas price)

Graph (2):daily gas & oil prices (High oil prices)



Graph (3): daily gas & oil prices (low oil prices)