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Fundamentals and US Natural Gas Price Dynamics

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Fundamentals and US Natural Gas Price Dynamics

Abstract

Investigation into the relations between market fundamentals and US natural gas prices is carried out in the regime-switching framework. To test the hypothesis that US natural gas market may switch between two states of market: bullish market and bearish market, a 2-state regime-switching model with Markov transition chain is carried out. GARCH effects are also built into the model to account for the conditional heteroskedasticity. Short-term forecasts based on the regime-switching model are also provided.

Empirical results suggest that real world natural gas price behavior is far more complicated than that predicted by fundamental models. Volatility which cannot be explained by fundamentals plays an essential role in natural gas price behavior. The major contribution of this study lies in the effort to ease the deficiency of current fundamental-based models on commodity pricing due to high volatility by applying regime-switching models.

I. Introduction

Natural gas prices in both spot and forward/future markets are characterized by high volatility, which has made forecast of price based on market fundamentals a very challenging task. The classic theory of storage states that fundamental factors such as supply, demand and inventory conditions affect the variances of spot and forward/future prices of storable commodities, and also the correlation between these two sets of markets. As Pindyck (1994, 2001) pointed out, the volatility of commodity prices links the commodity cash (spot) market with forward/future markets. The equilibrium of these two sets of markets also “affects and is affected by changes in the level of price volatility”. Ng and Pirrong (1994) investigates the industrial metal market and find “variations in volatility are largely attributable to variations in fundamental demand and supply conditions rather than speculative noise trading”, although speculation activities in commodity markets are quite common with the introduction of financial instruments. This paper uses a two-state regime-switching model to investigate the relationship between market fundamentals and US natural gas spot price variations.

Observations of US natural gas market suggest that there exist two states of the market: bullish market and bearish market, and the market switches between these two states according to a Markov chain. Therefore, these fundamentals which drive the natural gas price would function differently in different states. To test this hypothesis, a Markov-switching model is proposed and investigation of the relationship between fundamentals and return variances are examined in this framework. The results show that predicted and observed behaviors of natural gas price and return variances have very close correspondence which suggests market fundamentals determine price dynamics.

Meanwhile, the regime-switching model also improves forecast accuracy compared with the model which has the same structure except the regime switching assumption. As suggested by Ng and Pirrong (1994), generalized autoregressive conditional heteroskedasticity (GARCH) is also considered in the regime-switching framework to model the return variances. Based on Markov-switching model estimation results, short-term forecasts of natural gas price with/without Markov-smoothing effects are provided, and we find forecasts with Markov-smoothing effects are more reliable.

The remainder of this paper is organized as follows. The next section identifies fundamental drivers that affect natural gas market. Section III describes the theoretical model and also the data used for estimation and forecasts. Section IV reports and interprets the results. Section V provides conclusions of the work.

II. Fundamentals and US natural gas market

Fundamental factors that affect natural gas demand and supply, such as seasonality, weather events, storage changes, demand and supply shocks, are all drivers that determine natural gas price dynamics, especially in the short term. Because natural gas consumption is seasonal while production is constant, natural gas storage is built during the summer for winter use. This seasonality would result in the natural gas price in summer to normally be lower than the price in the winter. Variation in weather would also affect price because more heating and/or cooling degree days than average would increase the demand, and then the price.

The role of inventory on natural gas price dynamics is worth thorough investigation. The theory of storage, which was proposed by Kaldor (1939) first, then elaborated by Working (1948, 1949), William (1986) and Brennan (1991), asserts that stocks of

commodity bring “convenience yield” to stock holders, for the stocks-on-hand enable them to respond more flexibly and efficiently to unexpected supply-and-demand shocks. The theory posits that marginal convenience yield would decline while inventory level increases; hence, firms would have fewer tendencies to build up inventory. Empirical evidence has been provided by Working (1948, 1949) and Brennan (1991) to support this hypothesis. Since storage can function as marginal supply for storable commodity, changes of storage would have direct effects on natural gas prices. If the storage level is higher than normal level, the price of natural gas would be pressured downward; meanwhile, when the storage level is lower than normal level, the price would be expected to go up in short run, holding the other relevant factors constant.

Storage can also affect natural gas spot price via the existence of future/forward markets. The linkage between forward/future prices and spot prices is established due to arbitrage. Following Ng and Pirrong (1994), arbitrage-free relation between spot and forward prices can be expressed as:

$$F_t - SC_{t,T} = S_t e^{(r_{t,T} - c_{t,T})(T-t)} \quad (1)$$

Let F_t be the forward/future price at time t for delivery at time $T > t$, and S_t be spot price at time t . Moreover, let $SC_{t,T}$ be the cost of physically storing one unit of natural gas from time t to T , and denote $r_{t,T}$ as the default-free interest rate at time t over the same period. Finally, let $c_{t,T}$ denote the convenience yield generated by inventory of natural gas from time t to T . The relation between spot and forward prices can be expressed in terms of interest rate and storage adjusted spread as:

$$\frac{\ln(F_t - SC_{t,T}) - \ln(S_t)}{T-t} - r_{t,T} = -c_{t,T} \leq 0 \quad (2)$$

The left-hand side of equation (2) is so-called interest rate and storage adjusted spread which is proposed by Ng and Pirrong (1994). Since there is no storing cost of natural gas available and the forward price employed here is one-month prompt future price, log transformation of spread is used in this study instead of the interest and storage adjusted spread. It is obvious that (interest and storage adjusted) spread summarizes supply, demand and inventory conditions at time t . Although shocks in supply and demand are not predictable and hard to measure, market reactions to these shocks are reflected in spot and forward prices and also storage changes, therefore, spread between forward and spot prices and also volatilities of these two sets of prices would reveal this information. Inclusion of spread and volatility into the analysis is essential for the investigation of the relation between fundamentals and natural gas price dynamics.

In this study, impacts of crude oil price changes on natural gas prices are also considered. Fuel switching between natural gas and residual fuel oil makes natural gas prices move closely with crude oil price, but these two energy commodities are not perfect substitutes to each other. In short-run, fuel switching is subject to a technological constraint, while in the long run one would expect natural gas and oil use to stay aligned. Relationship between natural gas and crude oil prices has been studied by many researchers; however, the conclusions are not consistent. Bachmeir and Griffin (2006) reports a weak relationship between oil and US natural gas prices. Villar and Joutz (2006) find oil and natural gas co-integrated with unit root. Asche, Osmundsen and Sandsmark (2006) find co-integration between natural gas and crude oil prices in U.K. market after natural gas deregulation, with crude oil price leading the price of natural gas. In this study, crude oil price is treated as a short-term driver for natural gas price change. There

are two major reasons for this treatment. First, in general, natural gas and crude oil are substitutes for each other especially in industries like power generation; hence, prices of natural gas and crude oil share some common patterns. Secondly, the price of crude oil actually affects “sentiment” of the market. Technically, the price of crude oil is a major index of the whole energy market, which signals the overall trend of energy markets. Figure 1 provides weekly prices movement of natural gas and crude oil from Jan. 2, 2004 to July 4, 2008. It can be seen that there exists some co-movement between these two prices. There also exists obvious differential movement between these two prices. This fact confirms the common conjectures about natural gas price movement. The dramatic spike from August 2005 to February 2006 is mainly caused by Katrina and high winter demand for heating.

III. Theoretical Model and Data

Regime-switching model with Markov chain¹ will be adopted to model the weekly change of natural gas price. Under the assumption that market switching between two states: bullish market state and bearish market state according to a Markov transition matrix, U.S. natural gas price movement process would be modeled as a mixed process which follows different time series process over different sub-samples. Hence, these fundamental factors that affect the market conditions of natural gas would have different effects on price in different regimes. The use of regime-switching model would allow one to infer the probability information with which the market stays in each state at every time point. Also the advantage of using Markov chain over a deterministic specification for a data generating process involved with regime changes is to allow researchers to

¹ For more information about regime-switching model with Markov chain, see James D. Hamilton (1994), Time Series Analysis. Chapter 22, Modeling Time Series with Changes in Regime.

generate meaningful forecasts prior to the change that take into account the probability of changing from regime 1 to regime 2. A further advantage of Markov chain is its flexibility. As explained by Hamilton (1994), there exist some value in specifying a probability law consistent with a broad range of different outcomes, and choosing particular parameters within that class based on data available. Development of Markov-switching model with time-varying transition probability brings more flexibility into modeling.

For Markov transition probability matrix, it can either be exogenously determined (constant over time) or endogenously determined (time varying) by some major economic fundamentals. This paper explores both types of models to find the suitable specification.

Weekly data of spot and 1-month prompt future prices of US natural gas traded in New York Mercantile Exchange (NYMEX) are used. US storage data for natural gas are provided by Energy Information Administration, Department of Energy. Heating degree days (HDD) and cooling degree days (CDD) data are obtained from National Weather Service. West Texas Intermediate (WTI) Cushing Spot traded in NYMEX is used as spot price for crude oil. The sample period is from Jan. 2, 2004 to June 26, 2009.

The basic theoretical two-state Markov-switching model is defined as following:

$$\Delta \ln(p)_t = x_t \beta_{s_t} + \varepsilon_{s_t} \quad (3)$$

$s_t = 1$ if the state is bull market at time t

$s_t = 0$ if the state is bear market at time t

$$\beta_{s_t} = \beta_0(1 - s_t) + \beta_1 s_t \quad (4)$$

$$\varepsilon_{s_t} \sim N(0, \sigma_{s_t}^2) \quad (5)$$

$$\sigma_{s_t}^2 = \sigma_{s_0}^2 (1 - s_t) + \sigma_{s_1}^2 s_t \quad (6)$$

$$\Pr(s_t = j | s_{t-1} = i, y_t, x_t) = p_{ij} \quad i, j \in \{0,1\} \quad (7)$$

To account for the conditional variance h_{s_t} in spot price return, it is assumed that in each state there is a GARCH (1,1) process is involved and defined as:

$$h_{s_t} = \alpha_{s_t} + \delta_{1,s} h_{s_{t-1}} + \delta_{2,s} \epsilon_{s,t-1}^2 \quad (8)$$

For simplicity and ease of computation, linearity for the basic structure model in each state is assumed. Meanwhile, regime switching assumption allows certain non-linearity in the model specification. Dependent variable is the log transformation of natural gas spot price, differenced weekly. Figure 2 gives dependent variable. It can be seen that weekly difference of log of natural gas spot prices demonstrates high volatility.

In view of seasonality, monthly dummies are also included. Factors such as crude oil price change (weekly), weekly storage deficit/surplus change, weekly changes of HDD and CDD, and also lagged spread are all included. As stated before, due to availability of data, in this study spread constructed by using log of forward price minus log of spot price is used instead of the interest rate and storage adjusted spread which can be constructed as equation (2) expresses. The lagged value of spread is included in the regression to account for the fact that commodity price process is a mean-reverting process, as Ng and Pirrong (1994) suggested.

In the attempt to fit the time-varying transition probability Markov-switching model, factors that may influence the transition probability are specified as: HDD weekly change, CDD weekly change, storage deficit/surplus change, and crude oil weekly price change.

For the estimation of Markov-switching models, EM algorithm is applied to get all the parameter estimates and inferred probability with which the market can be viewed as bullish or bearish state.

IV. Results and Interpretation

A series of model have been fitted to see which model specification is more suitable. Fundamental linear model without regime-switching assumption but with GARCH (1,1) is supported by the data which suggests some variation of the natural gas price can be predicted given the current information set, and the significance of the fundamentals show that fundamental factors affect natural gas spot price return just as expected. Also LR test shows that the monthly dummies are significant collectively. Significance of lagged spread is consistent with the common conjecture that natural gas price is autoregressive. Table 1 presents the estimation results of GARCH (1,1) model.

Estimation results show that Markov-switching model with time-varying transition probability matrix is not support by the data. The main model specification used in this research paper is Markov-switching model with constant transition matrix. GARCH (1,1) is also built into the regime-switching model. However, the assumption that different state has different GARCH (1,1) specification is not supported by the data.

The estimation results of Markov-switching model are listed in table 2. The regime-switching assumption is supported by the data and the LR test shows that monthly dummies are collectively significant but don't switch across states. Fundamental factors such as weekly difference of log of crude oil price, weekly difference of storage, and lagged spread switch across states while other fundamental factors (HDD and CDD) show non-switching effects. The constant term in state 2 is not significantly different

from zero while in state 1 the coefficient is negative and significant, which suggests the state 1 is the bearish market state where price is experiencing some downward trend. On the other hand, in state 2 the constant term is close to zero which means the movement of the weekly natural gas spot price return is quite stable. Meanwhile, a close look into the variance estimates of different states also shows that when the market is in bearish state, the overall volatility is smaller than when the market is in bullish state. This is consistent with reality for trading activities are more active in bullish state than in bearish state. Although the GARCH (1,1) does not work in the regime-switching framework, the regime-switching assumption itself allows some certain level of variance decomposition by assuming different variances for the price returns in different states, and hence provides some tool to deal with high volatility.

Role of price change of crude oil is a little intriguing. The estimation results of fundamental model without regime-switching assumption show that price changes of crude oil are positively correlated with natural gas price changes, which is consistent with our observations. Meanwhile, in the Markov-switching model, both coefficients in two states are positive but not significant. But we can still see that in bullish state crude oil price changes have larger impacts on natural gas price than in bearish market.

The significance of storage change in state 2 confirms the conjecture of theory of storage which asserts that when inventory level increases, the prices of commodity face downward pressure. However, this effect is not that significant in bearish market. Similar situation applies to variable lagged spread. It seems only in bullish market state that past supply-demand conditions matter. The positive sign of this variable is also consistent with the theory of storage which states that spot price is more variable when the spread is

wide. All these observations suggest that market fundamentals have larger effects on natural gas price changes in bullish state than in bearish market. This is plausible since when economy is in recession or the market is bearish, market participants tend to be more cautious and hence, economic responses toward some shocks would be less dramatic.

The derived probability of market in bullish market or bearish market is also presented in table 2. It can be seen that market has some tendency to stay in one state until something triggers the market to switch. This is consistent with findings from some studies which apply stochastic modeling to crude oil market and find the mean-reverting coefficients for crude oil price is very low. This result also helps to explain the existence of high volatility. When shocks occur, the market may switch to another state and stay in the state for quite a while before finally revert back to its equilibrium point. Overall, market fundamentals can account for 45% of natural gas prices variation over the sample period. Figure 3.1 provides fitted against real weekly difference of log of natural gas prices together with 2 units of standard errors which provide upper and lower bounds for the fitted values. It can be seen that the real value can be contained within 2 units of standard errors. Figure 3.2 gives fitted vs. real weekly natural gas return. Comparison of fitted and original weekly differenced value of log of natural gas price shows that fitted values are in general smaller than the original data in magnitude which suggests that some variations in the original data cannot be captured by the 2-state regime-switching model.

Based on the 2-state Markov-switching model, short-term out of sample 20-week forecasts are presented in figure 4. Both forecasts with/without Markov-smoothing

effects are listed and it can be seen that the forecasts with smoothing effects perform better than those without smoothing effects. This suggests the market reacts to changes in fundamentals with certain level of persistency, and this is consistent with our previous finding that natural gas market tends to stay in one state until switching point is achieved. Also it can be seen that the forecast is doing fairly well in 8-10 weeks interval. As the time horizon goes longer, the forecast get poorer. When the market goes through some severe changes, the forecast model only has limited capability to capture those changes.

V. Conclusion

This paper uses fundamental-based regime-switching model to study short-term US natural gas price dynamics. Under the regime-switching framework, roles of fundamentals in natural gas price movements are closely examined. It is found that market fundamentals overall have larger impacts in bullish market than in bearish market. Empirical study also shows regime-switching model is doing a better job in forecasting than the fundamental model without regime-switching framework. However, the results also show that real-world commodity price behavior is far more complicated than that predicted by structure models based on fundamental factors and the regime-switching forecast model can only do a fairly good job in very short term.

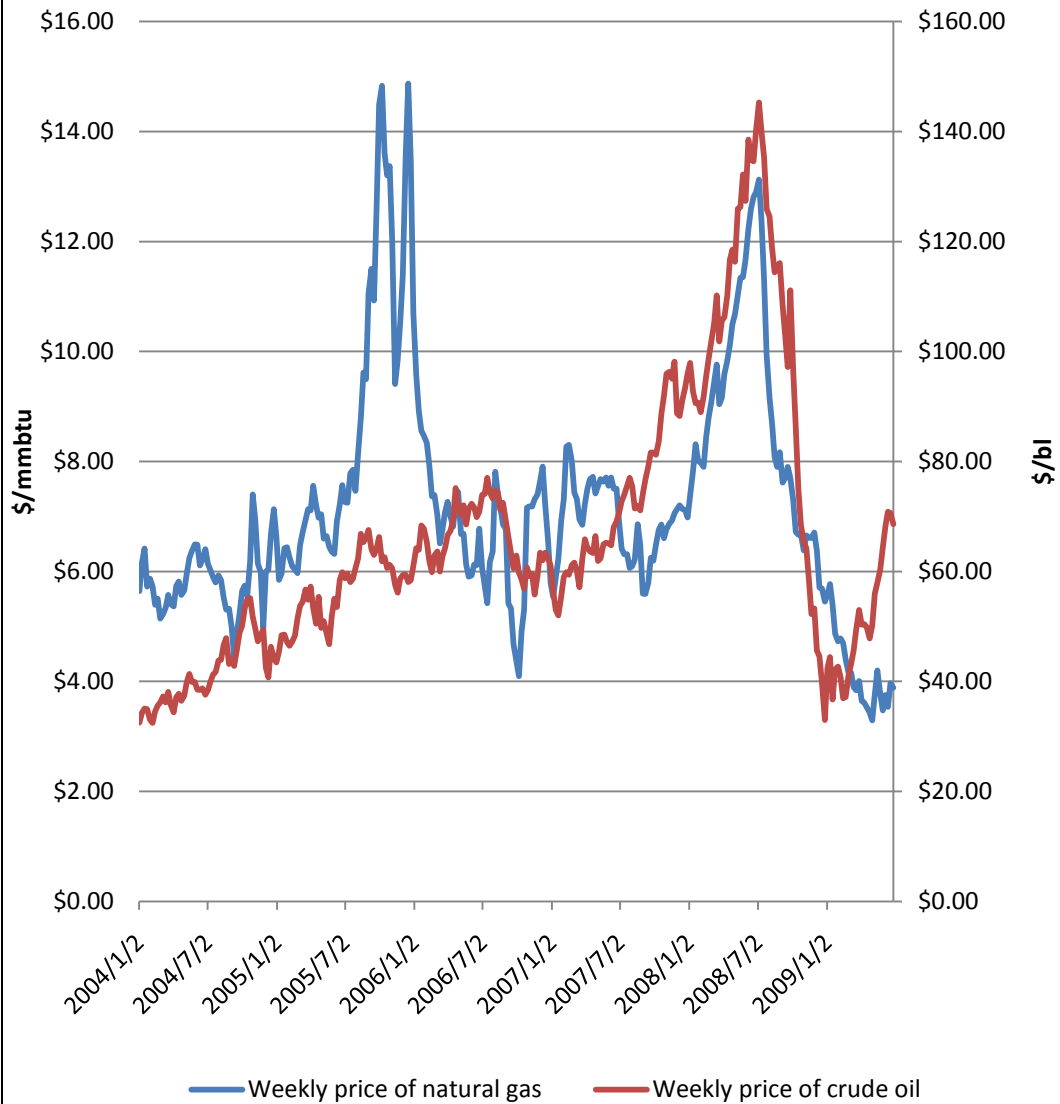
The major contribution of this study lies in the effort to improve the deficiency of current fundamental-based models on commodity pricing due to high volatility. Augmented GARCH in regime-switching model help better address the variation caused by fundamentals, and hence improve the forecast efficiency.

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Figure 1: Weekly price trend of natural gas and crude oil (Jan. 2004--Jun. 2009)



Note: The unit of left y-axis of figure 1 represents price of crude oil, denoted as dollar per barrel and the unit of right y-axis is price of natural gas, denoted as dollar per million British thermal units (MMBTU).

**Figure 2: Weekly change of natural log of natural gas price
(Jan. 2004--June 2009)**

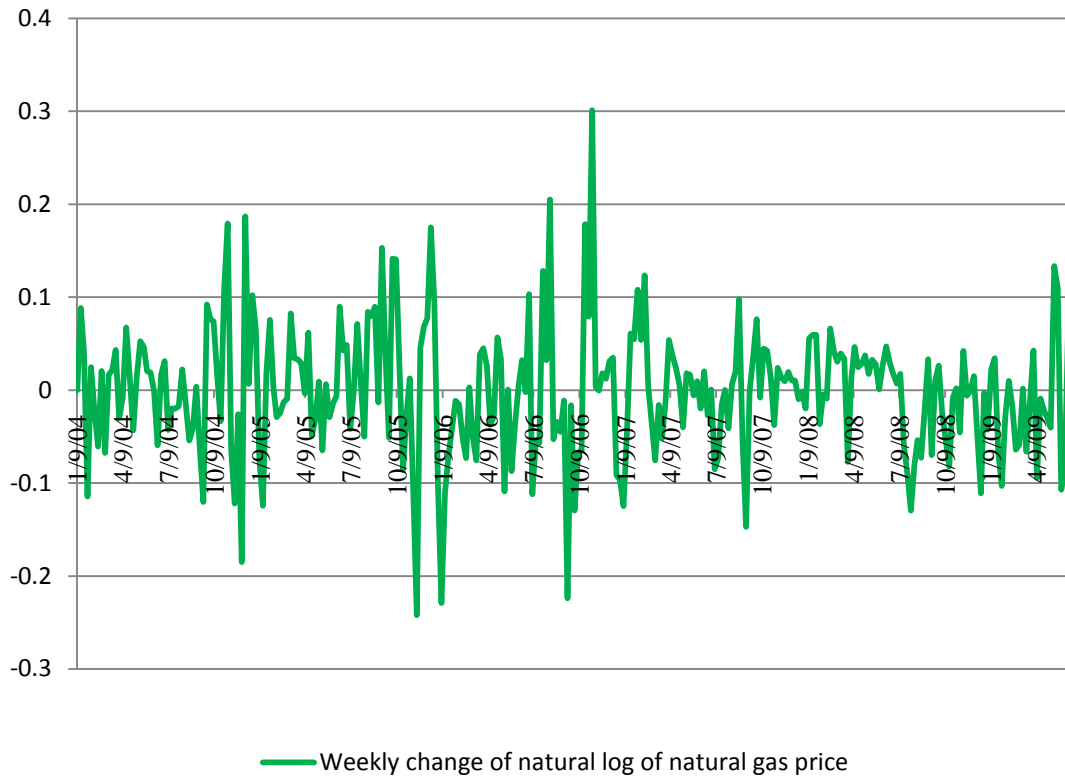


Figure 3.1: Fitted vs. real weekly natural gas price return

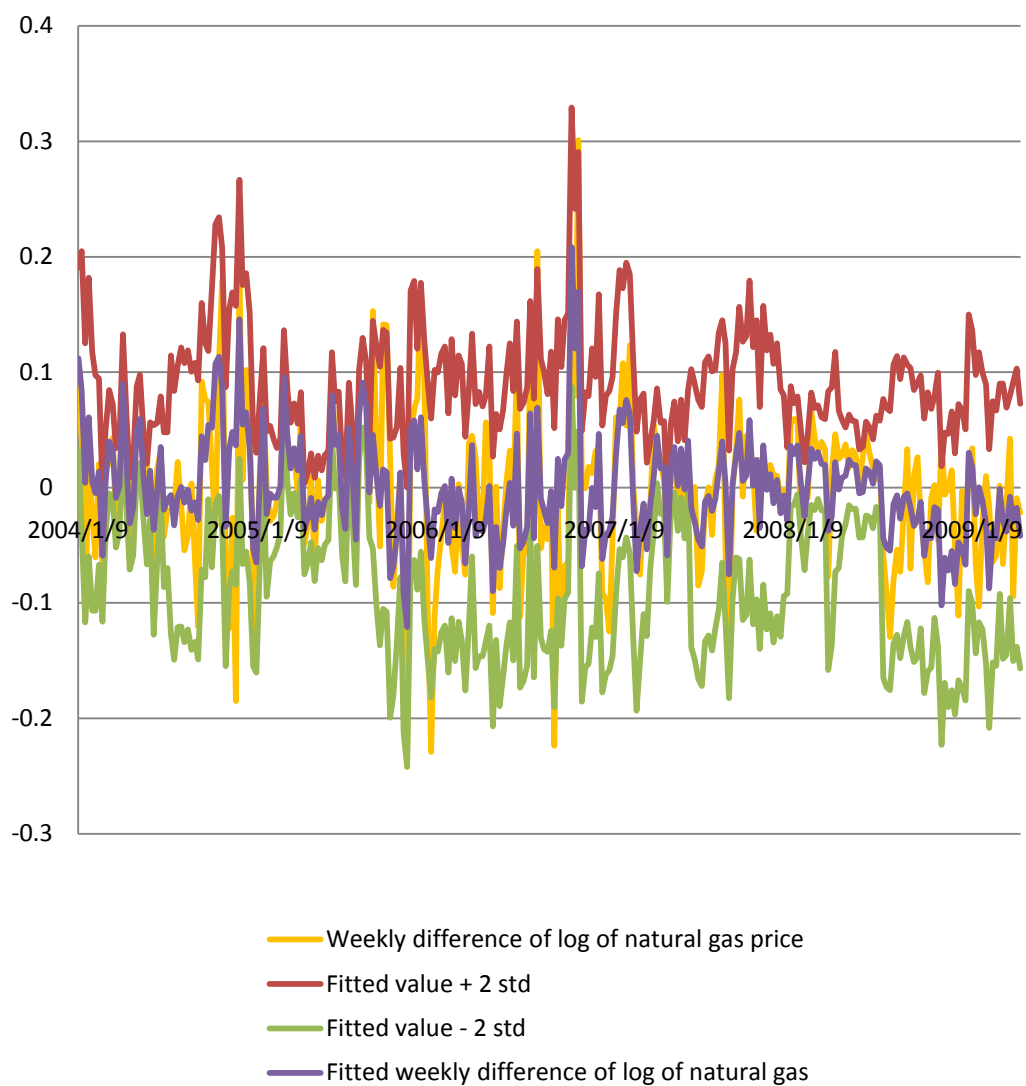


Figure 3.2: Fitted vs. real dependent variable (weekly natural gas price return)

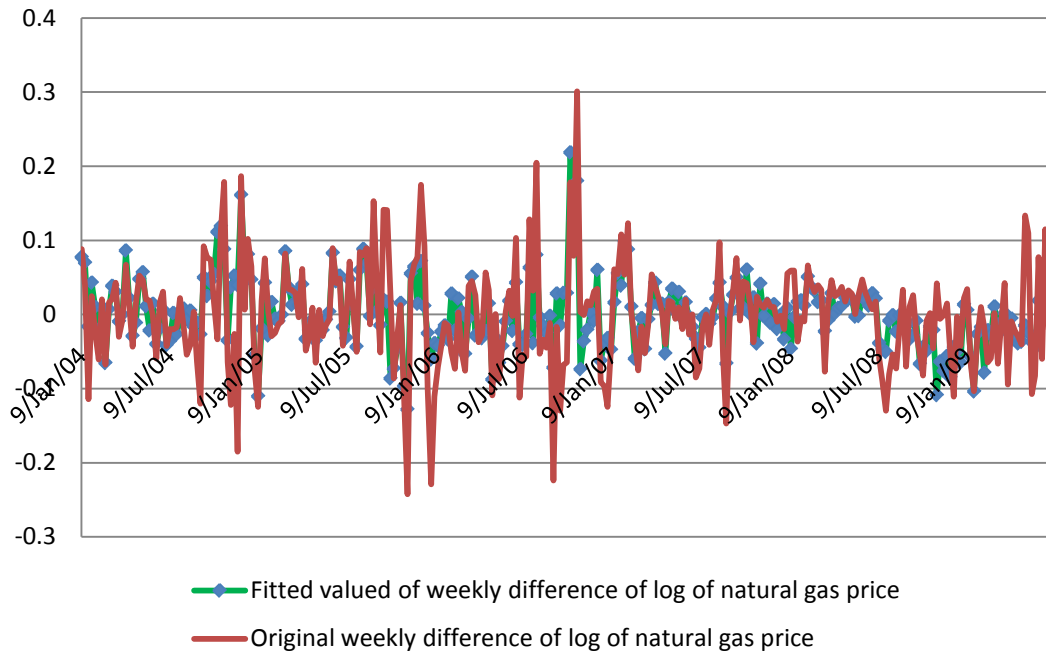


Figure 4: Out-of-sample forecast

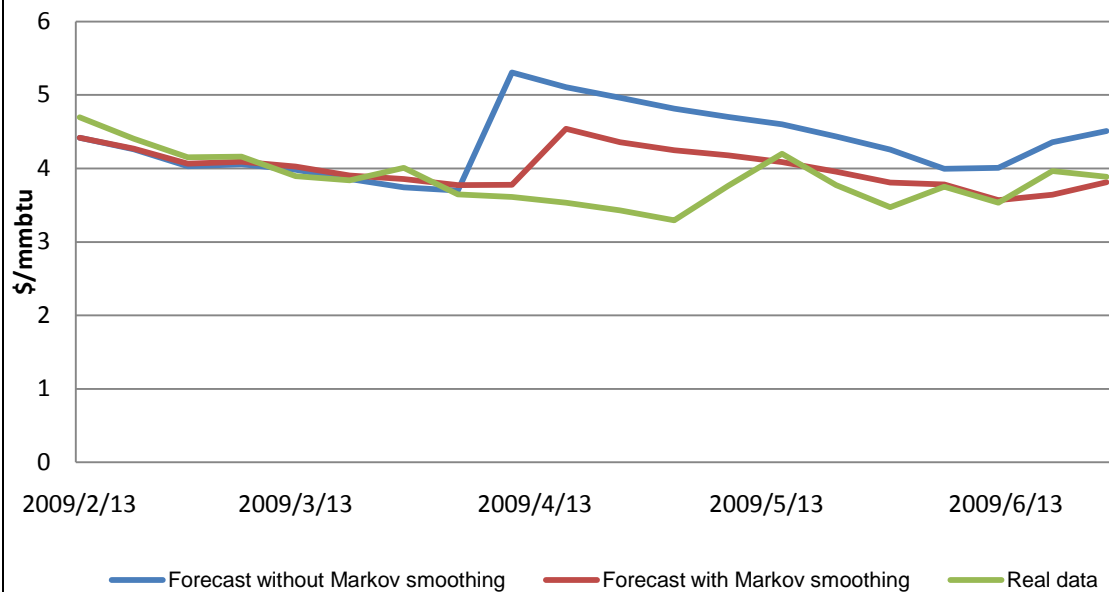


Table 1: GARCH (1,1) without regime switching assumption

DF: 269 Final log Likelihood: -854.67

Number of parameters: 20 Distribution Assumption -> normal

Method for standard error calculation -> white

RSS -> 8640.3264 TSS -> 13641.9606 R^2 -> 0.36664 AdjR^2 -> 0.32896

sigmasq -> 32.1202 sigma -> 5.6675

-----> Final Parameters <-----

-----> GARCH(1,1) Parameters <-----

GARCH(1,1) Constant: 1.5936

GARCH (1,1) Constant Std Error: 0.95212

GARCH(1,1) ARCH MA(1) Coefficient: 0.34343

GARCH (1,1) ARCH MA(1) Std Error: 0.095493

GARCH(1,1) GARCH AR(1) Coefficient: 0.64407

GARCH (1,1) GARCH AR(1) Std Error: 0.073669

Parameters for constant term:

Value: -8.171

Std error: 1.4826

Parameters for weekly difference of log of crude oil price:

Value: 20.2324

Std error: 5.2489

Parameters for weekly difference storage

Value: -0.03435

Std error: 0.0090523

Parameters for weekly difference HDD

Value: -0.0050324

Std error: 0.014791

Parameters for weekly difference CDD

Value: 0.0080062

Std error: 0.02998

Parameters for Monthly dummy 1

Value: 1.1769

Std error: 1.6072

Parameters for Monthly dummy 2

Value: 3.1328

Std error: 1.7459

Parameters for Monthly dummy 3

Value: 5.1721

Std error: 1.4232

Parameters for Monthly dummy 4

Value: 8.9519

Std error: 1.8335

Parameters for Monthly dummy 5

Value: 10.4688

Std error: 2.1848

Parameters for Monthly dummy 6

Value: 9.3829

Std error: 2.0904

Parameters for Monthly dummy 7

Value: 7.4422

Std error: 2.0699

Parameters for monthly dummy 8

Value: 8.5949

Std error: 2.0856

Parameters for monthly dummy 9

Value: 10.1507

Std error: 2.1705
Parameters for monthly dummy 10
Value: 5.6451
Std error: 2.0843
Parameters for monthly dummy 11
Value: 1.0338
Std error: 2.0546
Parameters for lagged spread
Value: 82.7245
Std error: 6.0984
LR test= 21.9152>chi square df 11 19.675 at 0.05

Table 2: Estimation results for 2-State Markov-switching model

DF: 259	Final log Likelihood: 472.4759	Number of parameters: 27	
Distribution Assumption -> Normal		Method for standard error calculation -> white	
RSS -> 0.70945	TSS -> 1.3642	R^2 -> 0.47995	AdjR^2 -> 0.44902
---> Non Switching Parameters <---			
Non Switching Parameter of weekly differenced HDD			
Value: 5.0762e-006			
Std error: 0.00054438			
Non Switching Parameter of weekly differenced CDD			
Value: -9.1301e-005			
Std error: 0.0010903			
Non Switching Parameter of monthly dummy 1			
Value: -0.010268			
Std error: 0.16076			
Non Switching Parameter of monthly dummy 2			
Value: 0.032333			

Std error: 0.13394

Non Switching Parameter of monthly dummy 3

Value: 0.040166

Std error: 0.093813

Non Switching Parameter of monthly dummy 4

Value: 0.062472

Std error: 0.012147

Non Switching Parameter at of monthly dummy 5

Value: 0.066789

Std error: 0.071233

Non Switching Parameter of monthly dummy 6

Value: 0.08488

Std error: 0.060254

Non Switching Parameter of monthly dummy 7

Value: 0.07982

Std error: 0.026802

Non Switching Parameter of monthly dummy 8

Value: 0.10592

Std error: 0.087416

Non Switching Parameter of monthly dummy 9

Value: 0.10846

Std error: 0.18505

Non Switching Parameter at of monthly dummy 10

Value: 0.080719

Std error: 0.068612

Non Switching Parameter of monthly dummy 11

Value: -0.0018537

Std error: 0.11295

---> Switching Parameters <---

State 1

Standard Deviation: 0.015744

Std Error: 0.028084

State 2

Standard Deviation: 0.059057

Std Error: 0.0063591

Switching Parameters for constant term

State 1

Value: -0.063132

Std error: 0.030458

State 2

Value: -0.078379

Std error: 0.14226

Switching Parameters for weekly difference of log of crude oil

State 1

Value: 0.13104

Std error: 0.21288

State 2

Value: 0.21169

Std error: 0.71246

Switching Parameters for weekly difference of storage

State 1

Value: -0.00014916

Std error: 0.0011103

State 2

Value: -0.00045108

Std error: 9.9752e-005

Switching Parameters for lagged spread

State 1

Value: 1.3007

Std error: 1.0066

State 2

Value: 0.63084

Std error: 0.4275

---> Transition Probabilities Matrix <---

0.92901 0.029978

0.070987 0.97002

