ESSAYS ON PRICING BEHAVIORS OF ENERGY COMMODITIES

A Dissertation

by

XIAOYAN QIN

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

May 2011

Major Subject: Agricultural Economics

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Approved by:

Co-Chairs of Committee,	David A. Bessler
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ABSTRACT

Essays on Pricing Behaviors of Energy Commodities.

(May 2011)

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This dissertation investigates the pricing behaviors of two major energy commodities, U.S. natural gas and crude oil, using times series models. It examines the relationships between U.S. natural gas price variations and changes in market fundamentals within a two-state Markov-switching framework. It is found that the regime-switching model does a better forecasting job in general than the linear fundamental model without regime-switching framework, especially in the case of 1-step-ahead forecast.

Studies are conducted of the dynamics between crude oil price and U.S. dollar exchange rates. Empirical tests are applied to both full sample (1986—2010) and subsample (2002—2010) data. It is found that causality runs in both directions between the oil and the dollar. Meanwhile, a theoretical 5-country partial dynamic portfolio model is constructed to explain the dynamics between oil and dollar with special

attention to the roles of China and Russia. It is shown that emergence of China's economy enhances the linkage between oil and dollar due to China's foreign exchange policy.

Further research is dedicated to the role of speculation in crude oil and natural gas markets. First a literature review on theory of speculation is conducted. Empirical studies on speculation in commodity markets are surveyed, with special focus on energy commodity market. To test the theory that speculation may affect commodity prices by exaggerating the signals sent by market fundamentals, this essay utilizes the forecast errors from the first essay to investigate the forecasting ability of speculators' net long positions in the market. Limited evidence is provided to support the bubble theory in U.S. natural gas market.

In conclusion, this dissertation explores both fundamentals and speculators' roles in the U.S. natural gas and global crude oil markets. It is found that market fundamentals are the major driving forces for the two energy commodities price booms seen during the past several years.

DEDICATION

This dissertation is dedicated to my mother, Aichun Liu, and my husband, Lujiang Hao.

ACKNOWLEDGEMENTS

I would like to thank my committee co-chairs, Dr. Bessler and Dr. Leatham, for their guidance and support throughout the course of this research. Dr. Bessler’s kind help and rigorous attitude toward research has always inspired me in my pursuit of professional achievement. Dr. Leatham has provided an excellent learning environment for my doctoral study here. His constant help and support is crucial for my study and research.

My thanks are also extended to my committee members, Dr. Wu and Dr. Gan, for their helpful comments and patient guidance; a benefit for my future professional life. Thanks also go to the department faculty and staff for making my time at Texas A&M University a great experience. I also want to extend my sincere gratitude to the Tom Slick Research Fellowship from the College of Agriculture and Life Sciences, Texas A&M University.

Finally, I would like to thank my mother and my husband for their patience, support and love all along the way.

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CHAPTER I

INTRODUCTION

The major purpose of the dissertation is to investigate the pricing behaviors of two major energy commodities, U.S. natural gas and crude oil, using times series models. Boom in commodity markets experienced during past several years has inspired a lot of discussions about impact of fundamentals and speculation on energy commodities price changes and volatility variations. This dissertation examines roles of market fundamentals and speculation in both U.S. natural gas market and global crude oil market from three aspects. Specifically, chapter II investigates the relation between U.S. natural gas price variation and changes in fundamentals within a two-state Markov-switching framework. Chapter III focuses on the dynamics between crude oil price and U.S. dollar exchange rate. Chapter IV pays special attention to the correlation between speculators' net long positions and energy commodity price variation.

Determination of storable commodity price can be explained by the theory of storage. The classic theory of storage was first introduced by Kaldor (1939), then elaborated by Working (1948, 1949) to explain the fact that forward prices of storable commodities are generally below the spot prices plus carrying costs of holding the inventory until maturity date. Many researchers have attempted to model the price movements of storable commodities based on market fundamentals, such as Deaton and

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This dissertation follows the style of Energy Economics.

Laroque (1992, 1996), Ng and Pirrong (1994), and Pindyck (1994, 2001, 2004a, 2004b). These studies provided empirical support for the linkage between market fundamentals and volatility of storable commodities prices. Chapter II proposes a two-state Markov-switching model to forecast U.S. natural gas spot price based on market fundamentals. The use of the regime-switching model provides a flexible way to deal with possible endogenous structural breaks and volatility changes, and hence improves forecast efficiency. The assumption of regime-switching is based on the observation that U.S. natural gas market experiences obvious downward or upward pressure when there are changes in market fundamentals such as storage, and this kind of market trend and trading sentiment prevail until new information flow comes.

To further test the forecast accuracy improvement of regime-switching model against fundamental model without regime-switching assumption, DM tests proposed by Diebold and Mariano (1995) are carried out for the 1-step, 4-step and 20-step-ahead forecasts by both models. It's found that the regime-switching model does a better forecasting job in general than the linear fundamental model without regime-switching framework, especially in the case of 1-step-ahead forecast. Since no model system encompasses the other, a regression-based linear combination of the Markov-switching model and also the alternative model is proposed.

With regard to the price boom in global crude oil market seen during past several years, fundamental factors, such as strong world demand, rigid oil supply, weakening U.S. dollar, peak oil fear, inventory variations, and also geopolitical instability, are initial drivers to push up oil price. Among all these factors, the dynamics between oil price and U.S. dollar is the major research theme of Chapter III. Krugman (1980)'s theoretical framework is extended to a 5-country (U.S., Euro Zone, OPEC, China and Russia) model to examine how these two newly emerging economies (China and Russia)' oil import/export and also international portfolio preference affect the dynamics between U.S. dollar and oil price.

Be´nassy-Que´re´ et al. (2007) study the co-integration and causality between real price[1] of crude oil and real U.S. dollar exchange rate against euro[2] over period 1974-2004, and finds 10% increase in oil price coincides with 4.3% appreciation of U.S. dollar in the long run and the causality runs from oil to dollar. Huang and Guo (2007) conclude that real oil price shocks seem dominant in the variation of the real exchange rate of China's currency, and emergence of China in both oil and foreign exchange markets could strengthen the positive causality found from the oil price to the dollar in the short run but reverse its sign in the long run. At the same time, it is also observed that from January 2002 to July 2008 oil price keeps rising while U.S. dollar depreciates, thus, a negative causality between oil price and U.S. dollar seems to exist and further investigation needs to be carried out to decide the direction of causality. If empirical study shows that causality runs from U.S. dollar to oil price, the argument that oil price increase is also a result of weakening U.S. dollar would be supported.

Besides fundamental factors, identifying the effect of speculative behaviors on energy commodity price volatility is also of interest to researchers. Chapter IV of this

[1] The crude oil price is deflated by the US consumer price index.
[2] This variable is constructed by deflating the nominal exchange rate of U.S. dollar against the euro using consumer price index for the Eurozone.

dissertation is dedicated to the study of speculation in crude oil and natural gas markets. Eckaus (2008) claims the sharp crude oil price increase seen in 2008 is a result of speculative bubble. Robles, Torero and von Braun (2009) argue that speculative activity in the futures markets may have caused increasing agricultural commodity prices in 2007-2008. On the other hand, some researchers, such as Pirrong (2008), Sanders, Irwin and Merrin (2009), report limited empirical evidence to support this assertion. The bubble or non-bubble debate is important in the sense that pricing efficiency of futures markets can be in serious doubt if speculation does distort the price away from the level supported by market fundamentals, as a result, the economy may respond to misleading price signals.

To test the theory that speculation may affect energy commodity prices by exaggerating the signals sent by market fundamentals, the forecast errors from Chapter II are utilized to examine the forecasting ability of speculators' positions with regard to U.S. natural gas price. Limited evidence is provided to support the bubble theory in U.S. natural gas market.

This dissertation follows the journal article style. Three major Chapters, Chapter II, III and IV, are dedicated to the three topics elaborated above. Each of the three Chapters is self-contained, including introduction, data and model development, results and interpretation, and conclusion. In addition, this dissertation also includes an abstract, introduction and conclusion Chapters of the whole dissertation, references and an appendix.

CHAPTER II

FUNDAMENTALS AND PRICE FORECASTS OF U.S. NATURAL GAS

INTRODUCTION

Natural gas prices in both spot and forward/future markets are characterized by high volatility, which has made forecasting their prices based on market fundamentals a very challenging task. Many researchers have attempted to model the price movements of storable commodities based on market fundamentals, such as Deaton and Laroque (1992, 1996), Ng and Pirrong (1994), and Pindyck (1994, 2001, 2004a, 2004b). These studies provided empirical support for the linkage between market fundamentals and volatility of storable commodities prices. Also, they found that real world commodity prices in both spot and forward/future markets are far more complicated than that captured by fundamental models, and the forecasting ability of these fundamental-based structural models is quite limited, hence it is hard to use these models for derivative pricing. This paper investigates the role of market fundamentals in U.S. natural gas price changes within a regime-switching framework, and also proposes a short-term price forecast model for natural gas based on fundamentals. The use of the regime-switching model provides a flexible way to deal with possible endogenous structural breaks and volatility changes, and hence improves forecast efficiency.

Determination of storable commodity price can be explained by the theory of storage. The classic theory of storage was first introduced by Kaldor (1939), then elaborated by Working (1948, 1949) to explain the fact that forward prices of storable commodities are generally below the spot prices plus carrying costs of holding the inventory until maturity date. Stocks of commodity bring so called "convenience yield" to stock holders, because the stocks-on-hand enable them to respond more flexibly and efficiently to unexpected supply-and-demand shocks. This stream of benefits generated by inventory explains the existence of uncompensated carrying cost in competitive storage markets, where future price is not sufficiently larger than spot price to fully cover the incurred interest and warehouse costs of holding inventory.

Scheinkman and Schectman (1983) expanded the theory of storage by introducing rational expectations into the partial equilibrium model of production and storage. It is assumed that the source of uncertainty is on supply side which equally affects all producers. The final demand is non-random and only depends on price. By assuming equilibrium, (rational) expectations of future prices by risk-neutral producers, and independently and identically distributed supply shocks over time, they showed that the equilibrium price is a function of one specific state variable—the total stocks kept until current period plus current period production. In their special case they found the equilibrium price follows a renewal process. That is, if today's price is low enough, then it is optimal for producer to hold stock for future consumption, hence the existence of inventory links today's spot price with future price. Furthermore, tomorrow's price is at least equal to today's prices divided by the discount factor, since producers make their decision based on their rational expectation of the future which is assumed to clear the forward market. On the other hand, if today's price is high enough, then the optimal decision for producers would be to hold zero storage, hence next period's price would be independent of the current period's price process. Fama and French (1988) studied the London Metals Exchange (LME) spot and future prices over the period 1972 through 1983 and concluded that inventory responses would spread the effects from demand and supply shocks between current spot prices and expected spot prices (future prices); therefore, the volatilities of spot and future markets are linked due to the existence of storage.

Williams and Wright (1991) took a close look at storage models to see "how and to what extent industry-wide storage stabilize a commodity's price over time." They acknowledged that storage has an asymmetric effect on price. That is, "storage is much more effective at supporting what would otherwise be very low prices than at reducing what would otherwise be very high prices." They further argued that due to the fact that the effects of storage on the distribution and time-series properties of prices are not fully acknowledged yet, some empirical techniques appear to be biased toward finding irrationality in expectation. Deaton (1992, 1996) noticed the existence of skewness, excess kurtosis, high volatility, and strongly positive correlation in commodity prices. He conducted empirical tests for the storage model and concluded that the positive autocorrelation of commodity prices is mainly caused by shocks on the demand side rather than by supply shocks or speculative storage behaviors as some earlier studies claimed.

Pindyck (1994, 2001) focused on the relationship between the variance process of commodity prices and market fundamentals. 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) investigated the industrial metal market and found "variations in volatility are largely attributable to variations in fundamental demand and supply conditions, rather than speculative noise trading", although speculative activities in commodity markets are quite common with the introduction of financial instruments. Modjtahedi and Movassagh (2005) found spot and future natural gas prices to be non-stationary processes and partial empirical support for the theory of storage in natural gas price basis determination is also provided.

This Chapter uses a two-state regime-switching model to investigate the relationship between market fundamentals and U.S. natural gas spot price variations. The regime-switching assumption is applied to deal with high volatility and also to test if there is structural change involved in the mechanism via which fundamentals affect natural gas price variations. Observations of U.S. natural gas market suggest that there exist two states of the market: a bull market and a bear market. These terms are generally used by traders to describe primary upward and downward market trends using technical analysis, respectively. In this study these concepts are borrowed to describe two sets of short term market trends in natural gas market. A bull market happens when increasing investor confidence is widely spreading and future price increases are anticipated. A bear market is associated with increasing investor fear and pessimism. In the bullish state, the market exhibits a clear upward trend and less volatility than in the bearish state. Therefore, these fundamentals which drive the natural gas price movement would function differently in different states. To test this hypothesis, a Markov-switching model is proposed under the assumption that the market switches between these two states according to a Markov chain. An investigation of the relationship between the fundamentals and the U.S. natural gas price return is examined in this framework.

Results show that predicted and observed behaviors of the natural gas price have very close correspondence which suggests market fundamentals affect price dynamics. Also it shows that linkages between the fundamentals and natural gas price variation are statistically different across different market states. The hypothesis of endogenous regime switching is supported by the data. Furthermore, the regime-switching model also improves forecast accuracy compared with the model which has the same structure except for 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 account for the time-varying volatility. However, the insignificance of the lagged spread in the augmented GARCH (1,1) specification shows that past supply and demand conditions do little to explain price variability. The endogenous volatility assumption is not supported by U.S. natural gas data. Based on Markov-switching model estimation results, short-term forecasts of natural gas price with/without Markov-smoothing effects are provided. We find forecasts with Markov-smoothing effects are generally more reliable.

The remainder of this Chapter 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.

FUNDAMENTALS AND U.S. 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 is stored during the summer for winter use. This seasonality results in lower natural gas prices in summer than in the winter. Variation in weather also affects price because more heating and/or cooling degree days than average increases the demand, and then the price.

The role of inventory on natural gas price dynamics is worth a thorough investigation. 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 pressured upward, holding the other relevant factors constant.

Storage can also affect the 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), the arbitrage-free relation between spot and forward prices can be expressed as:

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

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:

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

The left-hand side of equation (2) is the so-called interest rate and storage adjusted spread which is proposed by Ng and Pirrong (1994).

The log transformation of spread is used in this study, instead of the interest-and-storage adjusted spread, because there is no storage cost data available for natural gas. The forward price employed here is one-month prompt future price. As an opportunity cost of capital, changes in nominal interest rate would drive the spread to move in the same direction. When there is an increase in the interest rate, profit-maximizing traders of a commodity would naturally ask for a larger spread to cover the increased trading cost. When the interest rate decreases, the spread would naturally face downward pressure. Fama and French (1987) regress the 6-month basis (difference between forward and spot prices divided by spot prices) on interest rates and found for most agricultural commodities and metals the coefficients of interest rates are positive; however, the coefficients are only significant for metals (especially precious metals such as gold and silver). Some preliminary analysis of the U.S. natural gas data shows that the correlation between the spread and nominal 1-month interest rate is quite low and regression of the log of spread against monthly dummies and nominal interest rate yields an insignificant coefficient for interest rate, although the sign is positive as the theory predicts. It is also worth mentioning that the volatility of the 1-month default-free interest rate over the same period is much higher than that of the 1-month natural gas future-spot spread; hence, it is safe to claim that trading behaviors of natural gas is not so much driven by opportunity cost of capital, as in the case of gold and silver. The substitution of the log of the spread for storage-and-interest adjusted spread is justifiable in this study.

It is obvious that the 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 changes in storage; therefore, the 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 the regime-switching model, one-period lag of spread is included as an explanatory variable to account for the autocorrelation in natural gas price. Meanwhile, to test the hypothesis of endogenous volatility, augmented

GARCH is proposed to include one-period lag of the spread in the conditional heteroskedasticity specification.

In this study, the 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 the 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. The 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 U.S. 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 the 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, 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 2.1 provides weekly prices movement of natural gas and crude oil from Jan. 2, 2004 to June 26, 2009. 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. Pindyck (2004b) provides mixed empirical evidence on the interdependence between crude oil and natural gas price returns over the sample period from May 2, 1990 to February 23, 2003. Specifically, the daily crude oil return can predict natural gas return and the daily crude oil volatility also shows the prediction power for daily natural gas volatility. On the other hand, when the data are measured on weekly basis, these patterns are not so obvious.

THEORETICAL MODEL AND DATA

The regime-switching model with a Markov chain[3] is adopted to model the weekly change of the natural gas price. Under the assumption that market switching between two states: a bullish market state and a bearish market state according to a Markov transition matrix, U.S. natural gas price is 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 the price in different regimes. The use of the regime-switching model allows one to infer meaningful probability information with which the market stays in each state at every time point. A further advantage of Markov chain is its flexibility. As explained by Hamilton (1994), the Markov-switching model makes it possible to choose particular

[3] 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.

parameters based on data available while abiding by a probability law consistent with a broad range of different outcomes. Recent development of Markov-switching model with time-varying transition probability brings more flexibility into modeling. For the Markov transition probability matrix, it can either be exogenously determined (constant over time) or endogenously determined (time varying) by some major economic fundamentals. This study explores both types of models to find the suitable specification.

Weekly data of spot and 1-month prompt future prices of U.S. natural gas traded in New York Mercantile Exchange (NYMEX) are used. U.S. 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 the National Weather Service. West Texas Intermediate (WTI) Cushing Spot traded in NYMEX is used as the spot price for crude oil. The sample period is from Jan. 2, 2004 to June 26, 2009.

Some preliminary analysis of the natural gas price data shows that the original natural gas price exhibits severe skewness at 1.25, but the skewness for the dependent variable (first difference of the log of natural gas price) is 0.16. Excess kurtosis for price is 1.82 and for the dependent variable is 2.02. The asymmetry of natural gas price can be explained by the existence of storage and the excess kurtosis suggests the distribution of price data is very prone to outliers. With the presence of this non-normality, it is not appropriate to assume the price data may follow one standard stochastic process; instead, a mixed process may be needed.

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

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

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

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

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

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

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

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

To account for the conditional variance h_{s_t} in spot price return, augmented GARCH (1,1) is proposed as:

$$\sigma_{s_t} = \sqrt{h_{s_t}} v_t \tag{8}$$

$$h_{s_t} = \alpha_{s_t} + \varphi z_t + \delta_{1,s} h_{s_{t-1}} + \delta_{2,s} \epsilon_{s,t-1}^2 \tag{9}$$

v_t is i.i.d. with zero mean and unit variance. Set $\varphi = 0$, equations (8) and (9) are standard GARCH (1,1) specification. One-period lag of spread is used as the exogenous variable z_t in equation (9) to test if past supply and demand conditions affect volatility of natural gas price return.

For simplicity and ease of computation, the linearity for the basic structure model in each state is assumed. Meanwhile, regime switching assumption allows certain non-linearity in the model specification. The dependent variable is the log transformation of natural gas spot price, differenced weekly.

To account for the 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 forward-spot spread is substituted for the interest rate and storage adjusted spread, which is simply constructed by using the log of forward price minus the log of spot price. The lagged value of spread is included in the mean process equation (3) 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, lagged spread, and crude oil weekly price change.

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

RESULTS AND INTERPRETATION

A series of models have been fitted to see which model specification is more suitable. The fundamental linear model without the regime-switching assumption but with augmented GARCH (1,1) is first explored to see if lagged spread can explain part of the conditional heteroskedasticity. The insignificance of parameter φ suggests that past supply and demand conditions offer little help in predicting volatility. On the other hand, a standard GARCH(1,1) specification is supported by the data. This means some variation of the natural gas price can be predicted given current information set, although not by lagged spread variable directly. The MA coefficient in the GARCH (1,1) model is much smaller than the AR term, and the sum of these two parameters is close to 1, which suggest the variance is highly persistent. The significance of the fundamentals shows that fundamental factors affect the natural gas spot price return just as expected. Also the LR test shows that the monthly dummies are significant collectively. Significance of lagged spread in the mean equation is consistent with the common conjecture that natural gas price is autoregressive.

Estimation results show that the Markov-switching model with a time-varying transition probability matrix is not supported by the data, and the model fails to yield meaningful estimates. The main model specification used here is a 2-state Markov-switching model with constant transition matrix. Both augmented and standard GARCH (1,1) are built into the regime-switching model. However, the assumption that each different state has a different augmented or standard GARCH (1,1) specification is not supported by the data. This result is consistent with other findings in the literature where Markov-switching modeling is applied to weekly stock returns. Hamilton and Susmel (1994) proposed a SWARCH model (Switching ARCH) to study the weekly stock returns and found the ARCH effects captured by the SWARCH model die out very fast. Based on this finding, Kim and Nelson (1999) proposed a 3-state Markov-switching variance model for the monthly stock return and found no ARCH effects can be detected with the presence of the 3-state Markov-switching variance model. In our case, we find the 2-state Markov-switching variance model seems to be able to account for the persistent variance by decomposing the volatility into two variance processes.

Furthermore, a two-state SWGARCH model is also carried out which only allows the variance parameter of GARCH (1,1) process to vary according to an unobserved Markov chain. Unfortunately this trial fails to produce any useful result.

Table 2.1 presents the estimation results of the GARCH (1,1) model and also the regime-switching model. The regime-switching assumption is supported by the data and the LR test shows that monthly dummies are collectively significant. Also these dummy variables don't switch across states. Fundamental factors such as weekly difference of the 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 terms in both states are significantly different from zero and in state 1 the magnitude of the constant coefficient is smaller than in state 2. Given the negative sign, this suggests the state 1 is a bullish market state and state 2 is a bearish state. Meanwhile, a close look into the variance estimates of different states also shows that when the market is in bullish state, the overall volatility is smaller than when the market is in bearish state, which suggests the movement of the weekly natural gas spot price return is more stable in state 1 than in state 2, and the market trend is clearer in state 1 than in state 2. The negative signs of the constant terms in two states are consistent with the fact that sample mean of the dependent variable is negative and also the findings of the previous GARCH (1,1) model. These estimate results, however, are surprising in the sense that the mixed process of natural gas price movement does not consist of two processes of totally opposite moving direction; instead, we see the deviation of two processes from the sample mean is not that dramatic at all. Although the GARCH (1,1) does not work in the regime-switching framework, the regime-switching assumption itself allows a certain level of variance decomposition by assuming different variances parameters for the price returns in different states, and hence provides a tool to deal with high volatility.

The role of the price change of crude oil is intriguing. The estimation results of the fundamental model without the 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 and significant. However, we can see that in the bullish state crude oil price changes have smaller impacts on natural gas price than in the bearish market. This may result from traders' different decision-making behaviors in different market states. When the market shows less volatility and a clearer market trend, market participants may put more emphasis on other market fundamentals than changes in crude oil price when they make trading decisions; on the other hand, when market participants are less certain about the market trend, they may choose to play safe by observing the market trend of crude oil and making their decisions accordingly, since crude oil market dominates the whole energy commodity market.

The significance of the storage change variable in both states confirms the conjecture of storage theory, which asserts that when inventory level increases, the commodity prices face downward pressure. This effect is larger in the bearish market than in the bullish market. Increase in inventory means increase in marginal supply. When the market is already in a bearish state and traders hold a pessimistic opinion about a future possible price increase, news of an increase in inventory level would further enhance this opinion and hence diminish the price expectations further. At the same time, this downward price trend anticipation would negatively affect producers' current decision on building up inventory which may result in over-supply in a spot market. While in a bullish market, the same piece of information affects traders' confidence negatively but to a lesser extent as long as anticipation of future price increase is still widely held.

Lagged spread tells a different story in the Markov-switching model. Obviously, past supply-demand conditions matter in both a bullish and a bearish market state. This is consistent with the finding that natural gas price exhibits high autocorrelation. 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. The lagged spread has larger effects on natural gas price changes in a bullish market than in a bearish state, which suggests traders intend to take past supply-demand conditions into their trading decisions to a larger extent when market trend is stable, while in a bearish market, traders intend to put less weight on these conditions.

All these observations show that market fundamentals which would reduce natural gas price have larger impacts on price changes in a bearish state than in a bullish state. This is plausible since when the economy is in recession or the market is bearish, market participants tend to be more cautious and sensitive with respect to bad news, hence, the responses toward these negative shocks would be more dramatic than in a bullish state. Also, the linkage between crude oil price and natural gas price is weaker in a bullish state than in a bearish state. On the other hand, the effects of past supply-demand conditions on price changes are larger in a bullish state than a bearish state. This implies that in a bullish market, other independent drivers of natural gas market, rather than crude oil price, play major roles.

The dependent variable, the derived filtered and also smoothed probabilities of the market in the bullish or the bearish state are presented in Figure 2.2. It can be seen that weekly difference of log of natural gas spot prices demonstrates high volatility. The filtered probability of the market being at state 1 or 2 at time t is calculated by using the data up to time t, while the smoothed probability is derived post hoc using the full sample data. The high value of the diagonal element in the transition probability matrix shows that the market has high tendency to stay in the state until something triggers the market to switch. This is consistent with findings from other studies which apply stochastic modeling to the crude oil market and find the mean-reverting coefficient 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 the other state and stay in that state for quite a while until another shock triggers the switching process again or the impacts of the shock gradually die out. When the market is going through stable increases although very small, the probability of the market being in state 1 is very high; at the same time, when the market experiences big jumps and shows high volatility, the probability of the market being in state 2 is very high.

Overall, market fundamentals account for 45% of the natural gas price variation over the sample period. Figure 2.3 provides a comparison of the fitted and real weekly difference of the log of natural gas prices with 2 units of standard error bands which provide upper and lower bounds for the fitted values. It can be seen that the real values are contained within 2 units of standard errors interval of fitted values. Comparison of the fitted and the original weekly differenced value of the log of natural gas price show 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, and some factors other than those market fundamentals examined in this paper also have great influence on natural gas price movement over the sample period.

Based on the two-state Markov-switching model, short-term out-of-sample 1-step (a week), 4-step (a month) and also 20-step (5 months)-ahead forecasts are provided. Figure 2.4 presents 20 weeks' 1-step ahead forecasts over the period Feb. 13, 2009 to June 26, 2009 based on both 2-state Markov switching and GARCH (1,1) models. To calculate the 1-step-ahead forecast, we estimated the model using the first 266 observations, then we use the estimated parameters to make the first forecast, which is the predicted value at the 267th data point (week of Feb. 9-13, 2009). For the second forecast, the realization of the 267th data point needs to be added into the dataset, and the model is re-estimated using this new dataset. Then new 1-step-ahead forecast is calculated using the updated estimated parameters. This procedure is repeated until all the 20 weeks' 1-step-ahead forecasts are produced.

Figure 2.5 presents 20 weeks' 4-step-ahead forecasts. 4-step-ahead forecasts are calculated in similar way as the 1-step-ahead forecast. First, the model is fitted using first 266 observations, then the first 4 forecasts are made based on the estimated parameters; to make the next 4 forecasts, these first 4 actual values of the first 4 forecast periods are added into the dataset and the model is re-estimated using this updated dataset, then another 4-period-ahead forecasts are calculated using the newly estimated parameters and this procedure is repeated until all the forecasts are made. For the regime-switching model, the 4-step-ahead forecasts can be calculated with and without MS (Markov-smoothing) effects. For every set of 4-step-ahead forecasts, the first forecast is calculated by making use of the estimated Markov-transition probability matrix and all the switching and non-switching parameters, and the probability of market being at state 1 or 2 is derived by multiplying the filtered probability of last period with the transition matrix. When it comes to the second forecast, we can either derive the probability of market state at the second forecast period by simply applying the Markov chain rule, which gives the forecast without the Markov smoothing effect, or recalculate the probability of market state by taking the first predicted value into consideration, which yields forecast with the Markov smoothing effect. The forecast with and without MS effect at each data point can be derived using the following equations recursively:

$$MSProb(t) = E(t).* N(t)/sumN(t) \tag{10.1}$$

$$E(t) = P * E(t-1) \tag{10.2}$$

$$sumN(t) = P * E(t-1) * N(t) \tag{10.3}$$

$$forecast\ with\ MS\ effect = P * MSprob(t-1) * statevalue(t) \tag{10.4}$$

$$forecast\ without\ MS\ effect = P * E(t-1) * statevalue(t) \tag{10.5}$$

$MSprob$ is a 2×1 vector consisting of smoothed probability of market being at state 1 or 2 at time t. P is the estimated 2 × 2 Markov transition matrix, and $E(t)$ is a 2×1 vector consisting of the probabilities of market being at state 1 or 2 at time t, which can be derived by applying the Markov chain rule. $N(t)$ is a 2×1 vector consisting of the normal density of forecast error at state 1 and 2 at time t.

At each data point, the regime-switching model provides two conditional predicted values contingent on the market being in state 1 or 2. Actual value minus these two predicted values gives a vector of forecast errors at state 1 and 2, respectively. Symbol $.*$ represents multiplying two vectors, element by element. $statevalue(t)$ is a 1×2 vector of predicted values of the dependent variable at state 1 and 2 at time t. $sumN(t)$ is the probability weighted sum of the normal density of forecast error at time t. The reason for using normal density here to calculate the weight is that predicted values (the first difference of the log of natural gas price, the return) can either be positive or negative, meanwhile weights have to be positive and sum to 1. Therefore, the values of normal density of each state's forecast error at time t become an ideal choice for weight calculation, given the fact that the forecast error is assumed normally distributed in this study. When the forecast error at state 1 is large, the normal density of this forecast error is relatively small; hence, less weight would be given to probability at state 1 and more weight would be given to probability at state 2, then the predicted value at time t is calculated by using the updated Markov-smoothed probabilities.

Figure 2.6 presents 20-week-ahead forecasts from both 2-state regime-switching and GARCH (1,1) models. Similar to the 4-step-ahead forecast scenario, forecasts with and without Markov-smoothing effects are produced by the regime-switching model over 20 weeks forecast period.

To evaluate the forecast performance of the 2-state Markov-switching model, DM tests proposed by Diebold and Mariano (1995) are carried out for the 1-step, 4-step and 20-step-ahead forecasts by both regime-switching and GARCH (1,1) models. Table 2.2 lists the DM test results for the forecast comparison between the regime-switching model and the GARCH (1,1) model. Since the sample is relatively small, a 10% significance level is chosen instead of 5%. The tests show that forecasts by the regime-switching model outperform the simple GARCH model in 1-step and 20-step-ahead scenarios, although the difference between forecasts with and without Markov smoothing effect is not significant at all. While for 4-step-ahead (a month ahead) forecast, the regime-switching model fails to improve forecast accuracy compared with the GARCH model.

Following Wang and Bessler (2004) two-way and multi-way regression-based encompassing tests for all the 1-step, 4-step and 20-step-ahead forecasts from the regime-switching model and the GARCH model are also carried out. The two-way encompassing test is conducted by doing the following regression:

$$e_{it} = \lambda\left(e_{it} - e_{jt}\right) + \varepsilon_{it}, \tag{11.1}$$

$$e_{it} = realvalue_t - forecastvalue_{it} \tag{11.2}$$

where e_{it} is the forecast error from the forecast model i, and e_{jt} is the forecast error from the forecast model j. When coefficient λ is zero, it says the forecast model i encompasses the forecast model j, that is, there is no information included in the forecast model j, which is not already included in model i. The three-way encompassing test is constructed as the following regression:

$$e_{it} = \lambda_1(e_{it} - e_{jt}) + \lambda_2(e_{it} - e_{kt}) + \varepsilon_{it} \tag{12}$$

The null hypothesis is that the forecast model i encompasses the forecast model $j$and k if $\lambda_1 = \lambda_2 = 0$. If models i and j encompass each other, or neither of the models encompasses each other, then no single model can capture all useful information in the sample. As a result, it is possible to generate more accurate composite forecasts based on the two models. Table 2.3 presents these results.

It can be seen that the encompassing tests yield mixed results with respect to these forecasts' capability to "encompass" each other. As for the 1-step-ahead forecast, the DM test shows that forecasts by the regime-switching model outperform forecasts by the GARCH (1,1) model and encompassing test shows that the regime-switching model encompasses the GARCH model, meanwhile the GARCH model fails to encompass the regime-switching model, which confirms the DM test result. In the case of the 4-step-ahead forecast, the DM tests show that there are no significant differences among all three sets of forecasts, although the forecasts from the regime-switching model do outperform those by the GARCH model slightly. The two-way encompassing tests show that the regime-switching model and the GARCH model do not encompass each other, and this means each model has revealed some information about the natural gas price variation which the other model fails to discover. The three-way encompassing tests also confirm this conclusion. Hence, a combined forecast can be constructed by combining these two sets of forecasts to improve forecast accuracy. In the case of the 20-step-ahead forecast, the DM tests show that both sets of forecasts from the regime-switching model outperform forecasts by the GARCH model and the differences are significant at 10% level. The two-way encompassing tests show that forecast without MS effect encompasses forecast by GARCH while GARCH doesn't encompass forecast without MS effect. Neither forecast with MS effect nor GARCH encompasses each other. Hence, with regard to the 20-step-ahead forecast, forecasts without MS effect outperform GARCH forecasts and the former encompasses the latter.

When it comes to near-term forecast, such as the 1-step-ahead forecast, the 2-state regime-switching model produces better forecasts than the simple GARCH model and it can be seen from Figure 2.4 that forecasts by the Markov-switching model can follow those abrupt changes in reality very closely while the GARCH forecasts fail to capture these changes. However, we can also see from Figures 2.5 and 2.6 that all the 4-step and 20-step-ahead forecast fail to capture those sharp changes which the natural gas market went through during the month of May 2009. The observation, that the one-step-ahead forecasts from the Markov-switching model somehow capture those abrupt changes from May 1, 2009 to May 29, 2009 with an obvious lag of one period, while the 4-step-ahead forecasts fully miss these changes, shows that the regime-switching model can capture what already happened in the system but cannot forecast shock in the future. The 20-step-ahead forecasts by the regime-switching model smooth out those changes that the forecast system cannot predict and provide just mean values. All these observations suggest the natural gas market reacts to changes in fundamentals with a certain level of persistency, and this is consistent with our previous finding that the natural gas market tends to stay in one state until a switching point is achieved.

To further investigate if combined forecasts can improve prediction accuracy, linear combining method (with constant, without constraint on weights summing to unity) suggested by Granger and Ramanathan (1984) is applied to construct the combining forecasts based on regime-switching and GARCH forecasts. For comparison purpose, combined models for all 1-step, 4-step and 20-step-ahead forecast are provided. Furthermore, out-of-sample forecast error is calculated to test the prediction performance of these combined forecast models. The out-of-sample forecasts for combined model are calculated by first splitting the 20 forecast periods into 2 groups, and regression is carried out on the first 14 forecasts dataset to get the weights for each alternative forecast model, then the combined model forecast is calculated using these weights for the next 6 periods. These results are listed in Tables 2.4 and 2.5, respectively.

It can be seen that a combined model in general, improves forecast accuracy. As suggested by Granger and Ramanathan (1984), this simple regression combining method yields unbiased forecasts while a single forecast produces a somewhat unbiased forecast. Meanwhile, the improvement in the case of 1-step-ahead is relatively smaller than in other cases. Also the weight on the GARCH model is very small and insignificant. This observation is consistent with previous findings; the regime-switching model actually, encompasses and outperforms the GARCH model with respect to prediction accuracy.

For the 4-step-ahead forecast, the combining method yields considerable improvement. The DM test shows that there is no significant difference between forecasts from the regime-switching model and forecast by the GARCH model, and the encompassing tests show that no model encompasses the other; hence, the combination of the alternative forecast model is justifiable. The all-in-sample forecast error reported in Table 4 shows that the combined model improves forecast accuracy greatly compared with each alternative model, and all four combinations outperform each individual forecast model with respect to forecast mean error and sum of squared errors (SSE). Meanwhile, the out-of-sample forecast errors tell a different story. When a subsample of the forecasts of each alternative model is used to find the weights for the new combined forecast model, the combined model fails to improve the forecast accuracy compared with the regime-switching model. This could be a result of the small sample given the fact that only 14 forecasts are used in the regression to get weight for each alternative model. Similar observation can be seen in the case of the 20-step-ahead forecast. Since forecasts without MS encompass forecasts with MS and GARCH, and GARCH also encompasses forecasts from the Markov-switching model, it is normal to see the combination of these forecasts help improve prediction accuracy in view of the all-in-sample forecast error. Meanwhile, the linear combination of forecasts from the GARCH model and forecasts without the MS effect does improve out-of-sample forecast accuracy.

CONCLUSION

Chapter II uses a fundamental-based regime-switching model to study short-term U.S. natural gas price dynamics. Within the Markov-switching framework, roles of fundamentals in natural gas price movements are closely examined. It is found that switching market fundamentals such as crude oil price and storage changes have larger impacts in a bearish markets than in a bullish markets, while lagged future-spot spreads positively affect natural gas price changes less in a bearish than in a bullish market. Non-switching market fundamentals such as HDD and CDD fail to show statistical significance in both GARCH and regime-switching models.

The empirical study also shows the regime-switching model does a better forecasting job in general than the linear fundamental GARCH model without regime-switching framework, especially in the case of 1-step-ahead forecast. However, the results also show that real-world commodity price behavior is far more complicated than that predicted by structural models. Fundamental factors and the regime-switching forecasts are only reliable in the very short term. To further improve forecast accuracy, regression-based linear combination of the Markov-switching model and GARCH model is also tried. It shows that linear regression with constant, and without constraint on weights having to sum to 1 can yield unbiased and better combined forecasts compared with each alternative forecast model.

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. The Markov-switching model allows certain level of variance decomposition which is very helpful when dealing with highly persistent volatility. Meanwhile, the regime-switching model also allows non-linear model structure even though in each state the basic model could be linear. For further discussion, a 3-state model could be tried to account for possible third state, which considers the situation where the market expects little change for the next period.

CHAPTER III

DYNAMICS BETWEEN CRUDE OIL PRICE AND U.S. DOLLAR EXCHANGE RATES

INTRODUCTION

Given the fact that world crude oil price is denominated in U.S. dollars, crude oil price fluctuations in domestic currency may be quite different depending on the exchange-rate regime; hence, the economies in different countries would have different reactions towards changes in crude oil price, which would add more uncertainty the crude oil price volatility in addition to all the fundamentals. This study examines the dynamics between crude oil price and U.S. dollar's exchange rates vs. world's other major currencies by extending Krugman (1980)'s theoretical framework. Meanwhile, the roles of two newly emerging economies—China and Russia-- are examined to see how these two countries' oil import/export and also international portfolio preference affect the dynamics between U.S. dollar and oil price.

Figure 3.1 plots daily U.S. Dollar Index (USDX)[4] and nominal crude oil price[5] movement from July 2, 1986 to Sep. 2, 2010. Figure 3.2 provides U.S. Dollar Index and nominal crude oil price on daily basis especially for period January 2002 to Sep. 2, 2010. It can be seen that for the whole period July 1986—Dec. 2001, USD index and crude oil

[4] The USD Index measures the performance of the U.S. Dollar against a basket of currencies: EUR, JPY, GBP, CAD, CHF and SEK. The U.S. Dollar Index was launched in 1973 by the New York Board of Trade (NYBOT). At its inception, the U.S. Dollar Index was set at a base value of 100. The Index is calculated around the clock and is listed on the ICE Futures Exchange.

[5] The oil price quoted here is the daily prompt 1-month future prices of New York Mercantile Exchange (NYMEX) light sweet crude oil at Cushing, Oklahoma.

price share some common movement and the series roughly move in parallel. However, since 2002, the market witnessed the two series moving in opposite directions. Specifically, for period January 2002 – July 2008 (except for the second half of year 2006) it is obvious that U.S. dollar is depreciating accompanied by steady increase of oil price. Due to the 2008 financial crisis and also the following recession, crude oil price began to dive starting from August of 2008 while the U.S. dollar started to appreciate gradually. When oil price hit the bottom and started to climb up since January 2009, U.S. dollar appreciated first then began to depreciate slowly for the second half of 2009. While for the first 4 months of 2010, the dollar and oil price show some co-movement. Due (apparently) to the fear that rising debt levels in Europe and other developed economies would lead to another financial meltdown, and that China and other emerging markets may not be able to sustain their high levels of growth, oil price dropped from \$86.19/bl on May 3th, 2010 to \$68.75/bl on May 25, 2010. Meanwhile the U.S. dollar index slowly increased over the same period. When the U.S. dollar depreciated again, the oil price experienced slight increase.

All these observations raise the question about the causal relationship between U.S. dollar and crude oil price, that is, does crude oil price variation cause U.S. dollar changes or vice versa. The answer to this question would be crucial to a widely held suspicion that weakening U.S. dollar may also be a driving force for the steady increase of crude oil price seen for the past several years.

Krugman (1980) developed a 3-country (U.S., Germany, OPEC) dynamic partial-equilibrium portfolio model focusing on balance of payments, hence on the tradable sector and international asset (asset denominated in local currency) portfolio choices. A rise in oil prices is viewed as a wealth transfer from oil-importing countries to oil-exporting ones. The impact on exchange rates then depends on the distribution of oil imports across oil-importing countries and on portfolio preferences of both oil-importing countries (whose wealth declines) and oil-exporting ones (whose wealth increases). By assuming that OPEC would progressively use their accumulated wealth to import more goods from industrial countries, Krugman (1980) shows that in the long run the real exchange rate depends on the geographic distribution of OPEC imports, but no longer on OPEC portfolio choices. Assuming that oil-exporting countries have a strong preference for dollar-denominated assets but not for U.S. goods, an oil price spike would lead the dollar to appreciate in the short run but depreciate in the long run. Golub (1983) extends the dynamic partial-equilibrium model to include 4 countries and 3 currencies and comes into similar conclusions as Krugman (1980).

Be´nassy-Que´re´ et al. (2007) study the co-integration and causality between real price[6] of crude oil and real U.S. dollar exchange rate against euro[7] over period 1974-2004, and finds 10% increase in oil price coincides with 4.3% appreciation of U.S. dollar in the long run and the causality runs from oil to dollar. Huang and Guo (2007) conclude that real oil price shocks seem dominant in the variation of the real exchange rate of China's currency, and emergence of China in both oil and foreign exchange markets could strengthen the positive causality found from the oil price to the dollar in the short

[6] The crude oil price is deflated by the US consumer price index.
[7] This variable is constructed by deflating the nominal exchange rate of U.S. dollar against the euro using consumer price index for the Eurozone.

run but reverse its sign in the long run. However, we do observe that from 2002 to July 2008 oil price keeps rising while U.S. dollar depreciates, thus, a negative causality between oil price and U.S. dollar seems to exist and further investigation needs to be carried out to decide the direction of causality. If empirical study shows that causality runs from U.S. dollar to oil price, the argument that oil price increase is also a result of weakening U.S. dollar would be supported.

The quantitative analysis is carried out as follows. First, unit root tests, co-integration tests and also Granger causality analysis are conducted to the price data of oil and that of U.S. dollars; Then a 5-country dynamic partial-equilibrium portfolio model is constructed by extending Krugman (1980) to study how China and Russia, two major players on both oil and foreign exchange markets, affect the dynamics between oil and dollar. The last section concludes.

DATA AND ECONOMETRIC ANALYSIS

The data used for causality analysis between the U.S. dollar and crude oil price range from July 2, 1986 to July 30, 2010. The real prices of crude oil are calculated by deflating the nominal oil price using U.S. CPI index while setting July 1986 as the base month. Figure 3.3 presents U.S. dollar index, nominal and also real crude oil price for the whole sample period. Figure 3.4 presents these series in their logarithm terms where LOIL represents log of nominal oil price, LROIL denotes log of real oil price, and LUSDX is log of U.S. dollar index. It can be seen that the real oil price follows the same pattern as the nominal price and this confirms our previous observations about the movements of oil price and U.S. dollar. Also, the nominal oil price shows more volatility than the real price, although the oil price series overall are less stable than the U.S. dollar composite index. Meanwhile, the log transformation of these series “smoothes” out some variation compared with the original data series. The fact that oil prices in real terms exhibit less volatility than the nominal prices could be a result of CPI deflation, which helps reduce some of the variation in nominal oil prices caused by U.S. dollar value changes over the sample period. However, one should note that CPI only reflects inflation with respect to goods and services for final consumption by all U.S. urban consumers and overall the energy price changes (both housing/utility and motor fuel) accounts for roughly 10% of the CPI calculation in recent years, therefore, one should be cautious when using CPI deflator for purchasing power adjustment with respect to U.S. dollar.

Some preliminary analysis on both nominal and real oil price and also the U.S. dollar index are carried out and the empirical kernel density estimates of these data series are presented in Figures 3.5-3.10 listed in Appendix B. It can be seen that all the data series (in both original and logarithm terms) exhibit non-normality; meanwhile, skewness and kurtosis tests also confirm these observations. Not surprisingly, one can see that these series in logarithm yield smoother kernel density curves than the original data series. Also, the empirical density estimates of nominal and real oil prices suggest the underlying distribution of oil prices is a combination of different distributions, which could be a result of some structural change in the demand and supply conditions of crude oil market. To determine if there exists causality between oil price and U.S. dollar, co-integration and Granger causality analysis are conducted to the three data series: log of nominal oil price, log of real oil price and log of USDX. Meanwhile, to test if there is a structural change in the relation between oil and dollar since 2002, the same econometric analysis is also carried out on a subset of data which consist of all the data from year 2002 to 2010.

First, augmented-Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are carried out to the full sample data and also the subset which only includes these data spanning from 2002 to 2010. These test results are reported in Tables 3.1 and 3.2. For the full-sample data, it can be seen that both ADF and PP tests on log of USDX, nominal and real oil prices fail to reject the null hypothesis of a unit root, and the tests on first difference of these variables also confirm this observation that these variables are integrated of order 1, $I(1)$. Tests on subsample data yield the similar results which confirm the $I(1)$ conjecture.

Co-integration test is carried out to U.S. dollar index and oil prices to see if there exists long-run relationship between these two variables. For the comparison purpose, co-integration is tested on two datasets: one dataset includes the U.S. dollar index and the nominal crude oil price and the other consists of the U.S. dollar index and the real crude oil price. As proposed by Engle and Granger (1987), a two-step Engle-Granger co-integration test is carried out on these two datasets. First, a co-integration regression is estimated using OLS, then error correction models (ECM) are estimated to determine the co-integration direction and also the co-integration vector. In the first step regression, besides the constant term, a dummy variable (dummy05) is also included. Given the fact that China adopts a managed floating exchange rate regime against a basket of currencies with a small open window for floating range since July 2005, a time dummy variable is constructed to account for this change, which takes value 0 before July 21, 2005 and 1 otherwise. Similar to the unit root tests, Engle-Granger co-integration test is also carried out to a subsample dataset which only consists of the data from year 2002 to 2010.

For a two-variable system, existence of co-integration implies long-run equilibrium between these two series and the stationary equilibrium error which has zero mean suggests equilibrium could be achieved, at least to a close approximation. The typical error correction model would relate the change in one variable to past equilibrium errors, as well as to past changes of these two variables. Following Engle and Granger (1987), a series of ECM models are estimated and AIC (Akaike's information criterion) and SIC (Schwarz's information criterion) selection criterion are used to find the most proper specification to establish the joint distribution of these two variables. Three different ECM specifications are reported for each pair of variables. The first specification includes the error correction term from the first-step regression and also 5 lagged values of the first differences of both variables[8]. The second specification uses one-step lagged valued of these two variables to substitute for the error correction term while keeping all other lagged variables. The third specification is the final specification which only includes error correction term and lagged variables which are significant. Specifically, the Engle-Granger co-integration tests on oil price (nominal and

[8] To determine the number of lags, a series of models with maximum lags of 20 are estimated. AIC and SIC associated with models are used to decide the optimal number of lags by reducing the lags one by one.

real) and U.S. dollar index for full sample and subsample periods are reported in Tables 3.3-3.18. Table 3.3 lists the OLS forward regression result of log of USDX on log of nominal oil price for the full sample period, and the ADF and Philips-Perron test results on the regression residuals show that these two series are co-integrated at 1% significance level. Meanwhile, Table 3.7 presents the reverse regression (nominal oil price on USDX) and corresponding unit root test results, which also suggest the co-integration between these two variables. Results listed in Tables 3.11 and 3.15 also suggest co-integration between these two variables for the subsample period. The negative signs of the coefficients of regressors suggest negative correspondence between these two variables. In the long run when nominal oil price increases the U.S. dollar index would decrease, say U.S. dollar would depreciate, and vice versa. This empirical finding is consistent with Krugman (1980)'s conclusions.

Tables 3.4 and 3.8 list the ECM estimation results of USDX and nominal oil prices for the full sample period, while Tables 3.12 and 3.16 report the ECM results over the subsample period 2002 to 2010. For the full sample period, all the error corrections terms are significant, which suggest the causality direction runs both ways. When there is deviation from the two-variable equilibrium system (USDX and nominal oil price), changes in one variable would cause long-run adjustment from the other so that the system could revert back to the equilibrium state. For the USDX, the daily adjustment rate is -0.0022, hence, if the deviation from equilibrium caused by nominal oil price changes in last period is 1%, the long-run adjustment to USDX would be -4%[9] on monthly basis keeping all other things constant. While for nominal crude oil price, the adjustment rate is -0.0029, hence, only approximately -5.8% of adjustment in nominal oil price would be achieved in one month. Obviously, the nominal oil price is more sensitive to the change of USDX than USDX toward nominal oil price.

In Table 3.12 the error correction term is not significant in the first ECM specification, and in the second ECM specification neither the one period lag of USDX nor the nominal price are significant, which means for the period 2002-2010 long-run dynamics from nominal oil price to USDX is broken and the reverting process to the equilibrium is not supported by the data; that is to say, when there is a change in nominal oil price, the system may deviate from the equilibrium over the subsample period. Meanwhile, from Table 3.16 one can still see the long-run adjustment from U.S. dollar to nominal oil price is still supported by the data. Given the long-run daily adjustment rate -0.0104, 1% deviation in last period would result in roughly -21% adjustments toward equilibrium within a month for the subsample period. It can be seen for the 2002 – 2010 period the impacts of changes in USDX on nominal oil prices are larger than that for the full sample period. This finding seems to support the claim that for the past several years the steady oil price increase is also a result of weakening U.S. dollar.

The Engle-Granger tests on the other two-variable system --real oil price and USDX-- for the full sample period are reported in Tables 3.5, 3.6, 3.9 and 3.10. It's not

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[9] Since the daily data are used for the analysis, and the first difference of log of the variable can be interpreted as percentage change of the variable, the coefficient of error correction term represents the daily adjustment rate, and the monthly adjustment can be got by multiplying 20 (5 business days a week and 4 weeks a month).

surprising to see that these two variables are also co-integrated at 1% significance level and the corresponding adjustment rates are generally larger in magnitudes than those in nominal oil price cases. Specifically, the adjustment rate for USDX from real oil price is just slightly higher than that from nominal oil price, which means the dynamics from oil price to USDX is roughly the same no matter the oil price is in nominal or real terms. Meanwhile, the adjustment rate for real oil price from USDX is much higher than that for nominal price, which suggest the equilibrium between real oil price and U.S. dollar could be achieved much faster than that between nominal oil price and U.S. dollar. The slow adjustment rate of nominal oil price implies more persistent impacts of shocks and hence higher volatility and this can be seen from Figures 3.4. Real world traders in the crude oil market are more concerned with the real price of a commodity, hence, when the value of U.S. dollar (the denominated currency) changes the nominal price of this commodity would change accordingly so that the equilibrium between real price and U.S. dollar can be achieved. Tables 3.13, 3.14, 3.17 and 3.18 list the test results on the real oil price and USDX for the subsample period. Similar to the full sample scenario, these two variables are co-integrated over the subsample period and the adjustment rates are slightly larger in magnitudes than those in nominal oil price cases.

The significance of dummy variable (Dummy05) in first-step co-integration regressions (both forward and reverse regressions) and also the faster adjustment rates for the subsample period (2002—2010) show that the dynamics between U.S. dollar index and crude oil price (nominal and real) experience some structural change since year 2002, which confirms our previous observations from Figures 3.1 and 3.3.

Another finding worth mentioning is that for the full sample period, the coefficients of determination (R^2) for the reverse regressions, which take the value of 72% for the regression of nominal oil price on USDX and 67% for the regression of real oil price on USDX, are much higher than those of the forward regressions, which take value of 33.5% for the regression of USDX on nominal oil price and 36% of the regression of USDX on real oil price. For the subsample period, R^2 for the reverse regressions are 85.34% and 80.62%, while for the forward regressions R^2 are 76.67% and 73.38% respectively. These findings may suggest that variation in U.S. dollar has more power in explaining the changes of oil price than the oil price with respect to U.S. dollar even though the dynamics between these two variables run both ways most of the time.

Co-integration in a two-variable system implies at least one-way causality direction. The Engle-Granger tests conducted above assume two variables under investigation jointly endogenous, so the ECM test is carried out in both directions. In most cases the dynamics between oil and dollar run in both directions, except in the one subsample case where the error correction term from nominal oil price to USDX is not significant. To further investigate the direction of causality between oil and dollar, Granger causality tests with different lags are carried out to all the data series for both full and subsample periods. The corresponding Wald tests results are listed in Table 3.19. These results are consistent with the analysis above using ECM. The Granger causality runs from U.S. dollar to nominal oil prices for the full sample period no matter how many lags are included, while for the subsample data, Granger causality is significant at 5% level only when 10 lags are considered in the VAR model. Meanwhile, nominal oil price also Granger causes U.S. dollar index. As for real oil price and U.S. dollar index, the Granger causality also runs in two directions for both full sample and subsample periods. These results also support the conjecture that oil price and U.S. dollar are jointly endogenous.

DYNAMIC MODEL OF OIL AND DOLLAR: ROLE OF CHINA

This section revisits Krugman (1980) and extends the model to a five-country dynamic partial equilibrium model. Some detailed analysis is dedicated to the role that China plays in both crude oil market and U.S. dollar denominated assets market, especially U.S. bond market.

On July 15, 2009, the People's Bank of China announced China's foreign exchange reserve had reached \$2.132 trillion, by far the largest holders of foreign exchange reserves and the first time a country had surpassed the \$2 trillion benchmark. Meanwhile, China shows great interest in holding U.S. dollar denominated asset. Among China’s huge official reserve, \$800.5 billion have been invested in U.S. treasury securities and China has become the biggest holder of U.S. public debt. Up to July 2009, among all the American debt owned by foreign holders, China’s holding accounts for 23.35%, Japan owns 21.13%, oil exporters own 5.52%, and Russia owns 3.44%[10]. In July 2005, China moved to a managed floating regime against a basket of currencies although the open window for floating range is quite small. International Monetary Fund

[10] Source of data: http://en.wikipedia.org/wiki/United_States_public_debt

(IMF) 2008 classification of exchange rate Regimes and Monetary Policy Frameworks[11] lists China's exchange rate regime as "crawling peg", and Russia as "conventional fixed peg arrangement". On May 20, 2007, Kuwait discontinued pegging its currency exclusively to the dollar, preferring to use the dollar in a basket of currencies. Syria made a similar announcement on June 4, 2007. China and OPEC countries adopt similar foreign exchange rate regime and they all seem to prefer dollar dominated assets. Meanwhile, in September 2009, China, India and Russia said they were interested in buying IMF gold to diversify their dollar-denominated securities. It seems there may be some change in the future with regard to these countries' portfolio preference over dollar denominated assets. The major task of this section is to see how China, Russia and OPEC's portfolio preference over American asset may have impacts on U.S. dollar exchange rate changes.

Unlike OPEC, China is an oil importing country and China's growing economy also enhances the country's dependence on imported oil. According to Energy Information Administration (EIA), China consumed an estimated 7.8 million barrels per day (bbl/d) of oil in 2008, making it the second-largest oil consumer in the world behind the United States. China's net oil imports were approximately 3.9 million barrels per day (bbl/d) in 2008, making it the third-largest net oil importer in the world behind the United States and Japan. EIA forecasts that China's oil consumption will continue to grow during 2009 and 2010 while the recession may still haunt the world economy, and

[11] http://www.imf.org/external/np/mfd/er/2008/eng/0408.htm

in a foreseeable future China's dependency on foreign oil will increase steadily[12]. On the other hand, Russia is a major non-OPEC oil-exporting country, so far the second largest oil-exporting country in the world after Saudi Arabia, also Russia holds a large volume of dollar-denominated assets. The inclusion of China is especially relevant since a number of large emerging countries tend to follow similar exchange-rate strategies as China. At the same time, inclusion of Russia in this study is important in the sense that a non-OPEC major oil exporting country with managed floating exchange rate regime may have different impact on the dynamics between oil and dollar from China and OPEC.

Euro area[13] (or euro zone) is included in this model as a major oil importer and industrialized economy. The exchange rate between euro and U.S. dollar is treated as the price for dollar.

Suppose the world consists of 5 countries/regions: US (U), Euro Area (E), OPEC (O), Russia (R) and China (C). US, Euro Area, China and Russia sell manufactured goods to OPEC and each other, while OPEC has a single export product, oil. The price of oil is assumed to be exogenously determined[14] and denominated in U.S. dollar. There are two sets of market: goods market and asset market. In the goods market, industrial products and oil are traded internationally and in the asset market there are two assets: dollar-denominated assets denoted by D and euro-denominated assets noted by E. Two

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[12] Country Analysis Briefs—China, July 2009, EIA. http://www.eia.doe.gov/emeu/cabs/China/Full.html

[13] Euro area is an economic and monetary union of 16 European Union member states which have adopted the euro currency as their sole legal tender. It currently consists of Austria, Belgium, Cyprus, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia and Spain.

[14] For the first part of the theoretical model discussion, the focus is on oil price's impact on U.S. dollar. Hence, exogeneity of oil price is assumed to simplify the model construction. For the second part where the impact of U.S. dollar on oil price is discussed, this assumption is relaxed and the corresponding oil demand function for each country is defined then.

exchange rates exist in the model: euro dollar price of U.S. dollar V_{eu} and Russian ruble price of U.S. dollar V_{ru}. Since the floating window of exchange rate of Chinese Renminbi (RMB) against U.S. dollar is only 0.3%, in this model China and OPEC are still assumed to peg their currencies to the dollar. Therefore, the bilateral exchange rate of RMB against euro and Russian ruble would be decided by V_{eu} and V_{ru}, respectively. The trade balances T_i ($i =$ E, U, R, C, O) are all measured in U.S. dollars. The bilateral trade accounts B_m ($m =$EU, ER, EC, UC, UR, RC) are functions of bilateral exchange rates which are measured in U.S. dollar, and only include revenue generated by industrial products trading. In this study trading of oil among all these countries are calculated separately. The trade accounts of each country are defined as following:

Euro Area:

$$T_E = B_{EU}(V_{eu}) + B_{EC}(V_{eu}) + B_{ER}(V_{eu}/V_{ru}) + \gamma_E(V_{eu})X - P_{oil}(O_{EO} + O_{ER}) \tag{13}$$

where X is total volume of OPEC imports and γ_E is share of OPEC's spending on Euro area industrial goods. It is normal to assume that $\gamma'_E > 0$, which means when euro depreciates the EU goods become less expensive, as a result, exports of EU goods would increase. P_{oil} is real price of oil deflated by U.S. GDP deflator. O_{EO} and O_{ER} are oil imports of Euro area from OPEC and Russia, respectively, which are assumed to be determined exogenously. It is also assumed that $B'_{EU} > 0$, $B'_{EC} > 0$, $B'_{ER} > 0$. An increase in V_{eu} and/or V_{ru} represents appreciation of U.S. dollar and depreciation in euro and/or

Russian ruble. V_{eu}/V_{ru} is the euro dollar price of Russian ruble and increase of this value means appreciation of Russian ruble.

United States:

$$T_U = -B_{EU}(V_{eu}) + B_{UC} + B_{UR}(V_{ru}) + \gamma_U(V_{eu})X - P_{oil}(O_{UO} + O_{UR}) \quad (14)$$

where B_{UC} is the bilateral trade account between US and China, which is exogenously determined for the exchange rate of RMB against U.S. dollar is predetermined by Chinese financial authority and is fixed. $\gamma_U(V_{eu})$ is share of United States in OPEC's imports, and it is obvious to see $\gamma_U'(V_{eu}) < 0$. O_{UO} and O_{OR} are exogenous oil imports of US from OPEC and Russia respectively. To make the model more realistic, this restriction will be relaxed later to introduce the price elasticity of oil demand of each country/region into model.

Russia:

$$T_R = -B_{ER}(V_{eu}/V_{ru}) + B_{RC}(V_{ru}) - B_{UR}(V_{ru}) + \gamma_R(V_{ru})X + P_{oil}(O_{ER} + O_{UR} + O_{CR}) \quad (15)$$

where $\gamma_R(V_{ru})$ is share of OPEC's imports spending on Russian industrial products, which is a function of exchange rate of U.S. dollar against Russian ruble and $\gamma_R'(V_{ru}) > 0$. O_{CR} is oil import of China from Russia.

China:

$$T_C = -B_{EC}(V_{eu}) - B_{RC}(V_{ru}) - B_{UC} + \gamma_C(V_{eu})X - P_{oil}(O_{CO} + O_{CR}) \quad (16)$$

OPEC:

$$T_O = P_{oil}(O_{EO} + O_{UO} + O_{CO}) - X \quad (17)$$

Let $O_O = O_{EO} + O_{UO} + O_{CO}$, which denotes the total oil exports by OPEC. Similarly, the total oil export of Russia can be expressed as: $O_R = O_{ER} + O_{UR} + O_{CR}$. Also, we have $\gamma_U + \gamma_E + \gamma_R + \gamma_C = 1$.

Following Krugman (1980), OPEC's import X is assumed to adjust gradually according to its income level:

$$\frac{dX}{X} = \lambda(P_{oil}O_O - X),\ 0 < \lambda < 1 \tag{18}$$

Since it is assumed that there are five countries/regions in the world, we must have the following equality: $T_E + T_U + T_R + T_C + T_O = 0$.

In assets market, each country/region chooses to hold dollar-denominated asset D and also euro-denominated E to optimize their international portfolio. They will choose to buy D when dollar depreciates and sell when it appreciates. Hence, it is assumed that there is no arbitrage and US holds a fixed dollar value of euro in its portfolio and Euro zone countries hold a fixed euro value of dollar asset in its portfolio. Russia could hold both euro and dollar assets and keep a fixed ruble value of these two kinds of assets.

Euro Area:

$$D_E V_{eu} = \text{constant, or equivalently } \frac{dD_E}{D_E} = -\frac{dV_{eu}}{V_{eu}} \tag{19}$$

US:

$$E_U / V_{eu} = \text{constant, or equivalently } \frac{dE_U}{E_U} = \frac{dV_{eu}}{V_{eu}} \tag{20}$$

Russia:

$$E_R(\frac{Vru}{Veu}) + D_R V_{ru} =$$ constant, or equivalently

$$dE_R(\frac{Vru}{Veu}) + E_R d(\frac{Vru}{Veu}) + dD_R + D_R dV_{ru} = 0 \quad (21)$$

Rearranging equation (21), we get:

$$\frac{dE_R}{V_{eu}} = -\frac{E_R}{V_{eu}}\frac{dV_{ru}}{V_{ru}} + \frac{E_R}{V_{eu}} - dD_R - D_R\frac{dV_{ru}}{dV_{ru}} \quad (21.1)$$

For OPEC and China, it is assumed that they would allocate fixed share of their net foreign reserve in euro and dollar assets. These assumptions are made based on a fact that current account imbalances of these industrialized countries will have to be met by capital flows from OPEC and China. Let α_O and α_C be the share of dollar assets in OPEC and China's international asset portfolio, respectively, which are assumed to be constant. Also let W_O and W_C be the wealth level of OPEC and China measured in dollars. Then we have:

$$W_O = D_O + E_O / V_{eu} = D_O + (1-\alpha_O)W_O \quad (22)$$

$$W_C = D_C + E_C / V_{eu} = D_C + (1-\alpha_C)W_C \quad (23)$$

Taking first difference of equations (22) and (23), we get the rate of change of OPEC and China's wealth over time:

$$dW_O = T_O - (1-\alpha_O)W_O \frac{dV_{eu}}{V_{eu}} \quad (22.1)$$

$$dW_C = T_C - (1-\alpha_C)W_C \frac{dV_{eu}}{V_{eu}} \quad (23.1)$$

Hence, change in wealth level (measured in U.S. dollar) is equal to trade balance plus exchange rate variation effects on euro-denominated asset. Next, capital account balance of Euro Zone is established. Given the facts that fixed portions of wealth of China and OPEC are invested in U.S. dollar denominated assets, the following equations can be derived to express the net demand of euro denominated assets from China and OPEC:

$$\frac{dE_C}{V_{eu}} = (1-\alpha_C)dW_C + (1-\alpha_C)W_C\frac{dV_{eu}}{V_{eu}}$$

$$= (1-\alpha_C)\left[T_C - (1-\alpha_C)W_C\frac{dV_{eu}}{V_{eu}}\right] + (1-\alpha_C)W_C \tag{24}$$

$$\frac{dE_O}{V_{eu}} = (1-\alpha_O)dW_O + (1-\alpha_O)W_O\frac{dV_{eu}}{V_{eu}}$$

$$= (1-\alpha_O)\left[T_O - (1-\alpha_O)W_O\frac{dV_{eu}}{V_{eu}}\right] + (1-\alpha_O)W_O \tag{25}$$

Continuous capital flow into Euro Area would cause changes in continuous exchange rate, and vice versa. Net capital flow into Euro Area denoted as K_E measured in US dollar is equal to purchases of euros by US, Russia, China and OPEC minus purchase of dollars by Euro Area countries:

$$\begin{aligned}
K_E &= dE_U/V_{eu} + dE_R/V_{eu} + dE_c/V_{eu} + dE_O/V_{eu} - dD_E \\
&= \left[\frac{E_U}{V_{eu}} + D_E + \alpha_O(1-\alpha_O)W_O + \alpha_C(1-\alpha_C)W_C\right]\frac{dV_{eu}}{V_{eu}} + (1-\alpha_O)T_O + (1-\alpha_C)T_C \\
&\quad - E_R\frac{dR}{V_{ru}} - dD_R + D_R\frac{dV_{ru}}{V_{ru}} = (1-\alpha_O)T_O + (1-\alpha_C)T_C - dD_R - (D_R + \frac{E_R}{V_{eu}})\frac{dV_{ru}}{V_{ru}} \\
&\quad + (D_E + \alpha_O(1-\alpha_O)W_O + \alpha_C(1-\alpha_C)W_C + \frac{2E_R}{V_{eu}})\frac{dV_{eu}}{V_{eu}}
\end{aligned} \tag{26}$$

where $R = \dfrac{V_{ru}}{V_{eu}}$ is the arbitrage free exchange rate of Russian ruble against euro, the ruble price of euro. The change of R is decided by changes of V_{eu} and/or V_{ru} :

$dR = \frac{dV_{ru}}{V_{ru}} - \frac{V_{ru}}{V_{eu}} \frac{dV_{eu}}{V_{eu}}$, equivalently, we have: $\frac{dR}{R} = \frac{dV_{ru}}{V_{ru}} - \frac{dV_{eu}}{V_{eu}}$. The equilibrium exchange rate is determined by the balance of payments equilibrium for Euro Area, that is $T_E + K_E = 0$ and hence, we have:

$$\frac{dV_{eu}}{V_{eu}} = -\frac{(1-\alpha_O)T_O + (1-\alpha_C)T_C - dD_R - (D_R + \frac{E_R}{V_{eu}})\frac{dV_{ru}}{V_{ru}} + T_E}{D_E + \alpha_O(1-\alpha_O)W_O + \alpha_C(1-\alpha_C)W_C + \frac{2E_R}{V_{eu}}} \tag{27}$$

Similarly, we can write down US's capital account balance and derive the net capital flow into US as:

$$\begin{aligned} K_U &= dD_E + dD_O + dD_C + dD_R - dE_U / V_{eu} \\ &= -D_E(\frac{dV_{eu}}{V_{eu}}) - \alpha_O(1-\alpha_O)W_O(\frac{dV_{eu}}{V_{eu}}) - \alpha_C(1-\alpha_C)W_C(\frac{dV_{eu}}{V_{eu}}) \\ &+ \alpha_C T_C + \alpha_O T_O + dD_R - \frac{E_U}{V_{eu}}(\frac{dV_{eu}}{V_{eu}}) \\ &= -(D_E + \alpha_O(1-\alpha_O)W_O + \alpha_C(1-\alpha_C)W_C + \frac{E_U}{V_{eu}})\frac{dV_{eu}}{V_{eu}} \\ &+ \alpha_C T_C + \alpha_O T_O + dD_R \end{aligned} \tag{28}$$

In equilibrium $T_U + K_U = 0$, the rate of change in exchange rate of euro against dollar is:

$$\frac{dV_{eu}}{V_{eu}} = \frac{\alpha_O T_O + \alpha_C T_C + dD_R + T_U}{D_E + \alpha_O(1-\alpha_O)W_O + \alpha_C(1-\alpha_C)W_C + E_U / V_{eu}} \tag{29}$$

Since it is assumed that US keeps the euro-denominated assets in US dollar E_U / V_{eu} constant, the rate of change of exchange rate of US dollar as illustrated by equation (29) only depends on trade balance of each country and their investment portfolio preferences over the two assets.

Next the impact of oil price on U.S. dollar exchange rate in both short-run and also long run perspectives can be derived based on equation (27) or (29), and (14). By taking first derivative of dV_{eu}/V_{eu} with respect to P_{oil} based on equation (29), we would get the short-term effect of oil price on U.S. dollar $\partial(dV_{eu}/V_{eu})/\partial P_{oil}$:

$$\partial(dV_{eu}/V_{eu})/\partial P_{oil} = \frac{\alpha_O O_O - \alpha_C(O_{CO}+O_{CR}) + \partial(dD_R)/\partial P_{oil} - (O_{UO}+O_{UR})}{D_E + \alpha_O(1-\alpha_O)W_O + \alpha_C(1-\alpha_C)W_C + E_U/V_{eu}}$$

$$= \frac{\overline{O}(\tau_O(\alpha_O - \alpha_C\sigma_{CO} - \sigma_{UO})) - \overline{O}((1-\tau_O)(\alpha_C\sigma_{CR} + \sigma_{UR})) + \partial(dD_R)/\partial P_{oil}}{D_E + \alpha_O(1-\alpha_O)W_O + \alpha_C(1-\alpha_C)W_C + E_U/V_{eu}} \quad (30)$$

where σ_{CO} is share of China's oil import from OPEC in OPEC's total exports, σ_{UO} is share of American oil import from OPEC in OPEC's total exports, σ_{CR} is share of China's oil import from Russia in Russian total oil export, and σ_{UR} is share of American oil import from Russia in Russian total oil export. Let $\overline{O}$ be the total world oil export and $\tau_O = O_O/\overline{O}$ denote the market share of OPEC in world oil export market.

Without China and Russia, equation (30) would reduce to:

$$\partial(dV_{eu}/V_{eu})/\partial P_{oil} = \frac{\overline{O}(\alpha_O - \sigma_{UO})}{D_E + \alpha_O(1-\alpha_O)W_O + E_U/V_{eu}} \quad (30.1)$$

It is obvious that the short-run effect of oil on dollar depends on OPEC's preference over dollar-denominated assets and the share of US oil imports in OPEC's oil exports. If OPEC prefer dollar-denominated assets to the other assets, then U.S. dollar would appreciate in the short run following oil price increase, otherwise it would depreciate.

With the introduction of China and Russia into the model, it can be seen that asset investment strategies of OPEC, China, Russia, and also oil import shares of China and US from OPEC and Russia, respectively, would all affect short-term rate of change of US dollar exchange rate. The role of China and Russia in short-run oil and dollar dynamics is a little bit complicated. Since in the short-run wealth of each country is predetermined, the impact of oil price on exchange rate of U.S. dollar expressed by equation (30) would basically depend on the numerator. The term $\partial(dD_R)/\partial P_{oil}$ represents Russia's investment preference change following an oil price change. When oil price rises, in short-run Russia would increase its revenue and if wealth transfer makes Russia invest more in U.S. dollar denominated assets while keeping all other factors constant, U.S. dollar would appreciate otherwise it depreciates. Meanwhile, if the share of oil exports by OPEC increases while there is rise in real oil price, in the short-run the U.S. dollar would appreciate keeping all other factors constant, since OPEC allocates fixed proportion of their net foreign assets in U.S. dollar assets.

The term $(\tau_O(\alpha_O - \alpha_C\sigma_{CO} - \sigma_{UO})) - ((1-\tau_O)(\alpha_C\sigma_{CR} + \sigma_{UR})$ tells an interesting story about wealth transfer following an oil price change. First this term can be rewritten as the following:

$$\begin{aligned}&(\tau_O(\alpha_O - \alpha_C\sigma_{CO} - \sigma_{UO})) - ((1-\tau_O)(\alpha_C\sigma_{CR} + \sigma_{UR}) \\ &= \tau_O\alpha_O - \tau_O\alpha_C\sigma_{CO} - \tau_O\sigma_{UO} - (1-\tau_O)\alpha_C\sigma_{CR} - (1-\tau_O)\sigma_{UR}\end{aligned} \tag{31}$$

When oil price increases by one unit, in the short-run demand of oil is assumed to remain the same for it takes time to adjust the consumption behaviors, hence, τ_O of the increased oil revenue would go to OPEC and $1-\tau_O$ would go to Russia. $\tau_O\sigma_{UO}$ now represents the wealth transfer from US to OPEC and $(1-\tau_O)\sigma_{UR}$ is the wealth transfer from US to Russia, while $\tau_O\alpha_O$ represents the money that comes back to U.S. capital account from OPEC by their investment on dollar-denominated assets. Due to an oil price increase, China invests less on dollar assets by exact amounts $\tau_O\alpha_C\sigma_{CO}$ and $(1-\tau_O)\alpha_C\sigma_{CR}$, while the former amount goes from China to OPEC and latter goes from China to Russia. If the net demand for dollar assets $\tau_O\alpha_O - \tau_O\alpha_C\sigma_{CO} - (1-\tau_O)\alpha_C\sigma_{CR} + \partial(dD_R)/\partial P_{oil}$ from OPEC, China and Russia exceeds the actual need for foreign capital in US, expressed by $\tau_O\sigma_{UO} + (1-\tau_O)\sigma_{UR}$. As a result, the U.S. dollar would appreciate. Of course, if the flow of foreign capital into US fails to meet the actual need, the U.S. dollar would depreciate.

The long-run effect dV_{eu}/dP_{oil} can be derived from equations (13), (14), (15) and (16) by setting $dX/X = 0, dV_{eu}/V_{eu} = 0$ and $K_U + T_U = 0$. First, in the long run at equilibrium the wealth of China and OPEC are endogenous; second it is assumed the balance of payments of OPEC is zero, that is to say $T_O = 0$, and this is equivalent to state that OPEC will spend all the trade surplus from oil price rise on industrial goods from other countries; third, in the long run at equilibrium $dD_R = 0$, that is at equilibrium the value of denominated assets held by Russia will stay stable; forth, for US and Euro zone the sum of balance of payments and capital accounts is zero, say $K_U + T_U = 0$ and $K_E + T_E = 0$; finally, the change of independent exchange rate is zero at equilibrium, $\frac{dV_{eu}}{V_{eu}} = 0$. Based on equation (28), $K_U + T_U = 0$ leads to:

$$\alpha_C T_C + T_U = 0 \tag{32}$$

Taking first derivative of equations (14) and (16) with respect to P_{oil} yields $\frac{\partial T_C}{\partial P_{oil}}$ and $\frac{\partial T_U}{\partial P_{oil}}$, then substitute these two terms into equation (14) and rearrange all the terms to get:

$$\frac{\partial V_{eu}}{\partial P_{oil}} =$$

$$\frac{\alpha_C(\gamma_C\tau_O-\sigma_C)+\gamma_U\tau_O-\sigma_U}{B'_{EU}+\alpha_C B'_{EC}-P_{oil}O_O(\gamma'_U+\alpha_C\gamma'_C)}\bar{O}+\frac{\partial V_{ru}}{\partial P_{oil}}\frac{B'_{UR}-\alpha_C B'_{RC}}{B'_{EU}+\alpha_C B'_{EC}-P_{oil}O_O(\gamma'_U+\alpha_C\gamma'_C)} \quad (33)$$

where $\sigma_C = \frac{O_{CO}+O_{CR}}{\bar{O}} = \sigma_{CO}\tau_O + (1-\tau_O)\sigma_{CR}$, represents the share of oil imports of China in world oil market, and $\sigma_U = \frac{O_{UR}+O_{UO}}{\bar{O}} = \sigma_{UO}\tau_O + (1-\tau_O)\sigma_{UR}$ is the share of oil imports of US in the world oil market.

First, it can be seen that the denominator in equation (33) is positive simply by assumptions: $B'_{EU} > 0$, $B'_{EC} > 0$, $\gamma_U'(V_{eu}) < 0$ and $\gamma_C'(V_{eu}) < 0$. Before we proceed to detailed analysis of this equation, we can see that in the absence of China and Russia, equation (33) becomes:

$$\frac{\partial V_{eu}}{\partial P_{oil}} = \frac{\gamma_U-\sigma_U}{B'_{EU}-P_{oil}O_O\gamma'_U}\bar{O} \quad (34)$$

This is exactly the case studied by Krugman (1980). It is easier to see that the sign of $\gamma_U - \sigma_U$would determine the direction of the movement of U.S. dollar exchange rate following an oil price change. When the share of U.S. goods in OPEC's imports of industrial goods is larger than the share of U.S. oil imports in world oil market, the dollar would appreciate following oil price increase, otherwise it would depreciate. In a three-country setting, it can be seen that short-run and long-run effects of oil on dollar depend on different factors. In the short-run it is OPEC's portfolio preference that affects value of dollar directly while in the long run it is OPEC's trading (buying) behaviors that determine direction of dollar movement together with U.S. oil imports share.

In a five-country setting, the long-run effect of oil price on the dollar depends on the sum of two terms. For the first term in equation (33), the sign depends on just the numerator, $\alpha_C(\gamma_C\tau_O - \sigma_C) + \gamma_U\tau_O - \sigma_U$. It is worth noticing that the indicator of OPEC's preference over U.S. dollar denominated assets α_O does not enter into equation (33); instead, the shares of industrial products purchased by OPEC from the US and China together with China's preference over dollar-denominated assets α_C are affecting the dynamics between oil and dollar directly. Suppose that OPEC is the only oil exporter in the world or the share of OPEC oil is very close to 1, then this term can be reduced to $\alpha_C(\gamma_C - \sigma_C) + \gamma_U - \sigma_U$. If the share of industrial products bought by OPEC from US is larger than the share of the oil imports of US, and if the similar situation also applied to China, then this term is positive. Keeping other factors constant, oil price increase would cause the U.S. dollar appreciate in the long run; on the other hand, if OPEC prefers to buy industrial products from other countries rather than the US, and the share of China's buying of oil from OPEC is also larger than the share of OPEC's buying from China, then oil price increases would cause dollar to depreciate in the long run while keeping other factors constant. Another interesting scenario is to check what happens when the signs of $\gamma_U\tau_O - \sigma_U$ and $\gamma_C\tau_O - \sigma_C$ are opposite. When $\gamma_U\tau_O - \sigma_U < 0$, which means OPEC buys more of U.S. dollar denominated assets than US products, at the same time OPEC buys more from China so that in the end $\alpha_C(\gamma_C\tau_O - \sigma_C) + \gamma_U\tau_O - \sigma_U > 0$; as a result, the dollar would still appreciate following oil price increase; otherwise, U.S.

dollar would depreciate. Therefore, in the long run China's international trading behaviors and also portfolio preference would affect the dynamics between oil and dollar.

The second term in equation (33) is about Russia's role in the oil and dollar dynamics. It can be seen that the sign of $B'_{UR} - \alpha_C B'_{RC}$ is negative for $B'_{UR} < 0$ and $B'_{RC} > 0$. $B'_{UR} < 0$ means when U.S. dollar appreciates against Russian ruble, the bilateral trade balance between US and Russia would deteriorate (less export of US goods to Russia). When V_{ru} increases, China's currency would also appreciate for it is pegged to U.S. dollar; as a result, bilateral trade balance between Russia and China would increase in favor of Russia, hence, $B'_{RC} > 0$. In the end, the sign of the second term would depend on the sign of $\frac{\partial V_{ru}}{\partial P_{oil}}$. When oil price rises, Russia could improve the country's current account accordingly, therefore, Russian ruble could appreciate; on the other hand, if Russian's current account fail to improve or the financial authority intervenes the exchange market, $\frac{\partial V_{ru}}{\partial P_{oil}}$ could also be negative. Figure 3.11 shows that Russian ruble moves almost in parallel with U.S. dollar index and the variation of ruble is relatively small compared with U.S. dollar index and nominal U.S. exchange rate against euro.

In summary, equation (33) shows that long-run impact of oil price change on U.S. dollar exchange rates depends on China's portfolio preference, OPEC's industrial products imports from different countries, shares of US and China's oil imports and Russian ruble exchange rate movement. It can be seen the roles played by two major emerging countries: China and Russia are critical in the oil and dollar dynamics both in short run and long run perspectives.

So far in this theoretical model, the oil price is assumed exogenous. To investigate the impact of U.S. dollar on oil price, this restriction needs to be relaxed. The following section is dedicated to discussion on causality running from U.S. dollar to oil price. First, the oil demand function of each country O_i ($i =$ E,U,C) is assumed as the following:

$$O_E = P_{oil}^{-\varepsilon}\theta_E Y_E(V_{eu}) \tag{35}$$

$$O_U = P_{oil}^{-\varepsilon}\theta_U Y_U(V_{eu}) \tag{36}$$

$$O_C = P_{oil}^{-\varepsilon}\theta_C Y_C(V_{eu}) \tag{37}$$

$\varepsilon > 0$ is the price elasticity for each oil-importing country[15], and θ_j (j=E,U,C) are the energy intensity parameters for these industrial countries which reflect each economy's dependence on energy consumption. Y_k (k =E,U,C) represents aggregate demand of each country. Equations (35-37) suggest that each country's oil demand change would depend on their energy intensity and also aggregate demand keeping oil price constant.

As for oil supply, different supply elasticity parameters are assumed for OPEC and Russia due to the fact that OPEC countries set quotas for oil production and Russia's economy is more market-oriented. It is obvious to see that oil supply elasticity ρ for Russia is larger than supply elasticity φ for OPEC. Therefore, the oil market clearance condition means:

[15] Due to fact that both long-run and short-run price elasticity of oil demand are very low according to Cooper (2003), we assume the same price elasticity for each economy.

$$\bar{O} = O_O + O_R = P_{oil}^{\varphi} + P_{oil}^{\rho}$$

$$= P_{oil}^{-\varepsilon}(\theta_E Y_E(V_{eu}) + \theta_U Y_U(V_{eu}) + \theta_C Y_C(V_{eu})) \tag{38}$$

Differentiating equation (38) with respect to V_{eu}, we can get the impact of dollar on oil price:

$$dP_{oil}/dV_{eu} = \frac{\theta_E Y_E' + \theta_U Y_U' + \theta_C Y_C'}{(\varphi+\epsilon)P_{oil}^{\varphi+\epsilon-1} + (\rho+\epsilon)P_{oil}^{\rho+\epsilon-1}} \tag{39}$$

From equation (39) we can see that the sign of long-run effect of U.S. dollar exchange rate on oil price is determined by the term $\theta_E Y_E' + \theta_U Y_U' + \theta_C Y_C'$. When V_{eu} increases (U.S. dollar appreciates), Y_E would increase, $Y_E' > 0$. Similarly, we can see $Y_U' < 0$ for when dollar appreciates, U.S. economy would suffer from export loss. Since China's currency is pegged to U.S. dollar, the appreciation of dollar also implies appreciation of China's currency. As a result, China's economy would also suffer, $Y_C' < 0$. Without the inclusion of China, the sign of the impact depends on whether $\theta_E Y_E'$ is larger or smaller than $-\theta_U Y_U'$. In other words, if the economy of euro zones is more sensitive to depreciation of euro dollar against U.S. dollar (due to high reliance on export), oil price could rise as a long-run effect from U.S. dollar appreciation. Otherwise, the oil price would decrease if U.S. economy suffers more from the dollar appreciation. While in this 5-country model, it s obvious to see that emergence of China enhances the right hand side of this equation. Since China's economy is export-oriented and the energy intensity of the country is also very high due to low technology level, it is natural to assume that $\theta_E Y_E' < -(\theta_U Y_U' + \theta_C Y_C')$. Therefore, depreciation of U.S. dollar in the long run would cause rise on oil price and vice versa. This is consistent with our earlier empirical findings.

In the first part of this Chapter, a composite index of U.S. dollar is used instead of the U.S. dollar exchange rate against euro and this is because the theoretical model simply assumes the world economy consists of only five countries, hence the exchange rate between U.S. dollar and euro would yield the equilibrium price of U.S. dollar, given the fact that Russian ruble is not independently floating. In reality, evaluation of U.S. dollar's performance involves a basket of independently floating currencies, therefore investigation of the dynamics between the dollar and oil price, which is also the world market price, needs to be carried out to data series which reflect the overall world economy. As a matter of fact, the quantitative findings presented in the first part of this study are quite different from those by Be´nassy-Que´re´ et al. (2007), which uses real U.S. exchange rate against euro. Be´nassy-Que´re´ et al. (2007) find that real oil prices Granger cause real U.S. dollar exchange rate while the exchange rate fails to Granger cause the oil price. Meanwhile in our study we find the Granger causality runs in both directions, and this can also be seen from Figure 3.11 that the movement of nominal exchange rate between U.S. dollar and euro is quite different from that of the composite U.S. dollar index over the period (2001/01/04—2009/10/09).

CONCLUSION

This study examines the interactions between crude oil price and U.S. dollar by use of time series analysis method and a partial dynamic international portfolio model.

Engle-granger co-integration tests and also ECM results show that U.S. dollar index and crude oil price (real and nominal) are co-integrated for both full and subsample periods. Also Granger causality runs in both ways between U.S. dollar index and crude oil price (real and nominal) for both full and subsample periods. Different adjustment rates toward U.S. dollar and oil price shown in the ECM results suggest that oil price reacts more rapidly to variation in U.S. dollar than U.S. dollar to oil price, for performance of U.S. dollar is determined by economy in whole.

The interesting finding that for subsample period the dynamics between oil and dollar is quite different from that of the full sample period suggests that world economy goes through some structural changes due to these newly emerging economies such as China and Russia. As shown by the 5-country partial equilibrium dynamic portfolio model, introduction of China and Russia does change the dynamics between oil and dollar. China's role in the causality from U.S. dollar to oil price is very straightforward and it enhances the role of U.S. economy in this simple theoretical model. While for the other direction of causality from oil price to U.S. dollar, factors such as China's portfolio preference over U.S. dollar denominated assets and euro dollar denominated assets, OPEC's industrial products imports from different countries, shares of U.S. and China's oil imports and Russian ruble exchange rate movement determine the changes in U.S. dollar all together.

CHAPTER IV

SPECULATION AND ENERGY COMMODITY MARKETS

INTRODUCTION

This Chapter focuses on the role of speculation in two major energy commodity markets: global crude oil market and U.S. natural gas market. An empirical test incorporating both market fundamentals and traders' positions in U.S. natural gas future market is carried out to investigate if speculative activities contribute to the price deviation beyond the fundamental values.

The debate over bubble and non-bubble in commodity future markets has raised interests among industry practitioners, policy makers and also academic researchers. Bubble theory supporters claim excessive speculative activities in commodity future markets are responsible for the 2005-2008 commodity price spikes, especially in the crude oil market. Eckaus (2008) claims the sharp crude oil price increase seen in 2008 is a result of speculative bubble. Robles, Torero and von Braun (2009) argue that speculative activity in the futures markets may have caused increasing agricultural commodity prices in 2007-2008. On the other hand, some researchers report limited empirical evidence to support this assertion, such as Pirrong (2008), Sanders, Irwin and Merrin (2009), etc. The outcome of this debate is important in the sense that pricing efficiency of futures markets can be in serious doubt if speculation does distort the price away from the level supported by market fundamentals, as a result, the economy may respond to misleading price signals. From the policy-making perspective, the call for more regulation in commodity future markets is only justifiable if speculation is really the evil to blame.

Crude oil market may be one of the most important commodity future markets, given the fact that crude oil accounts for 40% of the total world energy consumption, and crude oil price has been viewed as one of the major indicators of world economy. Crude oil price movement is subject to fundamental economic factors effects, geo-political influence and possibly speculative noise. From year 2002 up to June 2008, crude oil price has been characterized by high volatility, high intensity jumps, and strong upward drift. Meanwhile, the abrupt drop of oil price ever since July 2008 is also overwhelming. A natural question arises: Do fundamentals account for all these dramatic price changes? Or some other factors such as speculation may also be responsible.

Fundamental market factors that affect the price of crude oil include rigid crude oil supply, fast expanding demand and inventory variations. Conjecture about OPEC’s market power has been supported by empirical studies, such as Kauffman et al. (2004). Studies such as Cooper (2003) found demand plays a crucial role in crude oil price change. Meanwhile, some researchers such as Davidson (2008) and industry practitioners, even U.S. Permanent Senate Committee, have claimed that excessive speculations may account for the sharp changes in both prices and volatility of energy market.

Speculation in definition is the assumption of the risk of loss, in return for the uncertain possibility of a reward. Signs that speculation may matter in oil market include:

1. According to IEA, oil future prices have increased by 86 per cent from year 2007 to 2008, while world consumption for oil has increased by approximately 2 per cent.
2. OECD commercial oil stocks remain above the five-year average, with days of forward cover at a comfortable level of more than 53 days.
3. $260 billion is invested in commodity index funds up to year 2008, 20 times the level of 2003[16].

Of course, there exist opposite views on speculation too. "The Oil Non-bubble" by Krugman in NYTIMES (May 12, 2008) claimed since there is no sign of "excess supply" existing anywhere in the world, speculation is not the major driver of high price, instead the market fundamentals are. Some empirical studies such as Pirrong (2008) claim that increase in speculative stock of commodities seen in 2005-06 period at best can be interpreted as a necessary but not sufficient condition for the existence of speculative price distortion. Bryant, Bessler and Haigh (2006) analyzes eight futures markets including New York Mercantile Exchange (NYMEX) crude oil over the sample period March 21, 1995 through January 8, 2003 and found the net positions of large hedgers (calculated as the number of open long futures positions minus the number of open short futures positions held by large hedgers) negatively correlated with the crude oil weekly return. Also it is found that the net position of large hedgers causes the crude oil weekly return for the sample period. However, no statistically significant correlation

[16] Michael Masters, in testimony before the US Senate in May 2008 estimated that assets allocated to commodity index trading strategies rose from $13 billion at the end of 2003 to $260 billion as of March 2008. These funds hold a portfolio of near-term futures contracts (70% of these contracts represent energy prices) following a trading strategy of selling the expiring contract the second week of the month and using the proceeds to buy the subsequent month contract.

between innovations from volatility of crude oil price and large speculator activity is found and both hypotheses that large speculators activity and small trader activity cause crude oil price volatility are weakly rejected.

Investigation carried out in the second Chapter of this dissertation on the dynamics between U.S. natural gas spot price and relevant market fundamentals found that fundamental factors can only explain overall 45% of the price variations over the sample period from Jan. 2, 2004 to June 26, 2009. For the rest of the variation which cannot be explained by market fundamentals, it can either be caused by pure shocks or speculative trading behaviors. The answer to this question is helpful in the sense that if speculation does play a noticeable role in U.S. natural gas market, trading decisions based on fundamentals need to be adjusted by the expected or conceived speculation level in the market. This study uses traders' position data released by the Commodity Futures Trading Commission (CFTC) and also the forecast errors obtained from Chapter II to explore the potential prediction power of information on traders' position.

Following this introduction, a brief review of theoretical discussion on speculation and price stability is provided. Then existing empirical studies on bubble theory in crude oil and U.S. natural gas markets are reviewed. An empirical test on the prediction ability of traders' net positions in U.S. natural gas market is carried out and conclusions with regard to speculators' role in U.S. natural gas and crude oil markets are drawn.

SPECULATION, HEDGING AND PRICE STABILITY

The traditional theory of speculation viewed the economic function of speculation as the smoothing effect for price-fluctuation caused by changes in market fundamentals, such as supply and demand shifts or shocks. It assumed that speculators have better than average market foresights; therefore, trading actions by these speculators would help better reallocate economic resources and stabilize price volatility. Speculators may step in the commodity market as a buyer if they correctly perceive the market is experiencing over-supply at current time point or seller when supply is short of demand. When this is the case, speculators gain profits by sending the goods from less important uses to more important ones. Kaldor (1939) argues speculators with worse than average foresight may also magnify the price fluctuation and increase volatility; however those speculators would be speedily eliminated by the market for they cannot make a profit. Only those speculators with better market forecasting ability can remain in the market permanently. This traditional theory also implies that supply and demand created by speculators is relatively small compared with the total demand and supply. Speculative activity may affect the range of price changes, but cannot reverse the direction of the change.

Another traditional theory on speculation is proposed by Keynes (1936) and later elaborated by Hicks (1939) which emphasize speculators' willingness to take risk in trading. The existence of speculators transfers price risk from more risk-averse traders to less risk-averse traders and hence provides some level of insurance in the market.

With the introduction of future markets for both agricultural and industrial commodities, roles of speculative activities in these markets start to gain more attention from researchers. Price discovering in commodity futures markets links expectation of future spot prices and current spot prices together and storage decisions from both producers and speculators play crucial role in commodity pricing behaviors. To deal with uncertainty of prices, forward/future contracts enable stocks holders to "divorce" risk premium from total carrying cost of inventory by hedging activity. Holding inventory can bring the producers "convenience yield" and also risk. By selling forward/future contract, stocks holders are able to transfer the risk attached to the stocks to buyers, meanwhile, they also need give up the convenience yield brought by inventory.

Within this framework, Kaldor (1939) establishes a formula to measure the degree of price stabilizing influence from speculative activity denoted by S:

$$S = -e(\eta - 1) \qquad (40)$$

e is the elasticity of speculative stocks, which is defined as percentage change of speculative storage as a result of a given percentage change in the difference between the current price and expected future price. η is the elasticity of expectation, which is proposed by Hicks (1939) in the famous book "Value and Capital". This elasticity is defined as unity when a change in the current price causes an equal-proportional change in the expected future price. Obviously, the sign of S is determined by sign of $(\eta - 1)$ since e cannot be negative. This equation explicitly states that the stabilizing/destabilizing effects of speculative activity are solely determined by the magnitude of expectation of price change. When there is change in market fundamentals, market anticipation about future price would change accordingly, which could affect current (spot) price via storage building up or reducing behaviors and also current consumption. If speculators narrow the range of this change via speculative stocks, they are stabilizing the price; otherwise, price volatility can increase.

Theory on speculation also evolves as the future markets of commodity and financial securities become more and more important in whole economy. Harrison and Kreps (1978) further develop the definition of speculation proposed by Kaldor (1939) and Keynes (1936) and state "investors exhibit speculative behavior if the right to resell the stock makes them willing to pay more than they would pay if obliged to hold forever". They constructed a simple model with heterogeneous expectation among a group of potential investors. Furthermore, some restrictive assumptions are also made: 1), investors are partitioned into a finite number of internally homogeneous classes, each class having (what amounts to) infinite collective wealth; 2), all investors have access to the same substantive economic information, although members of different classes may arrive at different subjective probability assessments on the basis of that information (this is due to heterogeneous expectation hypothesis); 3), members of each class are risk-neutral, so that any income stream is valued at its (subjective) expected present worth. Within this framework, Harrison and Kreps (1978) show that speculative phenomenon can be "sharply" seen in this kind of market, and some traders can get capital gain by reselling the asset at higher price.

Tirole (1982) investigates the possibility of speculation in a dynamic asset trading framework while assuming rational expectation equilibrium (REE). It is often thought in the literature of speculation that the price of an asset in a speculative market may reflect both speculative attributes and also the asset's basic value determined by market fundamentals. Two early works Sargent and Wallace (1973) and Flood and Garber (1980) show that in a monetary model with homogenous information the existence of speculative value or price bubble is not inconsistent with rational expectation assumption; furthermore, there even exist a positive possibility that the price bubble would "burst" at certain time and the price of the asset would revert back to its market fundamental value. Tirole (1982) shows that in a stock market with heterogeneous information the price bubbles are martingales given that short sales are allowed. In a stock market with homogenous information, the price bubble is the same for all the traders and has martingale property, no matter short sales are allowed or not. This case is somehow trivial for homogenous information means all traders have the same set of private information and price contains no extra information, and all the traders value the asset based on the same market signal. However, even in heterogeneous information case, if the information revealing system is complete and traders can still get the same market price signal, as a result, at rational expectation equilibrium the price bubble would still be the same for all the traders. The corresponding REE for stock market with heterogeneous information is called "myopic REE" for traders make decisions based on short-run consideration and they compare current trading opportunities with the expectation of trading opportunities in the following period.

Furthermore, Tirole (1982) proves in a fully dynamic rational expectation equilibrium price bubble is zero no matter short sales are allowed or not, when traders maximize their objective function based on long-run consideration.

Stein (1987) found that when more and more speculators enter the market, their trading behaviors could lead to improved risk sharing but could also change the informational content of prices. In this study, the speculators are still assumed rational but imperfectly informed. Therefore, the entry of these speculators introduces both noise and information into the market, which obviously inflicts an externality on those traders already in the market. If the new speculators bias the price and make the price carry less useful information about the real state of the economy, other agents' ability to make inference based on market signals would be compromised. The net result can be price destabilization and welfare reduction. This is true even when all agents are rational, risk-averse, competitors who make the best possible use of their available information.

Other than rational expectation equilibrium solutions, researchers also explore the impacts of the noisy or irrational trading behaviors on asset price movement in the financial markets. De Long, Shleifer, Summers, and Waldmann (1990a) proposed a simple overlapping generations model of asset markets in which irrational noise traders with erroneous stochastic beliefs could affect prices changes and hence earn higher expected returns. The unpredictability of noise traders' beliefs creates a risk in the price of the asset that prevents rational arbitrageurs from aggressively betting against them. As a result, prices can diverge significantly from fundamental values even in the absence of fundamental risk. Hence, noisy traders can earn higher expected returns solely by bearing more of the risk that they themselves create. The key point is that noise traders profit from their own destabilizing influence, and they do not perform the useful social function of bearing fundamental risk as the traditional theory of speculation posits. In this paper, the authors also argue that if the opinions/beliefs of these noisy traders follow a stationary process, there could still exist a mean-reverting process in the asset price movement, hence, the existence of stationary noisy trading behaviors in asset markets may not affect the mean-reverting property of the asset price process even though the volatility of the price series could be increased. De Long, Shleifer, Summers, and Waldmann (1990b) study rational speculators' trading behaviors in face of noisy traders. This paper argues in the presence of positive feedback investors[17], well-informed rational speculators would choose to "jump on the bandwagon" rather than "buck the trend". Rational speculators who expect some future buying by noise traders would choose to buy today in the hope of selling at a higher price tomorrow. Moreover, the buying behaviors of rational speculators would make positive feedback investors feel more confident about future price increase and hence push the price further away from the level which can be justified by fundamentals. As a result, rational speculators destabilize the asset price.

[17] As explained by De long, Shleifer, Summers, and Waldmann (1990b), positive feedback investors are those who buy securities when prices rise and sell when prices fall. These trading behaviors can result from: 1) extrapolative expectations about prices, or trend chasing; 2) stop-loss orders, which effectively prompt selling in response to price declines. Another common form of positive feedback trading is the liquidation of the positions of investors unable to meet margin calls.

SPECULATION IN ENERGY COMMODITY MARKETS

Investigation of speculation in energy commodity markets cannot leave out fundamental analysis, since there is no prior information about existence of noise traders, rational or irrational speculators in the commodity markets, and fundamental values of the assets are the base scenario. By comparing real price series with price levels justified by market fundamentals, researchers can derive how much the market has deviated from theoretical equilibrium. If speculation really affects volatility or even direction of price changes to a sensible level, one would expect that fundamental conditions respond to these market signals in order for the price to revert to its equilibrium level.

In the case of the crude oil market, a "bubble" theory implies that mispricing of the future markets could drive the producers to build up inventory or simply keeping oil underground. Before any conclusion can be drawn about speculation, detailed look at market fundamentals, such as supply and demand conditions need to be carried out first. The crude oil market experienced steady price increases since 2002, and the market price reached a historical high at $148/bl in June 2008. Several factors contributed to this rise: 1), strong global oil demand, especially from newly emerging economies, such as China, India, South Korea and Brazil; 2), oil supply disruption due to geopolitical turmoil in oil-producing countries, such as Nigeria, Venezuela, Iran and Iraq; 3), a greater worldwide awareness of peak oil, that is, crude oil as a depletable natural resource may have reached peak and oil reserves would be exhausted soon; 4), weakening U.S. dollar; 5) excessive speculation. This section is mainly dedicated to the speculation argument.

In the literature, both fundamental structure models and stochastic analysis have been used to model the crude oil price dynamics. Fundamental supply and demand models are developed to find the long-run equilibrium price for crude oil. Kauffman et al. (2004) found that there is a statistically significant relation among real oil prices, OPEC capacity utilization, OPEC quotas, the degree to which OPEC exceeds these production quotas, and OECD stocks of crude oil. Further analysis indicates that these variables 'Granger cause' real oil prices but not vice versa. These results indicate that OPEC plays an important role in determining real oil prices. The negative relation between price and production is part of the co-integrating relation for oil prices, not oil production. The effect of OECD oil stocks on real oil prices indicates that the private savings associated with recent reductions in inventories may be less than the social costs associated with higher oil prices. Meanwhile, price forecasts of crude oil in both short run and long run horizons utilizing market fundamentals are generally lower than realized values as shown by Zyren and Shore (2002).

Krichene (2002) analyzes the time-series properties of oil output and prices. Also demand and supply price elasticities of oil are estimated for two sample periods: 1918–1973 and 1973–1999. He found that the crude oil price series became stationary despite large price shocks in 1973–1999, and oil price stayed at a higher level during this period, which was consistent with OPEC producers' market power and a likely increase in long-run average cost. Demand and supply for crude oil were highly price-inelastic in the short run. However, demand for crude oil underwent a deep structural change in 1973–1999. Income elasticities were statistically significant for crude oil demand. Long-run supply price elasticity for crude oil fell sharply after the oil shock, reflecting a change from a competitive to a market-maker structure. Cooper (2003) investigates the crude oil market from 1971 to 2000 and reports long-run demand elasticities for crude oil of -0.2 and short-run elasticity of -0.05. The low price elasticity of demand of crude oil in both short run and long run certainly would result in a high price level given rigid oil supply.

Stochastic models have also been adopted to study the crude oil price series. Pindyck (1998) models crude oil, coal and natural gas prices series as mean-reverting processes with very low rate of mean-reversion and stochastically fluctuating trend, and found that these models were promising for long-run forecasting. For crude oil price series, Pindyck (1998) uses data from 1870 to 1996 and found that the stochastic model performs quite well in long-run forecasting. Askari and Krichene (2008) fit several different mean-reverting processes with different kind of jumps and found that oil prices attempted to retreat from major upward jumps, and there was a strong positive drift which kept pushing these prices upward. Volatility was high, which would make oil prices very sensitive to small shocks and new information arrivals.

So far, empirical studies fail to provide a convincing answer to speculation in crude oil markets. Sanders, Boris and Manfredo (2004) analyze the data released by Commodity Futures Trading Commission (CFTC)'s Commitments of Traders (COT) reports for crude oil, unleaded gasoline, heating oil, and natural gas futures contracts to examine the roles played by hedgers and speculators in energy commodity markets over the period from October 1992 to December 1999. Detailed examination of the data shows that the net positions of noncommercial traders (speculators) exhibit higher volatility than the other two categories of traders: commercial traders (hedgers) and non-reporting traders (small traders or small speculators). This means noncommercial traders/speculators trade very actively, although they are not a large percent of the market participants. In both oil and gas markets, commercial traders dominate in terms of total open interests over the sample period.

Sanders, Boris and Manfredo (2004) conduct Granger causality tests on market return and net positions held by each category of traders. It is found that a positive correlation between returns and positions held by noncommercial traders exists in all of the markets. This means a positive return would lead speculators to increase their net long position in the following period, which suggests this group of traders is positive feedback traders or follower traders. Also it finds that returns lead net positions of commercial traders and the impact is uniformly negative in both crude oil and natural gas markets. Commercial traders in these two markets increase long positions as prices fall. This is consistent with their trading category property as “hedgers”. For the other causality direction from net positions of traders to market price return, in general the study shows traders’ net positions do not lead market returns, with an exception of crude oil market where the null hypothesis (that net positions do not lead returns) is rejected at the 5% level and the corresponding directional impact is negative. This means there is little evidence to suggest that net positions of traders can predict market return, at least for the sample period.

Bryant, Bessler and Haigh (2006) study the CFTC’s COT data over sample period March 1995 through January 2003 for eight future markets: corn, crude oil, Eurodollars, gold, Japanese yen, coffee, live cattle, S&P 500. Their findings are consistent with Sanders, Boris and Manfredo (2004)'s with respect to the hypothesis that return causes net long position of large hedgers. As for the crude oil market, they show little evidence to support the claim that large speculators or small speculators' net positions are correlated with price volatility.

Pirrong (2008) notices that for period 2005-2006 the crude oil market witnessed rising prices and increases in inventory. This phenomenon has been interpreted as evidence for speculative distortion in crude oil market over the same period, since the historical negative correlation between price and storage seems broken. To examine this possibility, a dynamic rational expectation model with stochastic fundamental shocks is proposed. Also the model suggests there could be a positive relation between commodity price and inventory at competitive equilibrium. Pirrong (2008) argues that when the fundamentals exhibit stochastic volatility in the market, producers may choose to build up inventory to smooth out unexpected fluctuation and the direction of change in the relation between two economic variables (commodity price and inventory) can be result of structural change in the economic system, and increase in speculative storage can be a necessary instead of sufficient condition for the existence of speculative distortion.

For the past 2005-2008 commodity futures price spikes, Sanders, Irwin and Merrin (2009) utilize the CFTC's CIT[18] data to study the cross-market correlation

[18] Starting in 2007, CFTC began reporting the positions held by index traders in 12 agricultural futures markets in the Commodity Index Traders (CIT) report, as supplement to the traditional Commitments of Traders (COT) report. According to the CFTC, the index trader positions reflect both pension funds that would have previously been classified as non-commercials as well as swap dealers who would have previously been classified as commercials hedging OTC transactions involving commodity indices. However, caution should be taken by researches when analyzing these data. The CFTC admits that this

between market returns and positions held by long-only index funds. The data span from January 3, 2006 to December 30, 2008. No statistically significant correlation between these two is found. Meanwhile they also claim that there is some "moderate" empirical evidence that weekly cross-sectional market return may be positively correlated to the preceding week's change in the index funds' positions. Hence, they suggest that it is possible that correlation can be found over some shorter horizon or with uses of different measures of position changes.

All these papers utilize CFTC's COT or CIT data to study the causality between speculators' trading position and commodity future market returns and price volatility, however, one need note that the data collection method and traders' category classification of COT and CIT could cause some complications for the research. Studies such as Sanders, Boris and Manfredo (2004) and Sanders, Irwin and Merrin (2009) already pointed out that interpretation of traders' classification and trading activities reported by both COT and CIT should be done with caution. First, the non-commercial trader certainly has incentive to self-clarify themselves as commercial trader in order to circumvent speculative limits. On the other hand, there is little incentive for commercial traders to label themselves as speculators. Hence, the non-commercial traders' category is only a subset of total speculators in the market. Second, the data provide little information about non-reporting traders other than that they do not hold positions in excess of reporting levels. Third, the trading motives in the reporting commercial

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classification procedure has flaws and that "…some traders assigned to the Index Traders category are engaged in other futures activity that could not be disaggregated…. Likewise, the Index Traders category will not include some traders who are engaged in index trading, but for whom it does not represent a substantial part of their overall trading activity" (CFTC 2008).

classification are likely to extend beyond just hedging. That is, pure hedging positions are a subset of those represented by CFTC reporting commercials, although these trading activities are generally interpreted as hedging transactions for there is not enough information so far for researchers to further decompose these data. Finally, reporting non-commercial traders are the trader category least prone to reporting error. Since there are no incentives to self-classify as a speculator, the reporting noncommercial positions likely reflect a pure subset of true speculative positions. Therefore, these studies provide empirical evidence that fails to support the statement that excessive speculation is one cause for the energy commodity price spikes, but this alone cannot preclude the existence of speculative influence on commodity prices.

In the next section, an empirical test using U.S. natural gas price data and COT data on NYMEX natural gas futures market over the sample period January 9th 2004 through June 26th 2009 is carried out to see if speculation does affect the forecast errors of natural gas price solely based on market fundamentals.

SPECULATION AND FUNDAMENTALS: CASE OF U.S. NATURAL GAS

All the empirical papers reviewed above explore the role of speculation in commodity markets by investigating the dynamic relations between market price returns and trader's positions of each category. Another possible improvement in studying role of speculation is to combine fundamentals with CFTC's COT data. The underlying theory about this kind of treatment is that when speculation or noise trading push price beyond the level justified by fundamentals, the price becomes the sum of fundamental value and speculative value.

The second Chapter of this dissertation applies regime-switching model to study the dynamics between market fundamentals and U.S. natural gas prices, and the study shows that market fundamentals can do a fairly good job in short-term price forecasting, even though the fundamentals can only account for 45% of the price changes during the sample period January 2004 to June 2009. To further explore speculation's contribution to the price deviation from market fundamentals, Granger causality test is carried out to model errors from Chapter II and traders' positions by utilizing the COT Futures-and-Options-Combined data[19], then a VAR model is fitted for the errors and traders' position, based on which dynamic forecasts over 80, 40 and 20, 10 weeks intervals are provided. In the last, the DM tests proposed by Diebold and Mariano (1995) are applied to these newly constructed forecasts to check if incorporation of speculation improves price forecast accuracy.

Model errors from Chapter II represent the deviation of spot price return from values justified by market fundamentals. The market fundamentals include a variable called lagged future-spot spread which is supposed to summarize past supply and demand conditions. Information contained in future price of previous period has already been included in the fundamental-based 2-state Markov-switching model. Since storage data is announced on every Thursday, the Friday closing market price is used as the

[19] For the COT Futures-and-Options-Combined report, option open interest and traders' option positions are computed on a futures-equivalent basis using delta factors supplied by the exchanges. Long-call and short-put open interest are converted to long futures-equivalent open interest. Likewise, short-call and long-put open interest are converted to short futures-equivalent open interest.

weekly spot price of natural gas in order to incorporate market's response of new information arrival. Meanwhile, the COT data are announced on Friday, which actually describe traders' positions on Tuesday of the same week, hence, market's reaction to this new piece of information would be reflected immediately on the Friday prices until new information comes.

Figure 4.1 presents the market return of U.S. natural gas spot price along with the model fitting errors from the 2-state Markov-switching model presented in Chapter II for period 9th January, 2004 to 23rd June, 2009. It can be seen that the errors follow the same pattern as the spot price return (first difference of natural log of spot price) but vary in a smaller range.

In the COT report, the open interests are divided into reporting and non-reporting traders' positions, where reporting traders hold positions in excess of CFTC reporting levels[20]. Reporting traders are further categorized as commercials or non-commercials[21].

[20] CFTC requires clearing members, futures commission merchants, and foreign brokers (collectively called reporting firms) to file daily reports with the Commission. Those reports show the futures and option positions of traders that hold positions above specific reporting levels set by CFTC regulations. If, at the daily market close, a reporting firm has a trader with a position at or above the Commission's reporting level in any single futures month or option expiration, it reports that trader's entire position in all futures and options expiration months in that commodity, regardless of size. The aggregate of all traders' positions reported to the Commission usually represents 70 to 90 percent of the total open interest in any given market. From time to time, the Commission will raise or lower the reporting levels in specific markets to strike a balance between collecting sufficient information to oversee the markets and minimizing the reporting burden on the futures industry.

[21] All of a trader's reported futures positions in a commodity are classified as commercial if the trader uses futures contracts in that particular commodity for hedging as defined in CFTC Regulation 1.3(z), 17 CFR 1.3(z). A trading entity generally gets classified as a "commercial" trader by filing a statement with the Commission, on CFTC Form 40: Statement of Reporting Trader, that it is commercially "...engaged in business activities hedged by the use of the futures or option markets." To ensure that traders are classified with accuracy and consistency, Commission staff may exercise judgment in re-classifying a trader if it has additional information about the trader's use of the markets. A trader may be classified as a commercial trader in some commodities and as a non-commercial trader in other commodities. A single trading entity cannot be classified as both a commercial and non-commercial trader in the same commodity. Nonetheless, a multi-functional organization that has more than one trading entity may have each trading

Commercials are generally associated with an underlying cash-related business and they are commonly considered to be hedgers. Generally speaking, non-commercials are not involved in an underlying cash business; thus, they are referred to as speculators. Furthermore, reporting level non-commercial activity is generally considered to be that of managed futures or commodity funds. Overall, the COT data are broadly discussed in terms of hedgers (reporting commercials), funds or speculators (reporting non-commercials), and small speculators (non-reporting traders). Open interest, as reported to the Commission and as used in the COT report, does not include open futures contracts against which notices of deliveries have been stopped by a trader or issued by the clearing organization of an exchange[22].

Decomposition of open interests by different groups of traders can be explained by the following equation (40):

$$(NCL+NCS+2NCSP)+(CL+CS)+(NRPL+NRPS)=2*TOPI \quad (40)$$

NCL represents long positions held by non-commercial traders. Similarly, NCS denotes short positions held by non-commercial traders. NCSP means spreading by non-commercial traders, which measures the extent to which each non-commercial trader holds equal combined-long and combined-short positions in options-and-futures-combined report. CL and CS represent long and short positions held by commercial traders. NRPL and NRPS are long and short positions controlled by non-reporting traders. TOPI represents total open interest in the market.

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entity classified separately in a commodity. For example, a financial organization trading in financial futures may have a banking entity whose positions are classified as commercial and have a separate money-management entity whose positions are classified as non-commercial.

[22] More information about CFTC's COT report can be found at http://www.cftc.gov/MarketReports/CommitmentsofTraders/ExplanatoryNotes/index.htm.

Figure 4.2 plots the traders' total positions as a percent of total open interest (denoted as PCT) in natural gas market for the period 6th January, 2004 through 23rd June, 2009. These variables are calculated as equation (41), (42) and (43) indicate. Summary statistics of these three variables are presented in Table 4.1. It can be seen that hedgers and speculators' trading activities dominate the market. For the whole sample period, the speculators' share in the total open interests keeps an upward trend, especially for the whole year of 2008. Starting from January 2008, speculators' trading activities keep rising and stay in a relatively high level for the rest of the sample period. On the other hand, the share of hedgers' trading activities decreases for the whole year of 2008, then rises a little starting in January 2009, but stays at relatively low level for the rest of sample period. Also it is can be seen that small speculators' share of open interest position keeps at a steady level over the whole sample period.

Percent of total open interest by commercials=(CL+CS)/ 2*TOPI (41)

Percent of total open interest by non-commercials=(NCL+NCS+2*NCSP)/ 2*TOPI (42)

Percent of total open interest by non-reporting= (NRPL+NRPS)/ 2*TOPI (43)

Another measure for traders' positions is called percent net long positions (PNL)[23], which is calculated as equations (44), (45) and (46) indicate. Following De Roon, Nijman and Veld (2000) and Sanders, Boris and Manfredo (2004), PNL for commercial traders indicates the "hedging pressure" in the market. Similarly, PNLs for non-commercial traders and non-reporting traders represent the "speculative pressure" and "small traders (speculators) pressure", respectively. Table 4.2 lists the summary

[23] Sum of PNLs weighted by PCT of each category of traders is zero.

statistics for PNL of all categories of traders. Figure 4.3 plots these series for the same sample period. Interestingly, it can be seen that PNLs for hedgers and speculators are not significantly different from zero by the two-sided t-test. The net long position percent of small speculators seems very random, and for the whole sample period small speculators are net buyers in the market. Meanwhile the net long position percents of hedgers and large speculators vary around zero, and not surprisingly, these two categories of traders often take opposite positions in the market, which confirm the traditional view of speculators, that is, speculators make profits by assuming risks divorced by hedgers in the futures markets. Comparing Figures 4.2 and 4.3, it is obvious to see that commercials are net buyers for the whole year of 2008 while speculators are net sellers. Also it is very interesting to see that hedgers and small speculators share similar views on market trend, while large speculators hold opposite views. One reason for this observation may be that small speculators are positive feedback investors who make trading strategies following dominant market participants while large speculators constantly bet against hedgers to make profits.

For the sample period, only small speculators' PNL keeps at a steady level. The stationary property of smaller speculators' PNL implies predictability of small traders' trading strategy to some extent. While for hedgers and speculators, there is obvious deviation in the movement pattern of PNL for the whole year of 2008, when natural gas price experiences steady increases. The share of net long position in hedgers' total open interests keeps rising for the period January 2008 through July 2008. For the rest of the year, percent net long of hedgers gradually drops back to the average level. On the other hand, the share of net long positions of speculators experiences the opposite movement pattern as that of the hedgers. Hedgers are net buyers for the period January 2008 through July 2008 while speculators are net sellers. This means hedgers either "expect" the right market trend or simply just follow the market trend when making trading decisions. Meanwhile, speculators trade against hedgers constantly anticipating a sharp market trend turn at certain point.

Percent net long by commercials=(CL-CS)/ (CL+CS) (44)

Percent net long by non-commercials=(NCL-NCS)/(NCL+NCS+2*NCSP) (45)

Percent net long by non-reporting=(NRPL-NRPS)/(NRPL+NRPS) (46)

Granger causality test results for model fitting errors and PNL of each category of traders are presented in Table 4.3. For the sample period Jan. 2004 through June 2009, the small speculators' net long position Granger cause the errors; at the same time, the errors Granger cause PNLs of hedgers and speculators but not small speculators. This result is consistent with early studies' findings in the sense that deviation in spot prices from fundamentals is not the result but the cause of major market participants' (hedgers and speculators) position changes. Meanwhile, there is some new finding that small speculators' positions Granger cause the changes in natural gas price, which implies that small traders' speculation may have influence on natural gas price changes. To further explore this possibility, a VAR model is fitted for model errors and PNL of non-reporting traders and the estimation results are reported in Table 4.4.

The normality tests for these two equations reject the null hypothesis of normal disturbances. For the model error equation, it can be seen that sum of the coefficients of lagged PNL variables is negative, which means a unit increase of net long position percent of small traders would cause decrease in model error and this suggests the presence of small traders to some extent help to stabilize the market price return. As for the PNL of small speculators equation, lagged model error variables are not significant individually or jointly, which is consistent with the Granger causality test results. Meanwhile, the lagged values of PNL of non-reporting traders are significant, which confirm our earlier observation that small speculators' trading strategies are predictable to some degree.

Based on the estimation results of VAR(2) model, a linear forecast model for forecast error is constructed as equation (47) indicates:

$$forecast\ error_t = constant + \beta_1 forecast\ error_{t-1} + \gamma_1 PNL - nonrept_{t-1} + \gamma_2 PNL - nonrept_{t-2} + v_t \qquad (47)$$

To test if information about small speculators' position help to improve price forecast purely based on fundamentals, four sets of out-of-sample forecasts (80, 40, 20, 10 step-ahead forecasts) are constructed. Then DM tests proposed by Diebold and Mariano (1995) are applied to these forecasts to see if forecasts incorporating additional information improve the forecast accuracy compared with those solely based on market fundamentals. First, 80-step-ahead out of sample forecasts for natural gas price are provided. To do this, the 2-state Markov-switching model constructed in the first essay is first fitted using 226 observations, and 80-step-ahead price forecasts based purely on market fundamentals are calculated. Second, the 226 model fitting errors are used to fit the linear model as equation (47) specified. The new forecast error adjustment of the 80 forecasts by PNL of non-reporting traders is calculated. Third, the new price forecasts for natural gas incorporating fundamentals and speculation are calculated by adding up the 2-state Markov-switching model forecasts and forecast errors by equation (47). This procedure is repeated for 40, 20 and 10-step-ahead forecasts. As the final step, DM tests are conducted to the new price forecasts and fundamentals-based price forecasts and the results are presented in Table 4.5.

It is interesting to see that for the 80-step-ahead forecasts, the difference between fundamentals-based forecasts and newly incorporated forecasts is not significant and mean-squared errors of forecasts show that the forecasts solely based on fundamentals are better than the newly constructed forecasts. While for the 40-step-ahead forecasts, the DM tests show that incorporation of small speculators' net long position do improve the price forecasts. In the case of 20-step-ahead forecasts, the DM tests show that no significant forecasting accuracy improvement is provided by the incorporation of speculation. For the 20-period 10-step-ahead forecasts, the DM tests once again show that incorporation of speculator's net long position information fail to improve prediction accuracy beyond the fundamentals-based forecasts.

Since the error forecasts based on small speculators' net long position percentage is quite small in magnitude, the prediction accuracy of price forecasts is mainly determined by fundamental values. However, incorporation of speculation in short-term forecasting (both 10-step and 20-step-ahead forecasts) fails to improve prediction accuracy seems intriguing. A possible reason may be that the price forecast is a spot price while the speculation happens in future market. The interaction between the future and spot markets takes some time for the changes in futures market to be reflected in the spot market. Since major trading behaviors happen in future/forward markets, the cash (spot) market mainly function as supplement to smooth out some sudden changes in supply and demand conditions not fully covered by future/forward contracts.

CONCLUSION

A literature review on speculation and energy commodity markets is carried out to investigate what produced the high volatility and steady increases of prices in crude oil and natural gas markets for the 2007-08 period. The empirical test presented in last section shows that fundamentals play major roles in the natural gas market while small speculators' trading activities may also affect the price variation to some degree. However, there is no empirical evidence to support the claim that speculation is the major reason for the price spikes seen in the past few years.

CHAPTER V

CONCLUSIONS

This dissertation examines roles of market fundamentals and speculation in U.S. natural gas market and also crude oil. Chapter 2 proposes a two-state Markov-switching model to improve forecast accuracy of U.S. natural gas spot price purely based on market fundamentals. The assumption of regime-switching is supported by the data, and market fundamentals show different impacts on natural gas price across different state. Furthermore, the DM forecast accuracy tests show that forecasts by regime-switching model outperform the GARCH (1,1) model, where no regime-switching assumption is made, in terms of near-term forecasts. The adoption of regime-switching framework provides a flexible model to deal with high volatility and possible endogenous structural changes that may exist in U.S. natural gas market.

There is no doubt that market fundamentals such as strong world demand, rigid oil supply, weakening U.S. dollar and also peak oil fear all contributed to oil price spike seen in the past several years. All the fundamental factors are initial drivers to push up oil price and speculation could have further exaggerated these market signals to both producers and consumers so that current consumption is reduced, storage is built up while price still keeps going up due to low elasticity of oil demand. Meanwhile, newly emerging economies do bring changes to the existing equilibrium of the market. Before the market finds new equilibrium, speculators, noise traders and also hedgers in the market would all respond to new information arrival in the market differently, therefore, increased level of volatility is expected.

The third Chapter analyzes dynamics between U.S. dollar and crude oil price and finds there is a long-run equilibrium between oil and dollar. For the sample period from 2002 to 2010, weakening U.S. dollar could cause a big upward adjustment in crude oil price in order to revert back to equilibrium. Meanwhile, this study also suggests that there is structural change in crude oil price movement over the full sample period July 1986 to July 2010, specifically, the oil price stays in a stationary state for period from July 1986 to December 2001, and for the period 2002 through 2010 the crude oil price obviously climbs to a new high level with high jumps and volatility. Correspondingly, the long-run equilibrium between crude oil and U.S. dollar also experiences structural changes over the same period.

Although the argument of price bubble in energy commodity markets faces a lot of empirical criticism, existing literature still cannot rule out this possibility. Chapter IV gives a review of theory of speculation and also a survey of empirical studies on speculation in energy commodity markets. More importantly, data of Chapter II are utilized to test a hypothesis on speculation, that is, real world commodity price could be sum of fundamental value and speculative value if speculation does affect commodity price. However, the empirical test suggests the speculators' net long positions have limited forecasting power on natural gas price changes, although correlation between these two series is found and Granger causality is shown to run from speculators' net long positions to price changes not justified by fundamentals. Therefore, little empirical evidence is found to support the bubble theory in U.S. natural gas market over the sample period (01/06/2004—06/23/2009).

Both fundamental factors and speculation are functioning in the real world commodity markets. So far there is no single theory can encompass all the complexity involved in these markets, therefore, rather than thinking these theories are competing with each other in explaining commodity price variation, one may think there is an element of truth to all these theories. As it is pointed out earlier, further research about commodity markets, especially the pricing dynamics of crude oil, should take possible structural change into consideration.

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APPENDIX A

TABLES

Table 2.1 Likelihood estimates of a two-state Markov-switching model of the natural gas price return (weekly; 01/02/2004 – 06/26/ 2009)

Parameters	Linear model with GARCH(1,1)		Markov-switching model			
GARCH(1,1)			Transition Probability Matrix			
Constant	0.00016	(0.000095)**	0.92	(0.10)*	0.03	(0.014)*
ARCH MA(1) Coefficient	0.34	(0.095)*	0.08	(0.043)*	0.97	(0.065)*
GARCH AR(1) Coefficient	0.64	(0.074)*				
			Switching parameters			
			state 1		state 2	
σ	0.057		0.016	(0.0015)*	0.059	(0.0024)*
Constant	-0.082	(0.015)*	-0.072	(0.0018)*	-0.085	(0.0042)*
Return of crude oil price	0.20	(0.05)*	0.13	(0.04)*	0.21	(0.086)*
Weekly difference storage	-0.00034	(0.000)*	-0.00015	(0.00002)*	-0.0005	(0.000)*
Lagged spread	0.83	(0.06)*	1.30	(0.06)*	0.64	(0.042)*
			Non-switching parameters			
Weekly difference HDD	-0.00005	(0.00015)	0.000001	(0.00007)		
Weekly difference CDD	0.00008	(0.0003)	-0.00008	(0.00017)		
Monthly dummy 1	0.012	(0.016)	-0.005	(0.0077)		
Monthly dummy 2	0.031	(0.017)**	0.04	(0.0085)*		
Monthly dummy 3	0.052	(0.014)*	0.049	(0.0047)*		
Monthly dummy 4	0.09	(0.018)*	0.07	(0.0041)*		
Monthly dummy 5	0.11	(0.022)*	0.075	(0.0036)*		
Monthly dummy 6	0.094	(0.021)*	0.09	(0.0044)*		
Monthly dummy 7	0.075	(0.021)*	0.089	(0.006)*		
Monthly dummy 8	0.086	(0.02)*	0.11	(0.0067)*		
Monthly dummy 9	0.10	(0.02)*	0.11	(0.0076)*		
Monthly dummy 10	0.057	(0.02)*	0.089	(0.01)*		
Monthly dummy 11	0.01	(0.02)	0.0032	(0.0083)*		
Log Likelihood:	462.41		472.68			
AIC	442.41		451.68			
BIC	405.85		413.29			

Notes: Symbol * indicates that estimated parameters are statistically different from zero at the 5% level.

Symbol ** indicates that estimated parameters are statistically different from zero at the 10% level.

The value in parenthesis is the outer product of gradient (OPG) standard deviation of the parameter.

Table 2.2 Diebold-Mariano test results for 2-state Markov-switching model and GARCH (1,1) model (forecast period: Feb. 13, 2009 to June 26, 2009)

No. of observations	20
DM test	H0: alternative methods are equally accurate on average
One-step-ahead forecast	
Forecast with Markov smoothing effect vs. GARCH(1,1) model	p-value = 0.0922 (reject H0 at 10% significance level)
4-step-ahead forecast	
Forecast with Markov smoothing effect vs. Forecast without Markov smoothing effect	p-value = 0.2986 (fail to reject H0)
Forecast with Markov smoothing effect vs. Forecast by GARCH (1,1)	p-value = 0.1315 (fail to reject H0)
Forecast without Markov smoothing effect vs. Forecast by GARCH (1,1)	p-value = 0.1283 (fail to reject H0)
20-step-ahead forecast	
Forecast with Markov smoothing effect vs. Forecast without Markov smoothing effect	p-value = 0.7009 (fail to reject H0)
Forecast with Markov smoothing effect vs. Forecast by GARCH (1,1)	p-value = 0.0787 (reject H0 at 10% significance level)
Forecast without Markov smoothing effect vs. forecast by GARCH (1,1)	p-value = 0.0933 (reject H0 at 10%) significance level)

Table 2.3 Encompassing test results for regime-switching model and GARCH model

	Two-way encompassing test	
No. of observations: 20		
	One-step-ahead forecast encompassing tests	
	λ	p-value on $\lambda = 0$
2-state Markov-switching model encompasses: GARCH (1,1)	0.119 (0.093)	0.217 Fail to reject H0.
GARCH (1,1) encompasses: 2-state Markov-switching model	0.881 (0.093)	0.000 H0 is rejected at 5% significance level.
	4-step-ahead forecast encompassing tests	
	λ	p-value on $\lambda = 0$
Forecasts with Markov smoothing effect encompasses: Forecast without MS effect	2.702 (5.59)	0.634 Fail to reject H0.
GARCH (1,1)	0.329 (0.068)	0.000 H0 is rejected at 5% significance level.
Forecasts without Markov smoothing effect encompasses: Forecast with MS effect	-1.702 (5.59)	0.764 Fail to reject H0.
GARCH (1,1)	0.329 (0.067)	0.000 H0 is rejected at 5% significance level.
GARCH(1,1) encompasses: Forecasts with MS effect	0.671 (0.067)	0.000 H0 is rejected at 5% significance level.
Forecasts without MS effect	0.652 (0.097)	0.000 H0 is rejected at 5% significance level.
	20-step-ahead forecast encompassing test	
	λ	p-value on $\lambda = 0$
Forecasts with Markov smoothing effect encompasses: Forecast without MS effect	0.6 (0.24)	0.022 H0 is rejected at 5% significance level.
GARCH (1,1)	0.156 (0.059)	0.016 H0 is rejected at 5% significance level.
Forecasts without Markov smoothing effect encompasses: Forecast with MS effect	0.40 (0.24)	0.113 Fail to reject H0.
GARCH (1,1)	-0.042 (0.078)	0.594 Fail to reject H0.
GARCH(1,1) encompasses: Forecasts with MS effect	0.844 (0.059)	0.000 H0 is rejected at 5% significance level.

Table 2.3 continued

Forecasts without MS effect	1.042 (0.078)	0.000 H0 is rejected at 5% significance level.

Three-way encompassing test

4-step-ahead forecast encompassing tests

	λ_1	λ_2	p-value on $\lambda_1 = \lambda_2 = 0$
Forecasts with MS effect encompasses:			0.0003
Forecasts without MS effect	4.59	0.34	H0 is rejected at 5%
GARCH (1,1)	(1.78)	(0.068)	significance level.
Forecasts without MS effect encompasses:			0.0004
Forecasts without MS effect	-3.92	0.34	H0 is rejected at 5%
GARCH (1,1)	(1.80)	(0.068)	significance level.
GARCH (1,1) encompasses:			0.0000
Forecasts with MS effect	-3.92	4.59	H0 is rejected at 5%
Forecasts without MS effect	(1.80)	(1.78)	significance level.

20-step-ahead forecast encompassing tests

	λ_1	λ_2	p-value on $\lambda_1 = \lambda_2 = 0$
Forecasts with MS effect encompasses:			0.0642
Forecasts without MS effect	-0.185	0.193	H0 is rejected at 10%
GARCH (1,1)	(0.73)	(0.172)	significance level.
Forecasts without MS effect encompasses:			0.1763
Forecasts without MS effect	0.992	0.193	
GARCH (1,1)	(0.58)	(0.172)	Fail to reject H0.
GARCH (1,1) encompasses:			0.0000
Forecasts with MS effect	0.992	-0.185	
Forecasts without MS effect	(0.576)	(0.735)	Fail to reject H0.

Notes: In view of possible autocorrelation and heteroskedasticity of the errors, robust regression is conducted using STATA for all these encompassing tests.
The value in parenthesis is the robust error of the parameter.

Table 2.4 Weights for linear combined forecast models (forecast period: Feb. 13, 2009 to June 26, 2009)

1-step-ahead-forecast (Sample size=20)						
Forecast	Mean Error	SSE	Adj. R^2	weights for		
				Constant	MS effect	GARCH
MS forecast	-0.001	1.66		--	1	--
GARCH	-0.48	9.50		--	--	1
Combined model						
MS & GARCH	0	1.29	38%	1.16(1.04)	0.64(0.18)*	0.054(0.15)

4-step-ahead-forecast (Sample size=20)							
Forecast	Mean Error	SSE	Adj. R^2	weights for			
				Constant	MS effect	W/O MS effect	GARCH
MS forecast	0.211	3.43		--	1	--	--
W/O MS	0.215	3.40		--	--	1	--
GARCH	-0.475	9.61		--	--	--	1
Combined model							
All three	0	1.32	33%	0.40(1.33)	-3.44(2.40)	4.05(2.50)	0.29(0.19)
MS & W/O MS	0	1.47	29%	2.05(0.67)*	-1.80(2.87)	2.29(2.93)	0
MS & GARCH	0	1.42	32%	0.98(1.14)	0.54(0.19)*	0	0.21(0.15)
W/O MS & GARCH	0	1.39	33%	0.86(1.14)	0	0.56(0.19)*	0.22(0.15)

20-step-ahead-forecast (Sample size=20)							
Forecast	Mean Error	SSE	Adj. R^2	weights for			
				Constant	MS effect	W/O MS effect	GARCH
MS forecast	0.111	1.15		--	1	--	--
W/O MS	0.022	1.06		--	--	1	--
GARCH	-0.414	7.58		--	--	--	1
Combined model							
All three	0	0.62	69%	-3.15(0.94)*	1.27(0.62)*	0.19(0.78)	0.36(0.24)
MS & W/O MS	0	0.70	67%	-2.22(0.74)*	0.58(0.33)**	1.02(0.45)*	0
MS & GARCH	0	0.62	62%	-3.16(0.90)*	1.41(0.13)*	0	0.40(0.14)*
W/O MS & GARCH	0	0.79	62%	-2.36(0.87)*	0	1.69(0.17)*	-0.063(0.12)

Notes: Mean error is mean value of prediction errors from all the alternative models, calculated as the following equation: mean error = $mean(real\ natural\ gas\ price - forecast\ of\ natural\ gas\ price)$.
SSE, sum of squared prediction errors, or so called RSS, calculated for each alternative forecast model as: $\sum(real\ natural\ gas\ price - forecast\ of\ natural\ gas\ price)^2$.
The value in parenthesis is robust standard error.
Symbol * indicates significance at 5% level.

Table 2.5 Out of sample forecast error (forecast period: May 8, 2009 to June 26, 2009)

Total sample size=20
Model sample size=14
Forecast sample size=6

Forecast	Mean Error	SSE	Adj. R^2	weights for Constant	MS effect	W/O MS effect	GARCH
1-step-ahead-forecast							
MS forecast	-0.08	0.62		--	1		--
GARCH	-1.05	6.79		--	--		1
Combined model							
MS & GARCH	-0.86	4.84	71%	-4.01(1.81)*	0.64(0.18)*		1.15(0.38)*
4-step-ahead-forecast							
MS forecast	0.39	1.25		--	1	--	--
W/O MS	0.39	1.24		--	--	1	--
GARCH	-1.05	6.89		--	--	--	1
Combined model							
All three	-0.78	4.67	62%	-5.15(2.39)*	-13.74(8.77)	14.57(8.73)	1.45(0.54)*
MS & W/O MS	0.08	3.07	38%	1.73(0.92)**	-21.75(7.80)*	22.35(7.85)*	--
MS & GARCH	-0.91	6.64	59%	-5.96(2.12)*	0.81(0.13)*	--	1.65(0.48)*
W/O MS & GARCH	-0.91	6.48	60%	-5.95(2.11)*	--	0.81(0.13)*	1.64(0.48)*
20-step-ahead-forecast							
MS forecast	0.19	0.37		--	1	--	--
W/O MS	-0.23	0.41		--	--	1	--
GARCH	-0.87	4.65		--	--	--	1
Combined model							
All three	0.34	1.36	77%	-2.90(1.35)*	3.17(1.05)*	-1.85(1.28)	0.44(0.44)
MS & W/O MS	0.51	0.77	77%	-1.67(0.96)	2.80(0.95)*	-1.34(1.13)	--
MS & GARCH	0.19	0.41	74%	-3.16(1.76)**	1.63(0.23)*	--	0.20(0.52)
W/O MS & GARCH	-0.04	0.10	59%	-2.89(1.88)	--	1.72(0.38)*	0.04(0.69)

Notes: Mean error is mean value of prediction errors from all the alternative models, calculated as the following equation: mean error = $mean(real\ natural\ gas\ price - forecast\ of\ natural\ gas\ price)$.
SSE, sum of squared prediction errors, or so called RSS, calculated for each alternative forecast model as: $\sum(real\ natural\ gas\ price - forecast\ of\ natural\ gas\ price)^2$.
The value in parenthesis is robust standard error.
Symbol * indicates significance at 5% level.
Symbol ** indicates significance at 10% level.

Table 3.1 Unit root tests (whole period)

	US dollar index		Nominal oil price		Real oil price	
	LUSDX[a]	ΔLUSDX[b]	LOIL[a]	ΔLOIL[b]	LROIL[a]	ΔLROIL[b]
ADF test	-2.203	-77.857	-2.610	-78.667	-2.542	-78.598
	(0.4883)	(0.000)	(0.2753)	(0.000)	(0.3072)	(0.000)
PP test	-2.190	-77.859	-2.616	-78.817	-2.553	-79.092
	(0.4957)	(0.000)	(0.2725)	(0.000)	(0.3021)	(0.000)

Notes: [a] Represents model with constant, trend and lag of 5.
[b] Represents model with no constant, no trend, no lags.
The test statistic used here is ADF Z(t) statistic.
Between parenthesis is the MacKinnon approximate p-value for Z(t) statistic.

Table 3.2 Unit root tests (subsample period (2002-2010))

	US dollar index		Nominal oil price		Real oil price	
	LUSDX[a]	ΔLUSDX[b]	LOIL[a]	ΔLOIL[b]	LROIL[a]	ΔLROIL[b]
ADF test	-2.200	-46.858	-2.226	-48.267	-2.318	-48.170
	(0.4899)	(0.000)	(0.4754)	(0.000)	(0.4242)	(0.000)
PP test	-2.095	-46.856	-2.239	-48.315	-2.329	-48.220
	(0.5488)	(0.000)	(0.4679)	(0.000)	(0.4182)	(0.000)

Notes: [a] Represents model with constant, trend and lag of 5.
[b] Represents model with no constant, no trend, no lags.
The test statistic used here is ADF Z(t) statistic.
Between parenthesis is the MacKinnon approximate p-value for Z(t) statistic.

Table 3.3 Engle-Granger co-integration regression on U.S. dollar index and nominal oil price

Dependent Variable	Log USDX	EUSDX
Log nominal oil price	-0.04* (-10.84)	-
Dummy05	-0.10* (-19.95)	-
Constant	4.68* (407.01)	-
R^2	33.5%	
σ	0.088	-
DW	0.004	-
ADF	-	-2.697[a]
PP	-	-2.675[a]

Notes: EUSDX is the estimated error term (residual) from the Engle-Granger first step regression of log of USDX on log of nominal oil price and also the constant and dummy variable.
* Indicates significance at 1% level.
[a] Indicates rejection of the null hypothesis of unit root at 1% significance level.
Between parentheses is the t-statistic of the estimated parameter.

Table 3.4 Engle-Granger error correction model on U.S. dollar index and nominal oil price

Dependent Variable	ΔLog USDX	ΔLog USDX	ΔLog USDX
Log USDX (-1)		-0.0019* (-2.45)	
Log nominal oil price (-1)		-0.00017 (-1.15)	
EUSDX (-1)	-0.00214* (-2.68)		-0.0022*(-2.71)
Δ log USDX (-1)	-0.0019 (-0.15)	-0.0020 (-0.15)	
Δ log USDX (-2)	-0.01 (-0.79)	-0.010 (-0.79)	
Δ log USDX (-3)	-0.0125 (-0.97)	-0.013 (-0.97)	
Δ log USDX (-4)	0.0234*** (1.81)	0.023*** (1.80)	
Δ log USDX (-5)	-0.011 (-0.84)	-0.011 (-0.84)	
Δ log nominal oil price (-1)	-0.0025 (-0.90)	-0.0025 (-0.88)	
Δ log nominal oil price (-2)	-0.0003 (-0.10)	-0.0002 (-0.08)	
Δ log nominal oil price (-3)	-0.005**P (-1.90)	-0.0054*** (-1.88)	
Δ log nominal oil price (-4)	-0.0004 (-0.14)	-0.0004 (-0.13)	
Δ log nominal oil price (-5)	-0.0043 (-1.52)	-0.0043 (-1.50)	
Constant	-0.00005 (-0.70)	0.009* (2.40)	-0.00005 (-0.73)
σ	0.00547	0.00547	0.00547
DW	2.00	2.00	2.002

Notes: EUSDX is the estimated error term (residual) from the Engle-Granger first step regression of log of USDX on log of nominal oil price and also the constant and dummy variable.
* Indicates significance at 1% level.
***Indicates significance at 10% level.

Table 3.5 Engle-Granger co-integration regression on U.S. dollar index and real oil price

Dependent Variable	Log USDX	EUSDXR
Log real oil price	-0.082* (-18.85)	-
Dummy05	-0.0803* (-17.28)	-
Constant	4.785* (393.11)	-
R^2	36%	
σ	0.087	-
DW	0.0045	-
ADF	-	-2.812[a]
PP	-	-2.755[a]

Notes: EUSDXR is the estimated error term (residual) from the Engle-Granger first step regression of log of USDX on log of real oil price and also the constant and dummy variable.
*Indicates significance at 1% level.
[a] Indicates rejection of the null hypothesis of unit root at 1% significance level.
Between parentheses is the t-statistic of the estimated parameter.

Table 3.6 Engle-Granger error correction model on U.S. dollar index and real oil price

Dependent Variable	ΔLog USDX	ΔLog USDX	ΔLog USDX
Log USDX (-1)		-0.0021* (-2.64)	
Log real oil price (-1)		-0.0003 (-1.49)	
EUSDXR (-1)	-0.00225* (-2.76)		-0.00228* (-2.81)
Δ log USDX (-1)	-0.00183 (-0.14)	-0.0019 (-0.15)	
Δ log USDX (-2)	-0.01012 (-0.78)	-0.01018 (-0.79)	
Δ log USDX (-3)	-0.01246 (-0.96)	-0.0125 (-0.97)	
Δ log USDX (-4)	0.02337*** (1.81)	0.0233*** (1.80)	
Δ log USDX (-5)	-0.01087 (-0.84)	-0.0109 (-0.85)	
Δ log real oil price (-1)	-0.00238 (-0.84)	-0.0023 (-0.81)	
Δ log real oil price (-2)	-0.00014 (-0.05)	-0.00007 (-0.03)	
Δ log real oil price (-3)	-0.00536*** (-1.88)	-0.0053*** (-1.86)	
Δ log real oil price (-4)	-0.00036 (-0.13)	-0.0003 (-0.11)	
Δ log real oil price (-5)	-0.0045 (-1.58)	-0.0044 (-1.55)	
Constant	-0.00005 (-0.72)	0.01032* (2.60)	-0.00005 (-0.73)
σ	0.00547	0.00547	0.00547
DW	2.00	2.00	2.003

Notes: EUSDXR is the estimated error term (residual) from the Engle-Granger first step regression of log of USDX on log of real oil price and also the constant and dummy variable.
* Indicates significance at 1% level.
***Indicates significance at 10% level.
Between parentheses is the t-statistic of the estimated parameter.

Table 3.7 Engle-Granger co-integration regression on nominal oil price and U.S. dollar index

Dependent Variable	Log nominal oil price	ENOILP
Log USDX	-0.4765* (-10.84)	-
Dummy05	1.11126* (95.04)	-
Constant	5.2614* (26.26)	-
R^2	72%	
σ	0.30448	-
DW	0.0089	-
ADF	-	-3.867[a]
PP	-	-3.616[a]

Notes: ENOILP is the estimated error term (residual) from the Engle-Granger first step regression of log of nominal oil price on log of USDX and also the constant and dummy variable.
* Indicates significance at 1% level.
[a] Indicates rejection of the null hypothesis of unit root at 1% significance level.
Between parentheses is the t-statistic of the estimated parameter.

Table 3.8 Engle-Granger error correction model on nominal oil price and U.S. dollar index

Dependent Variable	ΔLog NOILP		ΔLog NOILP		ΔLog NOILP	
Log USDX (-1)			0.00044	(0.12)		
Log nominal oil price (-1)			-0.0026**	(-2.42)		
ENOILP (-1)	-0.0025**	(-2.41)			-0.0029*	(-2.78)
Δ log USDX (-1)	0.1176**	(2.00)	0.1170*	(1.99)	0.12998**	(2.22)
Δ log USDX (-2)	-0.0672	(-1.15)	-0.068	(-1.16)		
Δ log USDX (-3)	-0.0825	(-1.41)	-0.083	(-1.42)		
Δ log USDX (-4)	-0.0929	(-1.58)	-0.094	(-1.60)		
Δ log USDX (-5)	0.0696	(1.19)	0.069	(1.17)		
Δ log nominal oil price (-1)	-0.0089	(-0.69)	-0.0089	(-0.69)		
Δ log nominal oil price (-2)	-0.0615	(-4.76)	-0.062*	(-4.76)		
Δ log nominal oil price (-3)	-0.0002	(-0.01)	-0.0002	(-0.01)		
Δ log nominal oil price (-4)	-0.0095	(-0.74)	-0.0095	(-0.74)		
Δ log nominal oil price (-5)	-0.0274**	(-2.12)	-0.027**	(-2.12)		
Constant	0.0004	(1.12)	0.0063	(0.36)	0.00033	(1.03)
Dummy05	-		0.003**	(1.98)		
σ	0.02487		0.02487		0.02492	
DW	2.002		2.002		2.016	

Notes: Log NOILP is the nominal oil price in logarithm.
ENOILP is the estimated error term (residual) from the Engle-Granger first step regression of log of nominal oil price on log of USDX and also the constant and dummy variable.
* Indicates significance at 1% level.
**Indicates significance at 5% level.
Between parentheses is the t-statistic of the estimated parameter.

Table 3.9 Engle-Granger co-integration regression on real oil price and U.S. dollar index

Dependent Variable	Log real oil price	EROILP
Log USDX	-0.675* (-18.85)	-
Dummy05	0.756* (79.39)	-
Constant	5.847* (35.82)	-
R^2	67%	
σ	0.2481	-
DW	0.0116	-
ADF	-	-4.227[a]
PP	-	-3.884[a]

Notes: EROILP is the estimated error term (residual) from the Engle-Granger first step regression of log of real oil price on log of USDX and also the constant and dummy variable.
* Indicates significance at 1% level.
[a] Indicates rejection of the null hypothesis of unit root at 1% significance level.
Between parentheses is the t-statistic of the estimated parameter.

Table 3.10 Engle-Granger error correction model on real oil price and U.S. dollar index

Dependent Variable	ΔLog ROILP		ΔLog ROILP		ΔLog ROIL	
Log USDX (-1)			-0.00075	(-0.20)		
Log real oil price (-1)			-0.0039*	(-3.00)		
EUSDXR (-1)	-0.00075	(-0.20)			-0.0044*	(-3.42)
Δ log USDX (-1)	0.1192**	(2.03)	0.1191**	(2.03)	0.1313**	(2.24)
Δ log USDX (-2)	-0.0663	(-1.13)	-0.0663	(-1.13)		
Δ log USDX (-3)	-0.0872	(-1.49)	-0.0875	(-1.49)		
Δ log USDX (-4)	-0.0927	(-1.58)	-0.093	(-1.59)		
Δ log USDX (-5)	0.0708	(1.21)	0.070	(1.19)		
Δ log real oil price (-1)	-0.0094	(-0.73)	-0.0071	(-0.55)		
Δ log real oil price (-2)	-0.063*	(-4.87)	-0.0606*	(-4.69)		
Δ log real oil price (-3)	-0.0025	(-0.20)	-0.0004	(-0.03)		
Δ log real oil price (-4)	-0.011	(-0.83)	-0.0087	(-0.67)		
Δ log real oil price (-5)	-0.028**	(-2.15)	-0.026**	(-1.99)		
Constant	0.00025	(0.68)	0.0145	(0.80)	0.00022	(0.68)
Dummy05	-0.00006	(-0.08)	.00317**	(2.31)		
σ	0.02488		0.02486		0.02491	
DW	2.003		2.002		2.012	

Notes: Log ROILP is the real oil price in logarithm.
EROILP is the estimated error term (residual) from the Engle-Granger first step regression of log of real oil price on log of USDX and also the constant and dummy variable.
* Indicates significance at 1% level.
**Indicates significance at 5% level.
Between parentheses is the t-statistic of the estimated parameter.

Table 3.11 Engle-Granger co-integration regression on U.S. dollar index and nominal oil price for the subsample period (2002--2010)

Dependent Variable (2002--2010)	Log USDX	EUSDX02
Log nominal oil price	-0.2469* (-55.18)	-
Dummy05	0.0269* (6.62)	-
Constant	5.43363* (340.41)	-
R^2	76.67%	
σ	0.05528	-
DW	0.01725	-
ADF	-	-3.175[a]
PP	-	-3.053[a]

Notes: EUSDX02 is the estimated error term (residual) from the Engle-Granger first step regression of log of USDX on log of nominal oil price and also the constant and dummy variable for the subsample data.
* Indicates significance at 1% level.
[a] Indicates rejection of the null hypothesis of unit root at 1% significance level.
Between parentheses is the t-statistic of the estimated parameter.

Table 3.12 Engle-Granger error correction model on U.S. dollar index and nominal oil price for subsample period (2002--2010)

Dependent Variable	ΔLog USDX	ΔLog USDX	ΔLog USDX
Log USDX (-1)		-0.00313 (-1.47)	
Log nominal oil price (-1)		-0.00015 (-0.27)	
EUSDX02 (-1)	-0.0028 (-1.32)		-0.0031 (-1.47)
Δ log USDX (-1)	-0.0206 (-0.92)	-0.0221 (-0.99)	
Δ log USDX (-2)	0.0011 (0.05)	-0.0005 (-0.02)	
Δ log USDX (-3)	-0.019 (-0.85)	-0.0208 (-0.93)	
Δ log USDX (-4)	0.0284 (1.27)	0.0269 (1.20)	
Δ log USDX (-5)	-0.006 (-0.27)	-0.0074 (-0.33)	
Δ log nominal oil price (-1)	-0.008*** (-1.63)	-0.008*** (-1.68)	
Δ log nominal oil price (-2)	-0.0028 (-0.59)	-0.0031 (-0.64)	
Δ log nominal oil price (-3)	-0.0047 (-0.98)	-0.0049 (-1.03)	
Δ log nominal oil price (-4)	-0.0052 (-1.08)	-0.0054 (-1.13)	
Δ log nominal oil price (-5)	-0.0029 (-0.60)	-0.0031 (-0.66)	
Constant	-0.00016 (-1.33)	0.0144 (1.26)	-0.00016 (-1.38)
σ	0.00547	0.00546	0.00546
DW	1.999	1.999	2.02

Notes: EUSDX02 is the estimated error term (residual) from the Engle-Granger first step regression of log of USDX on log of nominal oil price and also the constant for the subsample data.
* Indicates significance at 1% level.
***Indicates significance at 10% level.

Table 3.13 Engle-Granger co-integration regression on U.S. dollar index and real oil price for the subsample period (2002—2010)

Dependent Variable	Log USDX	EUSDXR2
Log real oil price	-0.2497* (-49.03)	-
Dummy05	-0.00144 (-0.36)	-
Constant	5.313* (342.71)	-
R^2	73.38%	
σ	0.05904	-
DW	0.0152	-
ADF	-	-3.022[a]
PP	-	-2.910[a]

Notes: EUSDXR2 is the estimated error term (residual) from the Engle-Granger first step regression of log of USDX on log of real oil price and also the constant and dummy variable for the subsample data.
* Indicates significance at 1% level.
[a] Indicates rejection of the null hypothesis of unit root at 1% significance level.
Between parentheses is the t-statistic of the estimated parameter.

Table 3.14 Engle-Granger error correction model on U.S. dollar index and real oil price for the subsample period (2002-2010)

Dependent Variable	ΔLog USDX		ΔLog USDX		ΔLog USDX	
Log USDX (-1)			-0.0029	(-1.46)		
Log real oil price (-1)			-0.0001	(-0.18)		
EUSDXR (-1)	-0.00297	(-1.47)			-0.0032***	(-1.62)
Δ log USDX (-1)	-0.0207	(-0.92)	-0.0223	(-0.99)		
Δ log USDX (-2)	0.001	(0.05)	-0.0006	(-0.03)		
Δ log USDX (-3)	-0.019	(-0.85)	-0.0207	(-0.93)		
Δ log USDX (-4)	0.028	(1.27)	0.027	(1.20)		
Δ log USDX (-5)	-0.0066	(-0.29)	-0.008	(-0.36)		
Δ log real oil price (-1)	-0.0078***	(-1.63	-0.0081***	(-1.69)		
Δ log real oil price (-2)	-0.0028	(-0.59)	-0.0031	(-0.65)		
Δ log real oil price (-3)	-0.0046	(-0.96)	-0.005	(-1.01)		
Δ log real oil price (-4)	-0.005	(-1.06)	-0.005	(-1.12)		
Δ log real oil price (-5)	-.0032	(-0.67)	-0.003	(-0.73)		
Constant	-0.0002	(-1.35)	0.013	(1.24)	-0.00016	(-1.38)
σ	0.00547		0.00546		0.00546	
DW	1.999		1.999		2.02	

Notes: EUSDXR2 is the estimated error term (residual) from the Engle-Granger first step regression of log of USDX on log of real oil price and also the constant for the subsample data.

* Indicates significance at 1% level.

***Indicates significance at 10% level.

Between parentheses is the t-statistic of the estimated parameter.

Table 3.15 Engle-Granger co-integration regression on nominal oil price and U.S. dollar index for the subsample period (2002—2010)

Dependent Variable	Log nominal oil price	ENOILP2
Log USDX	-2.37* (-55.18)	-
Dummy05	0.366* (36.64)	-
Constant	14.36* (73.21)	-
R^2	85.34%	-
σ	0.17	-
DW	0.024	-
ADF	-	-3.628[a]
PP	-	-3.470[a]

Notes: ENOILP2 is the estimated error term (residual) from the Engle-Granger first step regression of log of nominal oil price on log of USDX and also the constant and dummy variable for the subsample data (2002—2010).
* Indicates significance at 1% level.
[a] Indicates rejection of the null hypothesis of unit root at 1% significance level.
Between parentheses is the t-statistic of the estimated parameter.

Table 3.16 Engle-Granger error correction model on nominal oil price and U.S. dollar index for the subsample period (2002—2010)

Dependent Variable	ΔLog NOILP		ΔLog NOILP		ΔLog NOILP	
Log USDX (-1)			-0.022**	(-2.19)		
Log nominal oil price (-1)			-0.0102*	(-3.14)		
ENOILP2 (-1)	-0.010*	(-3.12)			-0.0104*	(-3.22)
Δ log USDX (-1)	0.171***	(1.64)	0.173***	(1.66)	-0.026	(-1.18)
Δ log USDX (-2)	0.058	(0.55)	0.059	(0.56)		
Δ log USDX (-3)	-0.083	(-0.80)	-0.081	(-0.78)		
Δ log USDX (-4)	-0.138	(-1.32)	-0.137	(-1.31)		
Δ log USDX (-5)	0.196	(1.88)	0.197***	(1.89)		
Δ log nominal oil price (-1)	-0.025	(-1.11)	-0.025	(-1.11)	0.184***	(1.77)
Δ log nominal oil price (-2)	-0.021	(-0.96)	-0.021	(-0.96)		
Δ log nominal oil price (-3)	0.051**	(2.27)	0.051**	(2.26)		
Δ log nominal oil price (-4)	0.003	(0.12)	0.003	(0.12)		
Δ log nominal oil price (-5)	-0.05**	(-2.25)	-0.05**	(-2.25)		
Constant	0.0007	(1.26)	0.14**	(2.50)	0.0007	(1.23)
Dummy05	-		0.003***	(1.62)		
σ	0.025		0.025		0.026	
DW	2.001		2.001		1.998	

Notes: Log NOILP is the nominal oil price in logarithm.
ENOILP2 is the estimated error term (residual) from the Engle-Granger first step regression of log of nominal oil price on log of USDX and also the constant and dummy variable for the subsample data (2002—2010).
* Indicates significance at 1% level.
**Indicates significance at 5% level.
Between parentheses is the t-statistic of the estimated parameter.

Table 3.17 Engle-Granger co-integration regression on real oil price and U.S. dollar index for the subsample period (2002—2010)

Dependent Variable	Log real oil price	EROILP2
Log USDX	-2.114* (-49.03)	-
Dummy05	0.284* (28.39)	-
Constant	12.66* (64.36)	-
R^2	80.62%	
σ	0.17	-
DW	0.023	-
ADF	-	-3.523[a]
PP	-	-3.365[a]

Notes: EROILP2 is the estimated error term (residual) from the Engle-Granger first step regression of log of real oil price on log of USDX and also the constant and dummy variable for the subsample data (2002—2010).

* Indicates significance at 1% level.

[a] Indicates rejection of the null hypothesis of unit root at 1% significance level.

Between parentheses is the t-statistic of the estimated parameter.

Table 3.18 Engle-Granger error correction model on real oil price and U.S. dollar index for the subsample period (2002—2010)

Dependent Variable	ΔLog ROILP		ΔLog ROILP		ΔLog ROIL	
Log USDX (-1)			-0.018**	(-1.95)		
Log real oil price (-1)			-0.0077*	(-2.80)		
EROILP2 (-1)	-0.0105*	(-3.22)			-0.011*	(-3.40)
Δ log USDX (-1)	0.183***	(1.76)	0.179***	(1.72)	0.224**	(2.23)
Δ log USDX (-2)	0.062	(0.60)	0573	(0.55)		
Δ log USDX (-3)	-0.093	(-0.90)	-0.098	(-0.94)		
Δ log USDX (-4)	-0.142	(-1.37)	-0.147	(-1.41)		
Δ log USDX (-5)	0.201**	(1.93)	0.197***	(1.89)		
Δ log real oil price (-1)	-0.022	(-0.99)	-0.024	(-1.06)		
Δ log real oil price (-2)	-0.021	(-0.93)	-0.022	(-1.00)		
Δ log real oil price (-3)	0.049**	(2.18)	0.047**	(2.10)		
Δ log real oil price (-4)	0.003	(0.13)	0.001	(0.05)		
Δ log real oil price (-5)	-0.049**	(-2.20)	-0.05**	(-2.27)		
Constant	0.0006	(1.09)	0.108**	(2.16)	0.0006	(1.04)
Dummy05	-		-		-	
σ	0.0254		0.0254		0.0255	
DW	2.0015		2.002		2.040	

Notes: Log ROILP is the real oil price in logarithm.
EROILP2 is the estimated error term (residual) from the Engle-Granger first step regression of log of real oil price on log of USDX and also constant for the subsample data (2002—2010).
* Indicates significance at 1% level.
**Indicates significance at 5% level.
***Indicates significance at 10% level.
Between parentheses is the t-statistic of the estimated parameter.

Table 3.19 Granger Causality Wald test results ($p - values$)

	Full Sample	Subsample (2002—2010)
NOILP→USDX		
VAR(1)[a]	0.461	0.078***
VAR(2)[a]	0.744	0.181
VAR(5)[a]	0.271	0.319
VAR(10)[a]	0.096***	0.009*
VAR(20)[a]	0.055***	0.001*
USDX → NOILP		
VAR(1)[a]	0.032**	0.114
VAR(2)[a]	0.056***	0.321
VAR(5)[a]	0.041**	0.125
VAR(10)[a]	0.005*	0.020**
VAR(20)[a]	0.025**	0.123
ROILP→USDX		
VAR(1)[a]	0.481	0.077
VAR(2)[a]	0.765	0.178
VAR(5)[a]	0.256	0.314
VAR(10)[a]	0.087***	0.009*
VAR(20)[a]	0.044**	0.001*
USDX → ROILP		
VAR(1)[a]	0.029**	0.090***
VAR(2)[a]	0.054***	0.267
VAR(5)[a]	0.036**	0.089***
VAR(10)[a]	0.006*	0.019**
VAR(20)[a]	0.025**	0.110

Notes: → Indicates the causality direction runs from left side variable to the right side variable.
[a] Between the parenthesis following VAR is number of lags selected for vector autoregressive model (VAR) used in Granger causality test.
* Indicates rejection of null hypothesis that X does not Granger cause Y at 1% level.
** Indicates rejection of null hypothesis that X does not Granger cause Y at 5% level.
** *Indicates rejection of null hypothesis that X does not Granger cause Y at 10% level.

Table 4.1 Trader's positions as a percentage of total open interest held by Commodity Futures Trading Commission (CFTC) reporting categories (%, Jan. 2004–June 2009, 286 observations)

Traders category	Mean	Standard Deviation	Range (Min, Max)
Commercial traders	44.08	6.03	(32.37,61.20)
Non-commercial traders	49.97	6.97	(30.22,62.77)
Non-reporting traders	5.96	1.60	(3.57,10.10)

Table 4.2 Percent net long positions (PNL) held by Commodity Futures Trading Commission (CFTC) reporting categories (%, Jan. 2004–June 2009, 286 observations)

Traders category	Mean	Standard Deviation	Range (Min, Max)
Commercial traders	1.8	7.25	(-8.13, 24.3)
Non-commercial traders	-5.04	4.85	(-18.5, 3.51)
Non-reporting traders	33.1	4.96	(18.03, 46.91)

Notes: ADF tests show that PNL for non-reporting traders is stationary at 5% level; while for commercial and non-commercial traders these series are stationary at 10% level.

Table 4.3 Granger Causality Wald test results for percent net long position (PNL) and model errors (Jan. 2004–June 2009, 286 observations)

Null Hypothesis: PNL of each category of traders does not Granger cause model error			
	Commercial traders	Non-commercial traders	Non-reportable traders
VAR(2)[a] Wald test statistic	0.41	0.76	4.42**
p-value	0.82	0.68	0.11
R^2	7.4%	7.5%	8.7%
Null Hypothesis: Model error does not Granger cause PNL of each category of traders			
	Commercial traders	Non-commercial traders	Non-reportable traders
VAR(2)[a] Wald test statistic	6.9*	4.07**	2.48
p-value	0.03	0.13	0.29
R^2	96.7%	93.7%	53.8%

Notes: [a] Indicates the vector autoregressive model for Granger causality test, and between parenthesis is the number of lags chosen based on Schwarz's Bayesian information criterion (SBIC).

[*] Indicates significance at 5% level.

[**] Indicates significance at 15% level.

Table 4.4 VAR estimation for forecast error equation (full sample, Jan. 2004–June 2009, 286 observations)

	Model error equation[a]			
	Coefficient	Std. error	z-test	p-value
Model error (-1)	0.252*	0.059	4.12	0.000
Model error (-2)	0.057	0.059	0.95	0.341
PNL_non-reporting(-1)	-0.168*	0.081	-2.07	0.039
PNL_non-reporting(-2)	0.142**	0.08	1.74	0.083
Constant	0.008	0.02	0.40	0.701
	Normality test			
	Skewness	Kurtosis	chi2	p-value
Jarque-Bera test			46.147	0.000
Skewness test	-0.13		0.796	0.37
Kurtosis		4.96	45.35	0.000
	PNL_non-reporting equation[a]			
	Coefficient	Std. error	z-test	p-value
Model error (-1)	0.038	0.042	0.92	0.358
Model error (-2)	0.041	0.042	0.99	0.323
PNL_non-reporting (-1)	0.548*	0.058	9.51	0.000
PNL_non-reporting(-2)	0.235*	0.058	4.07	0.000
Constant	0.072*	0.015	4.92	0.000
	Normality test			
	Skewness	Kurtosis	chi2	p-value
Jarque-Bera test			41.356	0.000
Skewness test	0.162		1.24	0.27
Kurtosis		4.84	40.12	0.000

Notes: [a] The vector autoregressive model (VAR(2)) is selected by Schwarz's Bayesian information criterion (SBIC) for the optimal number of lags with the maximum lags of 24.

[*] Indicates significance at 5% level.

[**] Indicates significance at 10% level.

Table 4.5 Diebold-Mariano test results for predictive ability of fundamentals and Commitment of Traders (COT) data integrated model

No. of observations	80 (forecast period: Dec. 21, 2007 to June 26, 2009)
DM test	H0: alternative methods are equally accurate on average
80-step ahead forecasts	
Forecasts with Markov-switching effects and speculation VS. Forecasts with Markov-switching effects	p-value = 0.79 (fail to reject null hypothesis) Second forecast is a better forecast
Forecasts with speculation but without Markov-switching effects VS. Forecasts without Markov-switching effects	p-value = 0.83 (fail to reject null hypothesis) Second forecast is a better forecast
No. of observations	40 (forecast period: Sep. 26, 2008 to June 26, 2009)
DM test	H0: alternative methods are equally accurate on average
40-step ahead forecasts	
Forecasts with Markov-switching effects and speculation VS. Forecasts with Markov-switching effects	p-value = 0.000 (reject null hypothesis) First forecast is a better forecast
Forecasts with speculation but without Markov-switching effects VS. Forecasts without Markov-switching effects	p-value = 0.000 (reject null hypothesis) First forecast is a better forecast
No. of observations	20 (forecast period: Feb. 13, 2009 to June 26, 2009)
DM test	H0: alternative methods are equally accurate on average
20-step ahead forecasts	
Forecasts with Markov-switching effects and speculation VS. Forecasts with Markov-switching effects	p-value = 0.91 (fail to reject null hypothesis) Second forecast is a better forecast
Forecasts with speculation but without Markov-switching effects VS. Forecasts without Markov-switching effects	p-value = 0.62 (fail to reject null hypothesis) First forecast is a better forecast
No. of observations	20 (forecast period: Feb. 13, 2009 to June 26, 2009)
DM test	H0: alternative methods are equally accurate on average
10-step ahead forecasts	
Forecasts with Markov-switching effects and speculation VS. Forecasts with Markov-switching effects	p-value = 0.49 (fail to reject null hypothesis) Second forecast is a better forecast
Forecasts with speculation but without Markov-switching effects VS. Forecasts without Markov-switching effects	p-value = 0.48 (fail to reject null hypothesis) First forecast is a better forecast

APPENDIX B

FIGURES

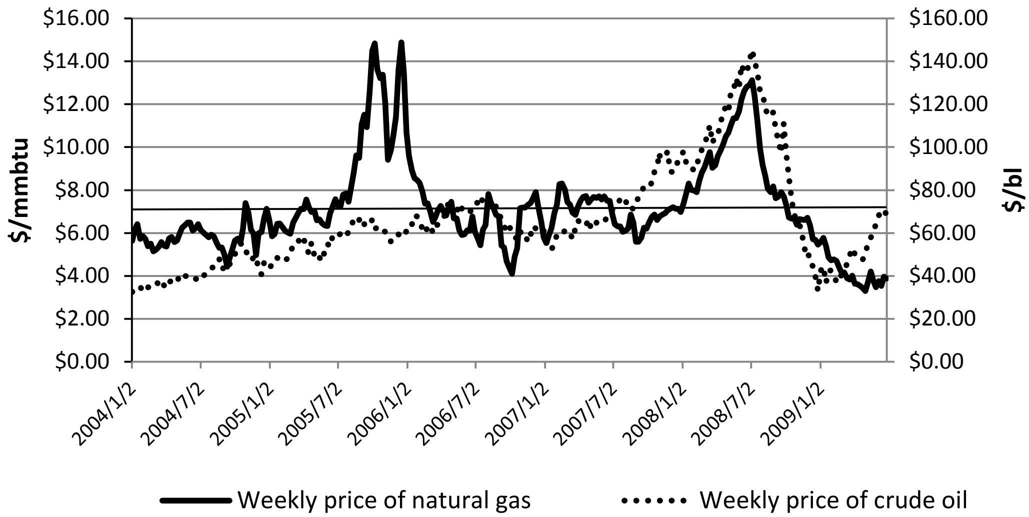
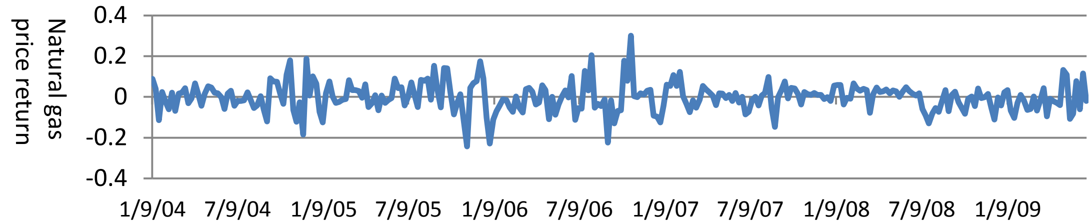


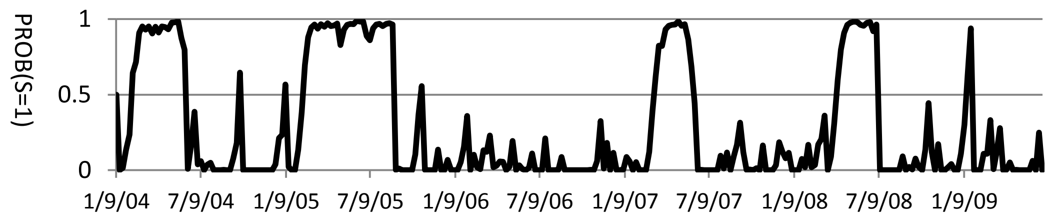
Figure 2.1 Weekly price trend of natural gas and crude oil (Jan. 2004--Jun. 2009)

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

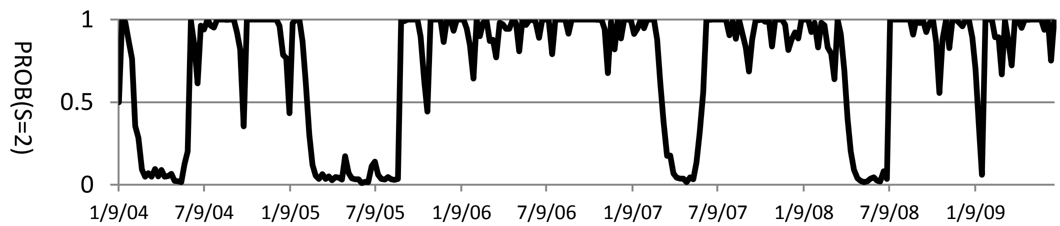
Panel 1: weekly natural gas price return (the first difference of log of natural gas price) from Jan. 9, 2004 to June 26, 2009



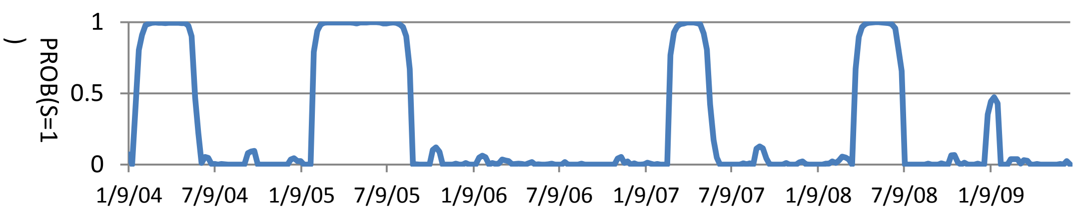
Panel 2: Filtered probability of the market being in state 1



Panel 3: Filtered probability of the market being in state 2



Panel 4: Smoothed probability of the market being in state 1



Panel 5: Smoothed probability of the market being in state 2

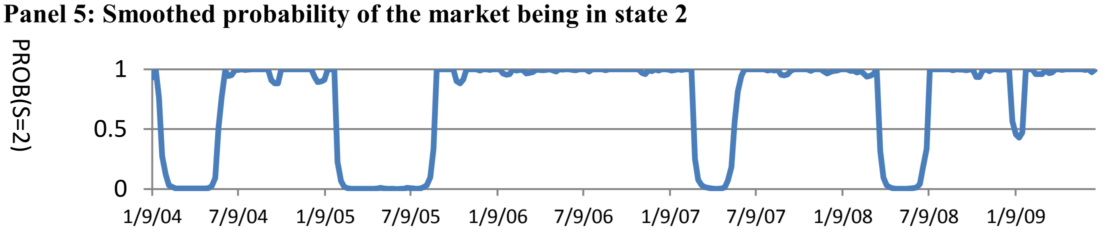
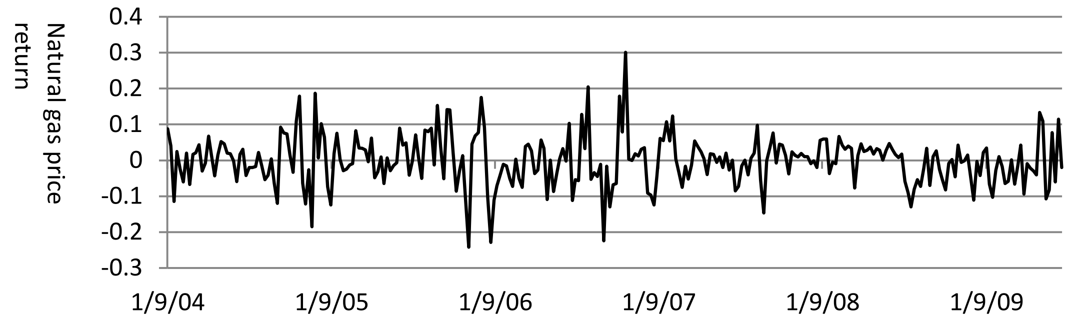
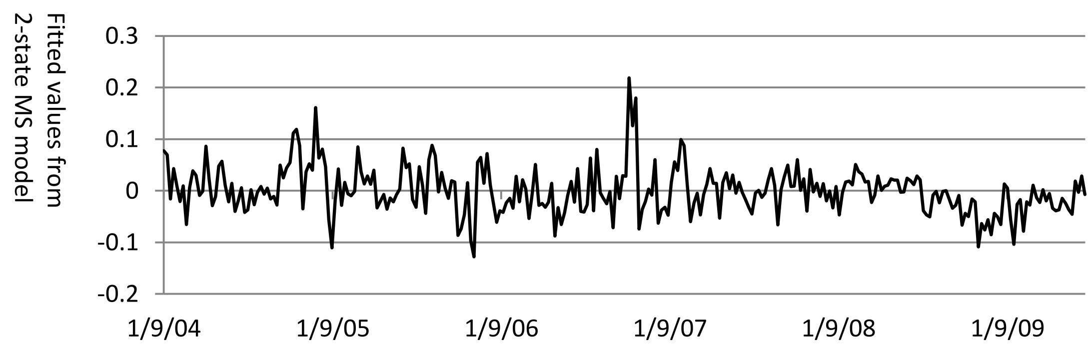


Figure 2.2 Probability of market being in state 1 or 2

Panel 1: weekly natural gas price return from Jan. 9, 2004 to June 26, 2009



Panel 2: fitted values of natural gas price return from the 2-state Markov-switching model



Panel 3: fitted value plus and minus 2 units of standard deviation

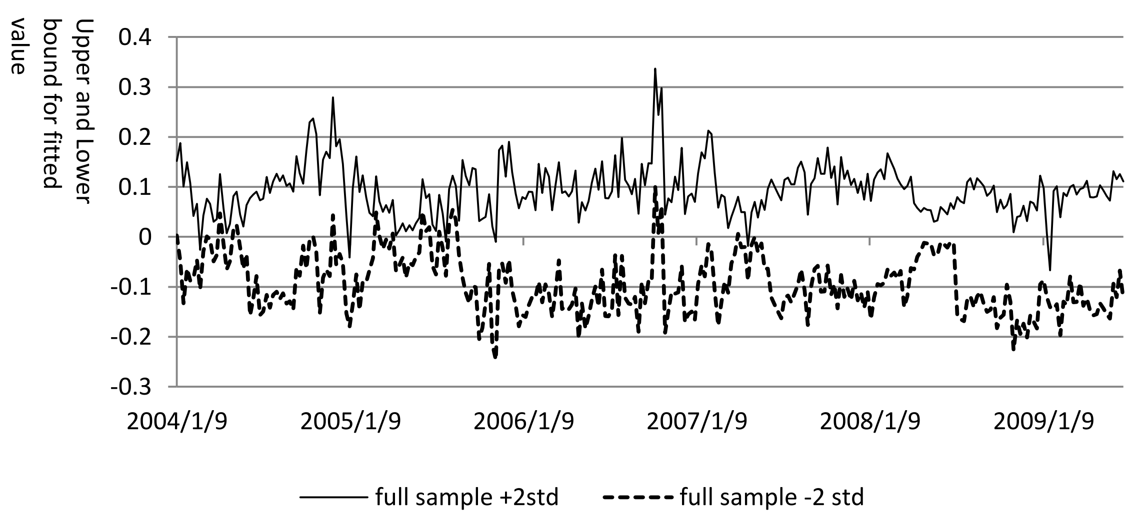


Figure 2.3 Weekly natural gas price return, fitted value and standard deviation

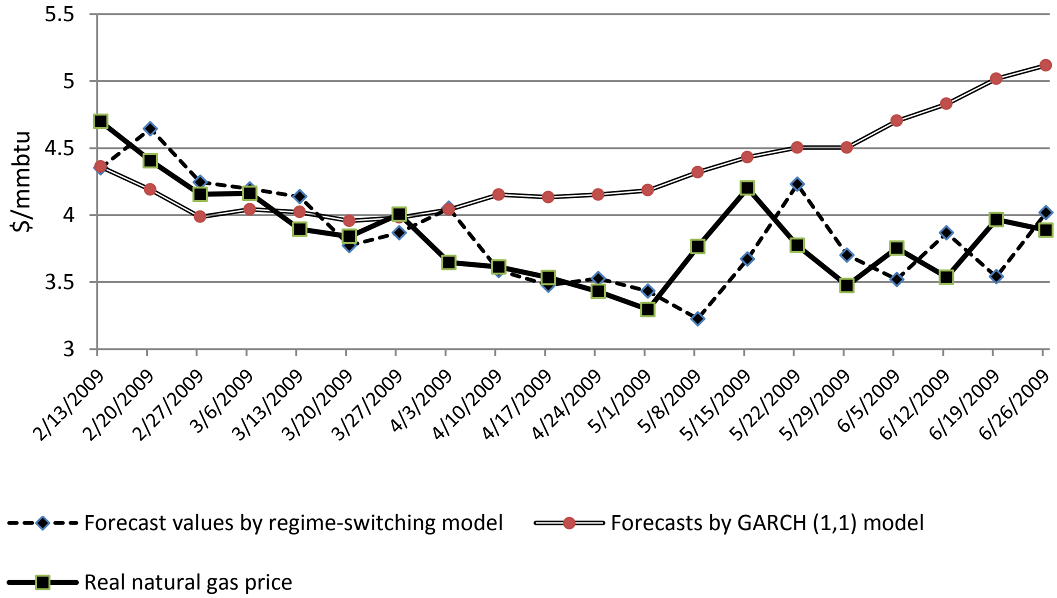


Figure 2.4 1-week-ahead forecasts using regime-switching and GARCH (1,1) models

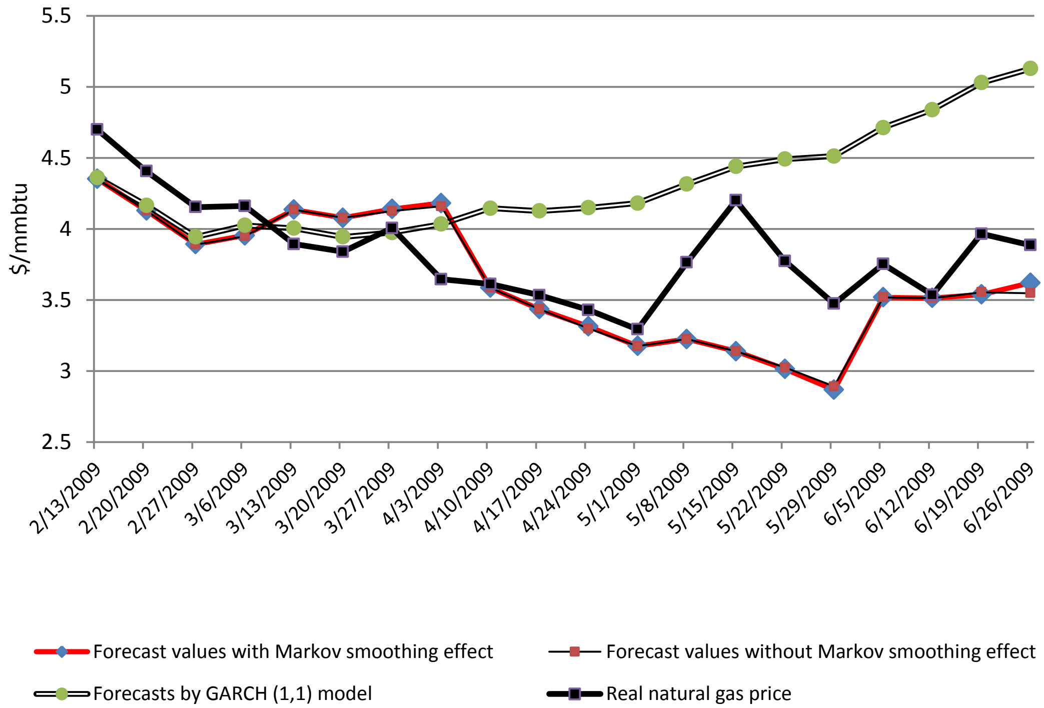


Figure 2.5 4-week-ahead forecasts using regime-switching and GARCH (1,1) models

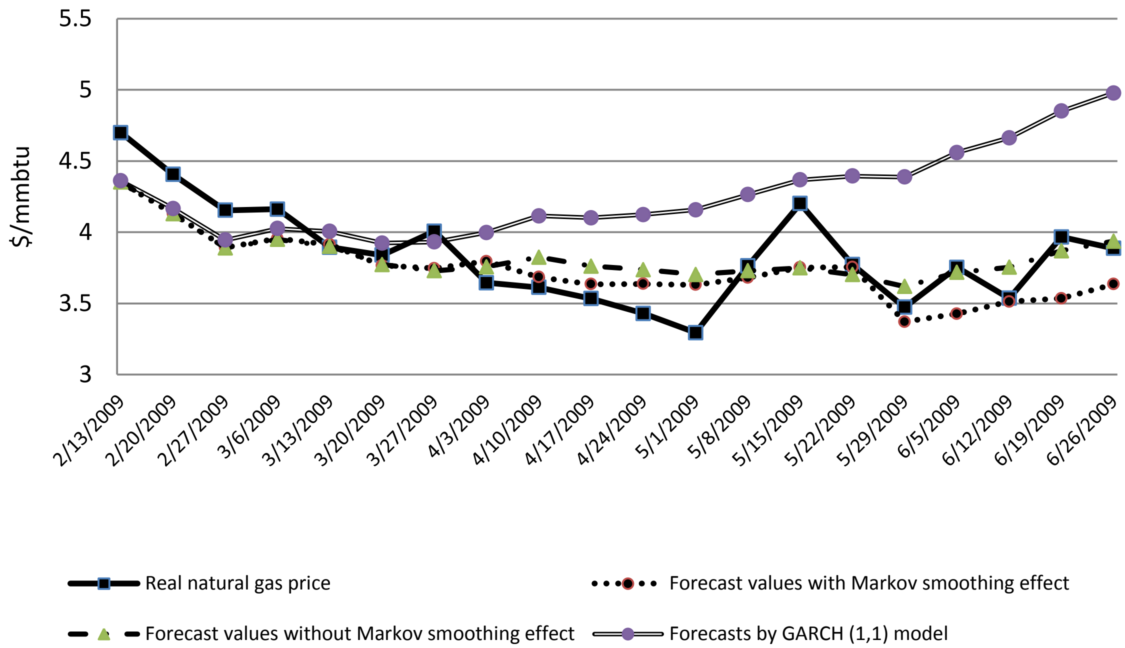


Figure 2.6 20-week-ahead forecasts using regime-switching and GARCH (1,1) models

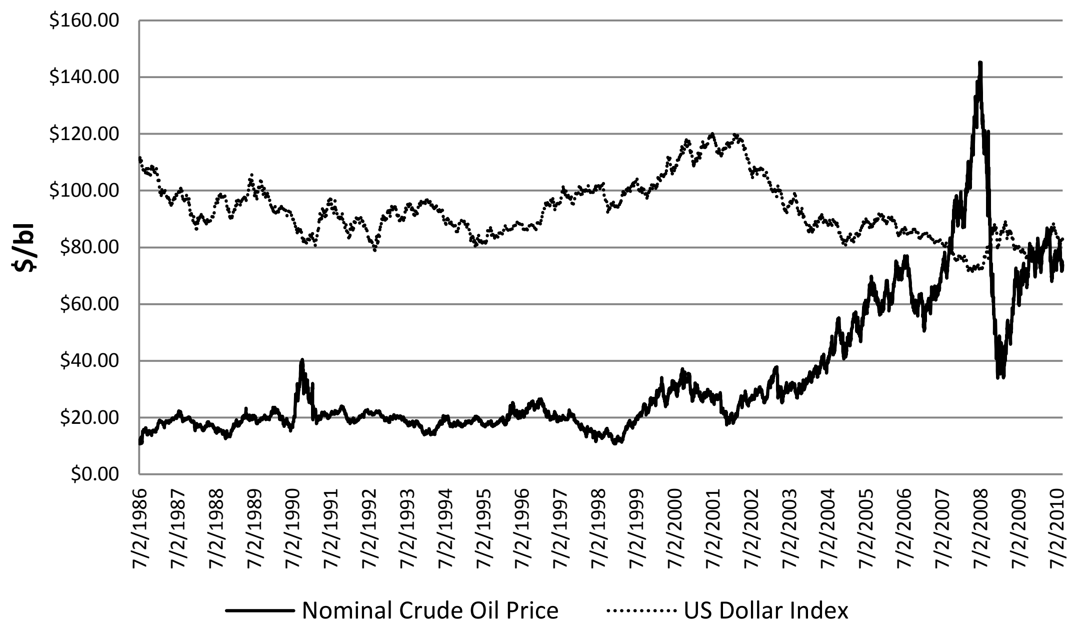


Figure 3.1 Daily U.S. dollar index and crude oil price (July 2, 1986—Sep. 2, 2010)
Source of data: Bloomburg

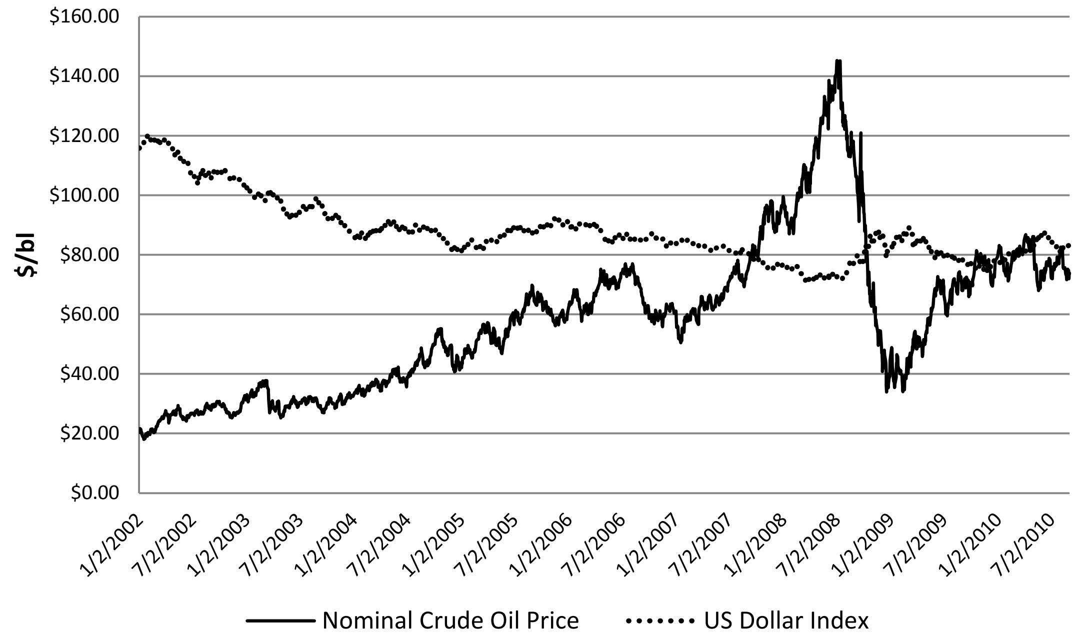


Figure 3.2 Daily U.S. dollar index and crude oil price (Jan. 2, 2002—Sep. 2, 2010)
Source of data: Bloomburg

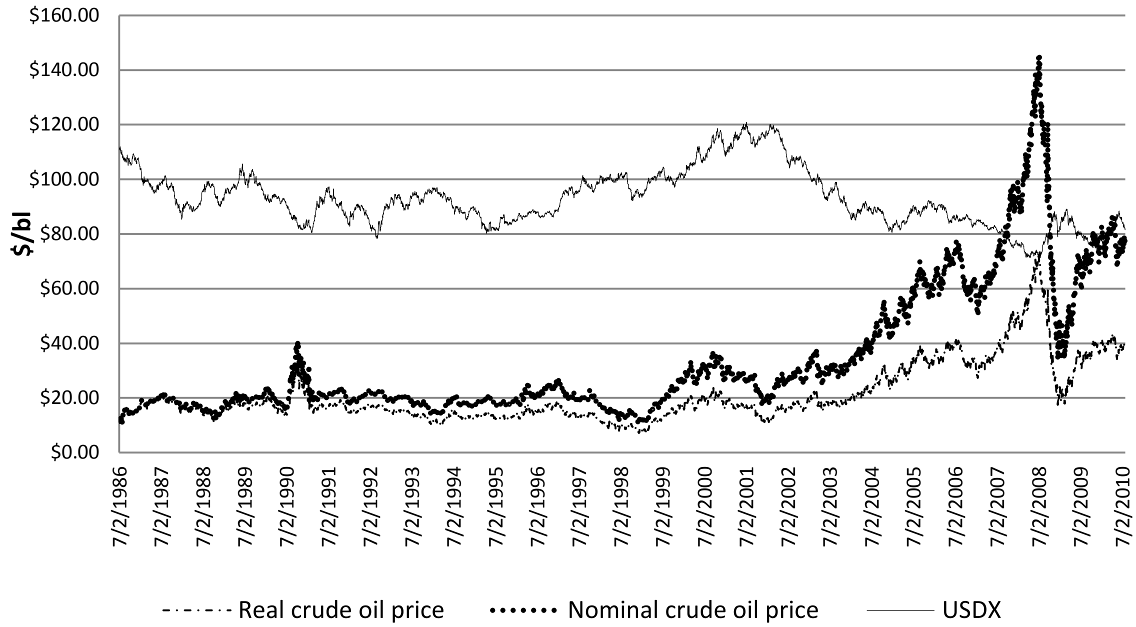


Figure 3.3 Daily U.S. dollar index, nominal and real crude oil price (July 2, 1986—July 30, 2010)
Source of data: Bloomburg

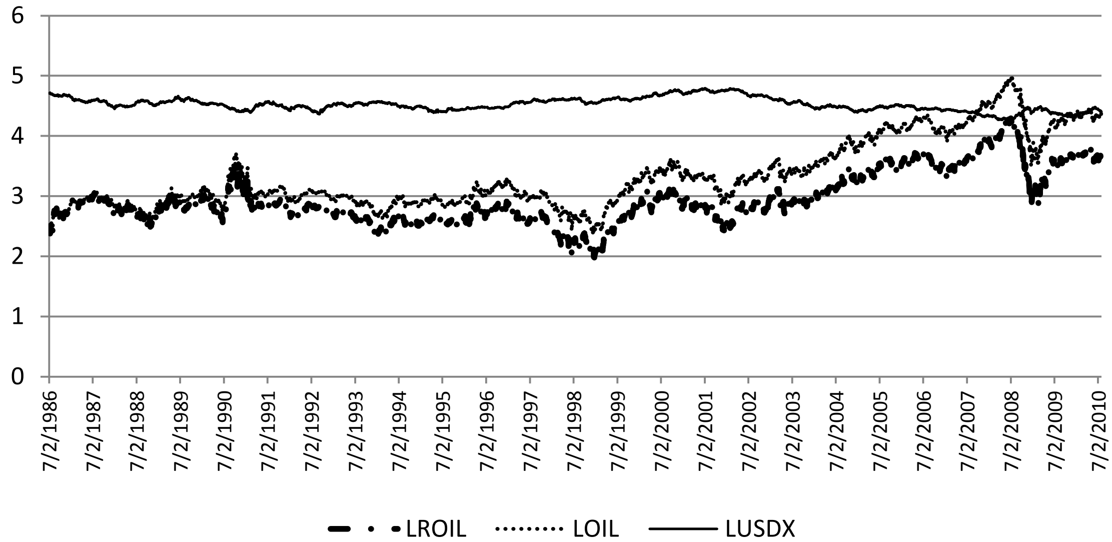


Figure 3.4 Daily U.S. dollar index, nominal and real crude oil price, in logarithm (July 2, 1986—July 30, 2010)
Source of data: Bloomburg

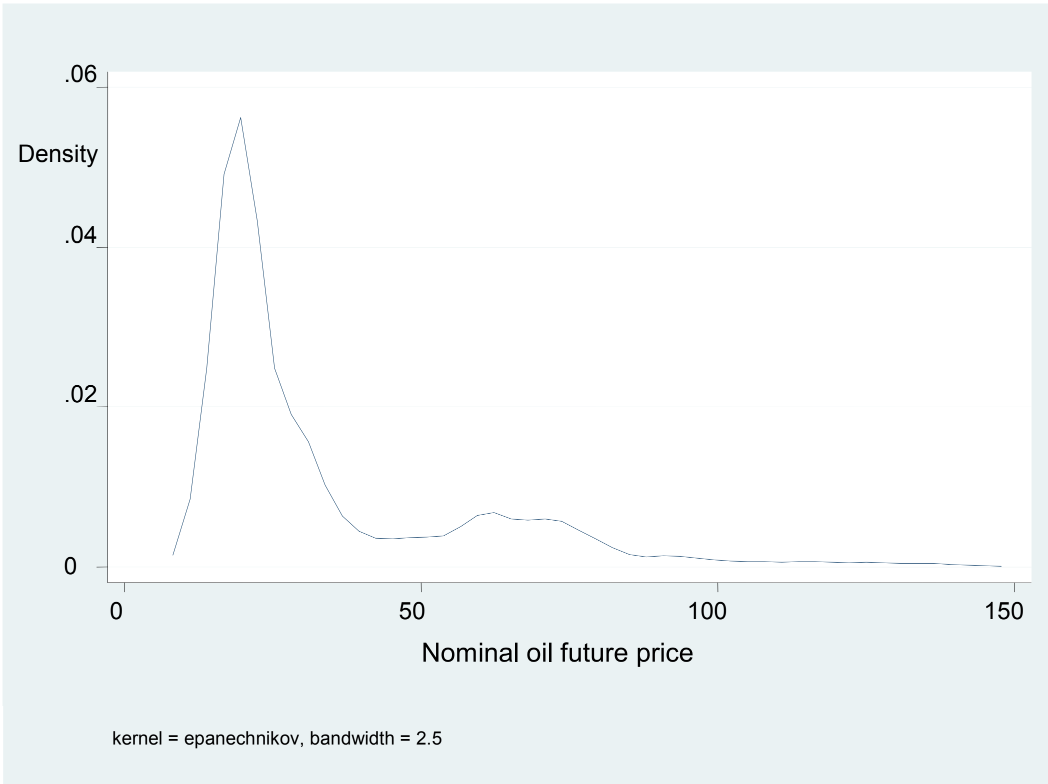


Figure 3.5 Kernel density of daily nominal oil price

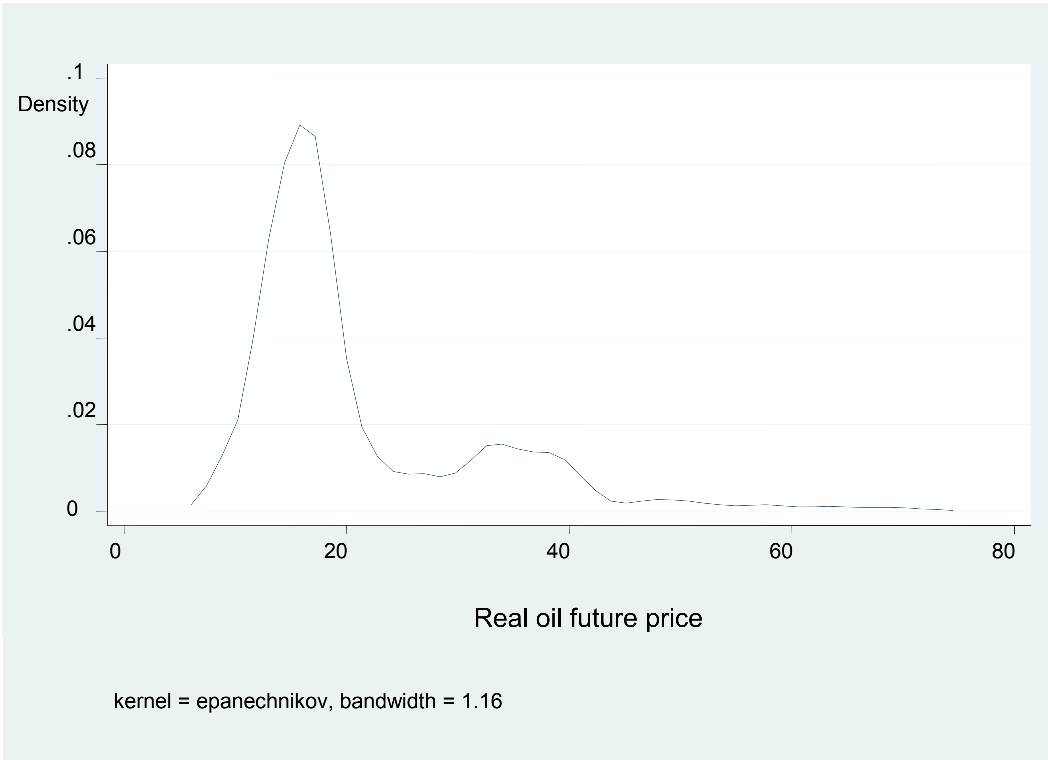


Figure 3.6 Kernel density of daily real oil price

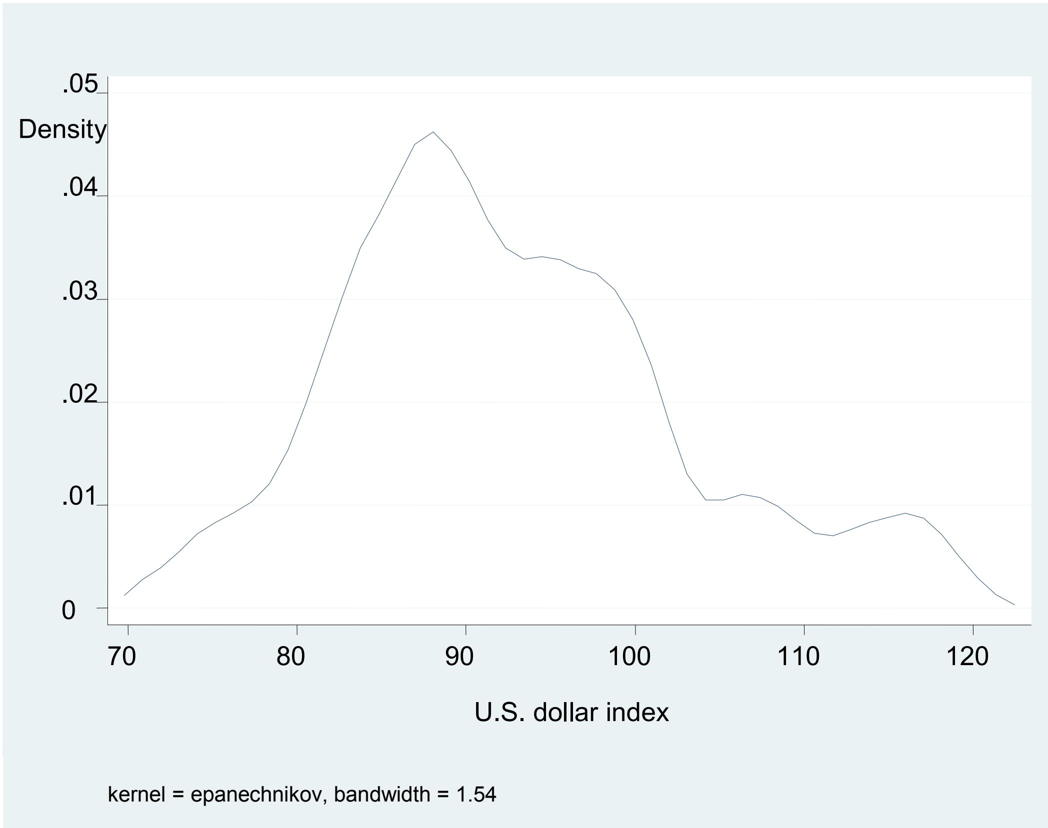


Figure 3.7 Kernel density of daily U.S. dollar index

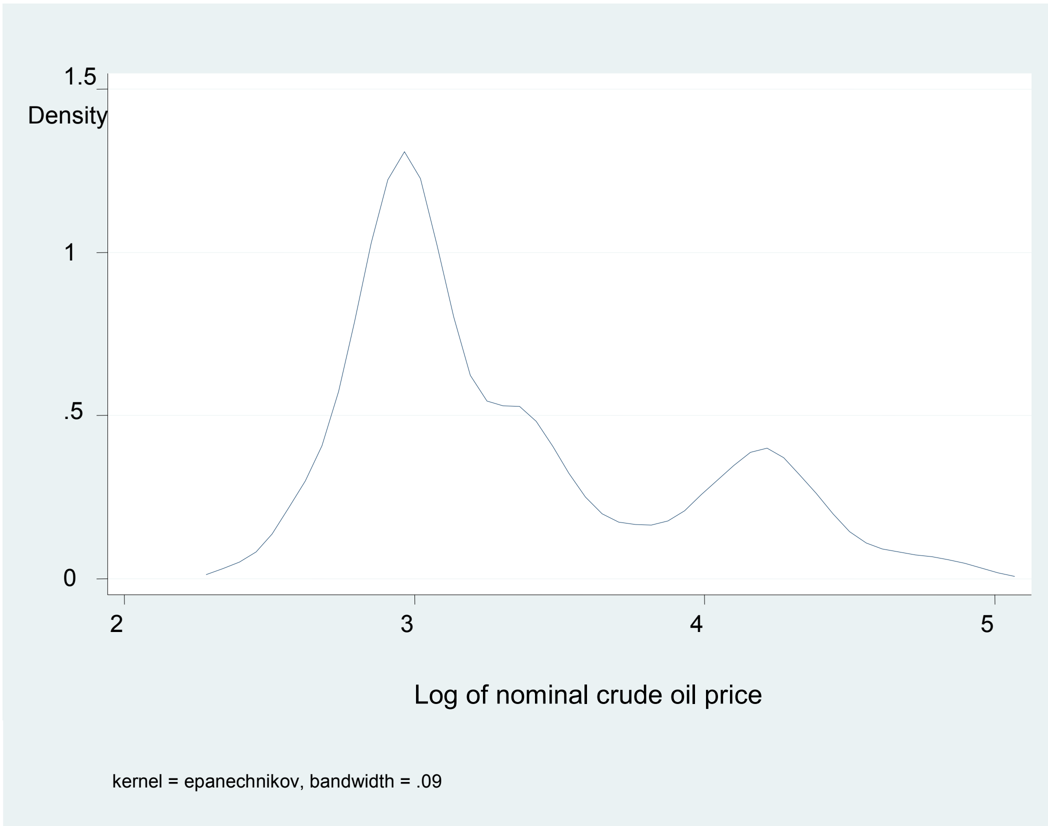


Figure 3.8 Kernel density of log of nominal oil price

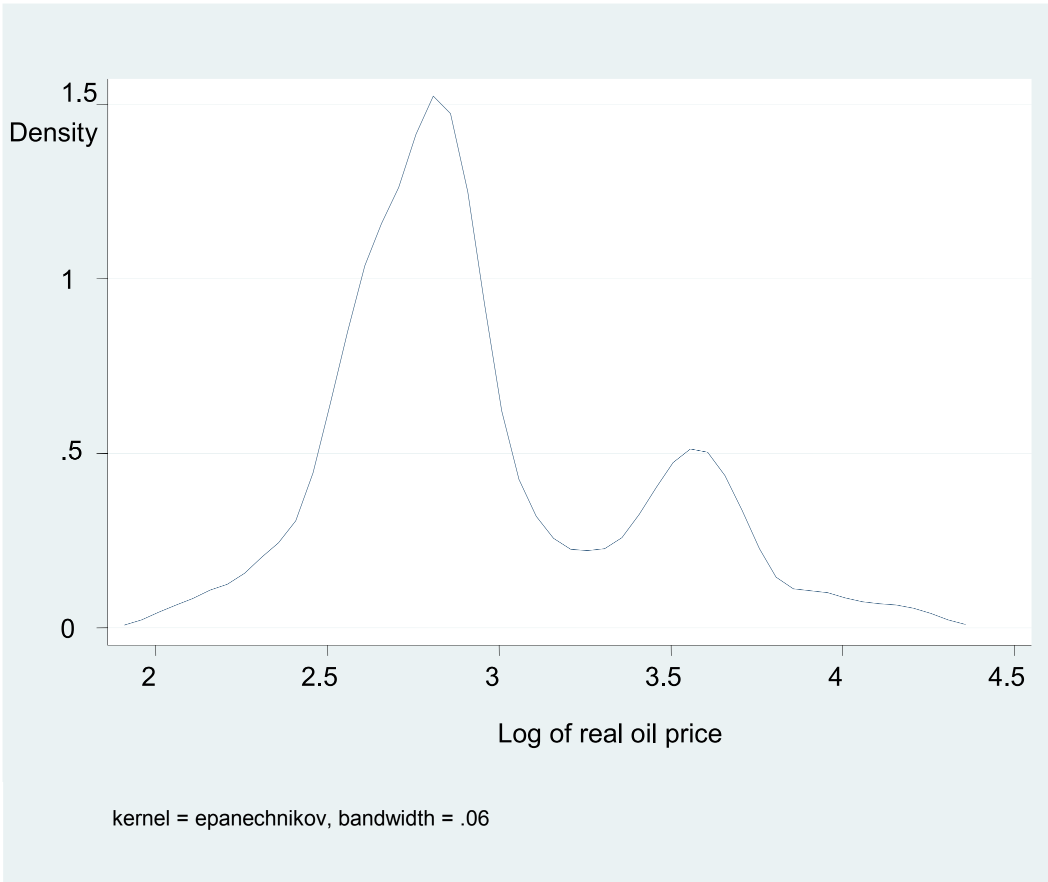


Figure 3.9 Kernel density of log of real oil price

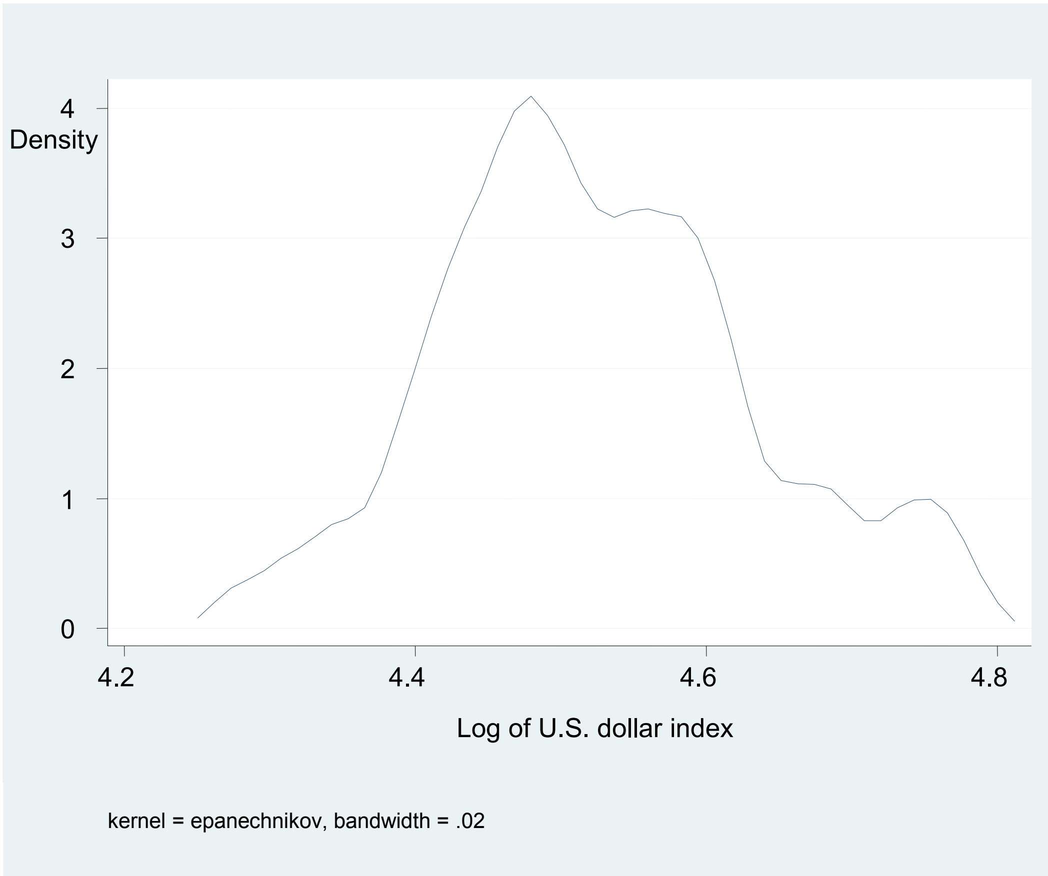


Figure 3.10 Kernel density of log of U.S. dollar index

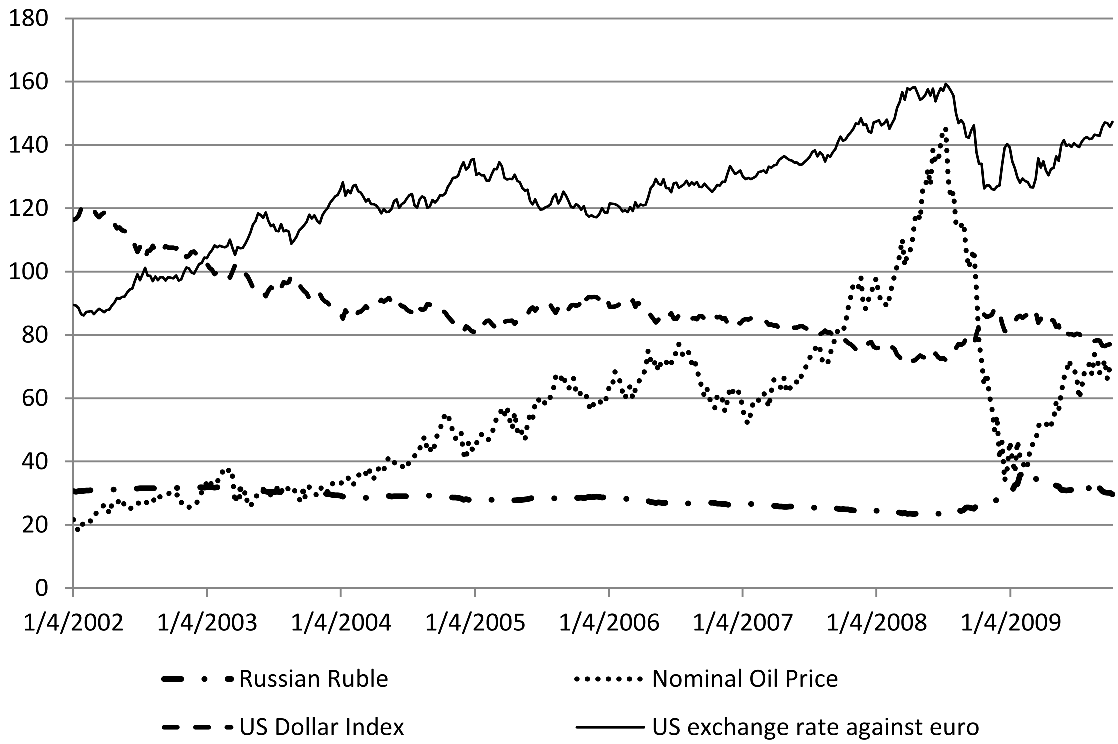
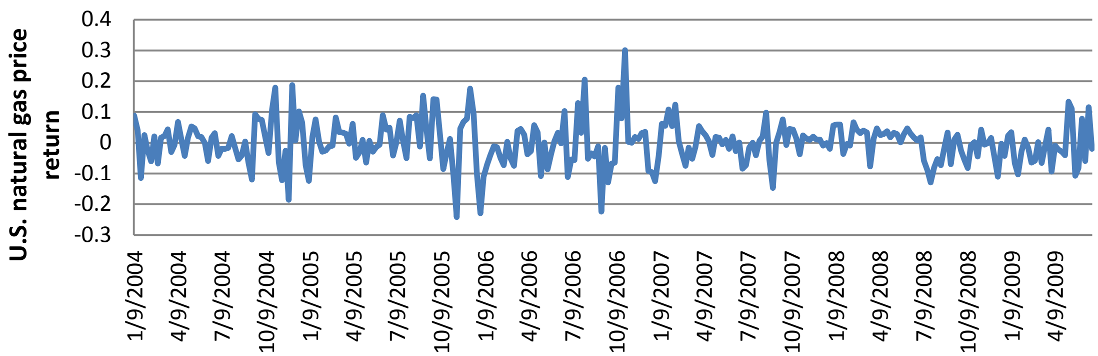


Figure 3.11 Daily U.S. dollar index, nominal U.S. dollar exchange rate against euro, nominal crude oil price and Russian ruble (Jan. 4, 2002—Oct. 9, 2009)
Source of data: Bloomburg

Note: Due to scale problem, the U.S. exchange rate against euro depicted in Figure 3.11 is the real data multiplying 100.

Panel 1: weekly natural gas price return (first difference of natural log of U.S. natural spot price) for period January 9, 2004 through June 23, 2009



Panel 2: 2-state Markov-switching model fitting errors for period Jan. 9, 2004 through June 23, 2009.

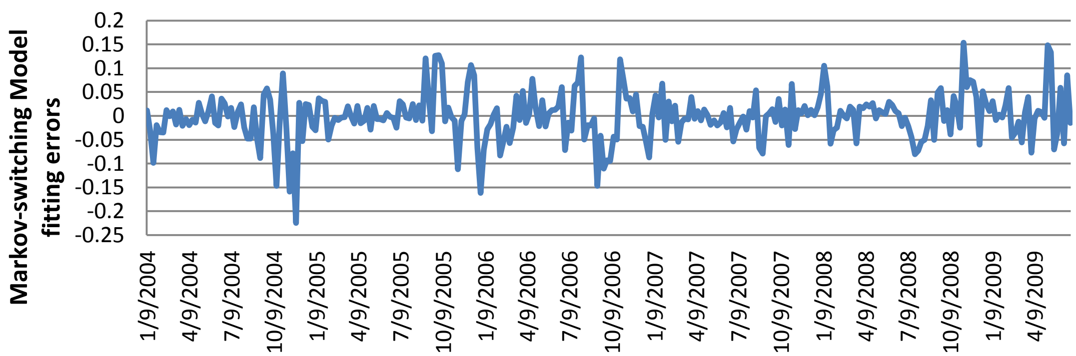


Figure 4.1 Weekly natural gas price return and fitting errors

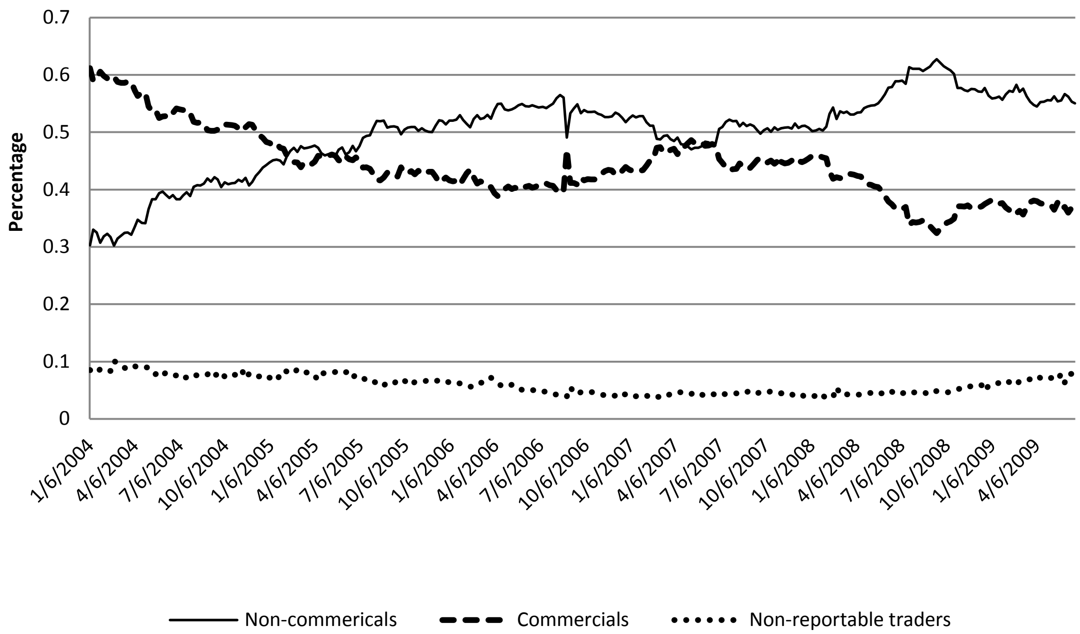


Figure 4.2 Trader's total positions as a percent of total open interest in natural gas future market (NYMEX) for period 01/06/2004—06/23/2009.

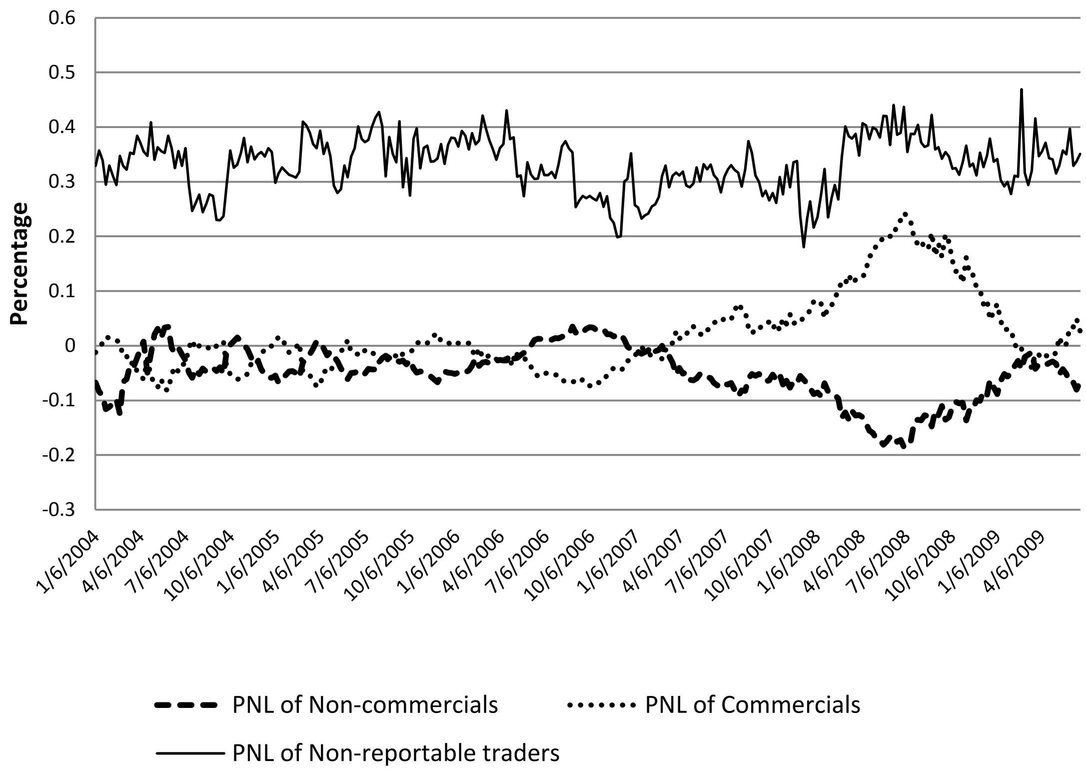


Figure 4.3 Trader's percent net long positions in natural gas future market (NYMEX) for period 01/06/2004—06/23/2009

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