Price dynamics of the natural gas futures market: the role of market fundamentals

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Abstract

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Yawei Wei

In this thesis, I examine the effect of market fundamentals upon the price of the natural gas futures contract. The market fundamentals that I address capture the effects of the demand for natural gas, such as weather effects, and the supply of natural gas, such as inventory effects. I also address the effect of key macroeconomic variables, such as the returns on the stock market, which is measured by the return on the S&P 500 futures contract, and the price of crude oil, which is measured by the returns on the crude oil futures contract. I focus my analysis on the conditional mean and the conditional variance of the return on the natural gas futures contract. My results indicate that weather and inventory shocks do not have a significant effect upon the conditional mean of the natural gas futures returns, which is, however, significantly negatively related to the return on the S&P 500 futures contract and significantly positively related to the return on the crude oil futures contract. The conditional variance of the natural gas futures return is significantly higher in winter, on inventory announcement days and on Mondays. Furthermore, by comparing the conditional variance of the three most liquid futures contracts, I find evidence supporting the "Samuelson effect" that the futures volatility decreases as the contract horizon increases.

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Chapter 1. Introduction

In recent years, natural gas futures prices exhibited an upward trend in the North American market. This raises the question as to what is the reason for this upward trend. The presumption is that economic fundamentals such as the demand and supply of natural gas, which include weather, inventory levels, imports, and transportation costs determine the price that American households and industries pay for the use of natural gas.

Many theories have been developed to explain natural gas futures price dynamics. The theory of storage (Fama and French, 1987) suggests that supply and demand, which influence inventory, directly affect futures prices and volatility. Samuelson (1965) asserts that futures contracts which are closer to maturity will exhibit greater volatility in prices as compared to more distant maturity contracts. Mu (2007) suggests that weather should also be recognized as one factor that is responsible for the seasonality pattern in futures prices and volatility. In contrast, other researchers (Kaufmann, 2011) maintain that futures price changes are caused by the structure of the market and speculation, and are not due to economic fundamentals.

The objective of my thesis is to investigate whether market fundamentals are the main drivers of natural gas futures prices and volatility. Since natural gas has become one of the most active commodities in the U.S. futures market, an understanding of the influential factors and volatility dynamics for risk becomes important for investment and hedging decisions.

My thesis contributes to the studies of natural gas futures price dynamics in several ways. First, few earlier studies have explored the importance of the weather effect in natural gas futures volatilities determination. My thesis fills this gap by addressing the effect of weather upon the volatility of natural gas futures returns.

Second, in my model, I address the impact of storage surprises. I construct a seasonal ARIMA model to forecast the expected storage level over the period 2003 to 2012 and use the difference between the current storage level and the expected storage level to represent the storage surprise. Lin and Zhu (2004) estimate the expected storage level as the sum of the previous period's inventory level and the net change in the inventory level in the previous period. Thus their indicator of storage surprises is represented as the difference in the net storage between the two consecutive periods. They disregard an important time series data characteristic. The weekly storage level provided by the Energy Information Administration (EIA) exhibits a seasonal pattern. Thus, in calculating the expected storage level, considering seasonality effects is important. I use a seasonal ARIMA model to address the seasonal effect, which is unaddressed by Linn and Zhu (2004).

Third, I use ARMA-GARCH model with exogenous variables to model the price dynamics of the natural gas futures contract. The ARMA-GARCH model addresses the autocorrelation in the equations for the conditional mean and conditional variance. This improves upon the model used in Mu (2007), which disregards the autocorrelation and seasonality in mean returns.

To conduct the analysis, I construct several hypotheses

Hypothesis 1: Market fundamentals have an impact on the natural gas futures price.

Hypothesis 2: There is a causal relationship between market fundamentals and natural gas futures price volatility.

Hypothesis 3: The seasonality in the natural gas futures price and volatility could be attributed to the effect of the seasons and inventory.

Use of updated empirical methods to examine the primary sources of price changes and price volatilities has provided several interesting results: (1) Weather shocks and inventory are negatively related with futures returns. (2) Changes in crude oil futures prices significantly positive affect natural gas futures returns. (3) The volatility of futures returns show a strong seasonal pattern, which is higher in winter and lower in other seasons. (4) On Mondays and on inventory announcement days, the volatility of natural gas futures returns is significantly higher than on other weekdays. Aside from these findings, we also provide evidence to support Samuelson's (1965) hypothesis that commodity futures contracts' volatilities decline with increases in the contracts' time to maturity.

Chapter 2 provides the necessary theoretical background for the analysis of natural gas demand, storage and other fundamental factors that have an influence on the natural gas futures price. Chapter 3 describes the possible driving factors for the natural gas futures price. Chapter 4 presents the characteristics of the data used to test the hypotheses. Chapter 5 specifies the model used for price and volatility. Chapter 6 reports and interprets the results. Chapter 7 provides conclusions and describes potential future research.

Chapter 2. Literature review

2.1 Futures prices and the theory of storage

A graph of futures prices against the time to maturity of a futures contract could be upward or downward sloping. When the futures price is below the current spot price and the curve is downward sloping, the situation is termed backwardation. The reverse situation, in which the futures price is above the current spot price and the curve is upward sloping, is termed contango. There is a wealth of literature, focused on the theory of storage, to explain such graphs. The theory of storage asserts that the fundamental factors, such as inventory and demand conditions, determine the basis which is defined as the difference between spot and futures prices. Working (1949) provides the theory of storage which implies that the inter-temporal price difference is related to inventories and the costs of holding the commodity. He shows that the supply of the commodity could be a significant indicator to influence the inter-temporal futures-spot price relation. When the nearby futures prices are not larger than the further futures prices, costs of carrying large stocks would play an important role in explaining the “inverse carrying charges” in futures market. Brennan (1958) and Brennan and Schwartz (1985) reworked the theory to include the convenience yield, a value introduced by Kaldor (1939) that could offset the cost of storage through the ownership of the physical commodity. They find that the net marginal cost of storage was equal to the sum of the opportunity cost of capital, a risk premium and direct warehousing and insurance costs minus the convenience yield. If the inventory of the commodity is low and its demand increases, the convenience yield would rise sharply. Therefore, the net marginal cost of carrying stocks could be negative if the convenience yield is sufficiently high, and the nearby futures price would be higher than the distant futures price, while the spot price would be higher than the futures price. Consequently, the convenience yield plays a central role in explaining backwardation in a futures market.

The theory of storage has also been used to explain the volatility of the futures price. Fama and French (1987, 1988) applied the theory to explain the dynamics of spot and futures prices and their relative volatilities. Based on the theory of storage, they confirmed that the convenience yield was negatively related to inventory. In addition, they found that in periods in which the basis was negative, which were periods characterised by low inventory levels, the volatility of changes in the spot price was greater than the volatility of changes in the futures price. In periods in which the basis was positive, the volatilities of spot and futures price changes were almost the same. The reason is that when the inventory level is low, the supply of a commodity cannot absorb the pressure from a sudden increase in demand. As a result, short-run demand shocks would create larger price changes in the spot price than in the futures price. So the volatility of the spot price would increase more than that of the futures price. In periods of high inventory, the quantity of supplies in storage can satisfy a sudden increase in demand, leading to a lower variation spot price changes, and volatilities of the spot and futures price changes which are close to each other. Ng and Pirrong (1994), Pindyck (1994), and Heaney (2002) demonstrated that the behavior of futures prices and of relative volatility are consistent with the theory of storage.

2.2 Mean reversion in spot and futures prices

Spot and futures prices exhibit mean reverting behavior, which is caused by the interaction between demand and supply. When a shortage occurs, the price of a commodity will rise, leading producers to enter the market, which will lead to a higher supply of the commodity and lower prices. Bessembinder et al (1995) tested for mean reversion in spot prices by using the term structure of futures prices with the assumption of no futures risk-premium. The test detected that mean-reversion occurred in equilibrium spot prices of eleven commodities, especially for agriculture and energy. Positive correlation between spot prices and convenience yield was mainly used to explain the behavior. According to the theory of storage, when the commodity is in short supply, the spot price of the commodity would rise and its futures price would not change so much, as the increase in the convenience yield would offset the predicted capital loss implied by the reversion in prices. With the assumption of no arbitrage, the futures price would be an indicator of the expected future spot price and would exhibit mean-reverting behavior. As an extension of Bessembinder et al (1995), Schwartz (1997) used a simple one factor (the logarithm of the spot price) model, a two factor model (adding a stochastic convenience yield) and a three factor model (adding stochastic interest rates) to analyse the stochastic behavior of commodity prices. His results support mean-reversion in spot price returns and volatility in copper and oil markets. Recently, Bernard et al (2008) also investigated the behavior of aluminium spot and futures prices with three models: 1) a random walk model with consideration of generalized autoregressive conditional heteroskedasticity (GARCH) effects; 2) a Poisson-based jump-diffusion model with GARCH effects; and (3) a mean reverting model with inclusion of a convenience yield. The mean-reverting model with a stochastic convenience yield outperformed the other two models in forecasting futures prices.

From the empirical tests, it is evident that mean-reversion is an important feature in the analysis of commodity spot and futures prices.

2.3 Relationship between futures price volatility and maturity

There is a relationship between the volatility of futures prices and the time to maturity of the contract. Samuelson (1965) showed that the volatility of futures prices would increase as the futures contract approaches closer to maturity, because the futures price would react more quickly to new information at that time. The work of Castelino and Francis (1982), and Milonas (1986) provides strong empirical support for the maturity effect for agricultural markets, while the evidence for other commodities is weaker. In recent studies, Movassagh and Modjtahedi (2005) applied several statistical procedures to analyze the efficiency of the natural gas futures market, using data from January 1991 to November 2003. They considered the martingale property of the futures price when they addressed the price increments in the futures price and the spot price. As a result, they found that the standard deviation of price increments became larger as the time to maturity decreased. This provided evidence to support the existence of a Samuelson effect in the natural gas futures market. In contrast, Routledege et al (2000) developed an equilibrium model of inventory with the assumption of nonnegative storage costs to analyse spot and forward prices. Their results indicate that the conditional volatilities exhibited the "Samuelson effect" when inventory levels of the commodity was low. However, at high levels of inventory, the long-term contracts' volatilities were higher than the short-term contracts' volatilities.

2.4 Seasonality in futures and spot prices

A fourth characteristic of futures price behavior is its seasonal pattern. In recent studies, seasonality in commodity markets has been addressed by many researchers. These are due to the cycles in demand and supply caused by fundamental factors. Srensen (2002) demonstrated the existence of a seasonal pattern in the prices of soybean, wheat and corn markets. Manoliu and Tompaidis (2002) conducted an empirical study of a one-factor model—a deterministic seasonality factor and one random factor driven by a mean-reverting process—and a two-factor model —a deterministic seasonality factor and two random variables in which one was driven by a mean-reverting process and the other was driven by Brownian motion. They used a dataset which included historical information on natural gas futures prices over the period September 1997 to August 1998 and estimated the parameters of the two models by a combination of a Kalman (1960) filter approach and maximum likelihood estimation. As a result, they found that for both the models, the monthly seasonality indices of the natural gas futures prices were higher in winter than in summer, which supports the conclusion that seasonality effects affect the natural gas futures price.

In addition to the seasonal pattern of the commodity futures price, the commodity spot and futures price also exhibit seasonal pattern in the volatility (Choi and Longstaff (1985), Milonas (1987), Symeonidis et al (2012)). Anderson (1985) examines two theories on the volatility of futures prices. The first theory is that of Samuelson (1965). The second theory emerged from analyses of the determinants of equilibrium prices in futures markets. It implied that the volatility of futures prices would be relatively high in periods in which supply and demand are significantly high. Anderson recognized that seasonality was a more important factor than maturity as an influence on the futures price volatility. Suenage et al (2008) analyzed the price of the natural gas futures contract traded on the NYMEX for the period January 2nd 1991 to December 31st 2003 by using the partially overlapping time-series model of Smith (2005), which treated the daily prices of a contract as a single time series. They found that the unconditional variance of daily price changes for each contract was greater in the winter than in the summer. The volatility displayed a large increase in the early winter (November to January) and reached the highest level in the late winter (middle of January to March). Such volatility dynamics have a very close relationship with the seasonal pattern in U.S. natural gas storage in a way consistent with the theory of storage. In winter, the marginal cost of natural gas production is high and the demand is highly inelastic, which means that the demand shock cannot be absorbed by inventory and thus a small change in demand would cause a large price swing.

For most energy markets, seasonality is a significant feature of futures price, which originates mainly from the demand side. Thus, when I consider the relationship between market fundamentals and futures price dynamics, seasonality is an important characteristic to analyse.

2.5 Empirical research on natural gas futures price dynamics and fundamentals

Over the last few years, a broad literature has emerged on natural gas futures price dynamics, especially in analysing the effect of market fundamentals. Pindyck (2004) examined the theory of short-run commodity price dynamics and inventory, focusing on the behavior and role of volatility. The higher the volatility, the higher the convenience yield and this would lead to inventory buildup, resulting in price increases in the short-run. Volatility may also have an effect onmarginal production costs. As volatility is increased, the production volume might decrease because of the real options held by producers, under which they can opt to decrease supply. As a result, the price would increase. This provides partial support that short-run commodity price dynamics can be explained by fundamentals.

Mu (2007) studies the short-term price dynamics of natural gas futures, focusing on the effect of weather shocks and storage shocks, and examined how the volatility of the futures price was influenced by the important fundamental factors. He used daily data on natural gas futures from the Commodity Research Bureau for the period January 1997 to December 2000. Using a single equation model with a GARCH error process, he found that in the mean equation, the estimated coefficient of the weather shock variable was positive and significant at the 1% level, which indicated that the price would increase (decrease) if the demand was high (low). The coefficient of the storage shock was negative and significant at the 5% level, implying that when the announced storage level was above the market expectation, the futures price would decrease. In the variance equation, the coefficient of the weather shock was positive and statistically significant and the coefficient of the storage shock was also significantly positive, which indicated that the release of the storage report was associated with increased volatility. These results demonstrate that shocks to natural gas supply and demand would shift the mean price or cause fluctuations around the mean.

Ates and Want (2007) used daily data from the Commodity Futures Trading Commission (CFTC) database to examine the inter-market dynamics of natural gas and heating oil spot and futures prices. They constructed a nonlinear error correction model with a bivariate GARCH error process to document that extreme low temperature and inventory shocks were the factors for demand and supply, which affected the spot and futures price change volatility. In the conditional mean equation for the nearby futures price change, the coefficient of the extreme low temperature variable was positive but not significant and the coefficient of inventory surprises was negative and significant at the 5% level. The conditional variance showed a strong monthly seasonal variation. In the conditional variance equation, both inventory and extreme low temperature variables showed negative signs and were significant at the 1% level. These results support the hypothesis that the natural gas futures price would increase as a result of an increase in demand due to the abnormally cold weather and of a decrease in supply due to the abnormally low inventory levels.

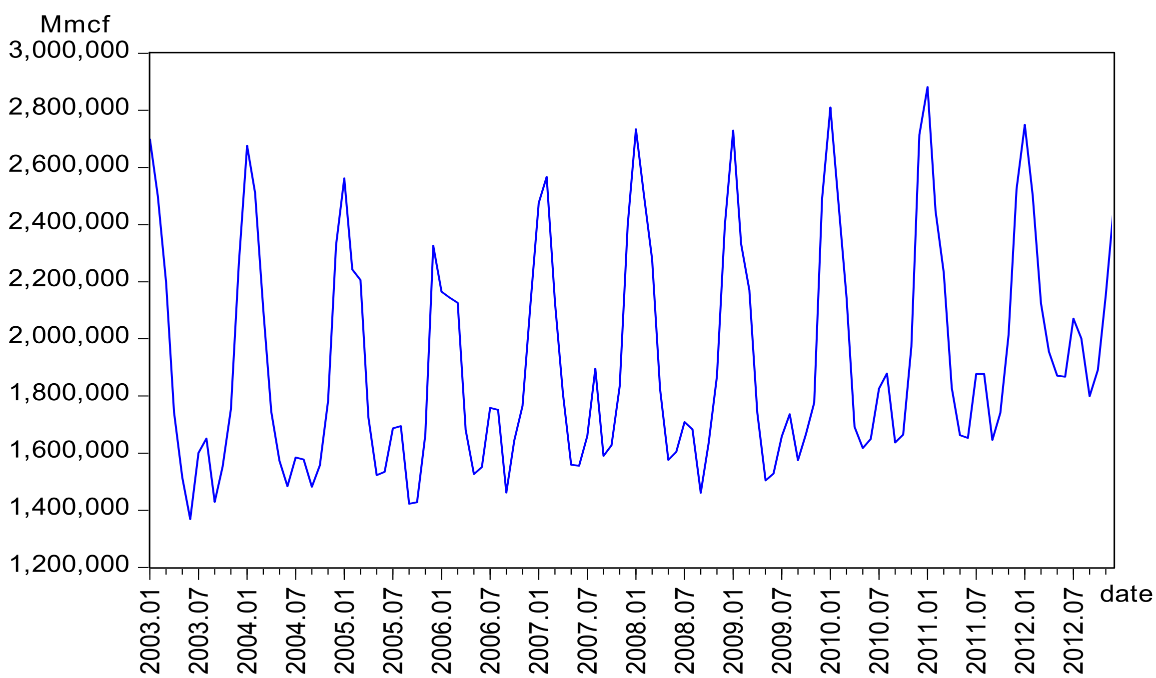
Fazzio (2006) attempts to explain the price dynamics of the natural gas Henry Hub futures contract through a statistical survey based on the analysis of the variables influencing the price and volatility of the contract. In accordance with the theory of storage (Working (1949), Samuelson (1971)) and the theory of shocks in natural gas (Engle (2001)), he chose weather shocks, a bullish/bearish inventory report indicator to represent the shocks which could affect either the demand or supply of natural gas and a inventory cycle which depended on exogenous demand shocks, analyst quality and several macro-factors to represent basic market fundamentals which could have an influence on the futures price volatility. His results show that the bullish/bearish inventory report indicator, backwardation and the steepness of the interest rate term structure are significantly negatively related with the natural gas futures returns. In addition, he finds that the price volatility exhibited a strong seasonal pattern and was significantly related to the inventory supply and the stage of the inventory cycle. When the natural gas market was under-supplied, the near-term Henry Hub natural gas futures contracts became almost twice as volatile as in an over-supplied market. The volatility was particularly strong in the extremes of the inventory cycle (near peak injection or withdrawal). His research suggests that the factors which may influence supply and demand will have a relationship with the natural gas futures price dynamics.

Chapter 3. Factors influencing natural gas futures prices

3.1 Demand

The EIA classifies the end-users for natural gas into four sectors: residential, commercial, industrial and power generators. Figure 1 shows the total consumption for natural gas in the U.S. from January 2003 to December 2012.

Figure 3. 1 Monthly total consumption of natural gas in the US



The total consumption of natural gas peaks between December and January, which is a result of increased residential and commercial customers' space heating demand. The total consumption tumbles to its lowest level in summer when the heating demand is low. In July and August, the consumption reaches a "local peak" as the increased cooling demand caused by the needs for natural gas from power generators.

Temperature is the main driver for heating and cooling demand and weather is an important factor that affects the natural gas industry demand side. Furthermore, weather variation is also a good indicator for the variability of natural gas demand as the industrial demand does not vary so much in the short term. Consequently, over the short term, residential and commercial heating demand is weather sensitive and exhibits a highly seasonal pattern.

3.2 Supply

On the supply side, inventory plays an important role to smooth production and to balance demand and supply. In winter (from November to March), the total consumption of natural gas is high, so natural gas is withdrawn from storage. In summer (from April to October), the total consumption of natural gas is low, and thus natural gas inventory builds up. The theory of storage states that the futures price is equal to the spot price plus the cost of storage minus the marginal convenience yield. During the injection period (summer), a sudden shift in demand which results from lower than usual temperature will lead to a high convenience yield. As a result, the price of natural gas futures will be lower. During the withdrawal period (winter), the high level of inventory will absorb any change in demand.

The convenience yield will be relatively stable and the futures price will be relatively higher due to the cost of storage.

The EIA conducts a weekly survey of natural gas storage levels across the U.S. These reports notify the market of current levels of inventory and have an influence on the change in natural gas prices. Also, the unexpected variations can lead to severe price volatility.

We attempt to capture the effect of the above factors which influence natural gas prices. These variables will serve as the main variables in the analysis.

Chapter 4. Data

Natural gas futures contracts began trading on the New York Mercantile Exchange (NYMEX) on April 3, 1990. The futures contract trades in unit of 10,000 million British thermal units (MMBtu). The price is based on delivery at the Henry Hub, the largest centralized natural gas hub in the United States which can interconnect the production regions, including the Gulf of Mexico and the onshore Louisiana and Texas regions, with the consumption area.

The liquid traded futures contracts are considered. This means that only contracts with maturities ranging from one to twelve months are included. We obtain the daily last traded price of each futures contract in US dollars per MMBtu from January 2nd 2003 to December 31st 2012 from Bloomberg.

Each day's maximum temperature, minimum temperature, cooling degree day and heating degree day from January 1st 1973 to December 31st 2012 are obtained from Bloomberg for Chicago, which is the main consumption area for natural gas. Therefore the Henry Hub price is more closely related to Chicago weather than any other areas. (Bopp (2002)).

The data on inventory of natural gas are from the EIA website and are obtained on a weekly basis for the period December 31st 1993 to December 31st 2012. The EIA provides historical information about overall natural gas inventory levels and the inventory levels in three regions—consuming region east, consuming region west and producing regions, in the "Weekly underground natural gas storage report". This report is released each Thursday.

Other variables that we use in are the daily prices of the closest to maturity West Texas Intermediate (WTI) crude oil futures contracts, which are obtained from Bloomberg, the three-month Treasury bill rate which is obtained from the Federal Reserve Economic Data (FRED) and the S&P 500 index which is from the University of Chicago Center for Research in Security Prices (CRSP) database, for the period January 2nd 2003 to December 31st 2012.

The sample period is from Jan 2nd 2003 to Dec 31st 2012. The sample period is limited by the availability of weather data. One variable —weather shocks—in the dynamic model for natural gas futures returns is obtained based on the previous 30 years' average degree days level. The earliest data on weather that I can find from Bloomberg is from January 1st 1973. Thus I will start my analysis from January 2nd 2003. For the price dynamics model, I will use daily data to estimate the relationship between market fundamentals and the natural gas futures price.

Chapter 5. Methodology

5.1 Variables used in the analysis

5.1.1 Returns and Unconditional Volatilities

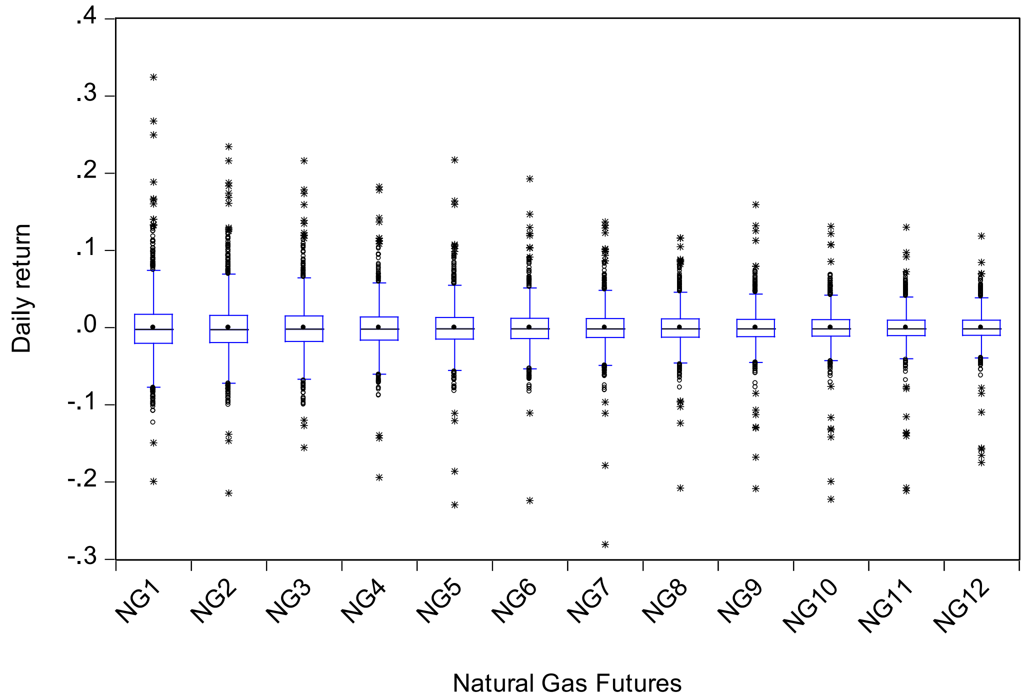
I calculate a time series of daily returns and unconditional volatilities for the futures contract as follows:

$$R_t = \ln P_t - lnP_{t-1} = ln\frac{P_t}{P_{t-1}} \tag{1}$$

P_t is the futures price at time t , P_{t-1} is the futures price at time t-1, and R_t is the return on the futures contract at time t.

Figure 2 shows a Box-Whisker plot of the natural gas futures daily returns. It indicates that for the twelve closest to maturity futures contracts, NG1-NG12, there are extreme outliers in returns, both on the up- and down-side. The nearby contract NG1 has the largest record high return. As the maturity increases, the largest return for each series decreases. The distance between maximum and minimum points in the box plot for NG1 is higher than that of contracts farther in the term structure, implying that the range of returns for the closest to maturity contract is higher than for the others.

Figure 5. 1 Daily returns for the 12 closest to maturity natural gas futures contracts



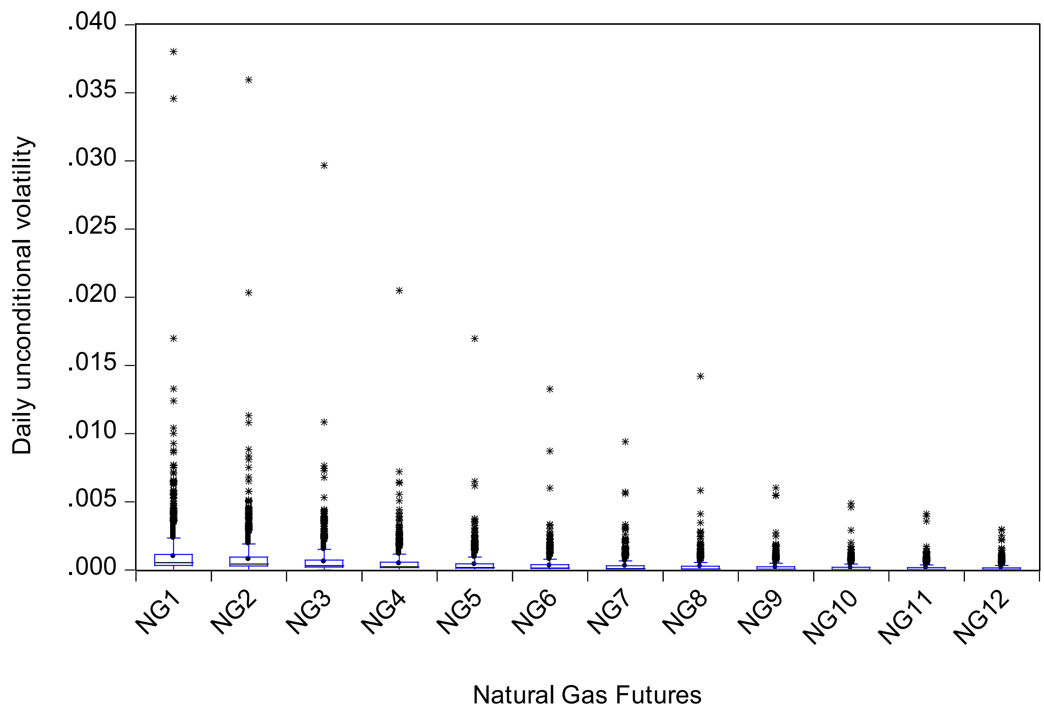
Volatility is a latent factor. I use the high-low, the range based on extreme values, to measure daily volatility of the natural gas futures price. This method is based on the assumption that the return is conditionally normally distributed with conditional volatility. I choose this method because it is less affected by market microstructure noise (Parkinson (1980)). The daily unconditional volatility estimator based on a price process which follows a geometric Brownian motion is (Bollen and Inder (2002)):

$$\sigma_t^2 = \frac{(lnH_t - lnL_t)^2}{4ln2} \tag{2}$$

σ_t is the unconditional volatility at day t, H_t and L_t denote the highest price and lowest price on day t , respectively.

Figure 3 shows the daily unconditional volatility for the 12 closest to maturity futures contracts NG1-NG12.It is clear from the figure that there is a downward trend in the unconditional volatility as the maturity of the contract increases. This provides evidence to support the Samuelson effect (1965).

Figure 5. 2 Daily unconditional volatility for the 12 closest to maturity natural gas futures contracts



I analyse the daily return and the daily unconditional volatility of the natural gas futures contract over a variety of time horizons. The efficient markets theory suggests that the asset price includes the best information about fundamental values and that volatility is driven by news about these fundamentals. To test the efficiency of the natural gas futures market, I first conduct unit toot tests (ADF) and tests of the autocorrelation of the daily returns and daily unconditional volatilities for the 12 contracts with times to expiration 1,2,3….12 months. In addition, non-stationarity in the data implies that any shocks to the data series will have a permanent effect. Unlike a stationary series, which reverts to its mean after a shock, a non-stationary time series does not revert to its pre-shock level. In such a situation, any conventional economic techniques applied to the non-stationary time series will provide misleading results.

Next, I examine the mean returns and standard deviations of the returns of the natural gas futures contracts over the entire time period as well as for each month and each weekday. By doing this, I can determine whether the prices and volatility of natural gas futures exhibit a seasonal pattern and whether the price dynamics of natural gas futures is related with the storage announcement day.

5.1.2 Weather

Temperature is the main driver of the demand in different seasons. In this thesis, I focus on temperature shocks, a proxy for demand shocks, and examine their effect on volatility.

There are two ways to measure weather shocks. One is the weather forecast error, which was used by Roll (1984) to investigate the effect of weather on orange juice futures prices. The other is to use "weather anomalies" which is the deviation of weather from the normal level. This paper adopts the second approach. Following Mu (2007), temperature is converted into degree days DD_t which is the sum of the cooling and heating degree days denoted by CDD_t and HDD_t, respectively as follows:

$$DD_t = CDD_t + HDD_t \tag{3}$$

$$CDD_t = Max\left(0, \frac{Tmax_t + Tmin_t}{2} - 65^0 F\right) \tag{4}$$

$$HDD_t = Max\left(0, 65^0 F - \frac{Tmax_t + Tmin_t}{2}\right) \tag{5}$$

where $Tmax_t$ and $Tmin_t$ are the maximum and minimum temperature at a certain day t, and DD_t is the degree days variable on day t. CDDs and HDDs are widely used in the energy industry and they represent the cooling demand and heating demand. Thus, DD is the measure for both heating demand in winter and cooling demand in summer.

Next, I create a standardized measure of the weather shock, as defined below:

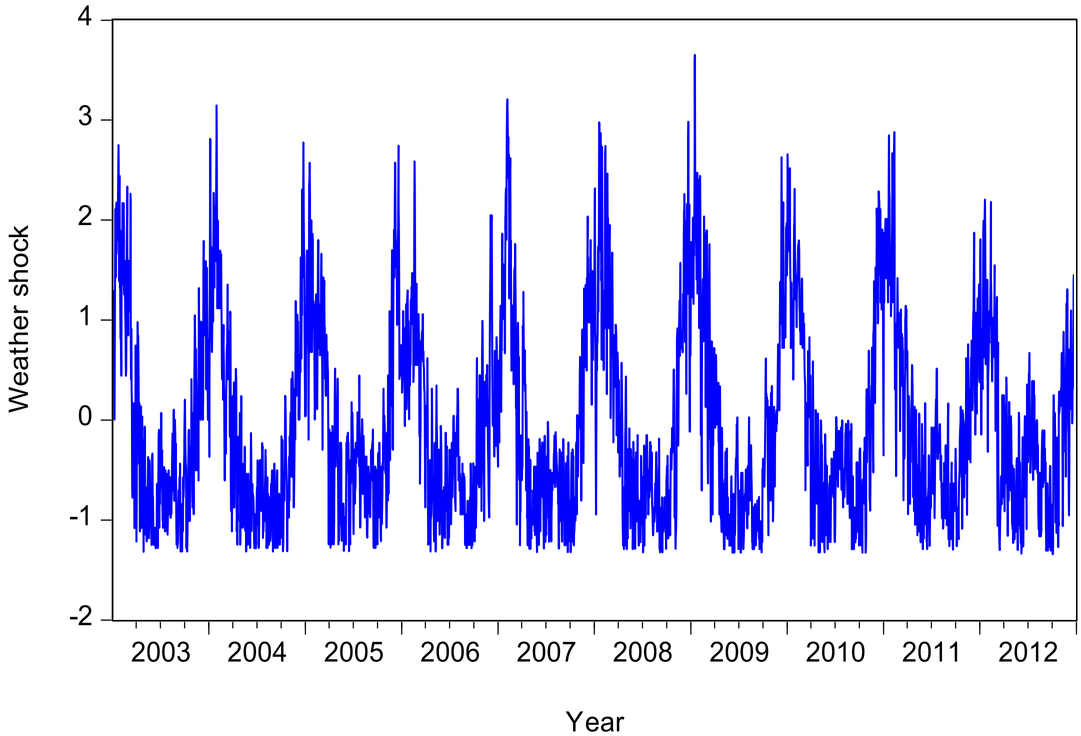
$$WS_t = \frac{DD_t - DDNORM_t}{\sigma NORM_t} \tag{6}$$

Following the convention of the National Weather Service, $DDNORM_t$, the normal degree days, is defined as the average normal degree days for the previous 30 years for a certain day t. $\sigma NORM_t$ is the standard deviation for the normal degree days based upon the previous 30 years for day t.

The time series plot of Figure 4 suggests that there are strong monthly seasonal variations in weather. In winter, the weather shock is large and in summer, the weather shock is small.

In addition to the weather shock variable and its squared value (a measurement of the level of demand shock), we also include one dummy for winter (W_t), which is equal to one from November to March and equal to zero in other seasons. This variable will directly capture the seasonal pattern, if any, in natural gas futures prices.

Figure 5. 3 The daily weather shock variable for the period January 1st 2003 to December 31st 2012



5.1.3 Storage

For the third part of the analysis of the influencing factors, I concentrate on the variable used to capture storage effects. Natural gas consumption is seasonal while its production is not. Thus in the summer, the inventory of natural gas is built up and in the winter it is drawn down. This seasonality leads to higher prices in winter and lower prices in summer.

As stated earlier, the theory of storage shows that shocks to demand and supply will have an impact on both the futures price and the volatility of the futures price. The periodic information about natural gas storage may shift the mean of returns and the volatilities to the extent that it surprises the market. Fama and French (1987) show that commodity prices are inversely related to inventory levels. So the price may increase if the reported inventory amount is below the market's expectation and vice versa. Linn and Zhu (2004) find that the natural gas report announcement is responsible for considerable volatility at the time of its release. Thus the release of the weekly natural gas storage report may increase the volatility in the market. I use weekly data on natural gas storage released by the EIA at 10:30 AM each Thursday to measure the storage surprise.

The storage surprise is the difference between the announced natural gas storage level change and its seasonal norm, which is defined as:

$$SS_\tau = \Delta S_\tau - \Delta E(S_\tau) \tag{7}$$

Where SS_τ is the storage surprise in week τ; $\Delta S_\tau$is the change in the storage level in week τ; $\Delta E(S_\tau)$ is the market's expected change in the storage level in week τ.

As the inventory level exhibits a seasonal pattern, to form the measure of the market's expectation of the change in the storage level, I use a seasonal autoregressive integrated moving average(ARIMA) model which predicts a particular value of a time series as a linear combination of past values, past errors, and seasonal terms. The data used to estimate the parameters of the seasonal ARIMA model is the weekly inventory storage level from January 1994 to December 2002. The seasonal ARIMA model requires the specification of differencing orders (d, D) and the order of both non-seasonal and seasonal autoregressive (AR) operators (p, P) and moving average (MA) operators (q, Q). Thus, the seasonal ARIMA model− $ARIMA\ (p, d, q) \times (P, D, Q)_s$ can be expressed as:

$$\emptyset_p(B)\Phi_P(B^s)(1-B)^d(1-B^s)^D S_\tau = \theta_q(B)\Theta_Q(B^s)\varepsilon_\tau \tag{8}$$

$\emptyset_p(B)$ and $\Phi_P(B^s)$ are the autoregressive operators. $\theta_q(B)$ and $\Theta_Q(B^s)$ are the moving average operators. All of them can be represented as a polynomial in the back shift operator:

$$\emptyset_p(B) = 1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p \tag{9}$$

$$\Phi_P(B^s) = 1 - \Phi_s B^s - \Phi_{2s} B^{2s} - \cdots - \Phi_{Ps} B^{Ps} \tag{10}$$

$$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q \tag{11}$$

$$\Theta_Q(B^s) = 1 - \Theta_s B^s - \Theta_{2s} B^{2s} - \cdots - \Theta_{Qs} B^{Qs} \tag{12}$$

where p is the order of the non-seasonal autoregressive terms, P is the order of the seasonal autoregressive terms, d is the order of differencing, D is the order of differencing based on season cycle, q is the order of the non-seasonal moving-average process and Q is the order of the seasonal moving average process. s represents the number of observations in a seasonal cycle. Since I use weekly data, "s" is set equal to 52. B is the backshift operator which could be defined as $B^k S_\tau = S_{\tau-k}$. $(1-B)^d$ is the nonseasonal operator and $(1 - B^s)^D$ is the seasonal operator. S_τ is inventory level at week τ. $\emptyset, \Phi\ \theta,$ and Θ are the parameters for each factor.

Before the parameter estimation, I preprocess the data of inventory level through non-seasonal and seasonal differencing, which are often used to stabilize the time series, as the seasonal ARIMA model requires that the time series be stationary. Then, I approach to the model building through an iterative process of model identification, parameter estimation and diagnostic checks. Based on the Schwarz information criterion (SIC) and autocorrelation test, the model ARIMA $(1,1,0) \times (1,1,1)_{52}$ fits the inventory data well. I estimate the parameters using maximum likelihood estimation. The resulting model is described by

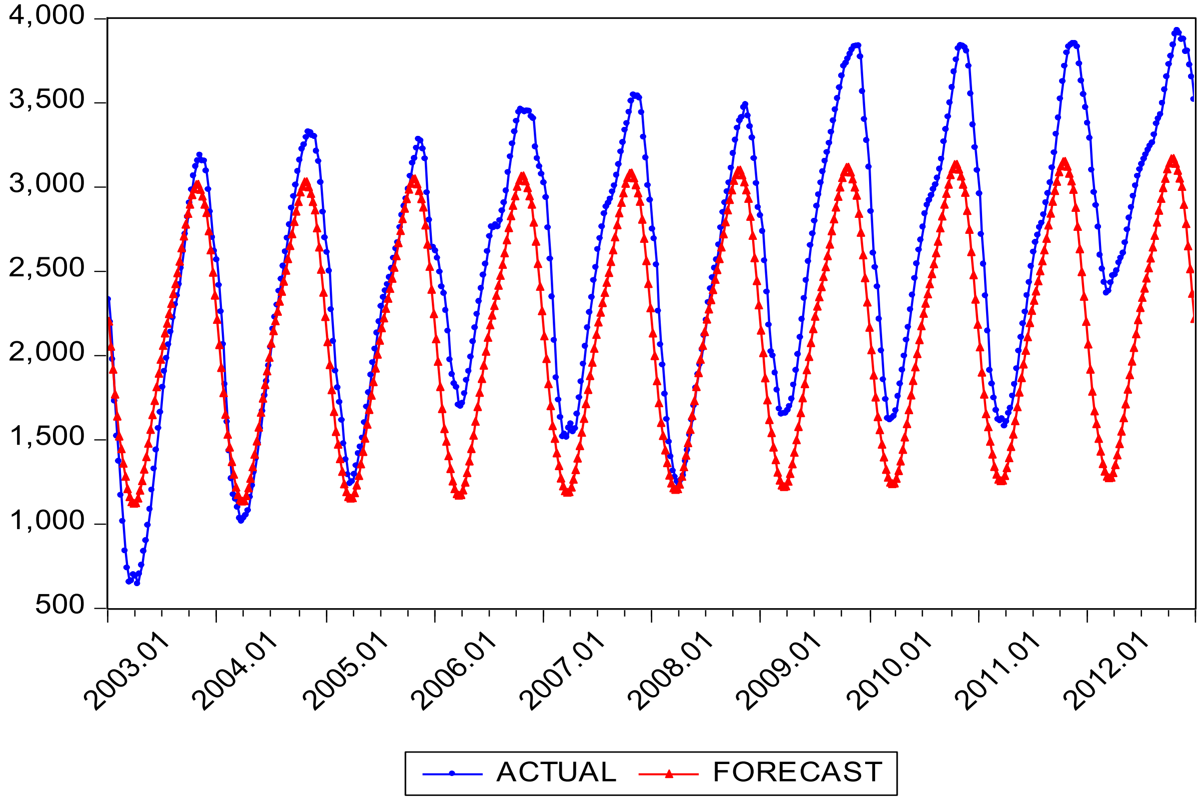
Table 5. 1 Maximum Likelihood Estimation

Parameter	Coefficient	Standard Error	t Value	Approx Pr > |t|
Θ_s	0.9996	45.8922	0.0200	0.9826
$\emptyset_1$	0.3120***	0.0409	7.6400	<.0001
ϕ_s	0.0241	0.0646	0.3700	0.7094

*** denotes statistical significance at the 0.01 level.

I use the result above to forecast the weekly inventory level for the period from January 2nd 2003 to December 31st 2012 to represent the market's expected inventory level. Figure 5 shows the forecasted inventory and the actual inventory in the sample period. The actual level of inventory follows a strong seasonal pattern which indicates that the futures price should exhibit seasonal variations. Low inventory levels are observed during winter months while high levels are observed during summer months. In the early years, the forecast inventory levels are generally closer to actual inventories. As time passes, the forecasting power of the seasonal ARIMA model weakens, but the forecasted inventory still follows the variation in the actual inventory.

Figure 5. 4 Forecast inventory and actual inventory over the period January 2nd 2003 to 31st December 2012



Next, I use equation (6) to obtain the weekly storage shocks SS_τ . As the analysis is based on daily data, the weekly series SS_τ is expanded to daily. Linn and Zhu (2004) find that the volatility caused by storage announcements disappeared in 30 minutes, which means that the price of the natural gas futures contract reaches a new equilibrium after 30 minutes of trading following the release of the storage report. Therefore, the distribution of natural gas futures price should shift from week to week due to the storage surprise. I define the storage surprise SS_t as

$$SS_t = SS_{\tau-1} \; when \; SAD_t = 1 \; otherwise \; is \; equal \; to \; 0$$

SS_t is the storage surprise on day t and $SS_{\tau-1}$ is the storage surprise at week $\tau - 1$. SAD is the dummy variable for the storage announcement day. It is equal to one for Thursday.

Also, I include SAD_t in the conditional variance equation to examine whether the "announcement day" has a significant effect on conditional volatility.

5.1.4 Crude oil price

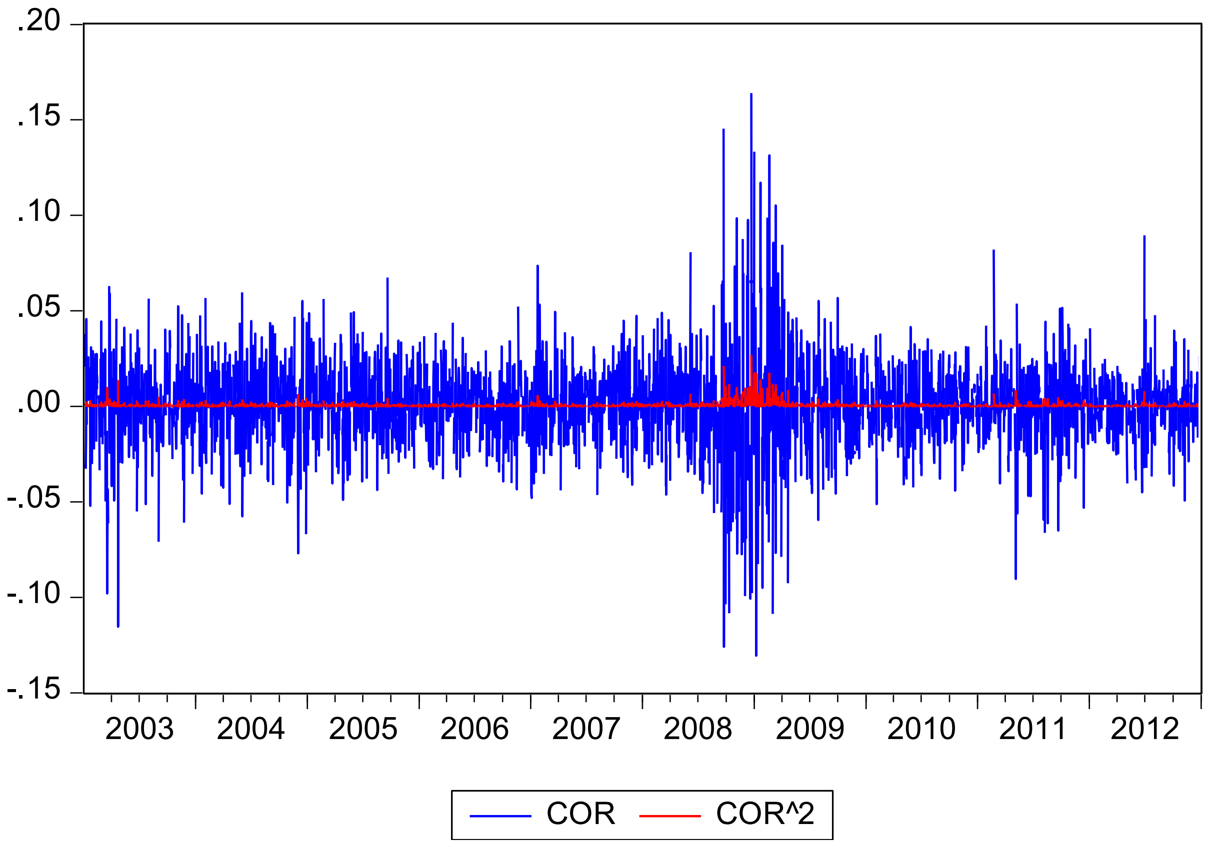
As the explanatory variable, I include crude oil futures returns (COR_t) in the conditional mean equation. Natural gas is seen as a close substitute to crude oil in the U.S. for industry use and electric power generation. Industry and electric power generators will choose the energy source which is less expensive. Thus, the crude oil price should influence the natural gas futures price directly. In addition, to cover the possible volatility spillovers between the crude oil and natural gas futures markets, I include the volatility of crude oil returns (VOR_t) in the conditional variance equation. The crude oil return COR_t is defined as:

$$COR_t = \ln(PO_t) - \ln(PO_{t-1}) \tag{13}$$

Where PO_t is the price of the closest to maturity crude oil futures contract on day t and PO_{t-1} is the price of the closest to maturity crude oil futures on day t-1. The daily crude oil price data is from Bloomberg. Figure 6 shows that crude oil futures returns evolve over time and the square of return, which represents volatility, exhibits volatility clustering in year 2008 and 2009. Thus to construct the time-varying volatility, I use an ARMA (Autoregressive Moving Average)-GARCH (Generalized Autoregressive Conditional

Heteroskedasticity) model to obtain the fitted conditional variance of crude oil futures returns. The ARMA(a,b)-GARCH (m, n) model is defined as:

Figure 5. 5 Daily returns COR and squared daily returns COR[2] for the crude oil futures contract



$$COR_t = c + \sum_{i=1}^{a} \mu_i COR_{t-i} + \sum_{j=1}^{b} \pi_j \epsilon_{t-j} + \epsilon_t \quad (14)$$

$$\epsilon_t = Z_t h_t \quad (15)$$

$$h_t^2 = d + \sum_{i=1}^{m} e_i \epsilon_{t-i}^2 + \sum_{j=1}^{n} f_j h_{t-j}^2 \quad (16)$$

Where COR_t is the crude oil futures' return at time t and ϵ_t is an independent and identically distributed standard normal random variable. μ is the autoregressive coefficient and π is the moving average coefficient. Z_t denotes an i.i.d location zero, scale unity random variable, which is represented as $Z_t \sim N(0,1)$. h_t^2 is the conditional variance of the process at time t, which depends on the squared residuals of the previous m periods and the conditional variance of the previous n periods. Furthermore, the coefficients in the conditional variance equation should satisfy the following requirements: $d > 0, e_i > 0 \; for \; i = 1,2,3, \dots \dots m$ and $f_j > 0 \; for \; j = 1,2,3, \dots \dots, n$. The polynomials $(1 - \mu_1 Z - \cdots \dots - \mu_a Z^a)$ and $(1 - \pi_1 Z - \cdots - \pi_b Z^b)$ have no common factors.

I perform a tentative ARMA order identification using the smallest canonical (SCAN) correlation method, the extended sample autocorrelation function (ESACF) method and the minimum information criterion (MINIC) method. Based on the minimum SIC, I choose to fit the data with a GARCH(1,1), which is the most effective one to model the conditional volatility. As the residuals in equation (14) exhibit non-normality, I use a student t-distribution for the standardized error to capture the observed fat tails in the return series. Thus the log likelihood function of the GARCH model with student-t distribution based error is:

$$L(\epsilon_t|X) = T\left\{ln\Gamma\left(\frac{v+1}{2}\right) - ln\Gamma\left(\frac{v}{2}\right) - \frac{1}{2}\ln[\pi(v-2)]\right\} - \frac{1}{2}\sum_{t=1}^{T}\left[\ln(\sigma_t^2) + (1+v)\ln\left(1 + \frac{z_t^2}{v-2}\right)\right] \quad (17)$$

v represents the degrees of freedom, which is equal to 10.66264. X is the vector of estimated parameters. Γ(.) is gamma function. The estimated model is:

Table 5. 2 ARMA-GARCH model for crude oil futures

Parameter	Estimate	Standard Error	t Value	Approx Pr > |t|
Constant	0.00091**	0.00040	2.30591	0.02110
Variance Equation				
Constant	0.00001***	0.00000	2.87607	0.00400
e_1	0.05350***	0.00927	5.76841	0.00000
f_1	0.93008***	0.01239	75.06138	0.00000
T-DIST. DF	10.66264***	1.81461	5.87598	0.00000

***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 level, respectively.

5.1.5 Macroeconomic factors

The risk free rate, which proxies for the current economic conditions in the U.S. and contains information about the market's expectation of inflation, is another important factor which should influence natural gas futures returns. Here, I choose the annual yield of 3-month Treasury bills (TBR_t), obtained from the Federal Reserve Economic Data, to represent the risk free rate. The interest rate is a significant component of the cost of carrying inventories. Thus the Treasury bill rate may affect the natural gas futures returns. I will use the variable in the conditional mean equation.

Another important factor is given by the daily return on the S&P 500 index (denoted as SPX_t), which is a proxy for the equity market return. The SPX includes overall information about market sentiment and thus economic demand for commodities like natural gas. I expect a negative impact of the variable on the commodity futures returns in the short term, as shown by Gorton and Rouwenhorst (2004).

5.2 Model Specification

I use the ARMA-GARCH model with exogenous variables, which can remove the serial correlation in the data and is appropriate for the residuals if conditional heteroscedasticity is detected, to construct the relationship between market fundamentals and natural gas futures return and its volatility. I choose the minimum SIC to find the appropriate order for the AR and MA terms. This accounts for serial correlation in the residuals. I also choose the appropriate GARCH model as the one that minimizes the information criteria. The estimation is done using daily data.

The ARMA process for the conditional mean of the futures returns is specified as:

$$R_t = \alpha_0 + \sum_{i=1}^{k} \gamma_i R_{t-i} + \sum_{j=1}^{l} \varphi_j \varepsilon_{t-j} + \alpha_1 WS_t + \alpha_2 SS_t + \alpha_3 COR_t + \alpha_4 TBR_t + \alpha_5 SPX_t + \alpha_6 Mon_t + \varepsilon_t \quad (18)$$

$$(\varepsilon_t | \Omega_{t-1}) \sim N\,(0, \sigma_t) \quad (19)$$

For conditional variance σ_t,

$$\sigma_t = \beta_0 + \sum_{i=1}^{p} \theta_i \sigma_{t-i} + \sum_{j=1}^{q} \delta_i \varepsilon_{t-j}^2 + \beta_1\, WS_t^2 + \beta_2 W_t + \beta_3 SAD_t + \beta_4 VOR_t + \beta_5 Mon_t \quad (20)$$

Where ε_t is an independent and identically distributed normal random variable. Ω_{t-1} is the information set available at time t-1 and σ_t is the conditional variance at time t. k is the order for autoregressive process. l is the order for moving average process. p, q are the best orders for GARCH model. $\gamma, \varphi, \alpha, \theta, \delta, and\ \beta$ are parameters to be estimated.

I estimate equations (19) and (21) by using maximum likelihood estimation. The likelihood function is

$$L(x_1, x_2, \dots \dots, x_n;\ \omega) = \prod_n f_x\,(x_i;\ \omega) \tag{21}$$

where there are n sets of sample data, $f_x(x; \omega)$ is the probability density function, ω represents the parameters of the probability density function which are assumed constant across the sampled data.

I select the orders of the ARMA process by using the Smallest CANonical correlation method, the extended sample autocorrelation function method and the minimum information criterion method. The best ARMA and GARCH models are based on minimization of the SIC The Ljung-Box test (LB hereafter) is used to test for the presence of autocorrelation and the Engle test (LM hereafter) for the presence of the ARCH effect. As the Generalized Error Distribution (GED) (Nelson, (1991)) is suitable for both leptokurtic and platykurtic distributions, I choose the GED to estimate parameters.

Thus, the density function is given by:

$$f_x = \frac{v\, e^{-\frac{1}{2}\left|\frac{x}{\lambda}\right|^{v}}}{\lambda 2^{\frac{v+1}{v}} \Gamma\left[\frac{1}{v}\right]} \tag{22}$$

Where

$$\lambda = \left[\frac{2^{-\frac{2}{v}} \Gamma\left[\frac{1}{v}\right]}{\Gamma\left[\frac{3}{v}\right]}\right]^{0.5} \tag{23}$$

v is the degree of freedom, $\Gamma(.)$ is gamma function

For the ARMA-GARCH model, causality relationships from market fundamentals to natural gas futures prices and to futures volatility exist if the coefficient of each term is statistically significant. The recent history of natural gas futures price movements and exogenous variables will shape the short-run pricing dynamics.

Chapter 6. Results

6.1 Data properties

6.1.1 Summary statistics

Table 6.1 presents the summary descriptive statistics of the returns for the twelve natural gas futures contracts. The means and medians are all negative. The distance between the maximum value and the minimum value of the return is highest for the closest to maturity contract NG1. The standard deviations of returns for longer maturity natural gas futures contracts are consistently smaller than those for nearby futures contracts. This is consistent with the "Samuelson effect", under which volatilities decline across time-to-maturity. I also note that the kurtosis of each series appears much higher than 3 (the kurtosis for the normal distribution), which indicates that the returns distribution is fat-tailed. Based on the Jarque-Bera statistics in Table 1, it is found that the hypothesis of normality of the returns distribution is strongly rejected. These results highlight the potential advantage of using the generalized error distribution of the ARMA-GARCH model in my analysis.

Table 6. 1 Summary Statistics of returns on the Natural gas futures contract

	Mean	Median	Max.	Min.	Std. Dev.	Skew ness	Kurtosis	Jarque-Bera test statistic

NG1	-0.00014	-0.00093	0.32435	-0.19899	0.03507	0.93454	10.06998	5599.60400***
NG2	-0.00013	-0.00108	0.23443	-0.21422	0.03233	0.69220	8.14676	2974.31800***
NG3	-0.00011	-0.00052	0.21636	-0.15510	0.02908	0.63645	7.29846	2104.32500***
NG4	-0.00010	-0.00036	0.18236	-0.19370	0.02625	0.38854	7.89096	2568.00900***
NG5	-0.00009	0.00000	0.21736	-0.22929	0.02484	0.23044	11.78297	8099.49300***
NG6	-0.00009	-0.00009	0.19295	-0.22367	0.02302	0.35906	11.05136	6841.65000***
NG7	-0.00009	-0.00024	0.13715	-0.28084	0.02232	-0.45137	17.44112	21921.82000***
NG8	-0.00008	-0.00025	0.11621	-0.20757	0.02070	-0.12220	9.86731	4944.30000***
NG9	-0.00008	0.00000	0.15934	-0.20828	0.02039	-0.34766	14.13914	13042.88000***
NG10	-0.00008	0.00000	0.13115	-0.22219	0.01962	-0.94200	18.66274	26058.84000***
NG11	-0.00007	0.00000	0.13022	-0.21108	0.01873	-1.24415	20.61758	33147.60000***
NG12	-0.00007	-0.00020	0.118611	-0.17438	0.01762	-1.03726	16.60946	19844.42000***

*** denotes statistical significance at the 0.01 level.

6.1.2 Stationary tests

Each return series is tested for the presence of a unit root by using the Augmented Dickey-Fuller (ADF) test. The results are reported in Table 6.2. In all instances, the null hypothesis of nonstationarity is verified. The observed level of futures returns and the first lag of futures returns reject the unit root hypothesis at the 1% significant level. Thus, the prices for all futures contracts are integrated of order I(1), while the returns are stationary. These findings support the choice of the ARMA-GARCH model since the series satisfies the requirement that data series should be stationary.

Table 6. 2 Unit root test in levels and differences for daily returns on the 12 futures contracts

	Level Tau-statistics	Probability	Difference Tau-statistics	Probability
NG1	-52.97***	<.0001	-92.18***	<.0001
NG2	-53.63***	<.0001	-93.69***	<.0001
NG3	-52.04***	<.0001	-92.26***	<.0001
NG4	-52.28***	<.0001	-92.08***	<.0001
NG5	-51.38***	<.0001	-91.2***	<.0001
NG6	-52.48***	<.0001	-92.34***	<.0001
NG7	-52.5***	<.0001	-91.03***	<.0001
NG8	-52.56***	<.0001	-89.82***	<.0001

NG9	-52.02***	<.0001	-89.04***	<.0001
NG10	-52.04***	<.0001	-88.36***	<.0001
NG11	-50.86***	<.0001	-88.07***	<.0001
NG12	-51.65***	<.0001	-89.64***	<.0002

*** denotes statistical significance at the 0.01 level.

6.1.3 Autocorrelation analysis

The autocorrelation structure tells us how a series is related to its past values. Table 6.3 reports the autocorrelation coefficients for the twelve return series. The returns for NG1-NG7 display significant serial correlation, while the returns for NG8-NG12 do not show any significant autocorrelation even at a large number of lags. Note that with regard to the autocorrelation coefficients for NG1-NG7, I find that there is evidence of statistically significant negative autocorrelation (mean reversion) at lag 1 for these returns, followed by positive autocorrelation (trend) at lag 2. At a large number of lags, the coefficients have alternatively negative and positive signs for the returns on NG1, NG2 and NG3, which means any shock effects for these three contracts price will disappear very soon. Thus, in the following analysis of the short-term dynamics of prices, I focus on these three contracts.

Table 6. 3 Autocorrelation of natural gas futures (NG1- NG12) daily return

lag	NG1	NG2	NG3	NG4	NG5	NG6	NG7	NG8	NG9	NG10	NG11	NG12
1	-0.054***	-0.066***	-0.037*	-0.042**	-0.024	-0.045**	-0.046**	-0.047**	-0.037*	-0.037*	-0.014	-0.030
2	0.039***	0.052***	0.056***	0.049***	0.051**	0.05***	0.028**	0.007*	0.004	-0.008	0.01	0.021
3	-0.033***	-0.031***	-0.032***	-0.039***	-0.04***	-0.031***	-0.02**	-0.007	-0.009	-0.027	-0.03	-0.026
4	0.008***	0.005***	0.001***	-0.019***	-0.028***	-0.022***	-0.021*	-0.01	-0.017	-0.01	-0.032	-0.018
5	-0.052***	-0.045***	-0.053***	-0.05***	-0.031***	-0.02***	-0.013*	-0.029	-0.029	-0.032	-0.027	-0.038*
6	0.002***	0.01***	0.018***	0.011***	0.002**	0.008**	0.006	0.033*	0.038	0.025	-0.007	-0.007
7	0.043***	0.022***	0.018***	0.006***	0.005**	0.031**	0.041**	0.024*	0.025	0.022	0.006	0.015

8	-0.008***	0.007***	0.019***	0.011***	0.006**	-0.016***	0.005*	-0.003	-0.006	-0.004	-0.015	0.005
9	-0.012***	-0.029***	-0.033***	-0.031***	-0.02**	-0.004***	0.01	0.002	-0.025	-0.029	-0.032	-0.015
10	0.015***	0.015***	0.022***	0.051***	0.05***	0.042***	0.037*	0.037	0.015	0.028	0.026	0.029
11	-0.018***	-0.034***	-0.045***	-0.042***	-0.037***	-0.037***	-0.034**	-0.036*	-0.029	-0.047**	-0.045*	-0.051*
12	0.041***	0.049***	0.041***	0.047***	0.045***	0.036***	0.03**	0.021*	0.008	-0.022**	0.004	0.001*

***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 level, respectively.

6.1.4 Natural gas daily returns by day of week and by month

Table 6.4 presents the mean returns and the standard deviations of RET1, RET2 and RET3. The means of returns on weekdays show a day of week effect, as the returns are positive on Monday and Friday, which could be due to the release of weekly storage information. The mean returns on months for the three contracts are negative from November to March in which supply and demand have greatest uncertainty.

Next, by studying pattern of volatilities for the three returns, I find that most of the standard deviations are higher than the means, which implies that the market has high volatility. The standard deviations of RET1 are higher than those of RET2 and the standard deviations of RET2 are consistently greater than that of RET3. The "Samuelson effect" is evident. Note the volatilities on weekdays, the standard deviations on Monday are the highest. And the standard deviations on Thursday are the second largest, which is the result of storage shock. Also, the standard deviations in winter are higher than other seasons, which is consistent with the winter cycle in natural gas. In winter, the demand for natural gas reaches the peak and the supply is short.

Table 6. 4 Mean returns and standard deviation of the three closet to maturity natural gas futures contracts

Panel A. NG1						
	Monday	Tuesday	Wednesday	Thursday	Friday	All days
Jan	0.0038	-0.0069	-0.0008	-0.0120	0.0080	-0.0018
	0.0480	**0.0389**	**0.0331**	**0.0397**	**0.0266**	**0.0377**
Feb	0.0047	0.0013	-0.0072	-0.0038	0.0073	0.0002
	0.0684	**0.0275**	**0.0250**	**0.0429**	**0.0288**	**0.0397**
March	-0.0072	0.0033	0.0002	-0.0047	-0.0028	-0.0022
	0.0329	**0.0258**	**0.0182**	**0.0381**	**0.0222**	**0.0284**
April	0.0035	-0.0041	0.0028	-0.0051	0.0017	-0.0003
	0.0279	**0.0250**	**0.0181**	**0.0279**	**0.0237**	**0.0248**
May	0.0095	0.0002	0.0070	-0.0049	0.0028	0.0026
	0.0289	**0.0253**	**0.0261**	**0.0331**	**0.0259**	**0.0281**
June	0.0043	-0.0062	-0.0028	0.0050	-0.0008	-0.0001
	0.0340	**0.0205**	**0.0286**	**0.0430**	**0.0196**	**0.0304**
July	-0.0009	-0.0018	0.0002	0.0020	-0.0023	-0.0005
	0.0396	**0.0275**	**0.0289**	**0.0391**	**0.0231**	**0.0320**
Aug	-0.0099	0.0062	-0.0019	-0.0109	-0.0062	-0.0045
	0.0441	**0.0273**	**0.0265**	**0.0349**	**0.0268**	**0.0330**
Sep	0.0099	0.0132	0.0106	-0.0013	-0.0027	0.0057
	0.0470	**0.0496**	**0.0487**	**0.0577**	**0.0358**	**0.0484**
Oct	-0.0030	0.0152	0.0004	0.0068	-0.0009	0.0036
	0.0385	**0.0345**	**0.0339**	**0.0530**	**0.0359**	**0.0399**
Nov	-0.0069	0.0012	0.0087	-0.0117	0.0000	-0.0013
	0.0365	**0.0324**	**0.0457**	**0.0287**	**0.0292**	**0.0358**
Dec	-0.0011	-0.0040	-0.0005	-0.0026	-0.0065	-0.0029
	0.0449	**0.0358**	**0.0297**	**0.0415**	**0.0310**	**0.0367**
All seasons	-0.0001	0.0015	0.0014	-0.0034	-0.0002	-0.0001
	0.0411	**0.0321**	**0.0315**	**0.0410**	**0.0279**	**0.0351**

Panel B. NG2						
	Monday	Tuesday	Wednesday	Thursday	Friday	All days
Jan	0.0046	-0.0073	-0.0006	-0.0131	0.0081	-0.0020
	0.0459	**0.0365**	**0.0321**	**0.0421**	**0.0253**	**0.0371**
Feb	0.0012	-0.0040	-0.0022	-0.0028	0.0063	-0.0004
	0.0455	**0.0338**	**0.0293**	**0.0427**	**0.0229**	**0.0350**
March	-0.0036	0.0037	0.0011	-0.0022	-0.0022	-0.0006
	0.0255	**0.0222**	**0.0183**	**0.0360**	**0.0211**	**0.0254**
April	0.0032	-0.0037	0.0019	-0.0042	0.0022	-0.0002
	0.0273	**0.0240**	**0.0189**	**0.0264**	**0.0241**	**0.0243**
May	0.0092	-0.0005	0.0061	-0.0049	0.0029	0.0022
	0.0278	**0.0245**	**0.0253**	**0.0327**	**0.0247**	**0.0273**
June	0.0038	-0.0063	-0.0026	0.0049	-0.0011	-0.0003
	0.0325	**0.0201**	**0.0267**	**0.0418**	**0.0191**	**0.0293**

July	-0.0007	-0.0031	0.0007	0.0031	-0.0017	-0.0003
	0.0396	**0.0276**	**0.0279**	**0.0391**	**0.0230**	**0.0319**
Aug	-0.0056	0.0055	0.0043	-0.0035	-0.0007	0.0000
	0.0493	**0.0264**	**0.0365**	**0.0449**	**0.0429**	**0.0406**
Sep	0.0059	0.0081	0.0095	0.0049	-0.0037	0.0049
	0.0389	**0.0351**	**0.0417**	**0.0500**	**0.0243**	**0.0389**
Oct	-0.0042	0.0100	-0.0009	0.0010	0.0002	0.0011
	0.0293	**0.0268**	**0.0246**	**0.0347**	**0.0269**	**0.0288**
Nov	-0.0086	-0.0019	0.0058	-0.0114	-0.0016	-0.0032
	0.0335	**0.0264**	**0.0384**	**0.0250**	**0.0262**	**0.0309**
Dec	-0.0006	-0.0041	-0.0008	-0.0033	-0.0071	-0.0031
	0.0427	**0.0321**	**0.0267**	**0.0397**	**0.0287**	**0.0342**
All seasons	-0.0001	-0.0002	0.0019	-0.0024	0.0001	-0.0001
	0.0368	**0.0285**	**0.0296**	**0.0387**	**0.0265**	**0.0323**

Panel C. NG3

	Monday	Tuesday	Wednesday	Thursday	Friday	All days
Jan	0.0063	-0.0058	0.0001	-0.0091	0.0067	-0.0007
	0.0365	**0.0306**	**0.0274**	**0.0324**	**0.0229**	**0.0303**
Feb	0.0002	-0.0041	-0.0029	0.0008	0.0060	0.0000
	0.0380	**0.0340**	**0.0228**	**0.0289**	**0.0209**	**0.0290**
March	-0.0032	0.0041	0.0014	-0.0010	-0.0020	-0.0001
	0.0244	**0.0200**	**0.0176**	**0.0343**	**0.0207**	**0.0241**
April	0.0033	-0.0035	0.0018	-0.0044	0.0015	-0.0004
	0.0260	**0.0228**	**0.0182**	**0.0257**	**0.0216**	**0.0231**
May	0.0089	-0.0003	0.0053	-0.0055	0.0025	0.0019
	0.0264	**0.0233**	**0.0243**	**0.0309**	**0.0230**	**0.0259**
June	0.0045	-0.0058	-0.0022	0.0056	-0.0010	0.0002
	0.0311	**0.0198**	**0.0247**	**0.0401**	**0.0183**	**0.0281**
July	0.0026	-0.0034	0.0025	0.0083	0.0018	0.0024
	0.0465	**0.0267**	**0.0281**	**0.0480**	**0.0347**	**0.0377**
Aug	-0.0035	0.0047	0.0036	-0.0005	-0.0002	0.0008
	0.0391	**0.0220**	**0.0272**	**0.0389**	**0.0309**	**0.0321**
Sep	0.0031	0.0036	0.0071	0.0003	-0.0023	0.0023
	0.0317	**0.0241**	**0.0314**	**0.0287**	**0.0192**	**0.0271**
Oct	-0.0039	0.0075	-0.0012	-0.0044	-0.0010	-0.0006
	0.0269	**0.0244**	**0.0219**	**0.0264**	**0.0240**	**0.0249**
Nov	-0.0089	-0.0026	0.0043	-0.0113	-0.0020	-0.0038
	0.0348	**0.0254**	**0.0365**	**0.0240**	**0.0248**	**0.0301**
Dec	-0.0005	-0.0056	-0.0006	-0.0050	-0.0068	-0.0036
	0.0381	**0.0332**	**0.0248**	**0.0414**	**0.0276**	**0.0334**
All seasons	0.0004	-0.0008	0.0016	-0.0020	0.0003	-0.0001
	0.0337	**0.0259**	**0.0258**	**0.0343**	**0.0245**	**0.0291**

6.1.5 Causality Tests

I examine causal relationships between the fundamental variables, including weather shocks, crude oil return, interest rates, the S&P 500 return, storage shocks and Monday effects, and the returns on the three closest to maturity natural gas futures contracts. The null hypothesis is the variable will not cause the change of daily returns of NG1, NG2 and NG3. Table 6.5 shows the chi-square statistics for the tests of Granger causality.

Table 6. 5 Granger causality test between fundamental variables and daily returns of NG1-NG3

variables	NG1	NG2	NG3
weather shocks	14.27**	10.17**	7.46
crude oil return	11.89**	8.48	9.66*
interest rate	4.58	7.59	8.07
S&P 500 return	1.60	2.34	3.76
storage shock	14.82**	15.80**	12.26**
Monday effect	5.10	2.11	2.84

***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 level, respectively.

The chi-square statistics strongly reject the null hypothesis that weather surprises do not “granger cause” natural gas futures returns for the two closest to maturity futures contracts NG1 and NG2. The crude oil return is significant for NG1 and NG3. Storage shocks exhibits strong causal relationship with futures returns for NG1, NG2 and NG3. These results provide support for hypothesis 1: that market fundamentals have an impact on natural gas futures prices.

6.2 Model Results

In this section, I empirically examine the influence of market fundamentals on the mean and conditional variance of the return on the natural gas futures contracts for the three closest to maturity futures contracts NG1-NG3, the most liquid futures contracts. Through Ljung-box test and Engle test, I find that the best model for NG1 is ARMA (0,1)–GARCH (2,1), for NG2 is ARMA(2,1)-GARCH (1,2) and for NG3 is GARCH(1.2). Detailed results are presented in Appendix A.1, A.2 and A.3). Tables 6.6 to 6.8 report the outcomes of the ARMA-GARCH model if I start from using the model without any explanatory variables and then add further additional factors until the model described in the former section is reached. All results are presented separately for each considered futures contract.

The closest to maturity natural gas futures contract (NG1)

In the mean equations, the coefficients of the weather shock variable (WS) are negative but insignificant. The crude oil return (COR) exerts a positive impact and is significant at the 1% level for all the regressions. The coefficients of the variable are around 0.42, which means one percent increase in crude oil return leads to a 0.42 percentage increase in the conditional mean of the return. The conditional mean of the return is also affected by S&P 500 return (SPX), as the coefficient is negative and significant at the 10% level. The storage shock (SS) does not influence the conditional mean return. The estimated coefficients of the interest rate (TBR) and the Monday effect (Mon) are not significant either.

In the variance equations the square of the weather shocks variable (WS^2) shows a positive effect on the conditional variance. The dummy variable for winter (W) exerts a significant positive impact. The ARCH and GARCH coefficients and the constant are also significantly positive. Both the storage announcement day (SAD) effect and the Monday effect (Mon) are positive and significant at the 1% level. The conditional volatility of crude oil (VOL) returns is positive but not significant.

The log likelihood increases from 5190.703 to 5199.675 as more exogenous variables are included.

Table 6. 6 ARMA-GARCH Model for the closest to maturity natural gas futures contract

	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Conditional Mean						
	(1)	(2)	(3)	(4)	(5)	(6)
constant	-0.001150	-0.000289	-0.001166	-0.001170	-0.001104	-0.001103
	(-1.58925)	(-0.198274)	(-1.613880)	(-1.617821)	(-1.525893)	(-1.533455)
MA(1)	-0.031397	-0.017437	-0.031475	-0.031701	-0.031800	-0.032284
	(-1.541131)	(-0.528975)	(-1.539130)	(-1.548794)	(-1.551223)	(-1.581854)
WS	-0.000727	-0.000864	-0.000702	-0.000705	-0.000755	-0.000768
	(-1.331647)	(-0.970898)	(-1.316644)	(-1.321968)	(-1.444788)	(-1.465646)
COR	0.427778***	0.424755***	0.428784***	0.42798***	0.422476***	0.421512***
	(19.764960)	(12.931470)	(19.758040)	(19.431790)	(19.308530)	(19.273820)
TBR	0.000151	0.000141	0.000160	0.000160	0.000196	0.000213
	(0.523357)	(0.268542)	(0.553236)	(0.556182)	(0.680394)	(0.741915)
SPX	-0.067729*	-0.048805	-0.069077*	-0.06911*	-0.064425	-0.060392
	(-1.664208)	(-0.635979)	(-1.685149)	(-1.651954)	(-1.548152)	(-1.443656)
SS	-0.000028	-0.000006	-0.000029	-0.000029	-0.000025	-0.000026
	(-1.099158)	(-0.139447)	(-1.165227)	(-1.17138)	(-0.931496)	(-0.944624)
MON	-0.000066	0.001627	0.000031	0.000030	-0.000193	-0.000199
	(-0.052733)	(-0.692427)	(-0.024899)	(-0.023567)	(-0.152987)	(-0.153002)
Conditional Variance						
constant	0.000018***	0.000906***	0.000018***	0.000016***	-0.000040**	-0.000064***
	(3.094925)	(29.740580)	(3.124079)	(2.668258)	(-2.334042)	(-2.778802)
ARCH(1)	0.091331***	0.122526***	0.092155***	0.092195***	0.095646***	0.092469***
	(4.432757)	(4.426630)	(4.286709)	(4.300178)	(4.487776)	(4.410171)
ARCH(2)	-0.015948	-0.023276	-0.026670	-0.027983	-0.031753	-0.026875
	(-0.717046)	(-1.242662)	(-1.196648)	(-1.260954)	(-1.438530)	(-1.222585)
GARCH(1)	0.909672***	0.455096***	0.922644***	0.922521***	0.922585***	0.919162***

	(63.334230)	(11.895640)	(74.866800)	(73.854520)	(74.899850)	(71.200760)
WS^2		0.000083***	0.000004	0.000001	0.000003	0.000002
		(8.886891)	(1.107740)	(1.035688)	(1.378208)	(1.607394)
W			0.000011**	0.000010**	0.000007	0.000007**
			(2.044926)	(1.966789)	(1.335938)	(2.532820)
VOL				0.005980	0.007073	0.007093
				(0.821271)	(0.967410)	(0.928674)
SAD					0.000278***	0.000318***
					(3.397338)	(3.819146)
MON						0.000338***
						(3.286746)
Adjusted R	0.078500	0.078200	0.078500	0.078500	0.078700	0.078700
Log likelihood	5190.703000	5191.636000	5192.938000	5193.478000	5199.675000	5200.903000

***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 level, respectively.

The second closest to maturity natural gas futures contract (NG2)

For NG2, the futures contract that is second closest to maturity, a different picture emerges. In the mean equation, both the autoregressive process and the moving average process are strongly significant. The coefficient of the variable weather shock (WS) is negative and significant at the 10% level. The coefficient of the variable is around -0.00076. The crude oil return (COR) exerts a strongly positive effect on the conditional mean of the returns. The coefficients are around 0.41, implying that a 1% increase in crude oil return leads to a 0.41% increase in NG2 returns. The interest rate (TBR), the S&P 500 return (SPX), the storage shocks (SS) as well as the Monday effect (MON) do not play a significant role. In line with the results for the closest to maturity futures contract NG1, the conditional variance is much better described by the included variables than the conditional mean. All the variables, except the square of weather shocks and the conditional volatility of crude oil futures returns have a significant positive influence on the conditional variance of returns.

The log likelihoods are higher than those of Table 6.6. Consistent with the results for the closest to maturity futures contract, the log likelihood is increased with exogenous variables added.

Table 6. 7 ARMA-GARCH Model for the second closest to maturity natural gas futures contract

	Coefficient	**Coefficient**	**Coefficient**	**Coefficient**	**Coefficient**	**Coefficient**
Conditional Mean						
	(1)	(2)	(3)	(4)	(5)	(6)
constant	-0.001137*	-0.001145*	-0.001158*	-0.001155*	-0.000956	-0.000917
	(-1.665391)	(-1.677027)	(-1.697210)	(-1.691241)	(-1.411958)	(-1.370643)
AR(1)	-0.932291***	-0.934891***	-0.938326***	-0.937362***	-0.953448***	-0.939129***
	(-14.457760)	(-15.520330)	(-16.051010)	(-15.806910)	(-20.618520)	(-16.858170)
AR(2)	-0.015735	-0.015884	-0.016420	-0.016466	-0.018778	-0.016957
	(-0.796519)	(-0.807399)	(-0.837424)	(-0.838452)	(-0.966141)	(-0.871298)
MA(1)	0.904369***	0.906885***	0.910316***	0.908955***	0.925234***	0.910566***
	(14.784190)	(15.997410)	(16.611690)	(16.318590)	(22.252700)	(17.478740)
WS	-0.000794*	-0.000764*	-0.000762*	-0.000762*	-0.000750*	-0.000775*
	(-1.680394)	(-1.659288)	(-1.654308)	(-1.656805)	(-1.655600)	(-1.689532)
COR	0.410593***	0.411681***	0.412433***	0.410918***	0.407300***	0.404512***
	(20.343070)	(20.479600)	(20.428060)	(19.952390)	(19.760760)	(19.560680)
TBR	0.000220	0.000223	0.000227	0.000227	0.000196	0.000218
	(0.806783)	(0.814130)	(0.832509)	(0.836501)	(0.722425)	(0.807724)
SPX	-0.059941	-0.059938	-0.060378	-0.060651	-0.053883	-0.044096
	(-1.594120)	(-1.594476)	(-1.595895)	(-1.558752)	(-1.390834)	(-1.129870)
SS	-0.000020	-0.000020	-0.000020	-0.000020	-0.000020	-0.000020
	(-0.976630)	(-1.015981)	(-1.013316)	(-1.014679)	(-0.793320)	(-0.845972)
MON	-0.000040	0.000010	0.000058	0.000049	-0.000137	-0.000210
	(-0.034207)	(0.008554)	(0.049760)	(0.041922)	(-0.113433)	(-0.158107)
Conditional Variance						
constant	0.000016**	0.000018**	0.000018**	0.000016*	-0.000059***	-0.000110***
	(2.237628)	(2.137121)	(2.086103)	(1.901149)	(-2.991488)	(-4.610961)
ARCH(1)	0.061053***	0.060054***	0.058793***	0.057349***	0.080751***	0.073420***
	(2.683085)	(2.671476)	(2.648644)	(2.616556)	(5.868900)	(5.767300)
GARCH(1)	0.902697**	0.906071**	0.880602**	0.874552**	0.284526***	0.380722***
	(2.199127)	(2.188985)	(2.079611)	(2.028995)	(3.339076)	(3.77681)
GARCH(2)	0.019932	0.018359	0.046315	0.051658	0.603818***	0.509502***
	(0.051854)	(0.047277)	(0.116252)	(0.127404)	(7.279196)	(5.211623)
WS^2		0.000003	0.000003	0.000010	0.000007	0.000004
		(1.012743)	(0.089376)	(0.277085)	(1.260454)	(0.967189)

W			0.000008	0.000007	0.000002	0.0000017**
			(1.321979)	(1.240800)	(1.193844)	(2.239825)
VOL				0.007161	0.012699	0.012009
				(0.987363)	(1.234663)	(1.206097)
SAD					0.000429***	0.000461***
					(4.727123)	(5.210411)
MON						0.000247***
						(3.392536)
Adjusted R	0.091684	0.091640	0.091601	0.091670	0.091649	0.091786
Log likelihood	5360.883000	5361.593000	5362.714000	5363.648000	5374.33000	5381.212000

***, **, and * denote statistical significance at the 0.01, 0.05, and 0.1 level, respectively.

The third closest to maturity natural gas futures contract (NG3)

In table 6.8, it is found that in all six specifications, the coefficients of the weather shock variable are around -0.00066. The coefficients of the crude oil return (COR) have positive signs and are statistically significant at the 1% level. The interest rate (TBR) is still not significant in the equations for the mean return. The coefficients of the S&P 500 return (SPX) have negative signs and are significant at least at the 10% level. The variable storage shock (SS) still shows a negative impact which is not significant. The Monday effect does not play a significant role in determining the conditional mean return.

In the conditional variance equations, the picture changes slightly. The ARCH and GARCH coefficients are positively significant at least at the 5% level. The square of the weather shock variable (WS^2) has a positive effect and is significant at least at the 10% level. The dummy variable for winter is still positive but not significant. The conditional volatility of crude oil returns (VOL) is also positive but shows less influence. Both the storage announcement day effect (SAD) and the Monday effect (Mon) are positive and statistically significant at the 1% level.

The log likelihood increases from 5592.311 to 5615.717 with the addition of exogenous variables.

Table 6. 8 ARMA-GARCH Model for the third closest to maturity natural gas futures contract

	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Conditional Mean						
	(1)	(2)	(3)	(4)	(5)	(6)
constant	-0.000803	-0.000818	-0.000820	-0.000828	-0.000612	-0.000636
	(-1.241325)	(-1.264827)	(-1.268576)	(-1.278335)	(-0.954874)	(-1.003054)
WS	-0.000721	-0.000695	-0.000696	-0.000691	-0.000658	-0.000703
	(-1.504511)	(-1.503450)	(-1.503547)	(-1.493128)	(-1.458902)	(-1.525612)
COR	0.392924***	0.392949***	0.393392***	0.391992***	0.386704***	0.383390***
	(21.178020)	(21.293170)	(21.280270)	(20.677190)	(20.368590)	(20.101850)
TBR	0.000167	0.000171	0.000172	0.000176	0.000149	0.000169
	(0.649078)	(0.657940)	(0.660936)	(0.681391)	(0.578755)	(0.658888)
SPX	-0.058218*	-0.057895*	-0.057869*	-0.057765	-0.050018	-0.043210
	(-1.670365)	(-1.660262)	(-1.654591)	(-1.590773)	(-1.381287)	(-1.185053)
SS	-0.000032	-0.000032	-0.000032	-0.000032	-0.000030	-0.000032
	(-1.470192)	(-1.503171)	(-1.505978)	(-1.500667)	(-1.125994)	(-1.221476)
MON	-0.000095	-0.000055	-0.000033	-0.000056	-0.000189	-0.000337
	(-0.087055)	(-0.050161)	(-0.030480)	(-0.051078)	(-0.167177)	(-0.267417)
Conditional Variance						
constant	0.000014**	0.000017**	0.000017**	0.000015**	-0.000470***	-0.000100***
	(2.270910)	(2.285794)	(2.264197)	(2.068575)	(-3.025507)	(-4.911763)
ARCH(1)	0.053924***	0.052963***	0.052419***	0.049901***	0.073021***	0.064070***
	(2.754485)	(2.797716)	(2.789989)	(2.720053)	(5.367643)	(5.223893)
GARCH(1)	0.907748**	0.887413**	0.882049**	0.876043**	0.248872**	0.364512***
	(2.426288)	(2.349672)	(2.320779)	(2.239619)	(3.212082)	(3.971871)
GARCH(2)	0.019444	0.041519	0.048104	0.053402	0.634987***	0.523945***
	(0.055390)	(0.116774)	(0.134288)	(0.144910)	(8.439618)	(6.005960)
WS^2		0.000004	0.000003	0.000003	0.000010**	0.000007*
		(1.426495)	(0.901885)	(1.094586)	(2.278318)	(1.838949)
W			0.000003	0.000002	0.000007	0.000008
			(0.644221)	(0.495888)	(0.980180)	(1.328515)
VOL				0.007663	0.014252	0.013600
				(1.216520)	(1.535585)	(1.543393)
SAD					0.000376***	0.000404***
					(5.172623)	(5.707512)

MON						0.000246*** (3.867365)
Adjusted R	0.093905	0.093893	0.093889	0.093909	0.094090	0.094156
Log likelihood	5592.311000	5593.843000	5594.056000	5595.622000	5607.011000	5615.717000

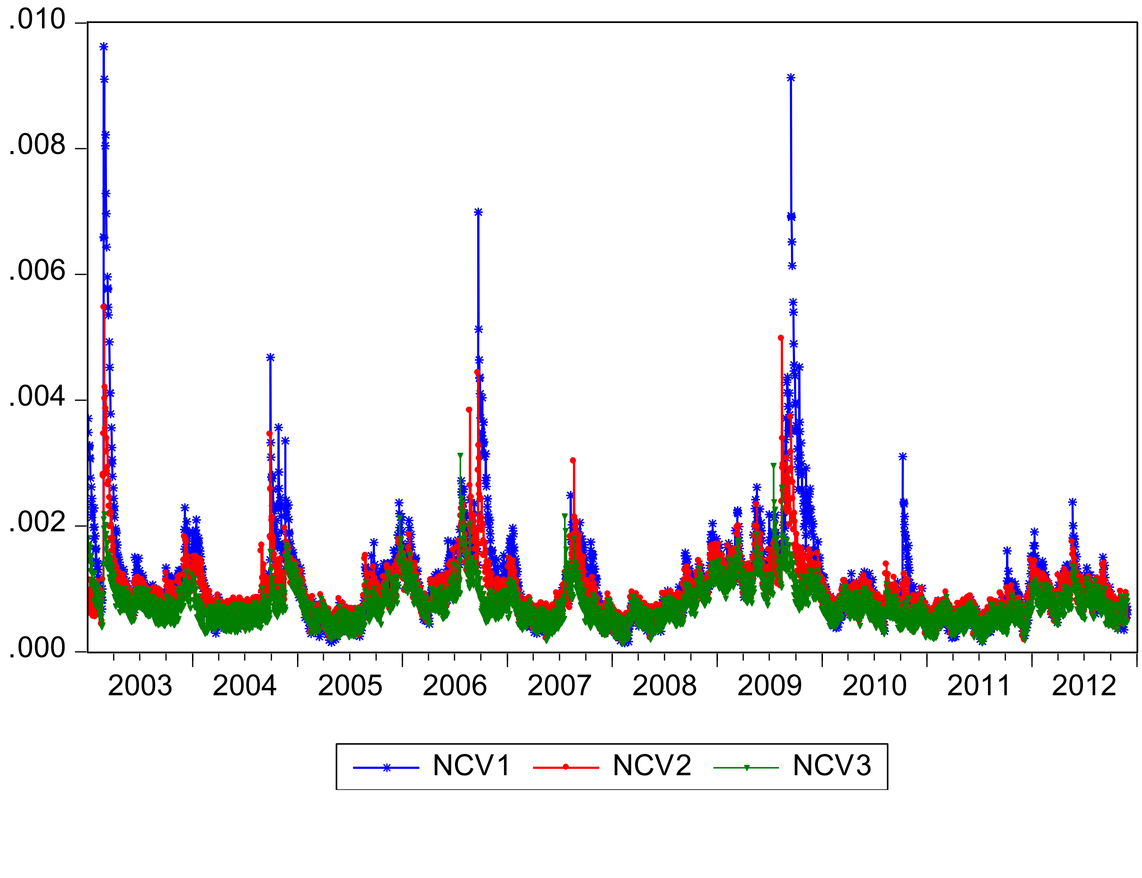
Discussions of the Results

Overall, I find that the results of Table 6.6-6.8 are similar. The negative effect of weather shocks indicates that an increase in temperature, which goes along with a decrease in demand, causes a decrease in the natural gas futures return. The sign of the effect agrees with the results of Kremser and Rammerstorfer (2012), who examine the impact of macrofactors and weather in the European natural gas markets . The crude oil return is an important factor that influences the price of natural gas futures, which is backed by the most significantly positive results from the conditional mean for the three closest to maturity futures contracts. The result supports the theory of the price of a substitute. For industrial use, crude oil is the closest substitute commodity for natural gas. When the price of crude oil increases, industries will choose natural gas as an alternative. Thus the returns of natural gas futures increase. The S&P 500 return represents the state of the equity market. For all three futures contracts, this variable is negatively and significantly related to the mean return at the 10% level, which is in line with Gorton and Rouwenhorst (2004). The results indicate that in recessions, when stocks perform badly, the natural gas futures perform well and in expansions, a good time for equities, the futures returns fall off. Thus, this futures contract may be used to diversify the systematic component of risk. The sign of the storage shocks, although not significant, is consistent with the results of Ates and Want (2007), who examine the inter-market dynamics for natural gas spot and futures price. When the announced storage inventory level is greater than the market expectation (supply is high), the price of natural gas futures will decrease. These results provide empirical evidence to support hypothesis 1, that market fundamentals partially influence natural gas futures prices.

Next, the results for the conditional variance of returns indicate that the volatility of natural gas futures prices depends on past futures market shocks (ARCH) and past futures returns volatility (GARCH). The positive coefficient of the square of the weather shock variable implies that a higher demand shock leads to greater volatility. Together with weather shocks, the significantly positive dummy variable for winter suggests strong seasonality of the conditional variance of natural gas futures returns. In the winter, a period of low inventory, the conditional variance is high. Thus, these results are consistent with the hypothesis that relatively higher conditional variance occurs in colder winters and in lower inventory periods. With regard to the volatility spillover effect, the non-significance of the conditional volatility of crude oil returns indicates that the volatility in natural gas futures is not significantly affected by the crude oil futures volatility. The significantly positive storage announcement day (SAD) and Monday (Mon) effects are in line with previous findings in the literature (Murry and Zhu (2004), Lin and Zhu (2004), which focus on the impact of information on futures volatility). As the price of natural gas is weather sensitive, the Monday effect indicates that individuals have time to process weather information over the weekend and may implement their trade decisions on Monday. Based on such trading behavior, the trading activity in natural gas futures tend to increase. As a result, the volatility is higher on Monday. Also, the significant storage announcement day effect reflects the importance of macro information upon volatilities. The release of storage information would generate volatilities of futures returns. The log likelihood, reported in the last rows of the three tables, is lowest when the exogenous variables are not included in the variance equation. When the exogenous variables are included, the log likelihoods increase. These results are consistent with hypothesis 2, which is that a causal relationship exists between market fundamentals and natural gas futures return volatilities.

To shed light on the existence of the Samuelson effect for conditional volatility, I obtained the estimated conditional variance for of returns for the three closest to maturity futures contracts and denote them as NCV1, NCV2 and NCV3, respectively (Figure 7). I find that the conditional variance of the return on the futures contracts increases when the time to delivery decreases, which is consistent with the Samuelson effect.

Figure 6. 1 Conditional volatility of returns on the three closest to maturity futures contracts



Chapter 7. Conclusion and Further Discussion

This paper quantifies the role of supply and demand fundamentals in order to determine the asset price dynamics in the US natural gas futures market. My results can be summarized as follows.

First, as predicted, weather shocks and inventory surprises have a negative impact on the conditional mean of natural gas futures returns, though the effects are not significant.

Second, crude oil futures prices influence natural gas futures prices based on the substitution effect.

Third, there are strong monthly seasonal variations in the conditional volatility of natural gas futures returns. The conditional volatility is higher in winter and lower in summer. This pattern is consistent with the implications of the theory of storage.

Fourth, I find that both storage announcements and the Monday effect have significant positive effects on the conditional variance of the natural gas futures returns.

Fifth, the increase in the explanatory power of ARMA-GARCH models with additional exogenous variables is consistent with the hypothesis that market fundamentals have an impact on the price and the volatility of the natural gas futures market.

In summary, the results for the natural gas futures contract provide clear support for the hypothesis that natural gas futures price dynamics are related to the variations in supply and demand conditions.

However, the model cannot explain the conditional mean very well. For the variable storage surprise, I use a seasonal ARIMA model to measure the market expectation of inventory level. The forecast power of the model decreases, which may lead to a bias in market expectations and hence decrease the explanatory power of storage surprises. While natural gas consumption displays a similar seasonal pattern with temperature, both consumption and temperature are related to storage levels. In future research, adding the consumption level and temperature into the model can be considered to improve the precision of inventory estimation.

Furthermore, to better understand the importance of market fundamentals, we could examine the impact of events, which occurred during period 2003-2012 such as the shits in Shale gas exploration, plummeting gas share from the Gulf of Mexico, which might have further influence on supply and demand conditions. Another extension could be addressing the effect of market fundamentals versus that of speculation on the sharp price changes of natural gas futures contracts.

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Appendix A.1

Table A.1 NG1 model selection

	AIC	SBC	LM	Q-stat	Adj. R-sq
GARCH(1,1)	-3.86439	-3.82701	8.71217***	2.78700*	0.07777
GARCH(1,2)	-4.16519	-4.12548	4.50771**	1.22430	0.07738
GARCH(2,1)	-4.15943	-4.11759	2.28805	1.32300	0.07728
ARMA(1,0)-GARCH(1,1)	-4.16107	-4.12134	5.70784**	0.51970	0.07872
ARMA(2,0)-GARCH(1,1)	-4.16039	-4.11832	5.13107**	2.34300	0.07808
ARMA(0,1)-GARCH(1,1)	-4.16008	-4.12037	4.17851**	0.51270	0.07875
ARMA(0,2)-GARCH(1,1)	-4.15932	-4.11727	4.25197**	2.35120	0.07816
ARMA(1,1)-GARCH(1,1)	-4.16035	-4.11829	5.54789**	2.06500	0.07832
ARMA(2,2)-GARCH(1,1)	-4.16158	-4.11483	6.82251***	4.91140**	0.07974
ARMA(1,2)-GARCH(1,1)	-4.16159	-4.11720	6.90118***	1.29480	0.08057
ARMA(2,1)-GARCH(1,1)	-4.16192	-4.11751	6.72386***	1.02400	0.08084
ARMA(1,0)-GARCH(1,2)	-4.16637	-4.12431	7.55757***	0.49420	0.07883
ARMA(2,0)-GARCH(1,2)	-4.16573	-4.12132	6.60000**	2.32840	0.07821
ARMA(0,1)-GARCH(1,2)	-4.16544	-4.12339	4.78670**	0.52700	0.07887
ARMA(0,2)-GARCH(1,2)	-4.16468	-4.12030	4.87381**	2.35520	0.07829
ARMA(1,1)-GARCH(1,2)	-4.16565	-4.12126	7.6221***	2.07950	0.07843
ARMA(2,2)-GARCH(1,2)	-4.16667	-4.11758	9.05587***	4.72750**	0.07982
ARMA(1,2)-GARCH(1,2)	-4.16480	-4.11807	6.42591**	1.94130	0.07776
ARMA(2,1)-GARCH(1,2)	-4.16702	-4.12028	9.49862***	0.86900	0.08094
ARMA(1,0)-GARCH(2,1)	-4.16066	-4.11860	3.79897*	0.42890	0.07872
ARMA(2,0)-GARCH(2,1)	-4.16001	-4.11560	3.30577*	2.25740	0.07807
ARMA(0,1)-GARCH(2,1)	-4.15963	-4.11972	2.51067	0.47850	0.07875
ARMA(0,2)-GARCH(2,1)	-4.15888	-4.11450	2.55803	2.27860	0.07815
ARMA(1,1)-GARCH(2,1)	-4.15995	-4.11555	3.84281*	1.97040	0.07831
ARMA(2,2)-GARCH(2,1)	-4.15871	-4.10962	5.03573**	6.38050**	0.07927
ARMA(1,2)-GARCH(2,1)	-4.15944	-4.11271	3.24848*	1.92000	0.07829
ARMA(2,1)-GARCH(2,1)	-4.16146	-4.11471	4.96782**	0.95240	0.08084
MA(0,5)-GARCH(1,1)	-4.15910	-4.11005	4.45867**	1.07180	0.08077
MA(0,5)- GARCH(1,2)	-4.16453	-4.11314	5.07436**	0.99700	0.08108
MA(0,5)-GARCH(2,1)	-4.15871	-4.10732	2.63761	1.00820	0.08077
ARMA(1,5)-GARCH(1,1)	-4.15941	-4.10800	5.95385**	2.88630*	0.08052
ARMA(1,5)-GARCH(1,2)	-4.16477	-4.11102	8.12806***	3.18280*	0.08082
ARMA(1,5)-GARCH(2,1)	-4.15932	-4.10558	5.48217**	7.09910***	0.07941

***, **,* denotes significant at 1%, 5%, 10% level respectively

Appendix A.2

Table A.2 NG2 model selection

	AIC	SBC	LM	Q-stat	Adj. R-sq
GARCH(1,1)	**-4.29754**	**-4.26017**	**0.62215**	**1.57460**	**0.08760**
GARCH(1,2)	**-4.30449**	**-4.25945**	**0.30548**	**1.54380**	**0.08765**
GARCH(2,1)	**-4.29016**	**-4.25045**	**0.0806**	**2.12660**	**0.08683**
ARMA(1,0)-GARCH(1,1)	**-4.29854**	**-4.25882**	**1.05064**	**0.31900**	**0.08970**
ARMA(2,0)-GARCH(1,1)	**-4.29798**	**-4.25591**	**1.04942**	**1.88080**	**0.08934**
ARMA(0,1)-GARCH(1,1)	**-4.29773**	**-4.25802**	**0.56191**	**0.38280**	**0.08970**
ARMA(0,2)-GARCH(1,1)	**-4.29693**	**-4.25488**	**0.56078**	**1.92450**	**0.08936**
ARMA(1,1)-GARCH(1,1)	**-4.29781**	**-4.25575**	**1.05298**	**2.02000**	**0.08924**
ARMA(2,2)-GARCH(1,1)	-4.29882	-4.25207	1.03332	4.26810***	0.09052
ARMA(1,2)-GARCH(1,1)	**-4.29701**	**-4.25261**	**1.04936**	**2.30690**	**0.08894**
ARMA(2,1)-GARCH(1,1)	**-4.29915**	**-4.25474**	**1.16590**	**1.61800**	**0.09167**
ARMA(1,0)-GARCH(1,2)	**-4.30557**	**-4.26351**	**0.69985**	**0.28830**	**0.08976**
ARMA(2,0)-GARCH(1,2)	**-4.305**	**-4.26059**	**0.55751**	**1.87340**	**0.08931**
ARMA(0,1)-GARCH(1,2)	**-4.30471**	**-4.26267**	**0.27930**	**0.34330**	**0.08976**
ARMA(0,2)-GARCH(1,2)	**-4.30391**	**-4.25953**	**0.28103**	**1.92120**	**0.08934**
ARMA(1,1)-GARCH(1,2)	**-4.30521**	**-4.26081**	**0.63175**	**2.37340**	**0.08803**
ARMA(2,2)-GARCH(1,2)	-4.3077	-4.25862	0.43693	8.92640***	0.08848
ARMA(1,2)-GARCH(1,2)	**-4.30404**	**-4.25731**	**0.70745**	**2.24920**	**0.08892**
ARMA(2,1)-GARCH(1,2)	**-4.30619**	**-4.26478**	**0.90784**	**2.39450**	**0.09179**
ARMA(1,0)-GARCH(2,1)	**-4.29236**	**-4.2503**	**0.09424**	**0.42210**	**0.08917**
ARMA(2,0)-GARCH(2,1)	**-4.29105**	**-4.24664**	**0.11225**	**2.25370**	**0.08883**
ARMA(0,1)-GARCH(2,1)	**-4.29066**	**-4.24861**	**0.06304**	**0.43980**	**0.08894**
ARMA(0,2)-GARCH(2,1)	**-4.28992**	**-4.24554**	**0.06351**	**1.99910**	**0.08869**
ARMA(1,1)-GARCH(2,1)	**-4.29091**	**-4.24652**	**0.09552**	**2.02420**	**0.08789**
ARMA(2,2)-GARCH(2,1)	-4.2907	-4.24161	0.05436	9.08450***	0.08762
ARMA(1,2)-GARCH(2,1)	**-4.29034**	**-4.24361**	**0.08146**	**1.92950**	**0.08745**
ARMA(2,1)-GARCH(2,1)	-4.29038	-4.24364	0.06592	2.90730*	0.08832
MA(0,5)-GARCH(1,1)	**-4.29736**	**-4.2483**	**0.78598**	**0.45410**	**0.09179**
MA(0,5)- GARCH(1,2)	**-4.30431**	**-4.25292**	**0.43196**	**0.60500**	**0.09173**
MA(0,5)-GARCH(2,1)	**-4.29029**	**-4.2389**	**0.10101**	**2.51460**	**0.09035**
ARMA(1,5)-GARCH(1,1)	**-4.29753**	**-4.24612**	**1.37263**	**1.39720**	**0.09154**
ARMA(1,5)-GARCH(1,2)	**-4.30452**	**-4.25078**	**0.94805**	**1.75380**	**0.09148**
ARMA(1,5)-GARCH(2,1)	-4.2906	-4.23686	0.11328	4.39201**	0.09019

ARMA(5,0)-GARCH(1,1)	**-4.29884**	**-4.2497**	**1.48534**	**0.46870**	**0.09188**
ARMA(5,0)- GARCH(1,2)	**-4.30576**	**-4.25429**	**1.07801**	**0.52900**	**0.09188**
ARMA(5,0)-GARCH(2,1)	**-4.29178**	**-4.24031**	**0.12114**	**1.62030**	**0.09071**
ARMA(3,1)-GARCH(1,1)	-4.29852	-4.25176	1.23639	4.84810**	0.08973
ARMA(3,1)- GARCH(1,2)	-4.30564	-4.25654	0.86452	4.79380**	0.08967
ARMA(3,1)-GARCH(2,1)	-4.29097	-4.24187	0.64327	5.76260**	0.08869

***, **,* denotes significant at 1%, 5%, 10% level respectively

Appendix A.3

Table A.3 NG3 model selection

	AIC	SBC	LM	Q-stat	Adj. R-sq
GARCH(1,1)	-4.48676	-4.44705	3.31014*	0.25920	0.09403
GARCH(1,2)	**-4.49542**	**-4.45338**	**1.98027**	**0.18110**	**0.09415**
GARCH(2,1)	**-4.48148**	**-4.43944**	**0.58308**	**0.20560**	**0.09406**
MA(0,5)-GARCH(1,1)	-4.48665	-4.43526	3.81863*	0.70440	0.09683
MA(0,5)- GARCH(1,2)	**-4.49527**	**-4.44155**	**2.41289**	**0.85400**	**0.09707**
MA(0,5)-GARCH(2,1)	**-4.48156**	**-4.42783**	**0.78387**	**2.52320**	**0.09695**
ARMA(5,0)-GARCH(1,1)	-4.48725	-4.43577	5.02973**	0.40290	0.09703
ARMA(5,0)- GARCH(1,2)	-4.49565	-4.44183	3.59486*	0.56210	0.09731
ARMA(5,0)-GARCH(2,1)	**-4.4841**	**-4.43029**	**0.82237**	**1.76700**	**0.09716**
ARMA(1,3)-GARCH(1,1)	-4.48615	-4.43709	4.53685**	4.30770**	0.09429
ARMA(1,3)- GARCH(1,2)	-4.49458	-4.44318	3.11158*	4.43910**	0.09446
ARMA(1,3)-GARCH(2,1)	-4.48106	-4.42965	0.73003	8.64350***	0.09419
ARMA(1,0)-GARCH(1,1)	-4.48629	-4.44423	4.41861**	0.42340	0.09418
ARMA(2,0)-GARCH(1,1)	-4.48595	-4.44154	4.40978**	4.10830*	0.09381
ARMA(0,1)-GARCH(1,1)	-4.48621	-4.44416	3.23830*	0.52570	0.09422
ARMA(0,2)-GARCH(1,1)	-4.48541	-4.44103	3.24300*	4.11730*	0.09399
ARMA(1,1)-GARCH(1,1)	-4.48671	-4.44231	4.47194**	3.94810**	0.09359
ARMA(2,2)-GARCH(1,1)	-4.48502	-4.43594	4.29767**	10.33300***	0.09307
ARMA(1,2)-GARCH(1,1)	-4.48597	-4.43924	4.47176**	4.10520*	0.09287
ARMA(2,1)-GARCH(1,1)	-4.48727	-4.44052	4.65660**	2.47680	0.09698
ARMA(1,0)-GARCH(1,2)	-4.49487	-4.45047	3.04488*	0.52490	0.09437
ARMA(2,0)-GARCH(1,2)	-4.49464	-4.44789	3.00244*	4.28790**	0.09400
ARMA(0,1)-GARCH(1,2)	**-4.49492**	**-4.45054**	**1.98606**	**0.61960**	**0.09439**
ARMA(0,2)-GARCH(1,2)	-4.49413	-4.44741	1.99016	4.32420**	0.09416

ARMA(1,1)-GARCH(1,2)	-4.49529	-4.44855	3.11911*	4.22400**	0.09370
ARMA(2,2)-GARCH(1,2)	-4.49743	-4.44601	2.43013	4.76960**	0.09891
ARMA(1,2)-GARCH(1,2)	-4.49451	-4.44544	3.10364*	4.29680**	0.09312
ARMA(2,1)-GARCH(1,2)	-4.49593	-4.44685	3.22009*	2.58010	0.09716
ARMA(1,0)-GARCH(2,1)	**-4.48217**	**-4.43778**	**0.60235**	**0.48950**	**0.09404**
ARMA(2,0)-GARCH(2,1)	-4.48119	-4.43444	0.60766	4.89560**	0.09375
ARMA(0,1)-GARCH(2,1)	**-4.48082**	**-4.43644**	**0.62083**	**0.44980**	**0.09413**
ARMA(0,2)-GARCH(2,1)	-4.48003	-4.43332	0.62241	4.63560**	0.09397
ARMA(1,1)-GARCH(2,1)	-4.48297	-4.43624	0.59525	5.47960***	0.09368
ARMA(2,2)-GARCH(2,1)	-4.48014	-4.42872	0.64543	11.21300***	0.09265
ARMA(1,2)-GARCH(2,1)	-4.48132	-4.43225	0.64914	4.32330**	0.09305
ARMA(2,1)-GARCH(2,1)	-4.48094	-4.43186	0.64441	4.33600**	0.09299

***, **,* denotes significant at 1%, 5%, 10% level respectively